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Developing A Bayesian Belief Network to Assess Collision Risks for Connected and Autonomous Vehicles in Urban Environments: A Socio-Technical Synthesis

by

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Abstract

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Intelligent Transportation Systems (ITS) with the aim of enhancing mobility and sustainability are gaining momentum across public policy sector. Connected and Autonomous Vehicles (CAVs) constitute an integral element of ITS. The rapid advances in the realm of Artificial Intelligence (AI) and relevant disciplines have accelerated the development and evolution of CAVs which are believed to thoroughly transform the transportation landscape in coming decades or even years. There are manifold potential benefits (e.g., increased safety and accessibility, convenience, saving time and energy, reducing traffic congestion, etc.) perceived for this disruptive technology. Nevertheless, there is a considerable extent of uncertainties over the safe and secure performance of intelligent self-driving cars in urban environments. These uncertainties can deteriorate the existing driving risks and incur new risks which can undermine the functional safety and technical reliability of those vehicles.

The interdependencies between risk factors have neither been yet studied within an integrative framework nor from the sociotechnical perspective. In this study, an interdisciplinary approach was adopted to construct a Bayesian Belief Network (BBN) in order to capture influential risk factors in urban settings as well as the interdependencies between them, thereby providing estimates for the risk indices under varying and volatile circumstances. This will enable us to estimate the collision risk for intelligent self-driving cars in urban environments and evaluate the impact of risk mitigation actions. Furthermore, such a model can be used to classify the urban districts based on the estimated risks and serve policymakers in allocating resources to maximise the benefits of CAVs and avoid potential safety consequences.

Sociotechnical theory as an interdisciplinary approach was adopted to form the foundation of BBN model. The factors were accordingly divided into four blocks and the intersection of these blocks represent collision risk index to quantify the safety risk in urban environments. To identify the risk factors, integrative literature review together with thematic analysis (TA) were used. A new technique was formulated to populate the node probability tables (NPTs) and generate uniform distributions. Afterwards, nine domain experts assigned weights to the identified links between the nodes and influence of the probability distributions. Sensitivity analysis was conducted to examine the influence of the incorporated nodes on the collision risk index. The outcome of the model (i.e., collision risk index) showed the highest sensitivity to traffic control infrastructure, weather conditions and traffic composition, respectively. Six scenarios were also devised to investigate the fluctuations of collision risk index due to variations in input nodes. The results of this research can provide insights for policymakers in contemplating policy choices such as investing in new or upgrading existing infrastructure, introducing new legislations, imposing regulatory requirements, licensing, and technology standardisation.

Table of Contents

Table of Tables

Table of Figures

Research Thesis: Declaration of Authorship

Print name: Seyed Mohammad Hossein Toliyat

Title of thesis: Developing A Bayesian Belief Network to Assess Collision Risks for Connected and Autonomous Vehicles in Urban Environments: A Socio-Technical Synthesis

I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

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Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;

Where I have consulted the published work of others, this is always clearly attributed;

Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;

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Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;

None of this work has been published before submission.

Date: 15/04/2022

To the soul of my father

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Abbreviations

AD	Autonomous driving
ADAS	Advanced driving assistant systems
AI	Artificial intelligence
ALFUS	Autonomy levels for unmanned systems
ALV	Autonomous land vehicle
ANN	Artificial neural network
ASIL	Automotive Safety Integrity Level
AUV	Autonomous underwater vehicle
AV	Autonomous vehicle
BNN	Bayesian belief network
CAV	Connected and autonomous vehicle
CPT	Conditional probability table
DARPA	Defence Advanced Research Project Agency
DBN	Dynamic Bayesian network
DfT	Department for Transport (UK)
DoS	Denial of Service
DoT	Department of Transport (US)
FMEA	Failure Modes and Effect Analysis
FTA	Fault tree analysis
GHG	Greenhouse gas
GPS	Global positioning system
HAZOP	Hazard and operability analysis
HAC	Human autonomy collaboration
HDV	Human driven vehicle
HMI	Human-machine interaction
HOF	Human and organisational factors
ID	Influence diagram
ILR	Integrative literature review
ITS	Intelligent transport system
JPD	Joint probability distribution
KPI	Key performance indicator
ML	Machine learning
NHTSA	National Highway Traffic Safety Administration

NPT	Node probability table
NUIC	No user-in-charge
OEM	Original equipment manufacturer
PDF	Probability density function
PRA	Probabilistic risk analysis
RSU	Roadside unit
SAV	Semi-autonomous vehicle
SD	System dynamics
SEM	Structural equation modelling
SITR	Systems Integration Technical Risks
SoS	System of systems
SoTeRiA	Socio-Technical Risk Analysis
STPA	System-Theoretic Process Analysis
TNC	Transportation Network Company
TTC	Time to collision
TTE	Time to escape
UAS	Unmanned autonomous systems
UAV	Unmanned aerial vehicle
V2I	Vehicle to infrastructure
V2V	Vehicle to vehicle
V2X	Vehicle to everything

Chapter 1

1. Introduction

The following chapter provides a background and highlights the motivations for the present study. To justify the relevance and importance of studying safety risks in the context of autonomous driving, the recent trends and progressions in evolution of autonomous vehicles (AVs) are reviewed. The uncertainties over disruptive technologies are reflected and an overall structure for vehicles with self-driving feature is sketched out. The criticality of scrutinising collision risk in urban areas as a major operating environment for AVs is discussed. The research objectives are stated and finally the chapter closes with conclusions and providing a lay out for the rest of the thesis.

1.1. The advent of Autonomous Vehicles and new challenges

The ever-expanding interest in developing and deploying autonomous systems together with the recent technological breakthroughs, particularly in computer sciences, has led to tremendous evolution of these systems (Bosch and Olsson, 2016). Driverless (or self-driving) cars, as a prime example of an autonomous system, have recently become one of the research focal points in both industry and academia (Gruel and Stanford, 2016). With the realisation of novel and disruptive technologies in the disciplines which make a direct contribution to the evolvement of AVs, this concept is not anymore a science fiction at least from technical and technological perspectives. Nevertheless, devising complex, disruptive and safety-critical technologies involves inherent and deep uncertainties over technological feasibility and reliability, commercial viability, organisational capability and social acceptability (Hall and Martin, 2005). These uncertainties—especially when are evaluated to be grave—can pose serious risks to securing the pre-defined objectives and expected benefits of the intended technology. Severe consequences of some risks associated with cutting-edge technologies emphasise the necessity of identifying and evaluating those risks as precisely and swiftly as possible. In spite of significant advancements in computing capabilities and development of tools to forecast the future, it is still a demanding task to predict the overall outcomes and impacts of such technologies on humans, environment and economy. This is, partially, due to the presence of uncertainties arising from diverse sources.

Conducting rigorous uncertainty and risk analysis, therefore, is indispensable and determinant to guarantee the promised returns and optimise the likelihood and/or the severity of drawbacks before fully and broadly operationalising the technology. Fatal accidents (Katrakazas, Quddus and Chen, 2019), statistics of disengagements, lack of sophisticated and clear regulations, accelerated pace of development and the potentiality of 'black swans' and 'perfect storms' (Paté-Cornell, 2012), all signal the urgency for conducting in-depth uncertainty and risk analysis before replacing current human-driven vehicles with AVs on the road.

According to our research and literature review, there has not been a general and multidisciplinary/interdisciplinary classification of risk factors/variables which impinge on the safety and reliability of driverless (i.e. fully autonomous) cars in urban environments where dynamism is relatively high. So far, the key factors influencing trust in self-driving cars (Carlson *et al.*, 2014; Kaur and Rampersad, 2018), Advanced Driver Assistance Systems (ADAS) risk factors (Sheehan *et al.*, 2017), cyber risks for connected and autonomous vehicles (Petit and Shladover, 2014; Parkinson *et al.*, 2017; Sheehan *et al.*, 2019), collision avoidance risk assessment (Fahmy, El Ghany and Baumann, 2018; Yu, Vasudevan and Johnson-Roberson, 2019), and trajectory risk analysis for surrounding vehicles and objects (Katrakazas, Quddus and Chen, 2019) were explored. Considerable scholarly literature has been published to cover safety and reliability risks of other divisions of AVs such as autonomous underwater vehicles (AUV) (Brito, Griffiths and Challenor, 2010; Brito and Griffiths, 2016) and unmanned aerial vehicles (UAV) (Zhang *et al.*, 2018; Allouch *et al.*, 2019). Nonetheless, the gap has not been fully addressed yet and a computational and predictive model is imperative to provide a reliable quantitative estimation of risks attached to the operation of AVs in any given circumstances.

A generic and multidisciplinary risk model involving a wider range of variables can assist decision makers and inform their decisions before adopting the technology. Further, in order to be able to quantify the risks, ascertaining the interdependencies between these variables is vital. To this end, Bayesian Belief Network (BBN) technique as an advanced and updatable means (Chen and Lin, 2019) is adopted in this study to model the interdependencies between the identified risk factors (variables) and produce estimates for those risks and evaluate the impact of policies and risk mitigation measures. Fundamental theories underpinning the model are socio-technical theory (Rasmussen, 1997), and Socio-Technical Risk Analysis (SoTeRiA) framework (Mohaghegh, Kazemi and Mosleh, 2009; Mohaghegh and Mosleh, 2009). Influential (risk) factors are subsequently divided into four main blocks: technical, environmental, traffic and human factors. To address the gaps and define the scope of research, five key research questions are formulated.

The research questions are as follows:

I. What are influential factors/variables which affect the reliability and collision risks associated with highly autonomous vehicles in urban settings?
II. What are the interdependencies (relationships) between the identified factors/variables?
III. What would be the quantity of collision risk for given road and traffic conditions?
IV. How the overall collision risk is sensitive to the identified factors/variables?
V. What active policies can be adopted to mitigate the collision risks in urban environments after the rollout of CAVs?

In order to find the answer of the first question, an integrative literature review (ILR) and thematic analysis framework are designed to pinpoint the factors/variables that have impact on the risks of AVs in the urban environments. ILR is also recommended for exploring future policies in a topic (Torraco, 2016). The detailed steps and criteria for conducting ILR are

The BBN modelling technique is employed to address the rest of questions. The BBN tool has been extensively used to measure and model risk problems in a tremendous variety of disciplines. The primary data for constructing the model is collected from the relevant literature through conducting integrative literature review in two platforms (databases): Web of Science and DelphiS. For the probability distributions of the nodes (variables in the model), a combination of a new quantitative method and a survey was used to elicit and incorporate the knowledge and expertise of field experts. The quantitative methods will be defined in detail in sections 3.8.2 and 3.8.3.

Table 1.1 summarises the contributions to the related disciplines after the above research questions are addressed. The applied research methods and techniques for answering each of those questions are mentioned too. The major contributions of this research are identification of risk factors for CAVs while operating in urban settings, the BBN model as a risk classification tool and policy recommendations. It is noteworthy that the risk identification through ILR is based on the state-of-the-art technologies, recent literature (between 2010 and 2021) and a few fatal accidents involving CAVs. As a consequence, some of the risk factors or variables may become redundant soon should we witness any breakthroughs in enabling technologies or infrastructure.

Table 1.1: major contributions, research methods and relevant research areas.

Question	Contribution after answering the research question	Methods	Disciplines
I	Providing a quantification means for the collision risk of a highly autonomous car (SAE level 4) in dynamic urban environments.	ILR, TA & BBN	Transportation Safety ITS Autonomous vehicles Uncertainty modelling
II	Weighing the strength of relationship (link) between the variables in the model through expert judgement elicitation allows to inform the model with assigning weights to the links.	Surveying domain experts & BBN	Human factors in accidents Applied artificial intelligence Urban traffic planning Environmental factors in robotics
III	Providing a decision-making tool for the key stakeholders of the technology for conducting preliminary risk analyses and classifying urban districts according to the collision risk levels for different types and models of CAVs.	Scenario analysis & BBN	Urban design Traffic law CAV regulatory
IV	Sensitivity risk analysis can also assist decision makers to split and distribute the remaining uncertainty in the output of the model to different sources of uncertainty in the model's input.	Sensitivity analysis & BBN	System Safety Risk Analysis Conditional probability
V	Recommending a set of policies based on the results of scenario and sensitivity analyses and literature to mitigate the collision risk for CAVs.	Scenario and Sensitivity analyses & BBN	ITS Autonomous vehicles Transportation policymaking

In the rest of this chapter, the motivations, history and important milestones in the evolution of driverless cars, safety risks and uncertainties surrounding this technology while operating in urban areas, and research objectives are discussed. The literature review and methodological frameworks to address the research questions are presented in chapters two and three respectively. In chapter four, the results and analysis are provided. Chapter five contains policy implications and discussions around the cruciality of accurately defining and classifying autonomy levels in safety considerations. Finally, chapter six includes a summary of main findings and contribution, closing remarks, and future research directions.

1.2. Motivations for delving into collision risks of CAVs

A few fatal car crashes involving self-driving cars have raised reasonable doubts about the reliability of autonomous driving technology. The first fatal crash with the Tesla self-driving car (while it was on autopilot mode) occurred in Florida, in July 2016 (Kohl *et al.*, 2018). On 18th of March 2018 an Uber self-driving car hit a 49-year-old woman and took her life when she was crossing the road in Arizona, US (the Guardian, 2018; Lisinska and

Kleinman, 2021). Just a few days later, another Tesla car during the time that its autopilot mode was active crashed into the roadside barrier in California and the driver died shortly after the accident (BBC, 2018). In December 2021 the largest Paris taxi firm suspended its Tesla model 3 fleet (which offer self-driving features) after one of them was involved in a road crash leaving one dead, three in critical conditions and over a dozen injured (BBC, 2021; the Guardian, 2021).

In addition to the above incidents, the reported disengagement statistics for AVs on US roads can also sound the alarm for risk analysts. The number of disengagements, on average, varies from nearly 1.1 per 1000 miles for Google to 980 for Mercedes-Benz between September 2014 to November 2015 (Dixit, Chand and Nair, 2016). There are two main groups of disengagements: automatic (passive) and manual (active) (Lv *et al.*, 2017). Automatic disengagements occur when the system recognises a failure or foresees a potential failure under autonomous driving (AD) conditions. On the other hand, manual disengagements refers to a state where the driver suspects a precarious situation in response to other road users, due to discomfort with the autonomous mode, adverse weather conditions, construction activities, poor road infrastructure, et cetera (Dixit, Chand and Nair, 2016). Hence, from exploring these incidents and proportion of them to the small number of operational AVs we can conclude that the AV technology can pose serious risks which must be addressed before this technology becomes ubiquitous.

As the technology matures, AVs are expected to be deployed in the same environments as manned vehicles, and this can raise problems (Vellinga, 2017). One of the main challenges for AVs on public roads is the dynamic nature of urban environments and presence of other moving road users which increases the risk of collision. Lipson and Kurman (2016) pointed out that "*while it's possible to set up a tidy closed-world environment in a factory setting, in the real world, streets and highways are chaotic and unpredictable*". Dealing with interactions that are guided by rules of conduct which can be either *vague* or highly *situation-specific* can profoundly challenge the software (Lipson and Kurman, 2016). Recent research has shown that environmental complexity is a key indicator of performance for mobile robot systems, but there are currently no agreed and satisfactory metrics to assess the performance of a robotic system in a complex and dynamic environment and define operational domains for a robot, particularly environmental complexity (Young, Mazzuchi and Sarkani, 2017). This lack of satisfactory metrics can imply how environmental complexity is challenging and complicating for AVs.

The amount of (real) data that an AV receives from different sources is ample. Recognising other vehicles and pedestrians, road signs and signals, traffic lanes and static/dynamic obstacles need extensive, precise and agile data processing capabilities. Some researchers assert that it is demanding for the vehicle (i.e. its software) to discern all the surrounding in urban settings (Abduljabbar *et al.*, 2019). Tackling other software challenges such as security and integrity of the system is a critical consideration in software architecture for AVs especially in the absence of consistent standards and detailed regulations. Ground vehicles are approximately two-ton metal boxes that commute on public roads and if any fault or glitch with the software system (e.g. path planning, navigation and actuator controllers) might result in a major and even tragic accident (Lipson and Kurman, 2016).

If AVs successfully evolve to be as competent and skilled as human drivers, we can expect a massive reduction in fatal accidents. This is because drunk-driving, distraction and fatigue (drowsiness) as the major causes of fatal accidents (cumulative of 53.5 percent) in the US will not apply to AVs (Kalra and Paddock, 2016). They may also be even safer due to higher precision in perceiving the surrounding and executing driving tasks. However, there are inherent safety risks which may be worse than the risks of manned vehicles (Manzur Tirado, Brown and Valdez Banda, 2019). We must be aware about the differences between human and AI decisionality (i.e., decision-making capacity) and that the artificial driving intelligence will fall short of certain decisional capacities at some point (Cunneen, Mullins and Murphy, 2019). The significant challenge with machine learning (ML) techniques is that they are more based on inductive training and reasoning approaches which are inherently difficult to be validated (Koopman and Wagner, 2017). Moreover, CAVs may not be able to eliminate all accidents immediately after they are launched. Factors such as inclement weather, complex driving environments and cybersecurity threats (for connected vehicles) still need to be addressed (Kalra and Paddock, 2016).

Having discussed earlier, lack of accurate, case-specific and reliable data is a major source of (epistemic) uncertainty in predicting the behaviour of the AV technology. To provide a few examples, lack of formal measures of the impact of spatially-extended characteristics on the network outputs (Kim and Canny, 2017) and restricted or absolute lack of exposure to various traffic scenarios (Schoettle and Sivak, 2015) were reported as the limitations of those research projects about autonomous driving. Lack of enough and effective test and evaluation (T&E) of AVs also add to the safety implications (Li *et al.*, 2016). Infeasibility of complete testing (requiring one billion operating hours or more) (Koopman and Wagner, 2016), complexity of the software autonomous features (Kim *et al.*, 2016; Mullins, Stankiewicz and Gupta, 2017) and high costs (Tao *et al.*, 2019) are among the main challenges in testing autonomous vehicles. More importantly, ambiguities about the regulations and regulatory bodies deepen the safety implications of public autonomous driving as the technology is still in its infancy.

Although the keyword 'risk' is one of the predominant themes in the AV literature, there has not been an integrative risk model yet developed to depict the main influential factors and analyse the interdependencies between them. In this research a risk assessment model encompassing environmental, human, traffic and technical variables is developed to evaluate the performance of AVs in urban environments from the perspective of uncertainty and risk. This model can be seen as a generic model which can be applied for various types of AVs, environmental and traffic conditions to estimate the collision risks based on the characteristics of the environment, human driver, traffic scene and technical reliability of the vehicle.

1.3. History of driverless (self-driving) cars

Almost a century ago, the ideas of substituting errant human drivers with technology started to emerge (Maurer *et al.*, 2016). Thanks to the technological advancements in aviation and radio engineering first *remote-controlled* vehicle was unveiled in the US, on 5th of August, 1921 (Maurer *et al.*, 2016; Kellerman, 2018). However, with current definitions of self-driving vehicles, that invention is seen to be neither self-driving nor driverless as the driver (or navigator) was just outside the vehicle. About two decades later, in 1939, General Motors exhibited a creative conception and vision of the then-distant future technological innovations mainly in the realm of transportation (Auer *et al.*, 2016). One of the thrilling showcases at the 1939 World's Fair in New York was the GM's "*Futurama: Highways & Horizons*" which introduced one of the contemporaneous concepts of driverless cars to the fairgoers (Lipson and Kurman, 2016). Although the main emphasis of Futurama was placed on automated highways and vehicles, the driver was still required to take the controls and carry out instructions which were going to be issued by "experts" and transmitted to the driver via radio (Maurer *et al.*, 2016, p.49). The reliance on the driver to decide on or perform driving tasks, kept these concepts and developments under the category of *radio-controlled* rather than driverless vehicles.

The second half of the 20th century witnessed new endeavours to realise automated driving. Massive investments in the military sector during the World War II resulted in the development of technologies such as computers, laser, radar, magnet detectors and guide-wire principle. After the war, some of these technologies were crossed into civil industries including car manufacturing and even play a critical role in the design of today's driverless cars (Clark, Parkhurst and Ricci, 2016; Lipson and Kurman, 2016, p.118). Media also played its role as in 1953 George Gibson put forward the idea of *crash-proof highways* and development of cars equipped with *automatic pilots* in the Mechanix Illustrated magazine. One of the clearest depictions of automated driving appeared in an advertisement which was published in LIFE Magazine, in 1956 (Maurer *et al.*, 2016). This was followed by a TV programme that was broadcasted by Disney in 1958. ‘Magic Highway U.S.A.’ tried to present an imaginary picture of the future transportation where punch cards could be used to code a destination into an automated vehicle guided by coloured highway lanes (Anderson *et al.*, 2014; Lipson and Kurman, 2016, p.121).

Apart from the futurists who had envisaged vehicles driving themselves without any human interventions, the actual prototypes of driverless cars came into view from robotics labs in the 1980s and 1990s (Lipson and Kurman, 2016, p.155). For instance, the DARPA Autonomous Land Vehicle (ALV) was assembled on an all-terrain platform with an array of sensors ranging from video cameras to laser detectors. The vehicle enclosed six computer racks programmed with algorithms and receiving images from a camera situated on the rooftop of the vehicle to steer safely along the path without need for human assistance. The ALV testing started in 1985 at a speed of three km/h over a one-kilometre straight route. Over the following two years, the ALV was upgraded to complete longer courses at faster speeds with varying turns and pavement types, while circumventing obstacles (Auer *et al.*, 2016). Other attempts were also made by the German autonomous vehicle pioneer Ernst Dickmanns who created several prototypes of robot cars that benefitted from probabilistic approaches and parallel computers to drive themselves (Vishnevsky and Kozyrev, 2016). Simultaneously, in Italy, Professor Alberto Broggi built a vehicle that exploited machine vision software to recognise and follow coloured lane markers (Lipson and Kurman, 2016). Developing and incorporating Advanced Driver Assistance Systems (ADAS) into cars was another step towards solving urban traffic problems through automation. Several European car manufacturers and research centres invested in multiple projects under the Prometheus research programme (initiated in 1986) to provide *intelligent driver support systems* for individual drivers (Brookhuis, De Waard and Janssen, 2019). Well-known examples of ADAS technologies are Adaptive Cruise Control (ACC), Anti-lock Braking System, Automatic Parking, Blind Spot Monitor and Lane Departure Warning System. As these technologies take over driving tasks from human driver, they are believed to increase the safety of roads. In contrast, a group of scholars including Lipson and Kurman (2016) do not support the staged transition for Autonomous Driving technology to evolve out of ADAS because of excessive risks.

The beginning of the 21st century coincided with the launch of competitions which is seen as a landmark in the evolution of modern driverless cars. For the first time, in 2004, DARPA sponsored a competition titled ‘Grand Challenge’ which was designed for field vehicles to autonomously (without any driver on board) complete a 150-mile course in Mojave Desert, California (Spenko, Buerger and Iagnemma, 2018). None of the 15 participants in the race could reach the final line and the best performer only travelled five percent of the planned route (Buehler, Iagnemma and Singh, 2007). The next round was held in Nevada desert in the following year where the race was shortened to 132 miles and five vehicles succeeded to cross the end line (Broggi *et al.*, 2010). This challenge was followed in 2007 (DARPA Urban Challenge), but this time requiring autonomous vehicles to compete in a simulated dynamic environment and interact with other vehicles, traffic signals and pedestrians (Spenko, Buerger and Iagnemma, 2018). The improved performance and number of vehicles that successfully managed to traverse the designed route under more dynamic and uncertain circumstances signalled that the attainment of autonomous driving is not far away from reality. The prominent presence of universities and scientific institutions rather than top leading auto and vehicle manufacturers was the peculiarity of these challenges. This point can reflect the significance of software programming against hardware sophistication in developing self-driving cars.

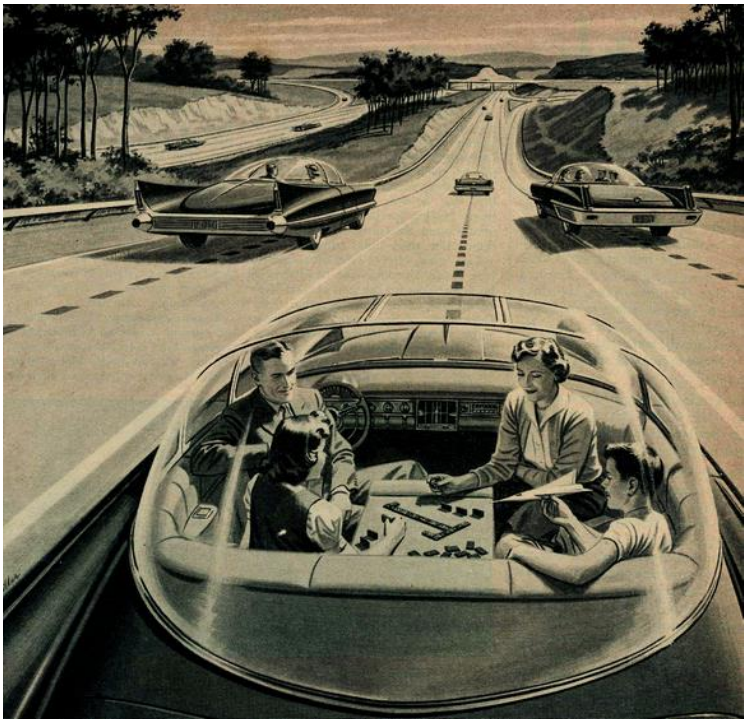


Fig. 1.1: a 20th century concept of driverless cars. LIFE Magazine, January 1956, p. 8. Adopted from Maurer et al. (2016, p.51).

It did not take long after the DARPA competitions that many IT corporations, major car manufacturing companies, research institutes and Transportation Network Companies (TNCs) set up to unveil their prototypes in testing sites and even on public streets. Google, as a known example, was one of the groundbreakers which joined the race and hired researchers form the teams who had been engaged in DARPA Challenges to develop its own driverless car (Clark, Parkhurst and Ricci, 2016; Meyer and Shaheen, 2017; Vanderbilt, 2018). Despite its different field of operation, Google has made notable progressions in developing and testing driverless cars and finally in 2010 announced that the prototype of a self-driving car (today known as Waymo) was completed (Poczter and Jankovic, 2014). Figure 1.2 depicts three types of Waymo self-driving vehicles. Commercialisation plans have been also announced by car vendors including but not limited to Mercedes Benz, Tesla, Toyota, Audi, BMW, Volvo, Ford, Jaguar, Land Rover, Nissan/Renault, and GM (Dimitrakopoulos and Bravos, 2017).

In September 2016, a headline from the Daily Telegraph reviled that Uber had planned to deploy a fleet of self-driving cars in Pittsburgh to lift its passengers. Although the service was claimed to be self-driving, there were two crew members on board: a safety driver and an engineer who was in charge of monitoring the performance of the vehicle (Wolmar, 2018). In addition to TNCs, there have been many other companies emerging or expanding in the past decade alone in the UK to design and provide test beds (e.g., HORIBA MIRA, RACE), develop software and self-driving technologies (e.g., Wayve), and offer consultancy (e.g., TRL, Zenzic).

Many technology firms and car manufacturers (including those mentioned above) have recently pursued joint ventures to merge their resources, technologies, know-hows and expertise into a vehicle which would be capable of safely driving itself and performing all driving tasks without any direct human assistance. The co-operation between Daimler AG and BMW Group to develop innovative automated driving (Tobin, 2019), the £5.57 billion Argo AI joint project undertaken by Ford and Volkswagen (Tobin, 2019), the Autolive Inc. and Volvo's Zenuity (Walz, 2017), and the £3.1 billion agreement signed by Hyundai Motor Group and Aptive Plc. in October 2019 (Park and Trudell, 2019), are just a few to name. Several similar ventures have been formed in like manner to secure a share for the investors and developers in any potential future market for self-driving cars. More recently, start-ups like Zoox (now subsidiary of Amazon) and Aurora are looking beyond just AVs and are developing concepts and prototypes to blend AVs with electric vehicles (EVs), robo-taxis, and logistics. We will discuss the future prospects of autonomous driving in section 2.1.3.

The share of universities and research institutes in the evolution of CAVs did not remain confined to DARPA competitions. Several universities including Carnegie Mellon University, Stanford University, University of Michigan and Massachusetts Institute of Technology are influencing and accelerating the development of CAVs technologies (Salter, 2021). In the UK, Oxbotica was founded by two professors at the University of Oxford in 2014 and has now become a leading innovator in CAV industry (Hopkins and Schwanen, 2018).

Fig. 1.2: three generations of Waymo self-driving car. Adopted form Vanderbilt (2018).

1.4. Uncertainties over disruptive technologies

Historians of media and technology have reported that an emerging technology is often a field onto which a wide range of hopes and worries are expressed (Natale and Ballatore, 2017). Innovation, by its nature is about dealing with *unknowns* and involves various degrees of *uncertainty* (Tidd and Bessant, 2014). Teece, Peteraf and Leih (2016) also assert that deep uncertainty is a prominent feature of connected interdependent economies confronting fast technological transitions. Uncertainties revolve mainly around the impacts of innovation, whether the technology will perform as expected, what will be the behaviour of market and probable changes may be introduced by the governments to regulations (Tidd and Bessant, 2014). Meanwhile, the degree of uncertainty is subject to steep increase as long as the global economy is becoming more interdependent and complex (Teece, Peteraf and Leih, 2016). Under such circumstances where there are incomplete facts and figures available to decision makers, and they feel themselves under pressure to announce a decision within time constraints, *heuristics* and *biases* are deemed to give rise to systematic error (Gilovich, Griffin and Kahneman, 2002). Much influential work has been done to avoid *systematic human cognitive biases*, but this is not to ignore the inevitability of subjectivity in expert knowledge elicitation.

Even allowing for the fact that innovation and disruptive technologies can offer tremendous competitive advantages to a business or strengthen its existing core competence, managing innovation is inherently challenged by some level of uncertainty (Tidd, Bessant and Pavitt, 2005; Gluckman, 2016). *Perceived technological uncertainty*, in scholarly literature refers to inability of an individual to comprehend all or some aspects of technological environment (Song and Montoya-Weiss, 2001). Most new technologies do not reach the stage of turning into commercial products or services, and a large number of those which pass through that stage do not achieve commercial success for developers (Walsh, 2004; Tidd, Bessant and Pavitt, 2005). Neglecting the trends of disruptive technologies, however, can lead to further consequences in terms of losing market share to pioneers of innovative technologies which currently seem to be inferior (Tellis, 2006). Thus, conducting detailed studies on different uncertain facets of any technologies is vital to avoid mentioned losses. Autonomous vehicles as a fast-growing technology are not exempted from those uncertainties which provoked prominent academics to urge their counterparts in industry and academia to take part in identifying and studying serious AV risks.

Lari, Douma and Onyiah (2015) recognise AV technology as disruptive since it displays the ability to transform transportation infrastructures, reshape urban landscapes, change the way cars are driven and liabilities are split among involved parties. Therefore, AVs are not exempted from being subject to uncertainties. When talking about uncertainties it is crucial to draw a distinction between *epistemic* and *aleatory uncertainty* (Hoffman and Hammonds, 1994; Renn, 2008; Eldred, Swiler and Tang, 2011; Haimes, 2018). The seventh principle in Haimes' framework for modelling risks in complex and interdependent systems advocates that risk analysis of those systems must entail both epistemic and aleatory uncertainties. Hoffman and Hammonds (1994) defined that epistemic uncertainty is "*due to the lack of knowledge*" and aleatory uncertainty is "*due to variability*". While studying the uncertainties around driverless cars, we face both epistemic and aleatory uncertainties. The criticality of epistemic uncertainty or "uncertainty on uncertainty" in the AI-assisted systems in AVs has been recently acknowledged, and there are ongoing research efforts towards assessing the robustness of AVs to rare events (Varshney and Alemzadeh, 2017).

Occurrence of worst-case variability and uncertainty may also adversely affect *vehicle permissiveness*, and in some situations can compromise safety of the vehicle (Koopman, Osyk and Weast, 2019). Furthermore, in designing intelligent systems, one of the most difficult problems is structuring the decision-making core (Chandler and Pachter, 1998). Practical reasoning itself, mostly carries implications of uncertainty (Walley, 1996). This uncertainty is categorised by Chandler and Pachter (1998) as: 1) unknown parameters; 2) unknown dynamics; 3) disturbances; 4) noise; 5) actions of non-co-operative agents; 6) actions of co-operative agents; 7) unmeasured or unmeasurable information; and 8) erroneous information. In the context of radically new transportation technologies, Rowe (1994, cited in Van Geenhuizen and Nijkamp, 2003) made a division into dimensions of uncertainty in the "absence of information". These dimensions and their definitions are summarised in Table 1.2.

Table 1.2: divisions of technological uncertainty in transportation systems (Van Geenhuizen and Nijkamp, 2003).

Dimension of Uncertainty	Description
Temporal	This dimension refers to the *prediction uncertainty* about the future state of the transport technology.
Structural	This dimension relates to modelling complexity of a transportation system. Number of parameters and interactions are determining here.
Metrical	The central issues here are the difficulty with deciding on an appropriate metrics to measure performance/preferences, precision and validity.
Translational	This arises from how results of analysis and modelling are communicated through the policy context. Interpretation of values and objectives of various stakeholders becomes vital.

Although automated driving systems are designed to eradicate human driver errors and reduce the possibility of collisions, there are still several sources of uncertainty and odds of failure that can lead to potential safety hazards in these systems. Unreliable, interrupted or noisy sensor signals (e.g., GPS data or video signals in adverse weather conditions), constraints of computer vision systems, and unpredicted changes in the surrounding environment (e.g. unknown driving scenes or unexpected objects on the road) can negatively impact the ability and/or capacity of control systems in learning and perceiving the environment necessary for making safe and timely decisions (Varshney and Alemzadeh, 2017). An immediate challenge in the development of an appropriate treatment of uncertainty in an analysis of a complex system is the selection of a mathematical structure to be used in the representation of uncertainty (Helton *et al.*, 2010). The appropriate methodology and modelling techniques are expanded in sections 3.4, 3.5 and 3.6.

1.5. CAV's structure and urban environment

Verifying and validating functional safety of highly autonomous vehicles demands a multi-disciplinary approach at every levels of functional hierarchy, from hardware fault tolerance, to resilient machine learning, to cooperating with other vehicles, to control systems for operation in both structured and unstructured environments, and to effective regulatory regimes (Koopman and Wagner, 2017). To adopt a multi-disciplinary approach, the overall architecture of AVs and their operational environment need to be defined.

Structure of autonomous vehicles can depend on several factors including but not limited to autonomy level, adopted technologies, regulatory requirements and purpose of use. This makes it almost impossible to speculate a universal structure for AVs. There are yet modules in autonomous vehicles that are ubiquitous in different classes and types of AVs: perception, planning, and control (Chu, Kim and Sunwoo, 2012; Pendleton *et al.*, 2017; Serban, Poll and Visser, 2018; Zhao, Liang and Chen, 2018). Perception module is one of those that is tasked to sense the surroundings and gather information of environment and nearby agents to feed the planning and decision-making module. The filtered and fused data is then transferred to the planning module to be analysed and determine a safe speed, de/acceleration, braking, trajectory, path, motion, behaviour, maneuverer, lane changing, etc. for a vehicle in self-driving mode. The control module continuously monitors the *execution competency* of an AV and translates the planned commands into inputs at hardware level for navigating the vehicle (Pendleton *et al.*, 2017). Although the architecture and integration of these three modules can differ fundamentally among AVs, every vehicle that is supposed at some point to navigate autonomously comprises them.

This abstraction helps us to identify risk factors that can arise from the replacement of human driver by hardware and software components (e.g., sensors, algorithms and actuators). Failure in any module and its components can result in degradation of the performance of vehicle and lead to a collision. Apart from the inherent uncertainties and risks of novel technologies, new and complex risks can emerge when human factors are not entirely absent and a degree of interaction between humans and AVs is still inevitable to avoid collisions (Bellet *et al.*, 2019). Among primary steps to locate and estimate safety risks, is the comprehension of the structure of a typical autonomous vehicle. The zoom range in mapping the structure depends on the theoretical framework and research questions. In the present study, the intention is to analyse collision risks from a sociotechnical lens and examine how causal variables in different spheres affect the probability of collision in urban environments. Based on that, the structure outlined above can provide sufficient insights into the mechanism and functionality of an AV.

According to Bellet *et al.* (2019) urban traffic is the most complex scenario among others for AVs. Presence of various agents, closure or obstruction of roads, volatile traffic situations, compliance with traffic rules and discrepancies in road infrastructure as well as driving behaviour of other road users mandate AVs to constantly perceive their surroundings and react to changes (Pendleton *et al.*, 2017). The aforementioned challenges give rise to both exposure and likelihood as two determinants of hazard. On the other hand, cities are a major part of transportation networks that currently host large number of human-driven vehicles (HDVs) and CAVs are anticipated to replace them. This makes urban areas perilous in nature for CAVs.

An extremely difficult task in urban driving is to predict the trajectories of agents in scenes (e.g., intersections and roundabouts) in which their behaviours have clear interactions (Luo *et al.*, 2020; Villagra *et al.*, 2020). This requires a CAV's planning unite to receive, process and analyse information in timely and precise manners and feed planned decisions into the control unite. Planning in dynamic environments is structurally reliant on a *predict-and-plan* mechanism. In the prediction phase, a planner depends on a forecasting module to map future positions of mobile traffic agents, and during the planning phase, the prediction is used for generating a safe path and behaviour for the ego vehicle (Hardy and Campbell, 2013; Sarkar *et al.*, 2017).

The control module in CAVs must also handle emergency situations to avoid colliding with appearing obstacles and moving traffic participants such as pedestrians and rapidly approaching vehicles (Berntorp, 2017). The control block is in charge of computing *adjusted control commands* and adopts the reference trajectories from the motion planner (Berntorp *et al.*, 2018). The control commands are subsequently sent to the actuator control unit which executes functions such as steering, (de)acceleration and breaking (Pérez, Milanés and Onieva, 2011). Any error or delay in receiving, processing and performing control commands can result in a collision. Autonomous driving remains yet as a challenge due to the immensely complex real-world urban environments and an infeasibility to test AVs in a wide variety of scenarios (Cai *et al.*, 2020). In this sense, risk analysis provides insights into safety critical situations and will enable designers, regulators and policymakers to make risk-informed decisions.

1.6. Research objectives

The research objectives actively state how this study plans to address the specified research questions in table 1.1 (Farrugia *et al.*, 2010). First, to locate the knowledge gaps and design a review framework for classifying relevant publications (e.g., journal articles, conference papers, technical reports, white papers, policy documents, etc.) that recognise the collision risk for AVs. The same framework should include a protocol for identifying the influential risk factors which can degrade the safe operation of AVs (in terms of collision risk) in urban environments.

Second objective is to construct a causal network (aka Bayesian Belief Network) which can be capable of estimating the collision risk for AVs in urban environments. Such model must reflect the influential strength between risk factors in the model. Expert knowledge can be fed into the model to assign weights to causal links in the model. The model will provide a tool for resolving the third research question.

Running a sensitivity analysis to determine the affectability of the outcome (i.e., collision risk index) against the influential risk variables is the next research objective. This can address the fourth research question of this thesis. Sensitivity analysis is a common approach for peritonising research in risk assessment studies (Christopher Frey and Patil, 2002; Saltelli, 2002; Saltelli *et al.*, 2008, p.11). Sensitivity analysis can be performed by using the BBN model.

Finally, possible policy implications will be discussed. Sensitivity and scenario analyses can indicate where policymakers need to concentrate their attentions in assessing safety implications of AVs. Some of the policy implications in section 5.3 of this thesis were merged into the response for a consultation on UK Connected and Automated Mobility (CAM) which was opened in July 2021 (Ramchurn *et al.*, 2021).

1.7. Conclusions and structure of the rest of thesis

The desire for developing autonomous mobility means has a longer history than just a few past decades. However, the recent technological advancements, in particular AI, have accelerated the development of CAVs. The discussions about uncertainties over the performance of CAVs in complex traffic scenarios, lack of sufficient and reliable historical data, and the fatal accidents involving CAVs in recent years all signify an urgency for identifying and analysing the factors that can lead to collision as far as AD is concerned. Therefore, identification and mitigation of those factors is necessary for creating a risk profile, computational risk models, and informing future policies based on reliable estimates. In this way, multi and interdisciplinary approaches can broaden the scope of analysis and lay a foundation for socio-technical synthesis of findings.

The rest of this thesis proceeds as follows. Chapter two provides a literature review on definitions, structure, operations, stakeholders and risks of CAVs. Chapter three discusses and develops the methodological approaches, Bayesian Belief Networks as the modelling framework, types of data and the means for collecting them, data analysis tools and the main assumptions which were made to construct the BBN model. Chapter four presents the findings including the identified risk factors, the BBN model, expert opinions, scenario and sensitivity analyses. Chapter five interprets the results, relates them to the research questions, recognises the research limitations, and explores the policy implications for safe operation of CAVs in urban environments. Finally, chapter six concludes the thesis with the main findings and contributions, key policy implications, and potential areas for future research.

Chapter 2

2. Literature review

The literature review chapter consists of three main sections. The discussions around AVs, their significance in the future mobility, benefits, definitions, and enabling technologies are presented in 2.1. The safety concerns and a high priority for risk-informed policymaking are reviewed in 2.2. Finally, in section 2.3 the knowledge gaps are pinpointed, and a theoretical framework is proposed. This chapter ends with a summary and conclusions.

2.1. Autonomous vehicles

2.1.1. The motives and challenges in designing autonomous systems

In fact, endeavours to create systems that have the ability to operate autonomously (i.e. without direct human control) originate from ancient times (Ieropoulos, Melhuish and Greenman, 2003). Nevertheless, the cross-disciplinary technological advances and the growing demand for replacing humans with robots in hazardous missions have driven the rapid proliferation of unmanned autonomous systems (UASs) in the past three decades (Perhinschi, Napolitano and Tamayo, 2010; Madan, Banik and Bein, 2019; Leslie *et al.*, 2022). Autonomous systems are currently being developed, deployed and operated namely but not exclusively in industrial minerals sector (Rogers *et al.*, 2019), railway maintenance sector (Vithanage, Harrison and DeSilva, 2019), harsh environments (e.g. where high levels of radiation, temperature or pressure is present) (Wong *et al.*, 2018; Leslie *et al.*, 2022), autonomous transport robotics (Aniculaesei *et al.*, 2018), space missions (Frost, 2010; Fong, 2018), healthcare (Aguiar Noury *et al.*, 2019; Tan and Taeihagh, 2021), unmanned aerial vehicles (Zhang *et al.*, 2017), logistics (Stampa *et al.*, 2021), stock-trading algorithms and household appliances (Scharre, 2015). The outlined prospects for autonomous systems in the literature also promise a more ubiquitous distribution across a wider range of industries and that they will become an integral part of our day-to-day lives in the near future (Lyons *et al.*, 2017; Mostafa, Ahmad and Mustapha, 2019; Nahavandi, 2019).

There are various reasons and purposes for heightening the autonomy of different systems in diverse disciplines. For instance, mitigating latency, cost-effect operation in long term, undertaking maintenance in the face of failure or damage, and extending the scientific team through *virtual presence* are among the main motives for equipping a space vehicle with autonomous systems (Frost, 2010). In railway maintenance, the introduction of robotic and autonomous systems (RAS) is expected to achieve cost benefits and release technicians from working under unfavourable and unergonomic conditions (Vithanage, Harrison and DeSilva, 2019). Furthermore, the crucial role of autonomous machines in lowering workload, increasing speed, improving efficiency, effectiveness and reliability in today's industrial setting is underscored in Rogers *et al.* (2019). In addition, improving the *self-sufficiency* of machines in a way that they can be relied on to act in a *self-directed* manner is a primary motivation to increase a machine's capabilities (Bradshaw *et al.*, 2013; Fong, 2018). Nonetheless, there remain challenges, questions and uncertainties about creating autonomous systems, levels of autonomy and how they can be measured, and the feasibility for an artificial system to reach full autonomy.

Despite the clear tendency towards fitting autonomy into systems and the promising applications in the successful examples described above, obstacles remain in the way of integrating autonomous systems into the existing platforms. Autonomy, undeniably, necessitates fundamental analysis from both theoretical and philosophical points of view (Hexmoor, Castelfranchi and Falcone, 2012). In practice, it becomes even more crucial to address key uncertainties and questions while designing an autonomous system. For example, in systems which possess adjustable autonomy it is critical to determine whether and how such a system should hand over decision-making control to another agent or entity depending on the situation (Scerri, Pynadath and Tambe, 2002). Bradshaw *et al.* (2013) identified seven prevalent misconceptions about autonomous systems. The article opposes the idea of "full autonomy" and casts doubt on whether such a concept is either possible or desirable. It also argues that higher autonomy of autonomous systems requires different sorts of human skills and expertise and not necessarily fewer or no human control. Even if possible, full autonomy does not eliminate the need for human-machine collaboration (Bradshaw *et al.*, 2013). Mostafa, Ahmad and Mustapha (2019) specified environment's dynamism complexity, heavy workload, and risk measurement as the roots of software and hardware challenges in developing autonomous systems. They subsequently projected seven requirements (i.e. representation, measurement, distribution, adjustment, human–agent interaction and assessment) of formulating adjustable autonomy. Above all other, the central question and one of the main concerns about autonomy is how to amalgamate ethics into intelligent autonomous systems (Charisi *et al.*, 2017; Winfield *et al.*, 2019). This dilemma is among major obstacles to mass deployment of AVs on public roads and warrants interdisciplinary research approaches (Bonnefon, Shariff and Rahwan, 2016; Maurer *et al.*, 2016; McBride, 2016).

Another difficulty in developing autonomous systems is the flexibility of the term 'autonomous' and its dependence on the context (Ieropoulos, Melhuish and Greenman, 2003). The definitions and aspects of autonomy are going to be more elaborated in sections 2.1.4 and 2.1.6. Hereupon, analysing the dimensions of any context that we aim to evaluate autonomy in that, is inevitable. Similar to other fields, the notion of autonomy has provoked serious debates in the realm of AVs and needs rigorous consideration. Promising benefits of autonomous systems continue to provide enough incentives to overcome the challenges.

2.1.2. Perceived benefits for AVs

Having explained in the introduction chapter, one of the main goals for creating a vehicle without human driver is improving safety as the very first concepts of AVs arose from the high number of fatalities that was effected by the mass motorisation of transportation system in the United States (Maurer *et al.*, 2016, p.95). Figures show that more than 90 percent of fatal accidents in the US involve human factors such as alcohol, drug, speeding, and distracted driving (Katyal, 2013; Fagnant and Kockelman, 2015; Kalra and Paddock, 2016; Ryan, 2019). Eliminating human from the loop, if other functions of the technology are at least as competent as human drivers, can make an enormous contribution to safety of vehicles. Indeed, numerous articles and papers put emphasis on the safety aspect of AVs to benefit humans (e.g., Katyal, 2013; Lutin, Kornhauser and Lerner-Lam, 2013; Lari, Douma and Onyiah, 2015; Kalra and Paddock, 2016; Chan, 2017; Faisal *et al.*, 2019; Rashidi *et al.*, 2020; Lundgren, 2021). This is not to say that AVs are risk free, but just to demonstrate how excluding human factors and errors can reduce the risk of fatalities (Milakis, Van Arem and Van Wee, 2017).

In every society, there are people who have limitations to drive a car by themselves. AVs can offer more accessibility and independence to elders, those without a valid driving license (including teenagers and kids), those suffering from severe disabilities and persons under the impression of drug or alcohol (Lari, Douma and Onyiah, 2015; Ryan, 2019). Increased efficiency and productivity are also two perceived benefits for AVs. The occupant(s) of a self-driving car can use his/her time more efficiently whilst do not need to actively drive (Lutin, Kornhauser and Lerner-Lam, 2013; Manfreda, Ljubi and Groznik, 2021). The vehicle is by default programmed to identify better (shorter and/or less congested) routs (Lari, Douma and Onyiah, 2015) and is capable to operate in a platoon (Zhang *et al.*, 2020), thus reduction in fuel consumption can be achieved. Reduction in operational costs of freight vehicles and permitting the transit vehicles to operate for longer hours are the presumable benefits for freight industries (Schlossberg *et al.*, 2018). There is ongoing debate about the impact of AVs on traffic congestion (e.g., Litman, 2017), but the fuel consumption is believed to decrease (Katyal, 2013; Litman, 2015; Faisal *et al.*, 2019). If realised, this will directly and positively impact the environment due to reduction in greenhouse gas (GHG) emissions (Chan, 2017; Milakis, Van Arem and Van Wee, 2017).

Capacity has often a bold presence among the perceived benefits for AVs (Lari, Douma and Onyiah, 2015). According to cost-benefit analyses that were made, the adoption of an automated system on the British motorways was projected to be repaid by end of the century, to increase the road capacity by at least 50%, and to prevent around 40% of the accidents (Lari, Douma and Onyiah, 2015). Overall, one estimate from the Eno Center for Transportation Studies, a DC-based industry research group, put cost savings in the range of $25 billion to over $450 billion, depending mainly upon the rate of technology adoption (Lari, Douma and Onyiah, 2015). Although there are on-going debates about the impact of AVs on carbon emissions, some studies (e.g., Fagnant and Kockelman, 2015; Taiebat *et al.*, 2018) suggest that AVs have great potentials for contributing to carbon saving policies in road transport sector. Enabled mechanisms such as eco-driving (Gawron *et al.*, 2018), vehicle light-weighting (Taiebat *et al.*, 2018), rightsizing (Rashidi *et al.*, 2020), shorter headway distances (Lu and Tettamanti, 2021), and efficient route planning (Massar *et al.*, 2021) are expected to lower GHG emissions.

AVs are supposed to transform the way transportation systems are operating around the globe and their impacts on traffic safety and traffic congestions are predominantly cited in the literature (e.g., Ye and Yamamoto, 2019). This can lead to change in the travel behaviour of people and alter different social structures and urban design. Car and ride sharing due to pushing the existing barriers and emergence of new business models will become more beneficial and popular among travellers (Abduljabbar *et al.*, 2019). Similarly, shift in car ownership may occur (Greene, 2016; Guerra, 2016). Consequently, land use (e.g. parking lots and sprawls) is subject to change (Riggs, 2018). Although increased safety is among primary expectations, the possibility for collision will be still present (Kalra and Paddock, 2016). Therefore, in case if there is any accident, sharing liability between involved parties with existing legal terms in many parts of the world poses a dilemma (Katyal, 2013; Taeihagh and Lim, 2019; Davey, 2020; Kassens-Noor *et al.*, 2020).

In the modern world, cars are a part of social identity of individuals. Transferring the driving skills of people to cars may trigger social and personal identity crisis (McBride, 2016). Controlling a car can mean as a form of freedom for a group of people, then loss of freedom may equate to loss of identity. Apart from societal impacts, the economy might be affected in different ways as well. KPMG estimated in a report that CAVs can create 320,000 jobs alone in the UK by 2030 (KPMG, 2015b). On the other hand, many professions such as taxi and lorry drivers inevitably and gradually fade (Thierer and Hagemann, 2015).

2.1.3. Anticipations on the future of AVs

While many concerns about the safety and security of AVs remain unaddressed, the rush to commercialise the technology and the race towards shaping the regulatory environment due to the fierce competition between multiple developers are adding to the complication of the problem. Reviewing the statistics on the investments and anticipations for the AV fleets to take over the roads from conventional vehicles reveals that we are not far from that point. Some observers estimated limited availability of driverless cars by 2020, with wide availability to the public by 2040 (Lari, Douma and Onyiah, 2015). In another study released in early 2014, IHS Automotive predicted that nearly 54 million self-driving cars will hit the roads worldwide by 2035 and almost all of vehicles are expected to be autonomous after the year 2050 (Cohen, 2015). Faisal *et al.* (2019) investigated the “smart city” agenda and prefigured that by 2045 AVs would account for half of the vehicles on roads. Some figures also hint that the first commercial generation of AVs must be available for sale in 2025, and by 2035, around ten percent of newly manufactured vehicles would be fully autonomous (Lipson and Kurman, 2016). The insurance market predicted that in 2025, a “broad-based transformation” will begin and all new cars will be equipped with autonomous capabilities (KPMG, 2015a).

Chan (2017) provided estimates for the time horizons that major AV developers were going to release their products. Several of those milestones are now passed, but the promised technologies have not become available yet. For example, it was estimated that Toyota and Volvo were going to sell “zero fatality” cars by 2020. Similarly, it was expected that Audi would introduce fully autonomous vehicles by 2021. Other authors (e.g., Pernestål Brenden, Kristoffersson and Mattsson, 2019) had also provided optimistic estimates for realisation of fully autonomous vehicles by early 2020s. Litman (2015), however, anticipated that level 5 AVs will be ready and legal to use before 2030.

The tendency towards investing in AV development is growing accordingly. The UK government alone has endorsed a plan to invest £200 million in AV research and development (McBride, 2016). Almost 5 years ago, the US government started to devise a national plan to invest 4 billion dollars over a period of ten years (Lardinois, 2016). The budget was allocated to co-operate with the tech companies and auto manufacturers to develop and test CAVs. The estimations of potential market size for AVs are promising. By 2030, it is estimated that the sales of AVs may reach 87 billion dollars (Zhao *et al.*, 2016). That is, however, distinct from the figures that Lipson and Kurman (2016) estimated for the global market of AVs, worth 38 billion dollars in 2035 (Lipson and Kurman, 2016).

Municipal departments and authorities around the world are revising their policies and plans to facilitate the transition and embrace AVs (Faisal *et al.*, 2019). This is mainly because urban planners along with other stakeholders need to proactively plan, ensure provisions and improve infrastructures for adopting AVs (Khan *et al.*, 2019). Faisal *et al.* (2019) listed the names of 36 cities in the UK, US, Netherlands, Australia, Japan, UAE, Finland, Sweden, France, Norway, Canada, Singapore, and Korea which had started pilot testing of AVs before 2017. Several other cities such as Auckland in New Zealand, São Paulo in Brazil and Buenos Aires in Argentina were also preparing to test AVs (Faisal *et al.*, 2019). In the European Union, recent projects have reported successful testing of autonomous transit in seven cities, conveying more than 60,000 passengers while sharing the infrastructure with other road users (Rojas-Rueda *et al.*, 2020). These reports besides the recent prototypes of partially automated vehicles all indicate that there is willingness to develop and adopt vehicles which require less or no human interventions.

In different modelling and simulation attempts for studying AVs (e.g., Fagnant and Kockelman, 2015; Lu and Tettamanti, 2021), adoption rate (aka penetration or deployment rate) is among underlying assumptions. The magnitude of some outcomes such as safety improvements and GHG reduction depend on the proportion of AVs to conventional vehicles. The literature suggests a broad range estimates for adoption of CAVs in the next three decades. Whereas some optimistic predictions that expect 100% adoption by 2040, there are other estimates that offer only a small proportion (i.e., 15%) of vehicles will be CAVs by 2050 (Rashidi *et al.*, 2020). Any mass adoption of AVs, however, is contingent on overcoming barriers such as integration of several intelligent vehicles, regulations, costs, cybersecurity, safety, liability, and data privacy (Raj, Kumar and Bansal, 2020).

2.1.4. The notion of autonomy in AVs

Despite the usefulness of the taxonomies provided for autonomous systems to categorise them based on their capabilities, there are still shortcomings in these categorisations which analysts must be aware of them. First, such representations appear to be over-specific in some dimensions, while are vague in others and even some descriptions contain hidden assumptions (Hancock, 2019). It is also arguable that whether we can measure machine autonomy on a *single ordered scale* with increasing levels (Bradshaw *et al.*, 2013). The conceptualisation of levels of autonomy might not be even a developmental road map for manufacturers. Ranking autonomy according to the function is problematic too, since autonomy is more related to the context of activity (Bradshaw *et al.*, 2013). Such typologies can offer technical clarity to some extent, yet there are ambiguities over functionality and system specifications for each step in the automation ladder. Hence, care must be taken about these caveats when applying those scales for analysing autonomous systems.

The topic of autonomy in ground vehicles in general, and particularly in cars, has attracted considerable attention across different disciplines comparing to other applications of autonomous systems (Xie and Zhong, 2016). After all, there are only a few organisations who have already provided a gradation and definitions for each level of autonomy in AVs. The Society of Automotive Engineers (2016) divided the autonomy (automation) for on-road vehicles into six levels from ‘No Automation’ to ‘Full Automation’ (please see Table 2.1). Similarly, the National Highway Traffic Safety Administration (NHTSA) defined five levels of vehicle autonomy for vehicles (please see Table 2.2). German Federal Highway Research Institute (BATs) proposes a similar taxonomy for varying levels of vehicle autonomy (Kaur and Rampersad, 2018). Frost, Goebel and Celaya (2012) also presented a categorisation for autonomous functions based on a four-stage information processing model of humans (figure 2.1). An autonomous system gathers data form multiple sources, analyses the data and makes a decision based on the processed data, and finally implements the decided action. Tables 2.1 and 2.2 provide classifications from two different organisations.

Table 2.1: illustrates the levels of autonomy (automation) for on-road vehicles (SAE International, 2016).

SAE Level	Name	Narrative Definition	Execution of Steering and De/Acceleration	Monitoring of Driving Environment	Fallback Performance of Dynamic Driving Tasks	System Capability (Driving Modes)
Human driver monitors the driving environment						
0	**No Automation**	Full-time performance by human driver of all aspects of dynamic driving task	Human driver	Human driver	Human driver	n/a
1	**Driver Assistance**	Driving mode-specific execution by a driver assistance system (e.g., steering or de/acceleration	Human driver and system	Human driver	Human driver	Some driving modes
2	**Partial Automation**	Driving mode-specific execution by one or more driver assistance systems	System	Human driver	Human driver	Some driving modes
Automated driving system monitors the driving environment						
3	**Conditional Automation**	Driving mode-specific performance by an automated driving system with the expectation that human driver will appropriately respond to a take-over request	System	System	Human driver	Some driving modes
4	**High Automation**	Driving mode-specific performance by an automated driving system even if human driver does not appropriately respond to a take-over request	System	System	System	Some driving modes
5	**Full Automation**	Full-time performance by an automated driving system under all road/environmental conditions	System	System	System	All driving modes

Table 2.2: NHTSA levels of vehicle autonomy and examples of automated tasks for each level (Rödel *et al.*, 2014).

	Description	**Example of (driving) automated tasks**
Level 0	*No-Automation:* The driver is in complete and sole control of the primary vehicle controls	none – all driving tasks are performed by driver
Level 1	*Function-specific Automation:* Automation at this level involves one or more specific control functions.	Examples include electronic stability control or pre-charged brakes, where the vehicle automatically assists with braking to enable the driver to regain control of the vehicle or stop faster than possible without assistance. A parking assist helps the driver with auditory feedback out of the parking space.
Level 2	*Combined Function Automation:* This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions.	An example of combined functions enabling a level 2 system is adaptive cruise control in combination with lane cantering. Steering is handled automatically by the vehicle. Exceeding the speed limit is prevented by a cruise control. In the stop-and-go traffic the speed and the distance to the car in front are controlled by an active cruise control.
Level 3	*Limited Self-Driving Automation:* Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time.	The Google car [by then] is an example of limited self-driving automation. The driver is supported by the parking assist. When vehicle is switched to autonomous mode and it handles accelerating, steering and braking completely autonomously. When reaching the highway exit, the car requires that the driver takes back control.
Level 4	*Full Self-Driving Automation:* The vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip.	Such a design anticipates that the (remote) driver will only provide destination or navigation input. During the ride the car operates within the speed limits, accelerates, brakes and steers fully autonomously, and avoids obstacles while the driver may be engaged in other activities than driving.

The degree of autonomy for an autonomous system depends on how autonomously it is capable of gathering data, processing them, making decisions and implementing them. The performance of an AV can be simplified in the basic functions above. An AV detects an object on the road through its sensors, analyses different characteristics of the object (e.g. type, size, distance, speed, direction, etc.), weighs up possible options available and decides, for example, to accelerate or deaccelerate, and finally puts that decision into action. Several papers tried to equate autonomy to intelligence and measure the level of system intelligence instead of examining the autonomy grade of the system (Clough, 2002). A system can be notably intelligent, but simultaneously not able to act autonomously. As a consequence, ranking the autonomy level of a vehicle is a critical step before studying it. However, definitional ambiguities about autonomy obstructs understanding and engineering autonomous systems as well as evaluating the degree of their autonomy (Froese, Virgo and Izquierdo, 2007). Durst and Gray (2014) reported that defining autonomy in a comprehensive and quantitative manner is among three biggest challenges that the ground vehicle test and evaluation (T&E) community confronts. Representatives from disparate US agencies initiated a joint effort in July 2003 to address autonomy issues of unmanned systems. Forming a common vernacular terminology (i.e. standard terms and definitions) to articulate capabilities as well as problems and devising metrics, methods and processes for measuring the autonomy of unmanned systems were overall objectives of this initiative (Huang *et al.*, 2005). Characterising the levels and facilitating the evaluation and measurement of autonomy can be the main contributions of such a framework. Pollard, Morignot and Nashashibi (2013) proposed an ontology-based model and define a spectrum of automation/autonomy levels exclusively for ground vehicles to represent knowledge.

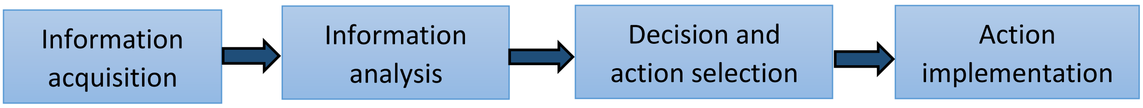


Fig. 2.1: basic functions of an autonomous system (Frost, Goebel and Celaya, 2012).

Although full autonomy of ground vehicles has been a major objective of the Intelligent Transportation Systems (ITS) community (Pollard, Morignot and Nashashibi, 2013), the concept of full autonomy has received fierce criticisms. According to McBride (2016), a fully autonomous car which has no reliance on infrastructure or connection with central systems must be *self-determining, self-correcting, self-healing* and ultimately *self-aware*. Regardless of feasibility and achievability, he casts doubt on desirability of creating such a fully autonomous car. Engineers, designers, technologists and manufacturers who are more concerned with technical aspects of the technology, are seriously challenged and constrained in dealing with social, moral, and political issues (Hancock, 2019). Thus, for many designers and manufacturers keeping the human driver in the loop and assigning some (but not all) of driving tasks to machine has been a start point towards fully automated/autonomous vehicles.

In the hierarchical control structure for an autonomous vehicle developed by Qu (2009), multi-level autonomy (control) plays the key role. In this structure (figure 2.2), reaching *high-level tactical decisions* is facilitated through human-machine interactions and a multi-objective decision-making construct which is capable to learn online (Qu, 2009). Adjustable autonomy, accordingly, can be a solution for autonomous systems which operate in dynamic environments (Scerri, Pynadath and Tambe, 2002; Mostafa, Ahmad and Mustapha, 2019). Adjustable autonomy is the underpinning principle of semi-autonomous vehicle (SAVs) architecture. The distributed autonomy between human and machine, however, can be a source of risk. For instance, Hancock (2019) asserts that the issue of taking over or handing over the control of a semi-autonomous ground vehicle in cases of emergency or likelihood of collision is not going to be as smooth and straightforward as in civil aviation. In the same context, drowsiness and overreliance are mentioned to be typical problems in the behavioural adaptation to Advanced Driving Assistance Systems (ADAS) (Eskandarian, 2012).

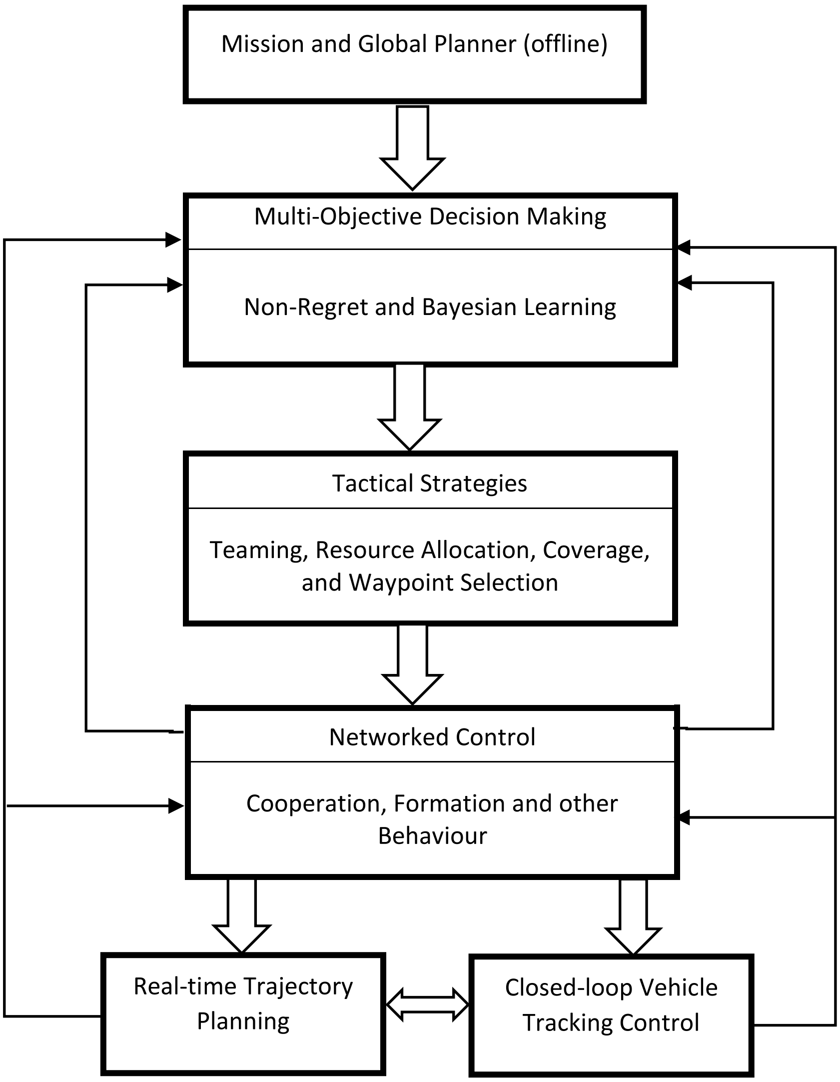


Fig. 2.2: control hierarchy for AV systems (Qu, 2009)

2.1.5. Definitions of AV from the perspective of diverse disciplines

Although it may not be always feasible to arrive at exact, precise and clear-cut definitions for a complex phenomenon or system, defining the boundaries, recognising the intended functions and outlining key entities can still yield insight into mechanisms and functional implications of them. This applies to AVs as well where there is much ambiguity on the definition of a ‘driverless’ or ‘autonomous car’ and a universal or at least widely agreed definition for autonomous vehicles is still missing (Wolmar, 2018). Drawing a comparison between the definitions provided for AVs in diverse disciplines as well as desired functionalities might help to ease this problem if not eliminate it.

Vellinga (2017) in an article discussing the legal challenges of driverless cars, refers to this technology as "*motor vehicle that can operate during a whole trip without human interference; it does not require a user to intervene when a problem occurs*". In a general description for AVs, Li *et al*. (2016) also pointed towards the ability of the vehicles to perceive information, retain knowledge, and adopt adaptive behaviours within an environment. From the transportation perspective, Abduljabbar *et al*. (2019) considered the desired functionality of fully autonomous vehicles as to move safely, in between other vehicles on road avoiding obstacles, and pedestrians. The authors further break down the overall architecture of AV technology into two major components which are hardware (e.g. sensors and actuators) and software (e.g. AI algorithms). Similar definition is adopted in the field of distributed computers and communication networks. Vishnevsky and Kozyrev (2016) define that an autonomous car is an autonomous vehicle which is capable of fulfilling main transportation tasks of a conventional car plus sensing its surrounding environment and navigating without human instruction. This is also endorsed by Craig and Liu (2018) in their article where they evaluate the impacts of AVs on real estate sector. The ambition for such a vehicle is claimed to be navigating and sensing the environment without human input and reach a level to transport without encountering traffic, struggling to find a car park and even needing to stay awake (Craig and Liu, 2018).

Governmental departments and organisations have offered definitions for AVs too. For instance, UK Department for Transport initially defined driverless cars as "*vehicles with increasing levels of automation will use information from on-board sensors and systems to understand their global position and local environment. This enables them to operate with little or no human input (be driverless) for some, or all, of the journey*" (Department for Transport, 2015). The US Department of Transport, however, based its definition of "highly automated vehicles" on the SAE automation levels and describe them as "*automated vehicle systems that are capable of monitoring the driving environment as defined by SAE J3016*" (Department of Transport, 2016). From these definitions and expected performance we can conclude that excluding the human driver from the loop (at least for a part of a trip), sensing the surrounding environment and navigating safely are three prominent features of AVs.

2.1.6. Discrepancies in the terminology

Interchangeably, and even confusingly, *driverless*, *self-driving*, *automatic*, *automated* and *autonomous vehicles* are the main terms employed in the academic and technical literature to refer to vehicles or cars which perform some or all driving tasks by themselves. Aside from 'driverless' and 'self-driving' cars which are more popular terminology in news articles and non-technical literature, *autonomous vehicles* and *automated vehicles* have provoked more debates on the grounds that each has a fundamentally different definition. Clough (2002) describes that the basic difference lies in delegating decision making to one or a collection of intelligent autonomous systems, whereas an automated system is one that implements a pre-programmed process. Similarly, Frost (2010) explains that an *automated system* is not designed to independently generate possible courses of action and make a choice between them and simply follows a script, but an *autonomous system* tries to achieve its defined objectives without human interference and does make choices. SAE International (2016) also considers the confusion and draws a line between these two terms: according to the Oxford English Dictionary, since automation involves the replacement of human labour with electronic or mechanical devices, then automation is a more precise term for those systems that perform *dynamic driving tasks*. Kellerman (2018) scrutinises the differences between these two terms. It is maintained that automation denotes *self-operating mechanisms* that are now an integral element in humans' operations, while the timings are still decided by human agents. On the other hand, autonomy in the context of mobility and driving refers to two automatic elements embedded in and autonomous vehicle (AV). First, automated decision-making processes for driving tasks during the entire vehicle journeys, and second, a wholly automatic operation of the vehicle including sensing its environment, navigating, driving, transmission and ignition. Therefore, "*autonomous mobility via AVs, as well as via other mobility modes, constitutes the most advanced level for the wider range of automated mobility modes and technologies*" (Kellerman, 2018).

The necessity for clarification on nomenclature before proceeding to an examination on different aspects of these vehicles is stressed in Hancock's work (2019) too. The focus of his discussion is upon differences between the definitions of automation and autonomy. Automation is defined as "*automated systems are those designed to accomplish a specific set of largely deterministic steps, most often in a repeating pattern, in order to achieve one of an envisaged and limited set of pre-defined outcomes*" (Hancock, 2019). An autonomous system, on the contrary, is characterised as a *generative* system which learns, evolves and constantly adapts its functional capabilities based on the contextual and operational information that it gathers (Hancock, 2019). Moreover, autonomous agents pursue goals that are *generated* within rather than *adopted* from other agents (Hexmoor, Castelfranchi and Falcone, 2012). Theoretically, an automated vehicle system can be denoted as an "autonomous" system, only when all the dynamic driving functions, at all driving environments, can be performed by the vehicle's automated systems (Faisal *et al.*, 2019). The discrepancy between autonomous and automated systems is apparent and requires researchers to pay immediate attention to this notion to avoid confusion, misperception and diminished credibility (SAE International, 2016).

Besides the disputes over the appropriate terminology to represent the technology, the concept of full autonomy in vehicles has received substantive criticisms. For example, McBride (2016) argues that a fully autonomous vehicle should rely on no external sources of information (i.e. receiving external input) such as GPS. Such a vehicle should be *self-contained* and have no dependency upon external sources and merely rely on its own capabilities (McBride, 2016). Thus, before recognising that a vehicle is autonomous, its dependence on communication and/or co-operation with external agents and entities must be questioned. There are driving systems that are truly autonomous as they can complete all of their defined tasks independently. However, if these systems still need to rely on communication or co-operation with external entities, they should be categorised under *co-operative* rather than autonomous (SAE International, 2016). Hence, with the above definitions it appears that terms such as *connected and autonomous vehicles* (CAVs) can sound paradoxical and controversial. Hancock (2019) accordingly asserts that although autonomy as defined earlier will be born out of pre-existing levels of automation, without a doubt, none of the current vehicles on the road can claim to be autonomous.

After all, as the term autonomy is concurrently and widely used in the literature and the aim of this research is to investigate higher levels of automation, we opt to use connected autonomous vehicles (CAVs) to refer to highly automated vehicles in the rest of this thesis. CAV has been also used as an abbreviation for connected and automated vehicles in many recent academic publications besides policy statements and includes the connectedness feature of those vehicles. There are instances where AV is used in the text. In those contexts, emphasis is placed on the autonomous (or automated) feature of the technology rather than connectedness aspects.

2.1.7. Advancements in pertinent technologies

To study and scrutinise implications and risks of CAVs, it can be illuminating to glance back and review the development trajectories of technologies and key components enabling the core functions and affecting safety records. This also allows breaking down the overall system into smaller and less complicated components to be analysed separately and later as a whole. For these reasons, this section is dedicated to the technological enhancements which have made a notable contribution to the evolution of AVs hitherto. A variety of technologies from diverse disciplines must be integrated into a vehicle to achieve autonomous navigation in dynamic environments such as urban areas. Computer science, mechanical engineering, electronics and electrical engineering as well as control engineering are prominent examples of these disciplines (Bimbraw, 2015). Merging innovations from the above disciplines has led to improvements in sensory (e.g. LiDAR), communication systems (e.g. DSRC), navigation systems (e.g., GPS), data analysis and data storage (Narla, 2013; Denaro *et al.*, 2014; Bimbraw, 2015; Lari, Douma and Onyiah, 2015; Russo *et al.*, 2016). More recent technological platforms such as could computing and Internet of Things (IoT) have also made a major contribution to the development of CAVs, especially in facilitating the communication between vehicles (V2V) and infrastructure (V2I) (Guerrero-Ibanez, Zeadally and Contreras-Castillo, 2015). In another research, Englund *et al.* (2018) classify enabling technologies within the field of automated driving into five categories. Table 2.3 summarises these categories and representative examples. In their comprehensive study, Winner *et al.* (2016) mapped a relatively complete picture on and investigated multiple facets of ADAS. Sensors, data fusion and environment perception, actuation and human-machine interfaces are the main focus. In addition to former and state-of-the-art systems, they try to portray the future of ADAS considering the current trends of technology development.

Table 2.3: Enabling technology contributing to the evolution of AV technology, adopted from (Englund *et al.*, 2018)

	Technology Category	**Example**
a.	Position, Localisation and Mapping	Global Navigation Satellite System (GNSS) GPS L1/L2, GLONASS, BeiDou and Galileo real-time kinematics (RTK)
b.	Algorithms for Guidance and Control	Deep learning algorithms
c.	Hybrid Communications	Dedicated Short Range Communication (DSRC) 3G/4G/5G/LTE
d.	Sensing and Perception	Powerful, yet low-cost cameras Radar LiDAR Fusion of Vision Online databases from sensor readings Vision-based systems to learn from e.g. driver behaviour
e.	Technologies for Data Ownership and Privacy	Cooperative Intelligent Transportation Systems (C-ITS) Cooperative Awareness Message (CAM) Decentralised Notification Message (DENM)

There is an apparent scholarly consensus that autonomous driving is well emerging out of pre-existing levels of automation (ADAS) or what SAE names as Automated Driving Systems (ADS) (Chan, 2017; Englund *et al.*, 2018; Hancock, 2019). Many (if not all) of the above technological advances and innovations have been used in the development of ADAS before (Winner *et al.*, 2016). In other words, integration of several driving assistance systems can bring about autonomous driving (Lipson and Kurman, 2016, pp.186-194). The integration of complementary technologies, quality and breadth of human-machine interactions can potentially add to the complexity and to the uncertainties. The notion of integration and human-machine interfaces will be covered in coming sections. For that reason, exploring the enabling technologies which form the backbone of CAVs and have been formerly tested in lower levels of automated driving can offer valuable insights into the uncertainty and risk analysis in this project.

2.1.8. The decisive role of AI in developing autonomous systems

The invention of semiconductor integrated circuits was just the beginning of the subsequent revolutions and breakthroughs in virtually all areas of industrial and economic sectors (Mack, 2011). Over the years, computing capabilities have grown to become faster and more efficient, but physical components have shrunk in size (Anderson, 2017). In other words, smaller devices mean to be faster devices. This trend is known as Moore's Law in academic literature which "*predicts that the number of electronic devices that can be crammed onto a little chip of silicon will double roughly every 1–2 years*" (Anderson, 2017). One of the fields which directly benefitted from increased computational power, without a doubt, is artificial intelligence (AI) (Yudkowsky, 2008). Thanks to computing power increase, many early obstacles of devising AI-based systems are quickly being overcome (Warwick, 2013). To reflect the extension and degree of the influence, Kuruczleki *et al.* (2016) indicated AI and machine learning (ML) as the two main pillars of the fourth industrial revolution (Industry 4.0).

Reviewing the literature on the current studies of AI applications advocates that almost every realm and industry is being currently touched by AI or will be in the near future. Well-known examples are e-commerce and marketing (Cannella, 2018), healthcare and medicine (Hamet and Tremblay, 2017; Briganti and Le Moine, 2020), autonomous vehicles (e.g., Hengstler, Enkel and Duelli, 2016), education (Wenger, 2014), data processing (Russell and Norvig, 2016), banking and finance (Bahrammirzaee, 2010; Rohmer, 2020), aerospace industries (Girimonte and Izzo, 2007; Rohmer, 2020), manufacturing (Li *et al.*, 2017), law (Abduljabbar *et al.*, 2019) and military. Undoubtedly and despite the widespread ambiguities around AI, it is the technology that is altering many aspects of the world (West and Allen, 2018). Figure 2.3 presents more details about the applications of AI across different industries as well as the economic, social and business values that adoption of AI can generate in each sector. In some disciplines the pace of change and extent of influence is considerable enough to cause deep concerns for prominent scientists and even can be considered as a national security issue. In the meantime, massive investments in AI research together with fast and remarkable technological progress in other areas (e.g. computability and software programming) can manifest the extent of future achievements which might completely overshadow the current performance (Hawking *et al.*, 2014). This acceleration has consequently convinced many individuals to call for regulations on AI development and imposing restrictions on AI operations (Scherer, 2015).

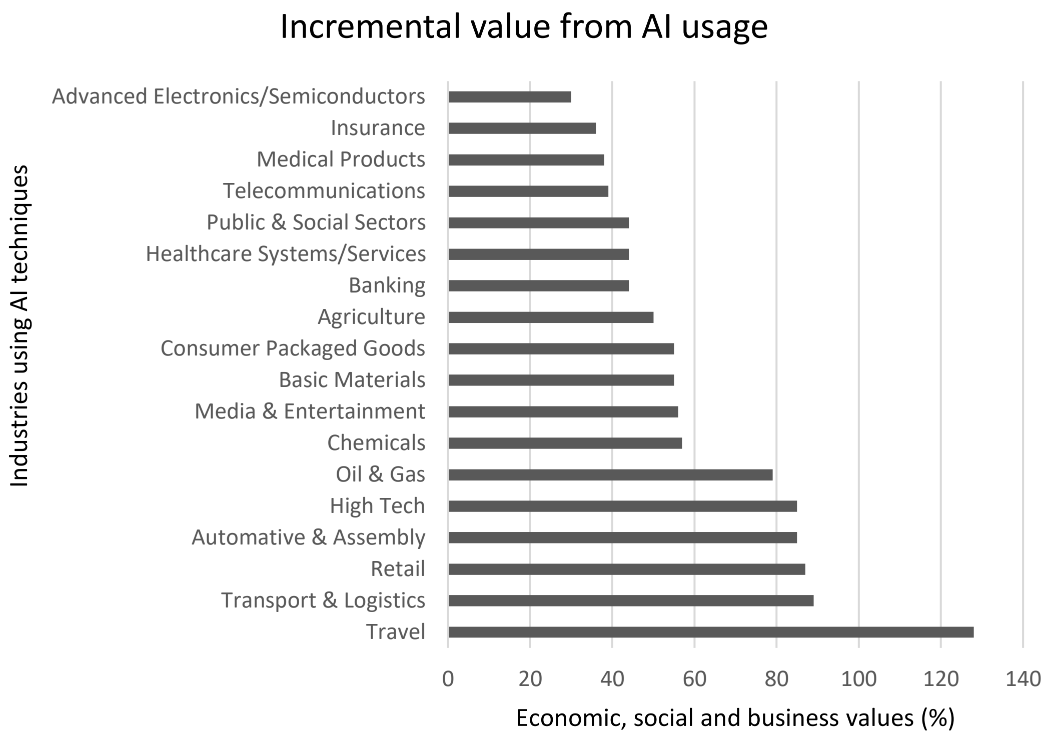


Fig. 2.3: economic, social and business values which AI can generate in diverse industries. Adopted form (Abduljabbar *et al.*, 2019)

Having mentioned earlier, autonomous driving has also been heavily impacted by the advances in AI systems. Figure 2.3 shows travel and transportation which are tightly linked with mobility and are expected to benefit most from AI. The inclusion of artificial intelligence allows designers to close the gap between purely analytical systems and rule-based systems which can mimic human decision-making and behaviour (Maurer *et al.*, 2016). The applications of AI in CAVs are vast and machine learning techniques have been broadly adopted to improve the performance of them (Kuderer, Gulati and Burgard, 2015). Computer vision (Lipson and Kurman, 2016; Mohammed, Khan and Bashier, 2016), object classification (Lipson and Kurman, 2016), steering and navigation (Kuderer, Gulati and Burgard, 2015), vehicle path control systems (Maurer *et al.*, 2016; Varshney and Alemzadeh, 2017), cybersecurity (Alheeti, Gruebler and McDonald-Maier, 2015), in-car problem diagnosis (Huang and Rust, 2018) and collision avoidance (Hardy and Campbell, 2013) are only a few examples of the wide applications of AI in developing CAVs.

Above examples besides other AI-based technologies implanted in CAVs can vividly demonstrate the central role of artificial intelligence in realisation of fully autonomous vehicles. In fact, the capacity of AV risk mitigation across the literature is evaluated based on the AV competence to make driving decisions (Cunneen, Mullins and Murphy, 2019). This explains the one billion dollar investment plan which has been announced by Toyota to be made in artificial intelligence research (Lipson and Kurman, 2016). The main concern with AI, however, is its potential risks (Wadhwa and Salkever, 2017). Hawking *et al.* (2014) maintain that there are huge benefits that can be derived from deployment of AI, but leaving the technology uncontrolled and neglecting the risks might have serious repercussions including elimination of human civilisation. Therefore, a very sophisticated and integrated risk assessment system must be in place to secure yielding the benefits and avoiding the risks. Notwithstanding the exigency of addressing consequential uncertainties around the technology, relatively little academic literature has been yet devoted to analysing and measuring risks associated with AI utilisation (Yigitcanlar *et al.*, 2020). The need for extensive and interdisciplinary research must be recognised for all kinds of risks from safety and security to business risks. In addition to adopting an overall and universal approach to analyse risks from AI at a catastrophic and existential level (Yudkowsky, 2008; Turchin and Denkenberger, 2018), a bottom-up strategy is also required to break down the overall risks into narrower and more technical areas to scrutinise them more deeply. In this regard, this research project has been proposed to model collision risk of CAVs in urban and suburban environments.

2.2. Associated safety risks with AVs

2.2.1. Uncertainties and risks surrounding the AVs

In section 1.3 it has been argued that disruptive and innovative technologies transfer and/or transform the risks rather than eliminating them completely. This section explores the uncertainties that can pose safety risks while AV technology is deployed in urban regions. Lipson and Kurman (2016, p.15) explain that 99 percent of the time, driving is predictable and therefore the AI can be trusted to accomplish its tasks with high reliability. In spite of that, in one percent of the time, the technology can find itself in an unpredicted situation which has not been yet trained to react safely or timely. There are different terminologies in the literature to refer to these types of events. ‘Black swans’ (Aven, 2013; Flage and Aven, 2015), ‘corner cases’ (Lipson and Kurman, 2016, p.16) and ‘unknown unknowns’ (Ward and Chapman, 2003; Aven, 2013; Flage and Aven, 2015). The inability to detect and predict these events is attributable to the ultimate epistemic uncertainty or lack of fundamental knowledge not only about the distribution of a variable but also about the existence of the event itself (Paté-Cornell, 2012). In another hand, occurrence of rare but known events may be overlooked by risk analysts. Notwithstanding the rareness, if such events occur, can have catastrophic or at least unpleasant consequences. Paté-Cornell (2012) referes to this type of events as ‘perfect storms’ which the existence is proven or imaginable, but the probabilities are still unknown. Hence, it becomes essential to measure the AV operation safety to avoid or reduce the collision risk by assessing the drive safety (Shangguan *et al.*, 2020).

While biological life forms (e.g. human beings) follow so-called ‘simple’ instinct to react to unforeseen events, robots may struggle to decide on the most appropriate course of action in a timely manner (Lipson and Kurman, 2016, p.16). For instance, a Tesla S sports car (operating in Autopilot mode) collided with a lorry trailer in May 2016 after failing to detect it, resulting in the death of the Tesla driver. This was the first reported fatality in over 130 million miles of testing the automated driving system by that time. The accident was caused under extremely rare circumstances of the extra height of the lorry, its white colour under the brightly lit sky which blinded the visual cameras of Tesla, combined with the positioning of the both vehicles across the highway (Varshney and Alemzadeh, 2017). While a broad consensus suggests that autonomous vehicles will improve driving safety, several steps still remain to secure these benefits (Lari, Douma and Onyiah, 2015; Ryan, 2019). These scenarios may seem to be unlikely, but when millions of AVs are on the roads even rare events are bound to occur (Bonnefon, Shariff and Rahwan, 2016). Although some scholars (e.g., Watzenig and Horn, 2016) advocate that most of core technologies enabling fully autonomous driving have become available and many are even mature, the reliability of the technological elements of AV systems is questionable. The fatal accidents together with disengagement statistics released by AV developers in the US can support the assertion that AI decisionality has shortcomings compared with human decisionality at least in early stages of development.

By accepting the fact that the key difference between AVs and conventional vehicles lies in replacing human drivers with AI, it becomes crucial to investigate the limitations of AI more closely. Abduljabbar *et al.* (2019) acknowledged a number of these limitations specifically in the field of transportation. Firstly, artificial neural network (ANN) establishes relationship between the input and output without demonstrating any knowledge about how these relationships are developed. Secondly, there is a suspicion that ANN makes generalisations when the data sets are imperfect or some information is missing. To tackle this challenge, some experts recommend combining the ANN technique with other AI tools, but this demand for hybridisation is also seen as another weakness for ANN. Thirdly, where AI needs real-world data to learn and improve (during training), deployment of the technology in real-world environment can pose excessive risks. Another limitation relates to biases which can be introduced in the training data sets owing to the involvement of humans who are prone to biases and error in labelling processes. In spite of the fact that an AV must be capable of forecasting traffic flows, unexpected events and overcoming poor weather conditions, current AI algorithms are inadequate to map out such events and circumstances. Furthermore, AI-based technologies pose a risk to the customer privacy. Restrictions on data collection affects the quality of the input into AI-based technologies (Agrawal, Gans and Goldfarb, 2019). On the other hand, the risk associated with privacy and data security in data-driven and AI-based technologies is serious and needs special consideration (Taeihagh and Lim, 2019). Lastly, the design of algorithms warrants a trade-off between effectiveness in terms of processing large amount of input data and sufficiency in terms of using computation capacity and time to analyse those data. An AV can receive data from multiple sources such as sensors, GPS, cloud applications, roadside units (RSU), etc. Hence, high computation complexity can also challenge the effectiveness and efficiency of the AI algorithms in an autonomous vehicle (Abduljabbar *et al.*, 2019).

Despite the fact that regulations and regulatory bodies play a pivotal role in ensuring the reliability of safety-critical systems, it appears that regulatory bodies cannot catch up with the rapid speed of advancements in autonomous driving (Schreurs and Steuwer, 2015). In the case of more disruptive technological developments which can cause more radical changes in the regulatory environment, decision makers are under pressure to make quick and maybe momentous decisions. The ambiguity around the regulatory environment is another major source of uncertainty for stakeholders of AVs. To avoid these ambiguities regulatory bodies must ideally take proactive rather than reactive approaches in regulating different aspects of AV technology (Lipson and Kurman, 2016).

Car manufacturers, insurers, buyers, legal authorities and other stakeholders need clear and detailed regulations to make decisions and judgments. For example, Kalra and Paddock (2016) mentioned about the lack of adequate statistics on autonomously driven miles and discuss how this hinders drawing a comparison between the performance of human and autonomous vehicle failures. Then they raise the question of "*how many miles would autonomous vehicles have to be driven without failure to demonstrate that their failure rate is below some benchmark?*" and try to address it. Lundgren (2020) estimated that 84-500 years will take for CAVs to statistically (with 95% confidence and 80% power) prove that their failure rates are 20% less than human drivers. Another example could be the Vienna Convention which may need amendments to allow the introduction of fully driverless cars to the UK roads (Glassbrook, 2017, p.18, p.38). These imply that there are still many questions about how the AV technology is or going to be regulated. Lack of regulations, therefore, is among primary sources of uncertainty in autonomous driving which can potentially affect the safety measures and erect barriers to establishing standardisation between manufacturers and states (Ryan, 2019).

In addition to the technological and legal facets, infrastructure readiness and public perception (acceptance) towards the safety of AVs need extensive research (König and Neumayr, 2017). The existing physical infrastructure has been designed and adapted to human driving. Saeed (2019) highlights the increased awareness about poor readiness of current infrastructure to accommodate AVs. Autonomous vehicles may necessitate changes to the existing road infrastructure such as traffic signage, lane width and colour, on-road telematics, crash barriers, etc. (KPMG, 2018). Several variables such as market penetration rates, the proportion of human driven vehicles and level of automation will drive changes in infrastructure. As a result, it is imperative to account for the AV-related infrastructure uncertainties and examine the readiness of the existing infrastructure and roadways to host AVs (Saeed, 2019).

Hengstler, Enkel and Duelli (2016) argue that perceiving risks of novel technologies is a social process and technologies are not separable from their social context and cultural values. There are discrepancies between scientifically calculated (or proven) risks and what public perceives as risk. The gap can become even broader when it comes to radical innovations and automated technologies with higher degrees of uncertainties and unknown consequences. This can further affect trust, attitudes, and the way individuals interact with the technology. How people would react to autonomous vehicles is still a dilemma for researchers. Research has shown that the reason for high failure rates, particularly in revolutionary technologies, often cross the technical boundaries and to some extent involve customer knowledge and levels of perceived risks (Hengstler, Enkel and Duelli, 2016). For this reason, AECON is testing mini-driverless pods (without any dedicated supervisor inside) in the UK city centres to study the reactions of pedestrians, prams and bikes to autonomous driving (Whitehead, 2020). Nevertheless, more research is required to pinpoint all aspects of human-machine interactions in the context of AVs. For example, the results of some studies (e.g., Hulse, Xie and Galea, 2018) reveal that although perceived risks for AVs appear to be low, participants expressed numerous concerns such as possible system/equipment failure, cyber-attacks and ethical issues. The latter together with moral and value-driven concerns play a critical role in shaping users' perception and acceptance (Kaur and Rampersad, 2018).

2.2.2. Collision risks and avoiding them

It has been discussed that reliability and safety of AVs are a chief concern for industry and policy makers to ensure their competence over human drivers and guarantee their safety benefits. As far as safety of AVs is at stake, one of the most challenging tasks for an AV is to plan an appropriate collision-free trajectory even under emergency circumstances when an unexpected obstacle abruptly blocks the pre-planned path of the vehicle (Hajiloo *et al.*, 2020). In such situations, an AV must be capable of deciding on and undertaking the safest action and using available actuators timely to optimally avoid any collision or reduce the severity when a collision is unavoidable. To achieve that level of reliability and an acceptable functional safety level, detecting and averting hardware failures, software bugs and firmware malfunctions are vital (Mariani, 2018).

It is noteworthy to draw a line between an accident and a collision. In Cambridge Dictionary an 'accident' is defined as "*something bad that is not expected or intended and that often damages something or injures someone*" (Cambridge Dictionary, 2008, p.8). Oxford English dictionary suggests almost the same definition for the word 'accident' (Glassbrook, 2017, p.135). For example, if a vehicle is being driven on road and suddenly catches fire because of a fuel tank leak, we can say that an accident has occurred, but it may not necessarily lead to a collision. On the other hand, a collision refers to "*an accident that happens when two vehicles hit each other with force*" (Cambridge Dictionary, 2008, p.268). Now it is useful to know that 97.8% of all traffic accidents in the US are collision type (He *et al.*, 2019). Thus, eliminating or mitigating factors that cause collisions will considerably level up road safety.

In road traffic (similar to maritime and aviation), one of the indicators of safety is the absence of collision or conflict between road participants (Campos and Marques, 2018). That being the case, avoiding collision becomes a primary objective for CAVs. He *et al.* (2019) explores several advanced collision avoidance systems and strategies for CAVs that evaluate risks of colliding with other vehicles, obstacles or pedestrians and adjust a vehicle's velocity and/or trajectory to safely navigate through traffic. Li *et al.* (2021) categorised current collision avoidance systems into three groups. Among them is the *risk-based assessment model* which first assesses the risk of colliding with the objects surrounding the subject (or ego) vehicle and then generates a prioritised series of actions to avoid collisions. Still risk sources remain in place and can incapacitate the collision avoidance systems. Examples of fatal accidents and disengagements highlighted in section 1.1 suggest that concerns over the safety of CAVs are legitimate and need to be investigated.

With increasing complexity of systems, number of subsystems and their interdependencies, the challenge of modelling and assessing risks in these systems becomes greater. Haimes (2018) manifested ten principles for modelling risk in interdependent complex system of systems (SoS). Since CAVs are categorised under SoS (Madni *et al.*, 2018), those principles provide a guiding framework for analysing risks for systems comprising many interconnected subsystems with multiple functions and operations.

Principles eight and ten in that framework advocate appropriate choice of metrics for measuring risks.

Different metrics can be used to measure collision risk. Time to collision (TCC), time headway (THW), and time to react (TTR) have been previously used in deterministic studies for that purpose (Noh, 2018; Li *et al.*, 2021). The problem with deterministic approaches is that they neglect the uncertainties in input data (Noh, 2018) and fail to model multi-lane scenarios (Li *et al.*, 2021). Those deficiencies of deterministic methods divert attentions to probabilistic approaches to measure collision risks. Modelling methods such as fuzzy logic, partially observable Markov decision process (POMDP), and Bayesian networks not only involve *temporal* and *spatial* relationships between traffic participant/environment but also takes input data uncertainty into account (Noh, 2018). Traffic dynamics and comparing traffic variables (e.g., flow and occupancy) can be utilised to estimate *spatio-temporal* risk in terms of hazardous traffic conditions (Katrakazas, Quddus and Chen, 2019).

The above discussion indicates two major sources of collision risk: 1) presence of objects (mainly other vehicles) in the vicinity of subject vehicle; and 2) lack of competence and capability of a human driver or an autonomous system (or a combination of both) to avoid a collision. These two sources comprise four major domains that include risk factors. Presence of object directly depends on the environmental and road (traffic) conditions. The competence of an autonomous vehicle to bypass a collision depends on software and hardware capabilities of the vehicle and reaction of its driver (when required). Fig. 2.4 illustrates the mutual interactions between the four domains. This classification scheme lays the foundation for the BBN model in this research.

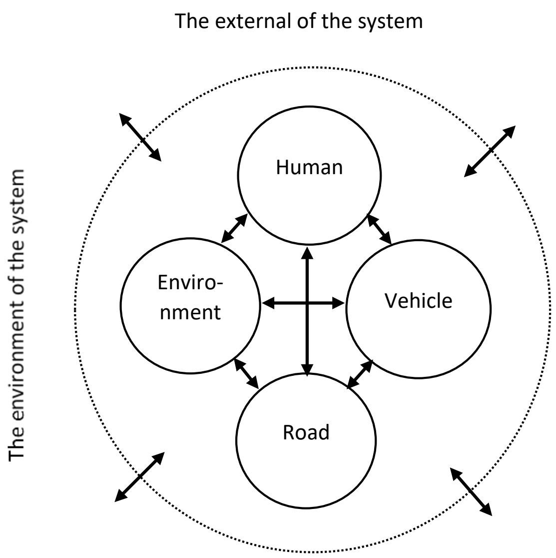


Fig. 2.4: the organic connections between elements that constitute a road system (Liu and Zhai, 2018)

2.2.3. Safety of CAVs and overall policies

Despite fast technical progresses and promising trials of CAVs, development of policy responses in this field is still in initial stage (Milakis, Thomopoulos and Van Wee, 2020). This lag between the evolution of technology and policy making can slow down the roll-out of CAVs at commercial scale and achievement of their benefits. A recent policy landscape review of AVs in the UK reveals that although some progress has been made to ensure the safety of CAVs, we are still away from a satisfactory and thorough policy response to this phenomenon (Lisinska and Kleinman, 2021). The authors highlight three major concerns that need to be addressed by introducing effective policies: 1) certification of the technology to overcome harsh circumstances such as adverse weather conditions; 2) transition of control between the vehicle and driver and clarity of human driver's responsibilities; and 3) cybersecurity and privacy.

Anderson *et al.* (2014, p.161) also reported three important policy gaps that are directly related to the safety of CAVs. According to their analysis, human-machine interfaces, standards and regulations, and state laws are the areas that policymakers together with other stakeholders should address. This gap still exists and needs immediate attention (Zhang, Shu and Yu, 2021). Furthermore, the rapid pace of technological development turns standardisation into an extremely challenging task since the risk of obsolescence and irrelevance is serious (Anderson *et al.*, 2014, p.162). Finally, variations in laws (e.g., traffic or liability laws) from one country to another (in Europe) or between the 50 states (in the US) can confuse the technology developers. While compliance with traffic rules appears to remain a requirement for CAVs at least as long as mixed traffic is the case, an unequivocal formalisation of traffic rules is a complicated task (Maierhofer *et al.*, 2020). The inconsistencies in traffic laws across the regions adds to the complexity of that task.

Mixed traffic environment merits new policy considerations to ensure the safety of CAVs and non-CAV road users. Straub and Schaefer (2019) found that ensuring public safety is the most significant challenge in the territory of AV policy. Reviewing other recent publications on policy directions and challenges for CAVs suggests that safety is of prime importance (e.g., Lundgren, 2020; Milakis, Thomopoulos and Van Wee, 2020; Sohrabi, Khreis and Lord, 2020; Acheampong *et al.*, 2021; Lisinska and Kleinman, 2021). There are also growing concerns over the impacts of cybersecurity failures/attacks on CAV safety (Katrakazas *et al.*, 2020). Since CAVs can disruptively affect the stakeholders across the transportation ecosystem, clear and coherent policies are integral to regulate different aspects of this technology including safety (Rebalski *et al.*, 2021).

2.2.4. Stakeholders

The integration of CAVs into existing transport system is a socio-technical transition that calls for active engagement with vast arrays of stakeholders (Rebalski *et al.*, 2021). Involving stakeholders and eliciting subjective expert judgements is a well-established method to tackle uncertainties during the design phase as well as probabilistic risk assessment (PRA) (Cooke, 1991, pp.27-29; Bedford, Quigley and Walls, 2006). Therefore, mapping the stakeholder groups that are going to encounter with CAVs in different ways is a primary step for recognising and engaging them in safety analysis and policymaking processes.

The development and emergence of AV technology widens the field of actors and gives rise to the emergence of new stakeholders (Schreurs and Steuwer, 2015; Maurer *et al.*, 2016). From different aspects it is crucial to identify the key stakeholders of AVs and evaluate how they will affect the safety and how will be affected by safety implications. It becomes even more important when we intend to elect experts for knowledge elicitation out of key stakeholders. Reviewing the relevant literature suggests several players at stake. The results are summarised in Table 2.4.

Table 2.4: summarises the key stakeholders of AVs cited in the literature.

Literature	Public	Transportation professionals	Automotive industry	Car insurance industry	Software developers	Regulatory bodies	Consultancies	ICT & communication industries	Lawyers	OEMs and automotive part suppliers	Urban planners and designers	Governmental departments and agencies	Academia	Research institutions
(Rebalski *et al.*, 2021)	✓	✓	✓				✓				✓	✓		
(Isaac, 2016)	✓		✓	✓	✓		✓					✓		✓
(Shannon *et al.*, 2021)	✓		✓	✓		✓				✓		✓		
(Anderson *et al.*, 2014)		✓	✓	✓	✓		✓	✓	✓	✓		✓		✓
(Clark, Parkhurst and Ricci, 2016)		✓	✓	✓			✓						✓	
(Holstein, 2017)					✓					✓				
(Schreurs and Steuwer, 2015)			✓	✓		✓		✓				✓	✓	✓
(Maurer *et al.*, 2016)	✓				✓	✓		✓						
(Nyholm and Smids, 2016)	✓		✓	✓				✓	✓	✓	✓			
(Hengstler, Enkel and Duelli, 2016)	✓		✓	✓	✓	✓		✓		✓		✓		

According to the reviewed literature and after excluding overlaps, the list of main stakeholders can be shortened to transportation professionals, car insurance industry, software developers (including AI community), automotive industry, regulatory bodies (e.g., Driver and Vehicle Standard Agency), consultancies, ICT & communication industries, lawyers, OEMs and automotive part suppliers, urban planners and designers, governmental departments and agencies (e.g., Department for Transport), academics and research institutions.

2.3. Theoretical framework

2.3.1. Related works and the knowledge gaps

The impact of AVs on traffic safety and safety-related risks are among the primary focuses of academic research and addressing them is one of the top priorities of technology developers and practitioners. The fact that safety perceptions have a critical influence on AV adoption is not deniable (e.g., Moody, Bailey and Zhao, 2020; Manfreda, Ljubi and Groznik, 2021). The criticality of safety considerations has resulted in a rich body of literature and industrial initiatives not only to ensure that AVs can outperform human drivers in driving safety, but also to influence public perception about the safety of them. This section investigates the studies that tried to capture and measure risks associated with CAVs at vehicular or network levels.

In the previous section road vehicle insurers were identified as one of the main stakeholders of the AV technology. As a result, it is a requisite for the car insurance industry to conduct full and detailed risk analysis before the technology becomes pervasive. To this end, Pütz, Murphy and Mullins (2019) performed rigorous qualitative analysis to assess the impacts of vehicle automation on motor-third party risks and future insurance policies. From an insurance perspective, the frequency of collisions is expected to decrease, although the average loss will go up due to technology expenses and complexity of repair works. Shannon *et al.* (2021) further examined four scenarios in how CAVs can change injury claims and discussed how CAV risk factors and traffic dynamics can transform road environments. Their actuarial results indicate that with an increase in automation level a reduction in frequency and severity of collisions will be experienced.

Ye and Yamamoto (2019) ran a simulation to calculate the frequency of hazardous situations and time-to-collision for CAVs in heterogenous traffic flow (i.e., a mix of conventional and autonomous vehicles). The findings of the simulation suggest that the overall traffic safety improves with the increase in CAV deployment rate. Li *et al*. (2021) carried out a probabilistic risk assessment to develop an algorithm for collision avoidance under various scenarios. They used time-to-escape (TTE) as a metric to measure lateral driving risk. In another attempt, Wang *et al*. (2021) proposed a low-risk and high-efficiency path planning algorithm for AVs. In that study, the trajectory and velocity of surrounding vehicles were used to assess the collision risk and plan a path with minimum risk and high driving efficiency.

Besides a wide range of approaches and modelling techniques for risk analysis, BBN models have also been used in several studies. For instance, Sheehan *et al*. (2017) adopted a network risk transfer approach and proposed a BBN model to quantify the risks of semi-autonomous vehicles. In a similar study, but in a different context, another BBN model was developed by Sheehan *et al*. (2019) to classify the cybersecurity risks in connected and autonomous vehicles. Allouch *et al*. (2019) also employed the BBN tool to carry out qualitative and quantitative risk analysis for UAVs. BBN technique was also used to assess the risks wind turbine in Ashrafi, Davoudpour and Khodakarami (2015). The structure of their model encompasses four major group of factors: technical, environmental, human and organisational. In addition, a BBN-based portfolio risk assessment framework was developed for evaluating R&D projects at NASA (Geuther and Shih, 2016). Brito and Griffiths (2016) benefited from BBN to assess the risks of deploying AUVs in harsh environmental conditions.

Apart from the applications of BBN in the field of CAVs (e.g., Sheehan *et al.*, 2017; Sheehan *et al.*, 2019) and other socio-technical system risk analysis (e.g., Trucco *et al.*, 2008; Ashrafi, Davoudpour and Khodakarami, 2015; Luxhøj, 2015), System-Theoretic Process Analysis (STPA) method was offered to deal with safety and security risks of AVs (Sabaliauskaite, Liew and Cui, 2018). The system interdependence analysis method together with BBN method were also applied to study the performance of autonomous systems (Lidoris *et al.*, 2011).

Many scholars, experts, technical communities and media have already warned about the newer risks and hazards that AVs can impose on the safety of roads (e.g., Maurer *et al.*, 2016, p.343; Bellet *et al.*, 2019; Shannon *et al.*, 2021). Deep uncertainties and lack of historical data complicate risk analysis and planning for safe deployment of such technology. Faisal *et al*. (2019) conducted a systematic literature review on capability, impact, planning and policy of AVs and identified a gap in the literature in planning for the future. Any rigorous analysis on the safety and reliability needs to be, to some degree, based on accurate quantification of risks and probability of failures under varying circumstances. This applies to policymaking as well where policy-makers need enough evidence for shaping public policy (Parkhurst, 2017).

To the best of my knowledge, there has not been any study to look at the risks of CAVs through the lens of socio-technical theory and model the influential variables and their interdependence to measure the collision risks in urban ambience exploiting BBN technique and experts' knowledge. The studies that used BBN to examine the risks of AVs (such as Sheehan *et al.*, 2017; Sheehan *et al.*, 2019) are different from this study in several ways. For instance, Sheehan *et al.* (2017) focused only on telematics data gathered from vehicles' sensors which are useful for measuring controllable risks such as speeding. The BBN model in that study was designed to measure 'aggregate claims loss' for insuring purposes. The selection of variables was not based on rigorous research and merely contained ADAS risk factors. Sheehan *et al.* (2019) only concentrated on cyber risks, but the extent of this research is broader and encompasses wider range of variables.

This study intends to identify influential variables in four diverse but interactional spheres (i.e., technical, road environment, human and traffic environment) by conducting an integrative literature review and amalgamating them into a modular BBN model to provide estimation for the collision risk index. The aggregation of risk factors at vehicle, environment, traffic and operator levels will satisfy the first principle of Haimes' framework (2018) for risk analysis of SoS. That principle puts forward a *holistic system-based* approach to account for the impacts of adverse initiating events on complex SoS (Haimes, 2018).

Denaro *et al.* (2014) called attention to ten major research areas in relation to AVs which were identified by industry, academic and government experts for further advanced multidisciplinary research. Some of these areas have not been addressed properly yet. Human-machine interactions (HMI), infrastructure, V2X communication and architecture, risks, cyber security and resiliency are among these research topics. Adopting a multidisciplinary approach besides socio-technical theory can enable us to bridge these areas. BBN has proved the capability to handle the complexity and generate satisfactory outcome especially in risk and uncertainty assessment. Furthermore, the safety issues of AVs are still a focal point in both industry and academia (Katrakazas, Quddus and Chen, 2019). The need for constructing decision-making support tools and delving into plausible scenarios become even more urgent while AV-related performance and collision data are still scarce (Pütz, Murphy and Mullins, 2019; Katrakazas *et al.*, 2020).

Although traffic (micro)simulation studies (e.g., Morando *et al.*, 2018; Papadoulis, Quddus and Imprialou, 2019; Wu *et al.*, 2020) offer insights and can reduce uncertainties around the integration of CAVs into existing traffic systems, still they suffer from limitations and assumptions have to be made for some of parameters and variables such as penetration rate and transportation demand after AVs hit the roads. A compelling alternative to simulation is real-world testing which may be confined to stringent regulations and high expenses. A risk classification model based on road characteristics, traffic conditions and vehicle reliability levels can therefore be exploited to rank municipal districts in a given time interval.

Likewise, insurers will require tools to estimate collision risk in the absence of sophisticated databases. A BBN model not only has the potential to satisfy this need, but also can learn from actual data when they become available and improve its accuracy. Miscalculating road and environmental condition risk levels by traffic agents (e.g., driving entities) can threaten safety of navigation (van Wyk, Khojandi and Masoud, 2020). Classification of collision risks based on spatio-temporal characteristics will also assist policymakers to prioritise the policy areas that need urgent and special attention for safeguarding road safety.

2.3.2. Theoretical underpinnings of risk analysis for complex socio-technical systems

Compound and modern technologies are bringing fundamental changes into the causality of accidents and are revealing the need for adapted approaches in the explanatory mechanisms (Leveson, 2004). As socio-technical systems are becoming more complex and more integrated, traditional approaches are proving to be less effective (Manzur Tirado, Brown and Valdez Banda, 2019). Traditional approaches to safety analysis do not usually account for organisational, societal and human role in accidents (Leveson, 2004). Those hazard analysis techniques including fault tree analysis (FTA) and event tree analysis (ETA) assume that component failure is the only cause of accidents, and therefore risk analysts must focus their efforts on thinking of plausible scenarios of component failures (Manzur Tirado, Brown and Valdez Banda, 2019).

Then, based on system theory, Leveson (2004) proposed STAMP (Systems-Theoretic Accident Model and Processes) to model component failures, *external disturbances*, and *dysfunctional interactions* between system components in the design, development and operation of a complex socio-technical system. STAMP benefits from system dynamic approaches and defines any safety problem as a control problem which violation or ignorance of any safety constraints signals inadequate control (Kazaras, Kontogiannis and Kirytopoulos, 2014). Based on *socio-technical system* theory, Mohaghegh and Mosleh (2009) presented a framework (i.e., SoTeRiA) to incorporate organisational, external environment and human factors into PRA. A socio-technical system must be seen as an *integrated whole* and the role of social factors in conjunction with safety and reliability should be recognised (Qureshi, 2008). This is consistent with the view of Liu and Zhai (2018) in defining traffic problems (e.g., collisions) as not only technical but also social problems. This approach has helped to inform the design of new technologies and explain the changes caused by novel technologies (Davis *et al.*, 2014).

The socio-technical philosophy concerns with the integration between machine, or in a broader term technology, and humans in designing operational processes and/or systems (Ropohl, 1999; Dekkers, 2018; Sony and Naik, 2020). Autonomous vehicles can also be defined as complex socio-technical systems, since technological, business and policy innovations are concurrently at stake (Marletto, 2019). A comprehensive structural safety framework, according to Mohaghegh and Mosleh (2009), should contain and combine macro and micro perspectives. Hence, a “cross-level” causation theory is desirable. Principles D and E of SoTeRiA describe the *multi-level framing* and *depth of causality* (Mohaghegh, Kazemi and Mosleh, 2009). Depth of causality and level of details are crucial decisions to be made by a researcher to maintain comprehensiveness and avoid excessive complexity (*parsimony*) which may cost the accuracy of the model. This decision essentially depends on the impacts of different dimensions of each element and the sensitivity of the overall risk to those dimensions (Mohaghegh and Mosleh, 2009). Another boundary which needs to be established is the level of *generality* and the scope of safety concerns (i.e., road users’ safety in this study).

Based on the above theoretical discussions, Mohaghegh, Kazemi and Mosleh (2009) concluded that hybrid methods including BBN are perfectly fitted to address uncertnity in socio-etchnical systems. To reduce the uncertainty and quantify the associated risks, a BBN model can be adopted which can provide accurate estimations for the identified risk indices in a considered scenario and/or analyse accident paths in a retrospective backward approach (Ashrafi, Davoudpour and Khodakarami, 2015). BBN model is the intersection of graph theory, probability theory and statistics (Ben-Gal, 2008). Probability theory (also known as inductive logic) is perhaps the oldest and best-established theory for representing and reasoning about a situation where categorical propositions can be only made by judging the likelihood or other ordinal attributes (D'Ambrosio, 1999). To develop the intended BBN model in this research, we follow the principles proposed in the SoTeRiA framework which are classified into four main categories: (I) designation and definition of objectives; (II) modelling perspectives (e.g., causality); (III) building blocks (e.g., link level); and (IV) techniques (e.g., measurement techniques).

In recent years, *context-aware* decision-making models are emerging to connect aspects of traffic environment with visibility conditions, occlusion and perception uncertainty that CAVs often face during their operation (Katrakazas *et al.*, 2020). This highlights the criticality of traffic scene characteristics in collision risk analysis. In fact, the physical space around road users consists of built environment and traffic state. Variables in either of these spheres interact with and affect each other in a mutual way. For instance, road geometry can impact traffic congestion and it can affect velocity of vehicles. To include the influence of traffic conditions in collision risk analysis for AVs, a block of the model is dedicated to measure the complexity of traffic scene and evaluate its impact on the collision risk.

Mohaghegh and Mosleh (2009) placed a heavy emphasis on inclusion of organisational factors in assessing risks associated with socio-technical systems. An organisation comprises four key interacting constituents, namely structure, technology, agents (actors) and task (Leavitt, 1965). Urban traffic can be thoroughly fitted to this definition of organisation. Agents (traffic participants) use technologies (e.g., vehicles) within the urban traffic structure (constrained by traffic rules) to accomplish their tasks (i.e., commuting safely between destinations). Meanwhile, all those constituents interact with each other and change in one of them can affect the rest. Therefore, in the present context, traffic state variables can represent the organisational factors.

2.4. Summary of the literature review and conclusions

In this chapter, an overview was provided to highlight the status of CAVs in the future of ITS. The amount of investments, trials, academic literature, and legislative works all suggest that AVs are going to be a core element of future transportation. This mandates careful risk analysis to ensure the safety of technology. The relevant definitions and terminologies were also covered to reflect the scope and discrepancies in use of language around CAVs. Next, the uncertainties and safety risks were discussed. It is evident that successful roll-out of AVs is intertwined with the safety of technology. The related works in this research domain were reviewed and the knowledge gap was ascertained.

Despite large number of studies that have already assessed collision risks and provided solutions to mitigate that risk, a wider view such as socio-technical approach to include the interactions and contributions of risk factors across environmental, technical, traffic and human levels is still lacking. Due to the complexity of CAVs, their operating environment, and their interactions with humans, a socio-technical approach is required to meet the objective of this research. A socio-technical lens can provide complementary insights into the problem of collision risk in AD beyond just vehicle kinematics. A theoretical framework was developed to lay a foundation for the methodological deliberations in the next chapter. SoTeRiA framework was concluded to be an appropriate and commensurate risk analysis framework to assess collision risks for CVAs as complex socio-technical system.

Chapter 3

3. Methodology

This chapter delineates the selected philosophical and methodological perspectives and approaches to answer the specified research questions in the introduction. It is also described why BBN is appropriate technique to model risk in this study and a comparison is drawn to show advantages and deficiencies of BBN against other risk modelling techniques. Types of data required to build the model as well as the methods of data collection and sources are discussed in this chapter. Since this research benefits from mixed methodology, both qualitative and quantitative parts are covered in separate sections and in-depth discussions are provided to justify the development of the model. A framework for integrative literature review (ILR) as the main method for collecting qualitative data is developed and presented. Likewise, the means and strategies for eliciting and analysing expert judgements are set out.

3.1. Ontology, epistemology, inductive or deductive?

In any kind of project, adopting clear and appropriate strategies is urgently important to achieve specified objectives. Along the same line, a PhD research project follows this rule. However, before formulating the strategies to answer research questions and pursue the objectives, it is vital to deepen an understanding of the nature of business research and explore the philosophical concepts behind the research questions and aims. This approach also provides insight into *deductive*/*inductive* and *epistemological*/*ontological* considerations which are cornerstones of the strategy adoption processes (Bryman and Bell, 2015). For this reason, and to facilitate the discussion upon reasonable strategies for this research study, we first need to discuss the pertinent philosophical concepts.

Research, in general view, is designed to generate knowledge and provide answer(s) to specific question(s) in a particular field. To this end, there have to be assumptions to be made and develop knowledge based on those assumptions and beliefs (Saunders, Lewis and Thornhill, 2015). These assumptions relate to human knowledge (epistemological assumptions), realities the researcher faces during the research (ontological assumptions) and how personal values can influence the research processes (axiological assumptions) (Saunders, Lewis and Thornhill, 2015). Therefore, we will start from examining these philosophical concepts in the next paragraphs and based on that discussion, conclude a fitting research strategy in the next section (3.3).

A key factor in determining the research strategy is epistemological considerations. Deciding on what is acceptable knowledge and how we should communicate it causes the main controversy in this sphere (Saunders, Lewis and Thornhill, 2015). Regarding and treating the social world with the same principles, methods, and ethos as used in natural sciences or taking a different approach is the central issue in this context too (Bryman and Bell, 2015). *Positivism* and *interpretivism* are two basic but contrasting epistemological positions, defining the relevance and the differences between social sciences and natural sciences (Bryman and Bell, 2015; Saunders, Lewis and Thornhill, 2015). Consequently, these two epistemological stances vary significantly on acceptability of knowledge, good-quality of data, types of contribution to knowledge (Saunders, Lewis and Thornhill, 2015). Supporting each of these positions plays a determining role in choosing the appropriate research strategy.

One of the fundamental questions which must be answered before deciding on the research strategy and consequently research methodology is about the relationship between the theory and research (Bryman and Bell, 2015). Depending on the research aims, there are two possible responses to define this relationship. Firstly, as Bryman and Bell (2015) explain, a researcher can use theory to form a hypothesis, and further by collecting data and analysing them confirm or reject the hypothesis. This view is called *deduction* and based on what is known so far about a field of study, the researcher deduces hypothesis (or hypotheses) according to his/her empirical findings (Bryman and Bell, 2015). This process is depicted in figure 3.1. On the other hand, if research is intended to build a theory (or a conceptual framework) out of observations/findings the process would be then opposite the sequence of *deductive theory*. This approach, known as *inductive theory*, is used when the researcher is trying to construct a new theory rather than testing an already developed theory (Bryman and Bell, 2015).

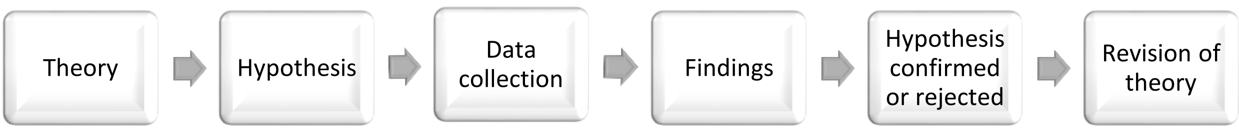


Fig. 3.1: the deduction theory steps (Bryman and Bell, 2015).

Along with epistemological assumptions, it also matters how a researcher sees the world of business management and defines phenomena in this world (Saunders, Lewis and Thornhill, 2015). Furthermore, the cause-and-effect relationship between social entities (e.g. organisation) and social actors (e.g. managers) has a meaningful impact on the methodological analysis of the research. Two common views concerning the social ontology are *objectivism* and *constructionism* (Bryman and Bell, 2015). Objectivism asserts that social entities and social actors are independent from each other and social actors do not have any influence upon social phenomena as they occur (Bryman and Bell, 2015). Contrary to this ontological position, constructionism maintains that social phenomena are the result of social interactions and therefore are continuously revised. Taking each side mentioned above suggests different requirements and strategies for the research to deal with every phase of it from formulating research questions to data analysis. Due to the adoption of mixed methodologies (which will be explored in coming sections), considering the uncertainties around and complex nature of AVs, state-of-the-art risk assessment frameworks, and practical implications for risk assessment in this study, we decided on a balanced approach towards philosophical underpinnings and research paradigms.

Depending on what we assume to be considered as data, there can be three major research methodologies available to researchers. Many authors including Saunders, Lewis and Thornhill (2015) categorise data into two groups. First, numeric data or numbers, and secondly any kind of data other than numbers. The latter encompasses a wider range of materials such as words, images, video, clips, etc. (Saunders, Lewis and Thornhill, 2015), although they can be also converted in the format of numbers. Similar to ontological assumptions, choice of methodology dominantly determines the type of required data and instruments for data collecting processes. Although a researcher may decide to employ more than one of those instruments or an instrument can prove its ability to collect data for any chosen methodologies. With regards to the above introduction and the outlined research questions, the next sections will justify the choice of methodology and techniques in this research project.

3.2. Applicable research methods and strategies

Studying the risks of a complex and multidisciplinary (if not interdisciplinary or even transdisciplinary) technology such as AV, accordingly, entails a comprehensive methodological framework to cover macro and micro risk factors to be able to accommodate multi-level and cross-level causation relationships. “Comprehensiveness”, in this context, denotes the inclusion of direct factors (e.g. physical components), indirect factors (e.g. safety practices), external environment, the regulatory environment, and the socio-economic environment (Mohaghegh and Mosleh, 2009). Nevertheless, it is vital to avoid unnecessary complexity by ignoring factors or variables that have small effect on the model output. It is not technically feasible to build an entirely accurate model and expanding the scope and level of details beyond a certain point may reduce the accuracy of the model (Robinson, 2008). Utilising computation models is subject to a *common fallacy* that adding more details to a model must necessarily advance its performance (Saltelli *et al.*, 2008, p.278). Figure 3.2 sketches a typical relationship between accuracy and complexity in modelling and simulation.

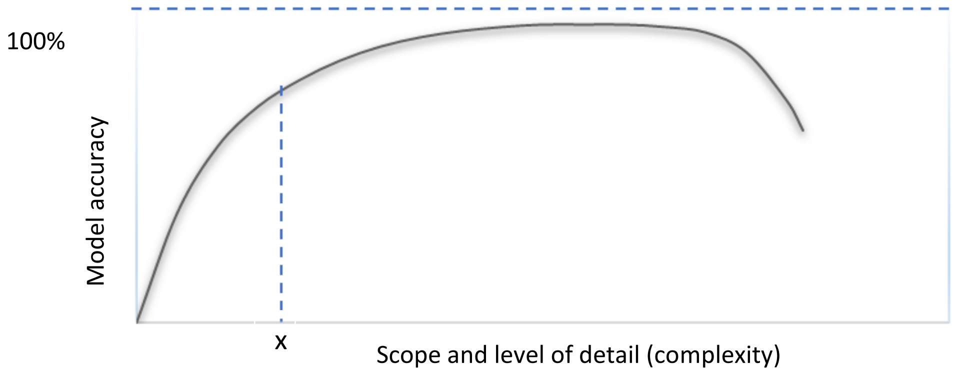


Fig. 3.2: simulation model complexity and accuracy (Robinson, 2008).

In addition to the scope of analyses, measurement methods are of critical importance in risk assessment (Mohaghegh, Kazemi and Mosleh, 2009). Although hybrid methods (i.e. combination of objective and subjective data) may result in more accurate analyses, they are also more resource-intensive and demand a method, such as Bayesian approach, for merging both sources of information into a single assessment (measure) of the state of a variable (Mohaghegh and Mosleh, 2009).

Reviewing the research questions in this project reveals the need for both qualitative and quantitative data. Risk identification is a process which requires *systematic* approach and may contain elements of both qualitative and quantitative methods (Drennan and McConnell, 2007). In other words, building most of risk models needs the combination of real-world quantifications (also known as *hard* data) and *soft* or qualitative data (Koller, 1999). This approach is supported by Pearl (2000) where he proposed practical methods for elucidating causal relationships from consolidation of knowledge and data. This approach provides the possibility for a more balanced evaluation (Teddlie and Tashakkori, 2009, p.13).

There is little doubt that risk analyses involve context-dependent assessments. Adopting mixed methods can deepen and broaden the scope of analyses and may offer more insight into the problem. Furthermore, "*classification of accident causes can not only provide a comprehensive understanding of accident but also benefit causes statistics*" (Li, Zhang and Liang, 2017). To clarify what is meant by causation it is helpful to quote the famous statement that "correlation is not causation" (Pearl and Mackenzie, 2018, p.5). Likewise, regression models fail to offer sufficient explanatory power in risk analysis (Fenton and Neil, 2012, p.31). These statements imply that mere statistics is not sufficient to identify risk causal factors, interpret data and construct a risk model (Pearl and Mackenzie, 2018). It is also supported by the fact that identification problems and statistical inference are mainly regarded separately in social sciences (Morgan and Winship, 2015). Mixed methodologies, above all, can pave the way to "causal inference". Causal modelling provides a base for making predictions on how a system would react to hypothetical interventions such as policy decisions (Pearl, 2000). By the same token, the primary aim for setting up a risk assessment programme is to deliver a predictive tool (Kabir *et al.*, 2015). Learning about cause-effect relationships is prerequisite to build a causal model and they can be deduced form a combination of qualitative causal assumptions and data (Pearl, 2000). Nevertheless, we must be aware of the constraints that social sciences encounter in gathering data (either qualitative or quantitative) and they can adversely affect the accuracy of causal inference (Morgan and Winship, 2015).

A large body of literature has emphasised on the interdisciplinary dimension of risk assessment (e.g., McDaniels and Small, 2004; Taylor-Gooby and Zinn, 2006; Renn, 2008; Büscher, 2011; Hansson and Aven, 2014). Renn (2008, p.68) explains that "*the purpose of risk assessment is the generation of knowledge linking specific risk agents with uncertain but possible consequences*". He also maintains that *inferential statistics* and *decision-analytics* tools have been developed to aggregate knowledge about cause-effect (causal) relationships and appraise the strength of them. Then the ambiguities and uncertainties can be characterised in the form of qualitative and quantitative data (Renn, 2008, p.70). The factors of a safety causal model, in this way, can be measured using subjective, objective, and hybrid methods. The main differences between the subjective and objective measurements lie in the sources of information and their related measurement instruments. Subjective and objective methods can be either qualitative (e.g. three or five-point Likert scale) or quantitative (e.g. rating from 0 to 10), or a mix of both (Mohaghegh and Mosleh, 2009).

Reviewing the literature on the safety and reliability of AVs reveals that there are valuable but, in many cases, incomplete qualitative or quantitative data gathered and generated to investigate different safety aspects of AVs. These data are usually complementary and can be merged to facilitate the intended risk assessment in this research. Smart transportation, in general, entails quantitative analysis combined with qualitative perceptions (McBride, 2016). In an attempt to model accidents of driverless cars (Geldmacher and Pleșea, 2016) and another study which was designed to assess safety of UAVs (Allouch *et al.*, 2019), the alignments of qualitative and quantitative data were utilised as well. On those grounds, we can conclude that applying capable and effective techniques and tools can to some degree secure the benefits of mixed methods in this study.

Although many scholars and researchers advocate that adopting and integrating multiple methods can improve the accuracy of results, mixed methods such as other methodological approaches face philosophical and methodological challenges. The main challenges can be: (a) there is no single mixed/integrated approach to regulate the level of integration. Depending on the research design, integration may happen, for example, at the research question or data analysis level (Teddlie and Tashakkori, 2009, p.133); (b) deciding between top-down or bottom-up approaches (Teddlie and Tashakkori, 2009, pp.317-318); (c) since both qualitative and quantitative methods have distinct basic assumptions/beliefs about a certain complex phenomenon, therefore merging the results can be problematic (Salehi and Golafshani, 2010); (d) there might be a degree of *incompatibility* between the techniques associated with either methods (Salehi and Golafshani, 2010); (e) deciding on which mixed methods are the best fitted to answer the research question is another pressing challenge (Almalki, 2016); and (f) requiring expertise and skills to manage the scope of research and reach accurate interpretations (Almalki, 2016). In the next sections we will introduce BBN technique and explain how it can exploit the benefits of mixed methods and deals with specified challenges.

3.3. BBN and mixed methods

It was discussed in the previous section that using appropriate and tailored techniques and/or tools is a pivotal part of employing mixed methods. It this section, we will elaborate on BBN as the central technique used in this research. BBN has the capability to accommodate data from various sources and combine qualitative and quantitative data into a single predictive/diagnostic model (Groth and Mosleh, 2012). This technique equips analysts with a tool which can exploit deterministic or probabilistic data in the presence of large number of interdependent variables (Trucco *et al.*, 2008). Building a rigorous risk assessment model requires scientific approaches to merge available knowledge and expert judgements (Kabir *et al.*, 2015). This is also endorsed by Groth and Mosleh (2012) where they signified the importance of incorporating observational data as well as expert information into a risk assessment model. BBN model has the ability to handle three predominant but distinct paradigms of risk assessment: 1) technical factor focused; 2) human factor focused; and 3) safety/organisational factor focused (Ashrafi, Davoudpour and Khodakarami, 2015). Formal synthesis of qualitative and quantitative evidence is an effective way to identify influential factors to a variable under consideration in a variety of studies across different disciplines (Weber *et al.*, 2012). For instance, The Bayesian approach was adopted to recognise influential factors in uptake of childhood immunisation (Roberts *et al.*, 2002). In order to improve these capabilities, especially in risk and reliability assessment, there have been modifications introduced to this technique such as Qualitative-Quantitative Bayesian Belief Networks (QQBBN) (Wang and Mosleh, 2010).

The widespread applications can demonstrate the effectiveness and strength of BBNs in handling uncertainty in absence or scarce availability of prior probabilities for events. Academic literature on risk and reliability assessment shows a broad range of applications comprising assessing the safety performance of subsystems and components of a nuclear plant, uncertainty analysis of complex systems, examination of integrated fire protection and prevention systems, estimating the unknown prevalence of chronic disease, and modelling organisational factors in maritime transportation (Trucco *et al.*, 2008). Besides, non-parametric BBNs (NPBN) have been widely used to analyse safety and risks of transportation systems, earth dams building fires and flood (Hanea, Morales-Napoles and Ababei, 2015).

3.4. Modelling dependable systems: Bayesian Belief Networks

Emerged from the field of cognitive science and artificial intelligence, probabilistic models based on directed acyclic graphs (known as DAG or BBNs) were initially developed in 1970s (Pearl and Russell, 2003). Over the last 30 years they also have elevated to a key method for reasoning under uncertainty in AI (Guo and Hsu, 2002). Judea Pearl (2018) in his book "*The Book of Why*" breaks down the calculus of causation into two languages: causal diagrams to represent what we already know, and a symbolic language to articulate what we aim to know. A BBN model comprises three basic components (Ismail *et al.*, 2011; Kabir *et al.*, 2015): a) a number of connected variables, b) a set of *mutually* and *exhaustive* states for each variable, and c) assigned conditional probability distributions for each variable which represents the conditional probability dependencies between variables. In the previous section we mentioned about the applications of BBNs in different fields to address distinct questions. More specifically, in risk assessment analysis, BBNs have proved to be an effective, flexible and reliable tool to reduce uncertainties and model interdependencies among variables. A cause-effect diagram or influence diagram is not frequently used in practice, despite graphically expressing the risks because some difficulties are faced such as complexity in detailed representation of the relationships. However, with a BBN it is possible to design a feedback loop for risk management (even if a Bayesian belief network has no feedback loop itself) (Lee, Park and Shin, 2009). This assists to present a cause-effect relation visually and provide conditional probabilistic estimations of risks.

A common approach to analyse dependability and reliability of a system is implementing probabilistic reasoning (Luigi and Daniele, 2015). Fenton and Neil (2012, p.31) argue that regression model remains ineffectual in risk assessment since it lacks explanatory power (comparing to causal models) and sometimes would mislead risk analysts with irrational information. Instead, they suggested introducing causal explanations into modelling processes to overcome limitations of traditional statistical approaches. Nevertheless, a sound probabilistic model comprising of a set of random variables has to rely on the joint probability distribution (JPD) over such variables (Luigi and Daniele, 2015). Having a joint probabilistic model allows for it to propagate probabilities from one node to others and compute *posterior* probabilities (Grover, 2016). To build this kind of model, Luigi and Daniele (2015) advocate the framework of *Probabilistic Graphical Models* (PGM). If nodes (causal and influential factors) represent random variables (*directed model*) we have *Bayesian (Belief) Networks*, while if nodes represent decision variables, we deal with *Decision Networks* which are also known as *Influence Diagrams* (Barber, 2012; Luigi and Daniele, 2015). Either model should be able to resolve three different types of uncertainty (Korb and Nicholson, 2003): *ignorance, physical randomness* or *vagueness*.

BBNs are acyclic graphical models widely used for reasoning under uncertainty or in other words representing knowledge in probabilistic systems (Korb and Nicholson, 2003, p.29; Luigi and Daniele, 2015). The term *Bayesian Networks* was first used by Judea Pearl in 1985 (cited in Pearl, 2000) to highlight the subjectivity of input information, Bayes' conditioning as the cornerstone of updating information and distinction between causal and evidential reasoning. The basic structure of BBNs consists of nodes which represent discrete or continuous variables and arcs representing direct dependencies between variables (Korb and Nicholson, 2003, p.29). A belief network, in general, is defined as follows (Barber, 2012; Luigi and Daniele, 2015; Ahmad *et al.*, 2021):

A Bayesian Network is a pair $N = \langle G, Pr \rangle$ where:

- $G = (V, E)$ is a DAG whose nodes $V = \{X_1, X_2, \ldots X_n\}$ are a set of discrete random variables and E is a set of arcs where an edge $e = (X_i \rightarrow X_j) \in E$ from X_i to $\mathrm{X_j}$ means that $\mathrm{X_j}$ depends on X_i (often interpreted as X_i causes X_j);
- Pr is a probability distribution over $\mathrm{X_1, X_2, X_3 \ldots X_n}$ such that,

$$Pr(\mathrm{X_1, X_2, X_3 \ldots X_n}) = \prod_{i=1}^{n} \mathrm{Pr}\,(X_i | pa(X_i))$$

where $pa(\mathrm{X})$ is the set of parent variables of X in the DAG G. We say that *Pr factorises* over G.

In order to construct a Bayesian Network, a practitioner or researcher needs to find answers for a number of questions (Korb and Nicholson, 2003):

1) What are the variables of interest (nodes)? What are their values/states?
2) What is the graph structure?
3) What are the parameters (probabilities)?
4) What are possible decision nodes? What will be their impact if they are effected?
5) What are utility nodes and their dependencies?
6) What are the preferences (utilities)?

Undertaking the above steps involves challenges and difficulties that can be even more severe where the model reflects higher levels of speciality and complexity. Determining edge directions, deciding between conditional and unconditional dependencies between nodes and choosing "divide" or "conquer" approach to cope with complexity are fundamental and common difficulties can be experienced (Fenton and Neil, 2012). There might be also ambiguities about the influential factors and number of nodes for a given problem. Conducting sensitivity analysis can test how sensitive the network is to changes in parameter values and validity of an expert-built model to see whether the network is robust or not (Korb and Nicholson, 2003; Fenton and Neil, 2012).

One of the basic requirements in modelling with Bayesian Networks is the assumption of the Markov property (Pearl, 2000; Korb and Nicholson, 2003). Pearl (2000) describes Markov property as: *"conditioned on its parents (directed causes), each variable is independent of its nondescendants"*. Many textbooks distinguish between global and local Markov properties for DAGs. The *"Handbook of Graphical Models"* (Maathuis *et al.*, 2018) defines the global Markov property for DAG as follows:

Every undirected acyclic graph *G* over *N* induces a formal independence model over *N* through the directional separation criterion. *N* represents the nodes (or random variables *A, B and C*), *G* stands for graph and $\tau(N)$ is the triplet model.

$$M_G = \{\langle A, B|C\rangle \in \tau(N): A \perp\!\!\!\perp B|C\ [G]\},$$

which is a disjoint graphoid. A probability measure *P* over *N* with $M_G \subseteq M_P$ is called *Markovian* with respect to *G* and we also say that *P* satisfies the *directed global Markov property* relative to *G*:

(DG) if *A* and *B* are directionally separated nodes by *C* in *G* then, $A \perp\!\!\!\perp B|C\ [P]$. M_G is therefore a probabilistic conditional independence structure for any *G*.

The local Markov property is also defined as:

If a node *j* is a descendant of a node i in *G* if a directed path exists in *G* from i to *j*; ds_G (*i*) denotes the set of all descendants of node $i \in N$ in *G*. Note that $i \in ds_G$ (*i*). A probability measure *P* over *N* satisfies a *directed local Markov property* relative to a DAG *G* over *G* if:

(DL) for all $i \in N \qquad i \perp N \setminus (ds_G(i) \cup pa_G(i)[P]$.

With respect to directed local Markov property, Korb and Nicholson (2003) categorised BBNs into three groups. First, Independence-maps or I-maps which have the Markov property, knowing that every independence suggested by the absence of an arc (direct cause) is real in the system. Minimal I-maps should be placed under this category too. In minimal I-maps, the removal of an arc should violate I-mapness by implying a non-existent independence in the system (Korb and Nicholson, 2003). Second, Dependence-map or *D-map* where every arc denotes a direct dependence in the system. Lastly, BBNs which can be regarded as both I-map and D-map are called perfect map.

Before starting the discussions on conditional probability tables (or CPTs), it is worth having a review on Bayes' theorem. There are three key axioms underpinning the Bayes' theorem (Grover, 2016):

- probabilities (chances for events to occur) cannot be negative, in other words they are at least zero, $\mathrm{P(A)} \geq 0$,
- the likelihood that something happens in the universe is always equal to one hundred percent, $P(\cup) = 1$, and
- if two events are mutually exclusive, the probability of either occurs equals to the sum of chances that each of them happens, $P(A \cup B) = P(A) + P(B)$. If A and B are non-mutually exclusive, then we have: $P(A \cup B) = P(A) + P(B) - P(A \cap B)$.

Based on these three axioms, the Bayes' theorem is defined as (Pearl, 2000; Korb and Nicholson, 2003; Fenton and Neil, 2012; Grover, 2016):

$$P(A \mid B) = \frac{P(A,B)}{P(B)} = \frac{P(B|A) * P(A)}{P(B)},$$

where $P(A \mid B)$ is the conditional probability of an observable event A, given the probability of another observable event B, which is equal to the *joint* probability of event B and event A (i.e. $P(A,B)$ or $P(A \cap B)$), upon the probability of the event B (Grover, 2016). The expansion of $P(A,B)$ would also result in the latter equation. Hence, both $P(A \mid B)$ and $P(B \mid A)$ are conditional probabilities in a way that in the first, A is conditioned on B and vice versa (Grover, 2016). Accordingly, $P(A)$ is the *prior* probability (either known or unknown, and subjective) and used as the initiating values. This likelihood is further updated during the Bayesian updating process (or inference) through *posterior* probability which here is $P(A \mid B)$ (Pearl, 2000; Grover, 2016). B is a set of observations and A is a set variables (discrete or continuous) which are chosen because of their weight in either prediction or diagnosis (Pearl, 2000). It is worth noting that a BBN can contain *unconditional* probabilities as well as conditional probabilities and conditionality is not necessary for these mathematical models (Grover, 2016). If this is the case the node with unconditional probability should have no parent node since are not conditioned on any other variable (Fenton and Neil, 2012).

After completing the structure of the BBN model, the next stage is to construct and elicit node probability tables (NPTs). These probability tables are also called *conditional probability tables* (CPTs) in Korb and Nicholson (2003) and Luigi and Daniele (2015) while only analysing discrete variables. The NPT for each node reflects the strength of the relationship between it and its parents (Fenton and Neil, 2012). In general, an NPT provide the probability of nodes conditioned on every possible state of its parent(s) (Fenton and Neil, 2012). When we manually update one or more nodes, through causal links (or *joints*) the posteriors will be automatically updated (Grover, 2016). Creating such a table for the nodes, first requires to specify all possible combinations of values of its parent nodes. Then, to complete the table we need to find the probability for each possible value of a given variable (node) (Korb and Nicholson, 2003).

Once the probabilistic assumptions as to how variables interact with each other are incorporated into the previously formed structure, all queries are answered through performing inference on the distribution. As a result, efficient and powerful inference algorithms are critical to generating reliable outcome (Barber, 2012). D'Ambrosio (1999) listed some of basic types of queries. *Single marginal* query refers to a situation which we want to know about the probability of some subsets of parameters in the model. Similarly, we may be interested to learn about the JPD function across a subset of the parameters. This type of query is called *subjoint*. The more general form of subjoint query is Boolean query an again the answer is the sum of probabilities that satisfy the query condition. Although we can iterate single marginal query for a set of parameters, applying *all marginal* query enables us to compute the marginal probability of all parameters rather than only a single one. When new evidence becomes available, *conditional* query can be performed to compute marginal probabilities given new evidence. Finally, *maximum a posteriori probability* can tell us about the most probable instantiation of two nodes in the net. A variety of *application-specific* queries including sensitivity analysis and expected utility can be devised based on the above queries (D'Ambrosio, 1999). There are also various methods of inference for BBN models to answer back to these queries. Those methods will be introduced in the next section.

3.5. Inference in BBN

As soon as an expressive and concise model is available, performing inference can be initiated (D'Ambrosio, 1999; Pearl, 2000). A completely specified BBN model contains necessary information to probabilistically address all queries about the variables in a domain (Pearl, 1988). Korb and Nicholson (2003) define "*belief updating*" or "*probabilistic inference*" as *"to compute the posterior probability distribution for a set of query nodes, given values for some evidence nodes"*. The evidence can be inserted about any node and results in updating beliefs in the rest of the structure (Korb and Nicholson, 2003). Three classes of efficient algorithms for inference in BBNs are reviewed in Daewiche (2003) corresponding to three notions including *conditioning*, *variable elimination* and *tree clustering*. The first class of algorithms comprises two subcategories known as *cutset* conditioning and *recursive* conditioning (Darwiche, 2003). The former group (cutset) of algorithms try to simplify the network to a tree, whereas the latter group (recursive) which try to decompose the network into smaller networks and solve it recursively (Darwiche, 2003). The second class of algorithms which stand on the basis of variable elimination, reduce a probabilistic model with n variables to a model over $n-1$ variables (Darwiche, 2003). The process is then iterated to the point that we can rapidly find the answers in a less complicated model (Darwiche, 2003). Lastly, the third class of inference algorithms transform the structure of a BBN to a *jointree* to facilitate performing tree-based inference (Darwiche, 2003). On the other hand, depending on the context and structure of the studied BBN there have been other categorisations of inference algorithms introduced in the technical literature. Exact and approximate inference algorithms are among those classifications (D'Ambrosio, 1999; Guo and Hsu, 2002; Korb and Nicholson, 2003). Figure 3.3 illustrates these taxonomies. *Max-product*, *most probable path*, *shortest path*, and *mixed inference* are also the main methods explored in (Barber, 2012).

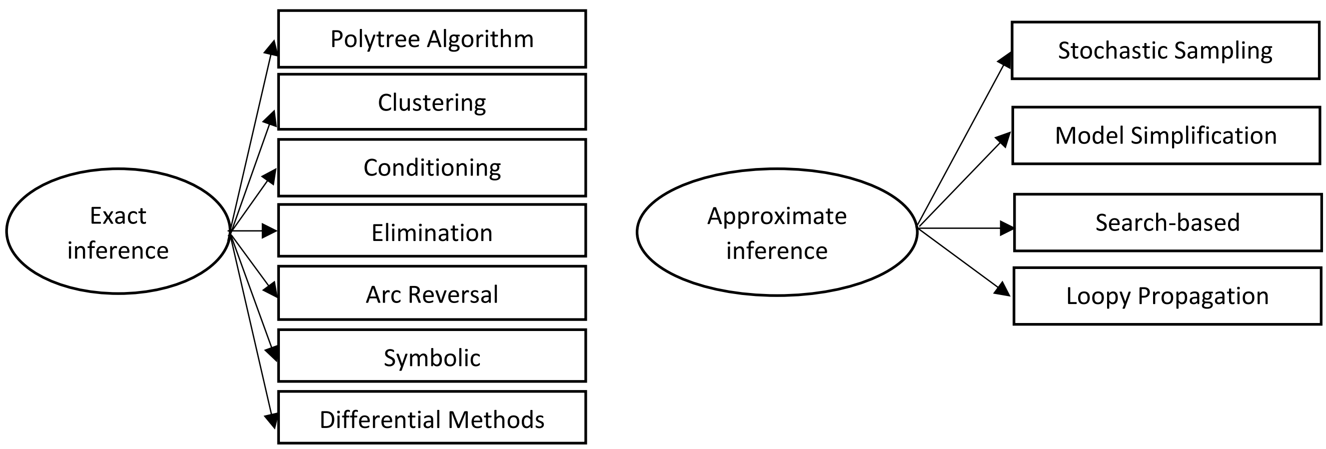


Fig. 3.3: Classification of real time inference in BBNs (Guo and Hsu, 2002).

In addition to the aforementioned methods, *junction tree* is the most well-known method which is capable to deal with multiple queries without any prerequisite for computing separate structure for each (D'Ambrosio, 1999). There have been several approaches introduced to these methods for the purpose of optimisation and increasing its efficiency.

Lifted junction tree (Braun and Möller, 2016), *incremental junction tree* (Agli *et al.*, 2016) and *hierarchical junction trees* (Puch, Smith and Bielza, 2004) are just a few to name.

Darwiche (2003) shows that any probability distribution computed by a BBN model can be expressed by a multi-linear function with certain properties and further develops a comprehensive framework on this basis for inference in BBNs. Such a function is defined over two types of variables: *evidence indicators* or *network parameters*. For variable X in the network, we assume a set of evidence indicators λ_x. We also consider a set of network parameters $\theta_{x|u}$ which represent *conditional probability* for each network family. Therefore, for a simple network containing two nodes (a and b), the multi-linear function can be defined as (Darwiche, 2003):

$$f = \lambda_a \lambda_b \theta_a \theta_{b|a} + \lambda_a \lambda_{\bar{b}} \theta_a \theta_{\bar{b}|a} + \lambda_{\bar{a}} \lambda_b \theta_{\bar{a}} \theta_{b|\bar{a}} + \lambda_{\bar{a}} \lambda_{\bar{b}} \theta_{\bar{a}} \theta_{\bar{b}|\bar{a}}$$

Hence, representing and evaluating the network polynomial prepare the ground for computing probabilities of instantiation. Furthermore, partial derivatives of the network polynomial disclose helpful information which can be used for answering a wide range of probabilistic queries. Figure 3.4 shows an example on inference in a BBN model with Boolean nodes.

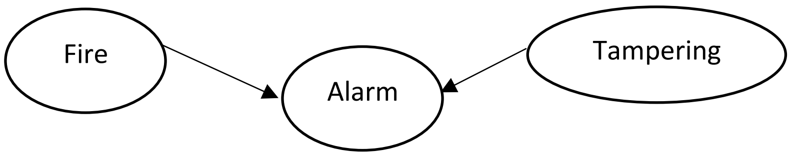


Fig. 3.4: an example of inference in BBN

To exemplify the inference process in BBN, imagine that the probability of fire occurring in the above example is 0.02 and the probability for tampering to happen is 0.05. Hence, the conditional probabilities for the alarm to sound are as presented in table 3.1. Performing an inference returns a probability of 0.0268 for true and 0.9732 for false alarms.

Table 3.1: conditional probability tables for the BBN model in figure 3.4.

Fire	*Pr*(fire)
Yes	0.02
No	0.98

Tampering	*Pr*(tampering)
Yes	0.05
No	0.95

Fire	Tampering	Alarm	*Pr*(alarm | fire, tampering)
Yes	Yes	True	0.9998
Yes	Yes	False	0.0002
Yes	No	True	0.99
Yes	No	False	0.01

Fire	Tampering	Alarm	*Pr*(alarm | fire, tampering)
No	Yes	True	0.85
No	Yes	False	0.15
No	No	True	0.0001
No	No	False	0.9999

We close this section with emphasising the importance of adopting efficient inferential techniques or tailoring a method to a model depending on the graphical structure of a BBN model. In principle, inference is computationally complicated and expensive (Barber, 2012). The prime reason for this complication is the multiplicity of parents of a given node which leads to exponential increase in the number of JPDs (e.g., Zagorecki and Druzdzel, 2012; Rohmer, 2020). The involvement of trivial variables adds to the complexity of the model and curtails the sensitivity of the network outcome to the key variables (Chen and Pollino, 2012). Instead, inclusion of intermediate nodes can decrease the number of JPDs which need to be computed (Provan, 1995). These considerations must be taken into account at the design and model development stage to avoid further implications in performing inference.

3.6. BBN: a powerful learning network

Modelling complex socio-technical systems which are deemed to operate under profound uncertainties is inherently demanding and requires several main characteristics to be considered in any model including (Weber *et al.*, 2012):

- the complexity and extent of the system,
- the consolidation of qualitative and quantitative data,
- the temporal aspects (system dynamics),
- the fact that some components have more than one state (multi-state characteristic),
- uncertainties on parameter estimation,
- the (inter)dependencies between events and variables.

The technical and academic literature suggests a number of classical modelling techniques such as Markov chains, fault trees (FT), dynamic fault trees, artificial neural network (ANN), Petri net, system dynamics (SD), fuzzy cognitive maps (FCM), fuzzy rule-based models (FRBM) and Bayesian belief network (BBN) to satisfy the above requirements. Among these modelling methods, BBN has received wide and prominent attention. "*It can be used as a machine learning algorithm to learn the fault patterns and required a full set of fault data for learning*" (Zhao, Xiao and Wang, 2013). BBNs have the capacity of structural learning from data by benefiting form a score-based algorithm, which tries to find a structure that maximises the chosen entropy scoring function or a constraint-based algorithm, which maps out the model structure based on the conditional dependencies existing between each pair of chosen variables (Uusitalo, 2007; Chen and Pollino, 2012).

If techniques and algorithms are constructed for Bayesian networks to automatically learn from data, not only this will reduce the burden of knowledge engineering problem, it will also enable the automatic refinement of a model's topology as new data is piled (Lam and Bacchus, 1994). For example, Hanea, Napoles and Ababei (2015) suggested a semi-automated version of a learning algorithm which only needs an empty graph to begin with.

Since acquiring full set of data might be expensive or impossible, expert knowledge can be replaced to construct the model. Four well-known ML algorithms for structural learning in BBN are K2, hill climbing (HC), tree augmented naïve (TAN) Bayes, and Tabu search (Ahmad *et al.*, 2021). The outcomes of structural learning can be enhanced when combined with expert input; for example, the expert specifies some known dependences in the system before the learning algorithm is run (Chen and Pollino, 2012). On the other hand, involving experts' opinions and judgements can increase the risk of bias (O'Hagan, 2019). Selecting a diverse group of experts can mitigate that risk and help to diversify the range of expertise/experience, impacting their judgements (Verdolini *et al.*, 2020).

BBNs offer some outstanding capabilities which make them distinctive from other modelling techniques. Being able to accommodate the modular structure of complex systems, especially in multidisciplinary problems is another prominent feature of BBNs (Chen and Pollino, 2012; Lee, Yang and Cho, 2015). Since in this study we are incorporating variables from diverse spheres and levels, this capability of BBN becomes very advantageous. It is also capable to rank different versions of AVs based on several key performance indicators (KPIs) (Ismail *et al.*, 2011). In this research, KPIs can be, for example, collision avoidance (or collision rates). Furthermore, BBN can be used as an interpretive tool. To exploit this advantage, it is necessary to instantiate a set of variables corresponding to the input data, then measure their impact on the probabilities of those variables which are defined as hypotheses, and lastly select the most probable combination of these hypotheses (Pearl, 1988). In return, a query can be made to interpret certain input data or choose the best course of action if utility information is given (Pearl, 1988). In addition, the graphical structure of BBN models visualises the information, especially the interdependencies, and makes it more accessible for non-statisticians (Gonzalez-Redin *et al.*, 2016). Swiftness of BBN in responding to queries, even in complex networks, can save time for analysts and accelerate the process of risk assessment (Uusitalo, 2007).

With BBN, it becomes feasible to articulate expert beliefs (or judgments) about the interdependencies between different variables of a complex system and to effectively propagate the impact of (recently found) evidence on the probabilities of uncertain outcomes, such as estimating the performance of certain key indicators or future system reliability (Fenton and Neil, 1999). It was explained in section 3.3 that analysing the risks of complicated systems, demands collecting and combing data from different sources. Bayesian network models are able to easily and in a mathematically coherent manner incorporate knowledge of different accuracies and from different sources (Uusitalo, 2007). Another strength of BBN lies in handling discrete and continuous variables alike (Moral, Rumí and Salmerón, 2001; Weber *et al.*, 2012; Marcot and Penman, 2019), although some software packages may not be able to deal with continuous variables. There are several software packages exclusively built to handle BBN models and we will explore available software packages in part 3.8.1.5.

One of the merits of BBN is that there is no minimum sample size required to run the model. Under circumstances where missing data or incomplete data can hinder implementation of other modelling techniques, BBNs can still deal with small and/or imperfect data sets (Uusitalo, 2007). Nevertheless, when a large number of AVs are launched for public services in a variety of conditions or current porotypes generate more data, probability distribution of some variables in the model may need to be modified. Recent evidence (or observations) can be inserted at any stage and into different nodes and update the states of other nodes through the network by using Bayes' rule (Korb and Nicholson, 2003; Ashrafi, Davoudpour and Khodakarami, 2015; Brito and Griffiths, 2016; Papakosta, Xanthopoulos and Straub, 2017; Matellini *et al.*, 2018).

Due to complexity of a problem, availability of data or extensive range of variables it might be desired to create a meta-model and incorporate distinct variables/scenarios in an uncertain framework (Uusitalo, 2007). Marcot and Penman (2019) in a recent study surveyed the advances in Bayesian network modelling and possibilities of integrating it with other modelling frameworks or tools such as agent-based modelling, *Quantum-like Bayesian Networks* (QBN) utilising both quantum probability theory and graphical models (Moreira and Wichert, 2016; Huang, Yang and Jiang, 2019), *object-oriented Bayesian Network* (OOBN) which defines complex domains as inter-related objects (Koller and Pfeffer, 1997), and *Bayesian Decision Networks* (BDNs) which contains decision and utility nodes (Marcot and Penman, 2019).

Although BBN tool has many advantages, it also requires that continuous variables be discretised. In an analysis including continuous variables, which need to be transformed to discretised variables, the discretisation process could cause information loss. To avoid this pitfall, the researcher can only involve discretised variables (Lee, Park and Shin, 2009). Another problem in BBN is the exponential growth in JPDs when the number of parents of a node increase (Lam and Bacchus, 1994). To circumvent this disadvantage, intermediate nodes can be exploited. Likewise, the increase in connectivity of the network leads to more computational demand and complexity (Lam and Bacchus, 1994). Multi-connected networks present a space complexity problem and this complexity grows with the degree of connectivity (Lam and Bacchus, 1994). *Causal interpretability* of BBN models is also debateable. A BBN model can bespeak the causal structure of a system if and only if (1) every node and its direct predecessors represent variables involved in a distinct mechanism in the system; and (2) nodes without any predecessors are exogenous variables (Druzdzel and Simon, 1993).

3.7. Comparing BBN with other modelling techniques

Principle *M* in the SoTeRiA framework (Mohaghegh and Mosleh, 2009) outlines the necessary steps and requirements for choosing appropriate 'modelling language' and building a safety causal model. It indicates that a safety causal model should cover a very broad range of causal factors (variables) and paths of influence (interdependence) and include performance of technical systems, behaviour of individuals and organisational characteristics. It further favours the hybrid modelling techniques due to *heterogeneity* of modelling domains and multidisciplinary nature of complex socio-technical risk analysis. A hybrid model can integrate deterministic and probabilistic modelling perspective which is believed to result in a flexible and generic risk assessment tool for a variety of high-risk and complex socio-technical systems (Mohaghegh, Kazemi and Mosleh, 2009). Then, four most common hybrid modelling techniques are introduced: SD, BBN, event sequence diagram (ESD), and FT. A detailed comparison on different modelling (soft computing) techniques and learning networks is provided in (Sadiq, Kleiner and Rajani, 2010; Ismail *et al.*, 2011) (please see Table 3.2). According to the table, BBN offers superior performance over DT, FRBM and ANN in most of attributes such as network capability and difficulty of modification. As far as the ability to express causality is concerned, BBNs demonstrate considerable competence. The main competitor to BBN in this table is (fuzzy) cognitive maps. Although there are studies (e.g., Liu, 2001; Douali *et al.*, 2014) advocating that the accuracy of FCM takes over BBN and that FCM propagates causality in a more natural way, its weaknesses in maturity of science and ability to handle dynamic data discouraged us to adopt FCM. On the other hand, BBNs have been widely applied not only in academia but also in practice (Mohaghegh, Kazemi and Mosleh, 2009) which has helped significantly to mature and integrated with other modelling techniques such as neural networks.

Nearly all traditional risk assessment techniques including Failure Modes and Effect Analysis (FMEA), Fault Tree Analysis (FTA), Hazard and Operability Analysis (HAZOP), and PRA are developed based on a chain of cause and effect analysis, but they face limitations in establishing an efficient link between risk models and organisational/human factors (Ashrafi, Davoudpour and Khodakarami, 2015). Dynamic Fault Trees suffer from exponential growth with size of the system and modelling spares (Ashrafi, Davoudpour and Khodakarami, 2015). Marcot and Penman (2019) also compared BBN with structural equation modelling (SEM) and reported two major differences. Firstly, SEM is purely statistical, whereas BBNs which are probabilistic models (trainable by data) and are mainly used for assessing the consequences of conditions or events on outcome(s). Secondly, SEM usually benefits from multivariate and frequentist approaches, whereas BBNs exploit conditional probabilities and Bayes' theorem.

ANNs have been widely adopted to address a broad range of problems in a variety of contexts (Carleo and Troyer, 2017). However, ANNs are not as efficient as BBNs in risk assessment. To identify cause-effect relationships, ANNs need significant historical data (and knowledge) (Kabir *et al.*, 2015), whereas BBNs can be deployed to address problems under grave epistemic uncertainty and with conflicting information (Zhao, Xiao and Wang, 2013). "*BBN has shown superior performance compared with neural networks, support vector machines, decision trees*" (Zhao, Xiao and Wang, 2013).

Table 3.2.: comparing five common soft computing modelling techniques (Ismail *et al.*, 2011).

Attributes	**Soft computing techniques**				
	DT	**FRBM**	**ANN**	**BBN**	**CM/FCM**
Network capability	N	L	N	H	VH
Ability to express causality	H	M	N	H	VH
Formulation transparency	H	H	N	H	VH
Ease in model development	H	M	M	M	VH
Ability to model complex systems	M	H	VH	H	VH
Ability to handle qualitative inputs	H	H	N	H	VH
Scalability and modularity	VL	L	VL	H	VH
Data requirements	H	L	VH	M	L
Difficulty in modification	VH	H	M	L	N
Interpretability of results	VH	VH	VH	VH	H
Learning/training capability	H	M	VH	H	H
Time required for simulation	L	L	H	L	L
Maturity of science	VH	H	H	VH	M
Ability to handle dynamic data	L	H	H	H	M
Ability to combine with other models	H	VH	VH	H	H

Ratings: N=No or Negligible; VL=Very Low; L=Low; M=Medium; H=High; VH=Very High
DT: Decision tree **FRBM:** Fuzzy rule-based models
ANN: Artificial neural network **BBN:** Bayesian belief network
CM/FCM: Cognitive maps/Fuzzy cognitive maps

3.8. Research methodology: steps in detail

The process of developing the BBN model is divided into two main phases. The development of the structure (structural learning) and eliciting knowledge and judgement of experts to build the CPTs (parameter learning) (Lee, Park and Shin, 2009). For the first phase, the data is collected through ILR which distinguishes this study from others in developing a BBN to address the risks of CAVs. A new method was also developed to construct the CPTs. Afterwards, a survey was designed and run to elicit the opinions of experts and determine the weights of influences that parent nodes have on their child nodes. Throughout this process, a multidisciplinary approach has contributed to the integrative risk analysis from the sociotechnical perspective.

3.8.1. Causal network model

3.8.1.1. Identifying main influential variables (nodes)

The topology of a BBN model consisting of nodes, causal links and states within the nodes can be shaped based on *priori* data including simulations, expert input, qualitative data or a combination of these (McDonald, Ryder and Tighe, 2015). The identification of influential variables started with reviewing the literature on three main themes as depicted in figure 3.5. Literature reviews involved identifying themes related to the research topic in the narrative material being searched. Themes are recurrent patterns in narrative data; therefore, a literature review is a kind of QUAL analysis (Teddlie and Tashakkori, 2009). Then based on the literature, a set of keywords have been compiled for the ILR. These keywords are provided in appendix A (nodes column). Next, according to the defined framework in figure 3.6, ILR was conducted to validate the selection of these nodes and identify the relation between chosen nodes. Web of Science, DelphiS and Google scholar (Zhang, Angell and Bao, 2021) are the search databases for the ILR. The selected keywords for autonomous driving were "autonomous vehicle*" OR "autonomous car*" OR "automated vehicle*" OR "automated car*" OR "self-driving" OR "driverless". These keywords gather a large pool of papers and studies corresponding to AVs. The number of results in DelphiS was 82,974 and in Web of Science platform was 18,234.

Afterwards, other keywords such as "risk", "collision", and those which were identified in the preliminary literature review (i.e. environmental, human, traffic, and technical exposures) were combined to narrow down the search to specific contexts and topics. Synonyms of the keywords and Boolean operators were applied where multiple terminologies for the same factor were detected in the reviewed literature. As explained in section 2.1.6, the inconsistencies and plurality in using terminology for AVs can pose a challenge in the ILR process. It might not be feasible to search for all these terms in a PhD project which is bounded by time limitations. As a result, it was decided to only search for the above keywords in the databases and exclude infrequent terms such as 'robotic car'. This can be considered as one of limitations of this research project. Finally, *thematic analysis* was conducted to identify, organise and interpret themes emerging from the reviewed literature (Gioia, Corley and Hamilton, 2013). This is discussed in detail in 3.8.1.4. 53 risk factors and indices were subsequently found across the four blocks which were reported to have influence on the collision risk in AD in urban areas. These factors shape the topology of the BBN model in this study.

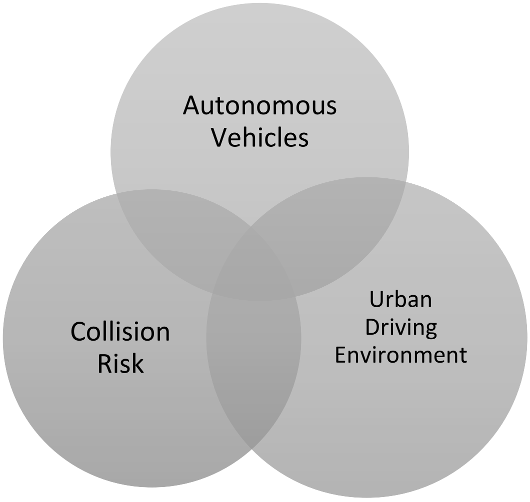


Fig. 3.5. Three central themes underpinning the ILR in this research

It has been argued earlier that to establish a causal relationship between a series of variables in studying complex systems, mere reliance upon quantitative methods/data (e.g. SEM) is not the best approach. As a result, qualitative data is involved to augment the quality of the model. According to the SoTeRiA framework the system is broken down into four main blocks (i.e. technical, human, environment and organisation) and variables are categorised accordingly, although overlaps are possible. This four-block structure was adopted by Ashrafi, Davoudpour and Khodakarami (2015) to analyse the risks of wind turbines. A similar approach is also supported in the ALFUS (autonomy levels for unmanned systems) (Huang *et al.*, 2005). ALFUS specifies mission complexity (e.g. performance, organisation and situation awareness), environmental difficulty (e.g. urban, rural and climate) and human independence (e.g. trust and supervisory control) as three axes of a detailed model to address autonomy issues. The 2008 NHTSA crash causation survey collected data on vehicles, environmental conditions and human behavioural conditions to analyse their contribution to the occurrence of crashes (Choi *et al.*, 2008). This can clearly show the importance of human, environmental and vehicular factors in any collision. In the same manner, Weber *et al.* (2012) suggested that to quantify failure scenarios and risks of complex systems modelling the interaction between different technical, human, organisational and nowadays environmental factors is requisite.

In addition to the verification for the structure, some relevant studies and accident/disengagement reports e.g. Sheehan *et al*. (2018 & 2019); Pollard, Morignot and Nashashibi (2013) can support the selection of nodes since there are several common variables in these studies. Notwithstanding the commonalities, differences are mostly due to the underlying theories and assumptions, adopted frameworks and scope of the analysis. The main aspects of the BBN model which distinguishes it from other models is the comprehensiveness (includes 54 nodes) and integrating the variables from four distinct but interacting areas into a single model through the sociotechnical theory. The adopted methodology in this project (i.e., ILR, thematic analysis and scope of search) significantly reduces subjectivity in selecting variables whereas the above studies that relied on a narrow literature review, extreme assumptions or limited data to identify their nodes.

3.8.1.2. Integrative literature review

The number of publications on the technical and social aspects of AVs is already large and this opens up the opportunity for researchers to base their research on the existing literature. In the meantime, the literature is scattered across diverse disciplines and this mandates a multidisciplinary approach to review and synthesise the collected data (Snyder, 2019). Along with that, a scientific framework including clear criteria is required to minimise the subjectivity and maintain the quality of results. For this purpose, ILR was chosen to regulate the processes including selection of papers and defining a framework for identifying variables affecting the collision risks of AVs in urban environments.

Munn *et al.* (2018) classified systematic review types into ten categories and proposed a typology for systematic reviews in medical and healthcare sciences. "*Etiology and/or risk reviews*" are mainly designed to ascertain the existence and strength of any relationships between a risk factor (aka exposure) and a health outcome (illness) to inform clinical decision- and policy-making (Moola *et al.*, 2015; Munn *et al.*, 2018b). The overarching question in this type of review is to determine if there is a causal association between an independent variable (exposure) and a dependent variable (outcome). In Moola *et al.* (2015) two methods are suggested for narrative synthesis of data: *textual description* and *thematic analysis*. A tabular format can be further used to synthesise the collected data and group them based on, for example, context or results (Moola *et al.*, 2015). In this process, transparency in defining the frameworks and criteria for identifying risk factors, the outcome and assessing the association between them plays a critical role (Munn *et al.*, 2018b; Borgström, Daneback and Molin, 2019; Snyder, 2019).

3.8.1.3. Defining a framework for ILR

For conducting rigorous analysis and generating reliable and replicable results, conventional reviews appear to be insufficient and lack thoroughness (Snyder, 2019). Thus, tailoring and applying a research protocol are indispensable to evaluate the rigour, completeness and replicability of a study for the sake of reducing any effects of arbitrary inclusion and increasing the legitimacy of findings (Righi, Saurin and Wachs, 2015). ILR has been used in medicine (e.g., Kashani *et al.*, 2013), business analysis (e.g., Benzaghta *et* *al.*, 2021), education (e.g., Osam, Bergman and Cumberland, 2017) and engineering management (e.g., Yassine, 2019) and is becoming popular in other fields. Snyder (2019) introduces literature review as a research methodology and discusses three types of review in business research. Although there are similarities between these review approaches (i.e. systematic, semi-systematic and integrative review), each of them can show more competence in tackling certain research questions depending on the purpose, research question(s) and search strategy (Snyder, 2019). Exploring the studies which relied upon the literature as the main source of data reveals that a mixture of the aforementioned approaches also can be utilised to address a research problem. For instance, Borgström, Daneback and Molin (2019) combined a systematic and an integrative literature review approach to single out peer-reviewed studies for further thematic analysis.

Torraco (2005) suggested that ILR can be conducted to review, critique and synthesise ‘representative literature’ on a particular research topic in an integrated manner. This method is applicable for both mature and emerging research areas (Torraco, 2005; Snyder, 2019). Risk assessment of CAVs in urban environment has both features of maturity and emergence since there is a large body of literature investigating, measuring and analysing various risk factors that can give a rise to (or reduce) the probability of collision, while developing a socio-technical approach towards AI-based autonomous systems is still in its infancy.

Based on the above discussions, the formulated protocol for selecting and reviewing pertinent literature borrows some characteristics from both systematic and integrative literature reviews. in order to find and assess causal relationships between risk factors and outcome variables, qualitative studies as well as quantitative studies can be useful. There are ample number of studies which underscore and explain a cause-effect relationship between two variables of interest in the format of text rather than presenting any correlative analysis. Therefore, whilst inclusion of both qualitative and quantitative evaluations satisfies one of the conditions for semi-systematic review, extending the search to books, technical reports, theses and patents can represent integrative review (Snyder, 2019). Table 3.3 summarises the main features of integrative review and semi-systematic review.

Table 3.3: comparing two types of literature review in business research (Snyder, 2019)

Approach	Semi-systematic	Integrative
Purpose	Overview research area and trace development chronologically	Critique and synthesise
Research question	broad	Narrow and broad
Search strategy	Systematic/not systematic	Usually not systematic
Sample characteristics	Research articles	Published text e.g., articles, books
Analysis and evaluations	Quantitative/qualitative	Qualitative
Main contributions	State of knowledge, themes in literature, theoretical model, historical overview and research agenda	Taxonomy and classification Theoretical model

The protocol for identifying influential risk factors of AVs in exhibited in figure 3.6. Web of Science, DelphiS (internal to the University of Southampton), and Google scholar are the three main databases elected for searching relevant published text. The main criteria for including papers were relevance to the context, date of publication and clear specification of one or several risk factors which can affect the safe driving of AVs. These publications consist of journal articles, conference papers and proceedings and symposiums, technical reports, books, patents and a few news articles. Almost all of the included papers were published after 2005 (the first round of DARPA competitions). After screening the papers, they were populated into classified folders based on the main investigated theme in the paper. For example, if a study pinpointed the role of adverse weather conditions, it was stored under the category of environmental factors or if a paper studied the impact of sensor failure on collision risk, it was saved under technical risk factors category. In the final stage, thematic analysis was undertaken to determine the main sources of risks and their association with safe performance of the vehicle. Many of the reviewed papers specify more than one exposure. The redundant themes (other than the central focus of the paper) are labelled as 'other themes' in appendix A.

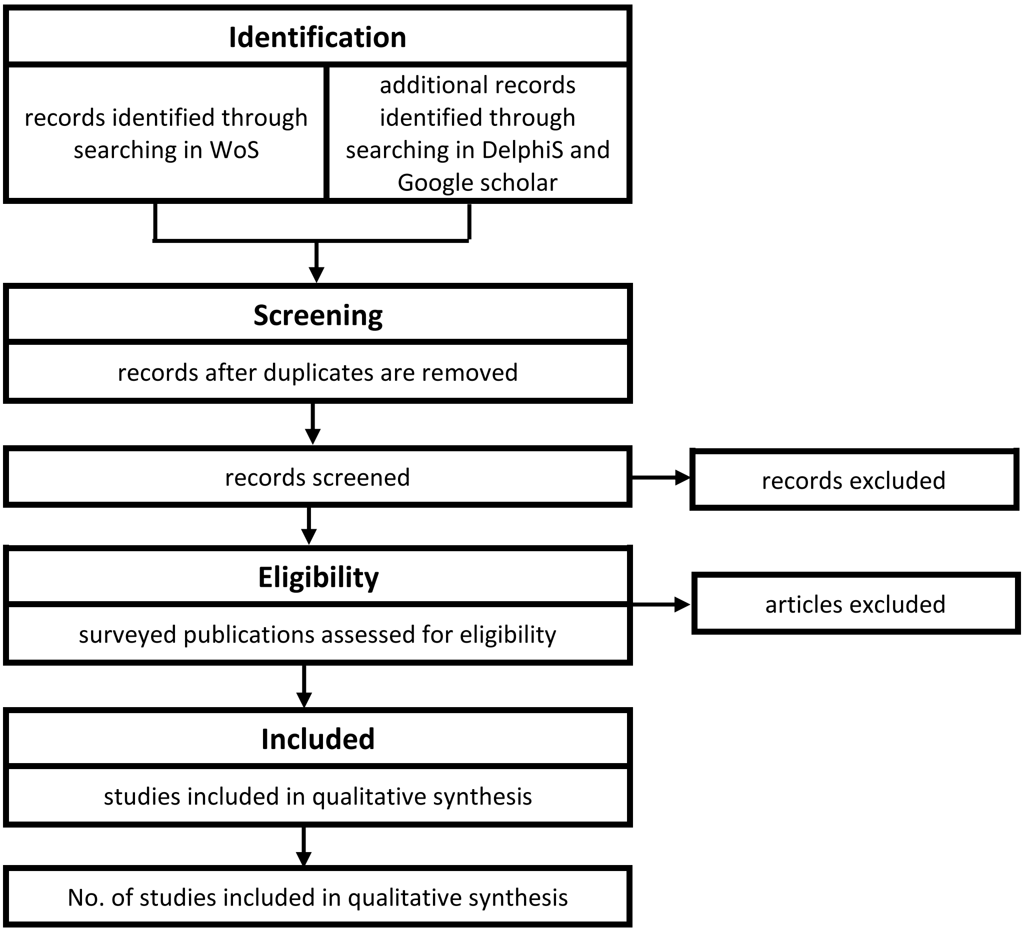


Fig. 3.6: The protocol for paper identification, adopted from (Liberati *et al.*, 2009).

3.8.1.4. Thematic analysis (TA)

Despite the comprehensive use of qualitative methods specially in social sciences, lack of rigour and being prone to biases raise questions about the credibility and validity of results generated by grounded theory (Gasson, 2004). According to Mackieson, Shlonsky and Connolly (2019) 'applied thematic analysis' can discount those criticisms by setting up a structure and integrating 'reflexivity' in qualitative research. In qualitative research, *reflexivity* refers to a continuous process of researcher's self-awareness and self-evaluation of his/her position in the research process and critically examine the effects that this position may have on the outcome (Berger, 2015). Applied thematic analysis is used to analyse collected textual data (e.g. interview transcriptions) and text from data sources (Mackieson, Shlonsky and Connolly, 2019). The key objective is to recognise themes (patterns) across given qualitative data sets through conducting interpretive analysis (Braun *et al.*, 2019). A theme, as Braun *et al.* (2019) describe, is a *reflecting pattern* of shared semantic (or surface) meanings connecting scattered data across varied contexts. For example, in the literature concerned with the AVs' risks, 'poor' or 'adverse' weather conditions are often correlated with the impaired performance of the technology. This pattern can reveal a cause-effect relationship between the weather conditions and the collision risks for AVs. Like ILR, devising a transparent framework which can exhibit traceability and replicability is deemed to be requisite. Fig. 3.7 presents a schematic framework for analysing themes emerging from the selected papers in this research. This framework complies with the Gioia methodology which proposed '1st Order Concepts', '2nd Order Themes', and 'Aggregate Dimensions' for conducting qualitative inductive research (Gioia, Corley and Hamilton, 2013).

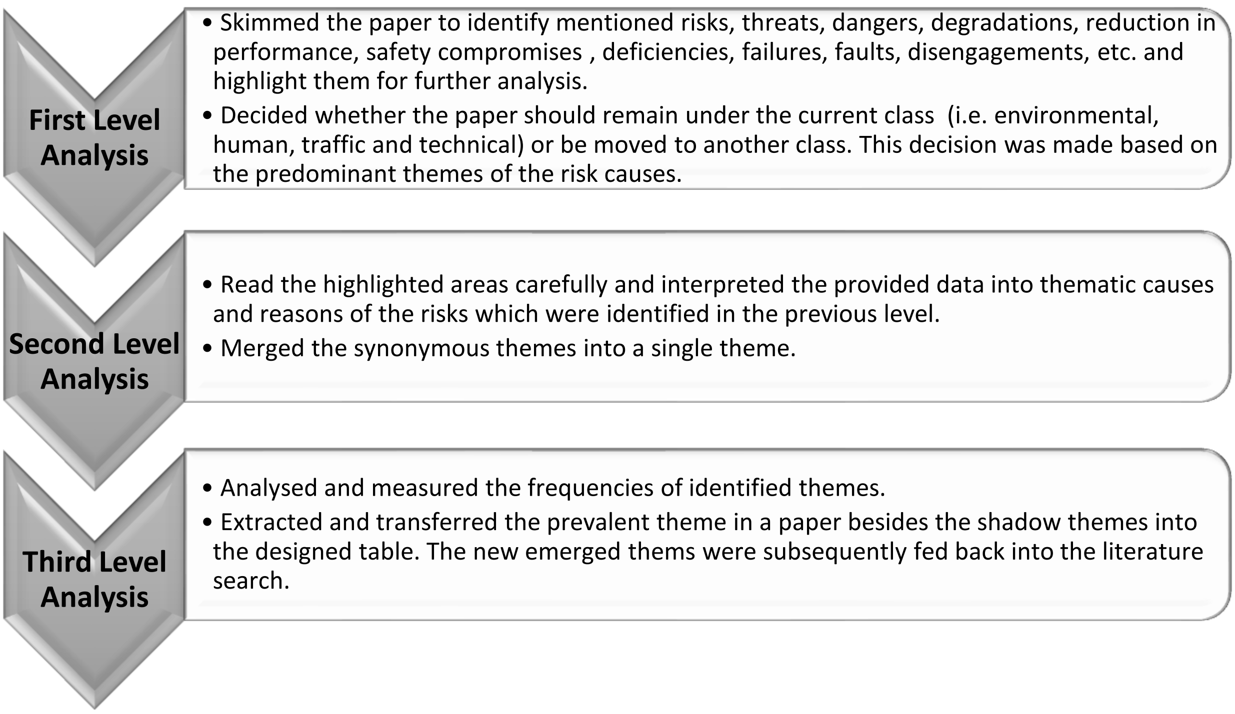


Fig. 3.7: The thematic analysis framework (Mackieson, Shlonsky and Connolly, 2019).

First level analysis consisted of two major tasks. Firstly, the gathered and grouped papers and documents were skimmed to locate the sections and paragraphs which hold discussions on the sources of collisions risks. Then, a decision needed to be made to whether keep the paper/document within the current predefined class (block) or move it to another class. It occurred that usually the reviewed paper encompassed a range of risks and their causes, but one theme (e.g. cybersecurity or human-machine interactions) predominated other themes in that paper. The stronger theme sometimes was not corresponding to the keywords used to find the paper. This mandated the researcher to change the class of the paper. For instance, searching “reaction time” AND “risk” AND “autonomous vehicles” in Google scholar returns a paper published by Sheehan *et al.* (2019) on the first page; however, the prevailing theme in that paper is ‘cybersecurity’ of AVs not ‘reaction time’. Consequently, reorganising the papers according to the main themes and overarching risk factors took place in the first level analysis.

In the next level, an interpretive analysis was attempted to indicate if a causal relationship exists between the specified malfunctions in the previous level and collision risk. Interpretation of the text becomes crucial where some of the mainstream themes in the collated literature, such as ‘trust’, do not always signify a risk to the safety of AVs. As a sample, Kaur and Rampersad (2018) investigated some of the factors which affect the safe operation of AVs and the concept of ‘trust’ in the technology is repeatedly brought up in this paper. Nonetheless, no association is reported to exist between ‘trust’ and collision risks. Instead, this paper shows a significant correlation between trust in the technology and users’ willingness to adopt it (Kaur and Rampersad, 2018). Next step in this level was dedicated to merging and unifying some parallel themes in the literature. Synonyms are often used to refer to an identical concept or variable. ‘Traffic congestion’, ‘traffic volume’, ‘traffic density’ and ‘traffic flow’ can be a clear example. These four variables have attracted considerable attention in the technical and accident literature for autonomous vehicles. Despite the differences in the proposed formulae for calculating these variables (Twagirimana, 2013), they all contribute to or measure a single variable which is number of vehicles on roads. Another example can be ‘roadway configuration’, ‘road layout’, ‘road design’, ‘road characteristics’ and ‘road geometry’. To avoid ‘information double-counting’ such as what frequently happens in Naïve Bayes models (Langseth and Nielsen, 2006) and prevent overcomplication of the model these variables were merged into one group.

Finally, the frequency and strength of the link between an emerged theme and any risk to the safe function of the vehicle (i.e. the collision risk) were evaluated. ‘Urban design’ can serve as an example here as it is common sense that the way urban areas are planned and designed can have a great impact on the frequencies and severity of the accidents and those factors can mitigate the likelihood of fatality and severity of injuries in motor vehicle crashes (Thompson *et al.*, 2020). Even though that causal relationship is proven to exist in the literature, the reverse relationship (the effect of launching AVs on the urban design) is widely discussed in the literature on autonomous driving risks. Thus, the 'urban design' theme which is not frequently and explicitly cited to have influence on the 'road condition' risk index as far as AVs are concerned, was broken down to its elements such as 'road type', 'roadway configuration' and 'road infrastructure' to capture its impacts. The number of papers on the succeeding themes also shows there exists an association between the aforementioned themes and collision risk. In the final stage, the reviewed and analysed papers/documents were sorted in a table as suggested in 3.8.1.2 (please also see appendix A). Figure 3.8 shows the process of qualitative data collection in three major phases.

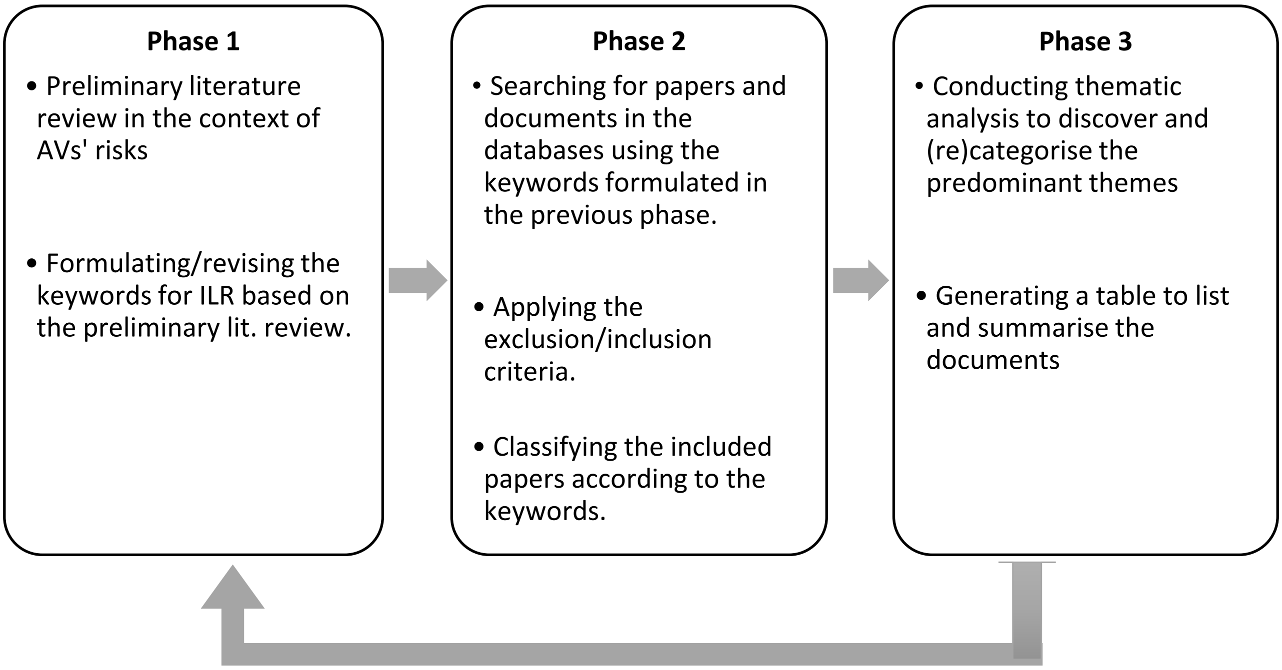


Fig. 3.8: a schematic summary of the three phases to identify the influential factors.

3.8.1.5. Developing the causal model

After the results of qualitative data collection (i.e., literature review) became available, the construction of the BBN model began. For this purpose, Hugin Lite software package (Madsen *et al.*, 2003; Fenton, Neil and Caballero, 2007; Uusitalo, 2007; Ashrafi, Davoudpour and Khodakarami, 2015) was used to develop the network and NPTs. The developed causal model is demonstrated in figure 4.4. According to the socio-technical theory the environmental variables, traffic conditions, and human factors are accompanied by a technical module to represent a comprehensive and integrated assessment of system reliability beyond common reliability models constrained by the reliability of their physical components (Ashrafi, Davoudpour and Khodakarami, 2015). In environmental, traffic, and human reliability blocks, discrete variables are used in the form of ranked nodes to describe the system state and interactions. By applying this BBN model, risk analysts (e.g. in insurance and regulatory sectors) will be able to trace the impacts of various influential factors on the collision risk. In the meantime, it provides the possibility of analysing the role of on-board drivers and circadian mode through a cognitive approach in the reliability of AD.

The *Hazard Classification and Analysis System (HCAS)* outlines a taxonomy for discovering the hazard sources in aircraft operations (Luxhøj and Topuz, 2012). The hazard sources are categorised into four major groups: 1) environment such as weather conditions and obstacles; 2) airmen and operators; 3) vehicle related factors such as sensors and antennas; and 4) operation hazards including flight planning and airspace (established or temporary). This taxonomy besides the discussions in sections 3.8.1.1 and 4.2 formed the idea of structuring the model with four separate modules that the aggregated impact of each block affects the collision risk index.

Marcot *et al.* (2006) set out nine general guidelines for developing a BBN model. They favour having three or fewer parents for a node, as far as possible. This guideline was observed for most of the nodes in the model except for the aggregate nodes (e.g., risk indices). Next, using *parentless* nodes which typically represent environmental factors and *indicator habitat* nodes such as 'date' that their information can be extracted from existing data (e.g. geographic information). This criterion was satisfied in developing the BBN model by incorporating nodes such as 'time of day' and 'day of week'. Designing intermediate nodes is another guideline recommended to summarise the major themes (or latent variables). An example can be risk indices designed to accumulate the influence of the variables in each block and link them to the overall risk (i.e. collision risk). As far as possible, nodes should be observable and quantifiable, although in some cases intermediate nodes or latent variables may not meet this criterion (Marcot *et al.*, 2006). In framing the states for nodes, there must be a trade-off between having the fewest discrete states and achieving the desired precision. This guideline was also observed by ensuring that the states are enough for the range of input values and are not excessive causing exponential increase in the CPTs and confusion for the experts during elicitation process.

The guidelines suggest that the number of layers between a parentless node and the output of the model should not exceed four to prevent unnecessary uncertainty propagating in the model. Except a few cases, all layers in the model were kept at four or less. If an intended model contains several spatial scales, they should be developed simultaneously. In that way, output of one BBN model is used as input to another through *instance node* tool in Hugin.

This criterion was waived in this project to avoid complicating the model, however, can be a potential area for future research and extending the model. An explanation for the nodes and selection of states are attached to each node in the model to track their authorship. Finally, arcs must link the input nodes if they are likely to be correlated and any lack of link between the prior probabilities and input nodes reflects the assumption that they are uncorrelated (Marcot *et al.*, 2006). Following the above guidelines, a Bayesian network was constructed in Hugin (please see figure 4.4).

3.8.2. Conditional probability tables (CPTs): incorporating experts' knowledge

In addition to the DAG which is also known as the 'qualitative' part of the model, CPTs (i.e. quantitative part) must be specified as well (Ben-Gal, 2008). It is necessary then for each (discrete) variable of the model to have a CPT which consists of a number of labels. The labels give information about the state of variables and can be changed manually when evidence on one or a set of variables becomes available. For instance, the states for weather conditions can be *sunny, rainy,* and *snowy* or alternately it could be Boolean like *adverse* and *fair*. The number and types of risk indices depends on several factors including complexity of system, scope of research, and complexity of the model. The next step is to indicate the prior probability distributions for variables in the model. In this study, the judgment of experts is the main ground for obtaining and incorporating JPDs into the model. In the next subsection, this process will be justified and explained.

A novel method was developed to populate the NPTs in a way to generate uniform distributions for most of the nodes, except for those that were directly influenced by 'time of day' such as drowsiness and traffic density. For the nodes that are directly influenced by time of day, an approximation of the graphs and data provided in the literature (please see figures 4.1 & 4.2) were used to populate their NPTs accordingly. It starts with two assumptions. If all the parent nodes are in the most desirable states, the probability for the least risky state of the child node is one and it is zero for the rest of states and vice versa. Consider table 3.4 as an example for an NPT with n parents and m states. S_1 is the state 1 for Parent 1 and a is the number of states for this node. S_N'' is also the state 1 for Parent n and z is the number of states for this node and so forth. Therefore, this table consists of $a \times b \times ... \times z = q$ rows to be populated. The number of cells subsequently equals $q \times m$. The states in the left are the most and those in the right are the least desirable in terms of contributing to collision risk and other states are sorted between in accordingly. j_{xy} denotes the probability value for the cells in the table (x: column; y: row). The rest of rules are as follows:

Table 3.4: an example for NPTs in Hugin.

Parent 1	S_1		…					S_a	
Parent 2	S'_1			…				S'_b	
…	…								
Parent n	S''_N			…			S''_z		
State 1	j_{11} =1	…	0.5	…	0	…	0	…	j_{q1} =0
State 2	j_{12} =0	…	0.5	…	0.5	…	0	…	j_{q2} =0
…	j_{1y} =0	…	0	…	0.5	…	0.5	…	j_{qy} =0
State m	j_{1m} =0	…	0	…	0	…	0.5	…	j_{qm} =1

Rule (1): $\sum_{y=1}^{m} j_{1y} = \sum_{y=1}^{m} j_{2y} = \cdots = \sum_{y=1}^{m} j_{qy} = 1$;

Rule (2): $\sum_{x=1}^{q} j_{x1} = \sum_{x=1}^{q} j_{x2} = \sum_{x=1}^{q} j_{x3} = \sum_{x=1}^{q} j_{x4}$

and

Rule (3): for columns 0 to $\frac{q}{4}$: $j_{(x+1)1} = j_{x1} - (\frac{0.5}{\frac{q}{4}-1})$; $j_{(x+1)2} = j_{x2} + (\frac{0.5}{\frac{q}{4}-1})$; $j_{x3} = 0$; and $j_{x4} = 0$

for columns $\frac{q}{4}$ to $\frac{q}{2}$: $j_{(x+1)1} = j_{x1} - (\frac{0.5}{\frac{q}{4}-1})$; $j_{x2} = 0.5$; $j_{(x+1)3} = j_{x3} + (\frac{0.5}{\frac{q}{4}-1})$; and $j_{x4} = 0$

for columns $\frac{q}{2}$ to $\frac{3q}{4}$: $j_{x1} = 0$; $j_{(x+1)2} = j_{x2} - (\frac{0.5}{\frac{q}{4}-1})$; $j_{x3} = 0.5$; and $j_{(x+1)4} = j_{x4} + (\frac{0.5}{\frac{q}{4}-1})$

for columns $\frac{3q}{4}$ to q: $j_{x1} = 0$; $j_{x2} = 0$; $j_{(x+1)3} = j_{x3} - (\frac{0.5}{\frac{q}{4}-1})$; and $j_{(x+1)4} = j_{x4} + (\frac{0.5}{\frac{q}{4}-1})$

The tables must be symmetric (as shown in table 3.4) to the centre in a way that j_{11} and j_{qm} are equal to one and other states in their columns are equal to zero. Depending on the number of states (either 3 or 4) the values for the columns on the edge of the first ($\frac{q}{4}$), second ($\frac{q}{2}$), and third quarter ($\frac{3}{4}q$) can vary between 0, 0.33, 0.5 and 0.67. The probability values for each child node were calculated in Microsoft Excel and transferred to Hugin. In cases where rules contradicted each other, rule 2 was prioritised over the first rule to generate uniform distributions. Hugin allows for the sum of values for each column to exceed 1.00 and automatically converts them to a percentage when instantiating. All probability distribution functions (PDFs) were automatically *normalised* after the model was run. When the sum of all possible results of a PDF is equal to one it is called to be normalised. Fig. 3.9 provides two examples of the NPTs for 'hardware reliability' and 'other road users' nodes.

Hardware reliability

Control equ...	ASIL D				ASIL C				ASIL B				ASIL A			
Self awaren...	SAIL D	ASIL C	ASIL B	ASIL A	SAIL D	ASIL C	ASIL B	ASIL A	SAIL D	ASIL C	ASIL B	ASIL A	SAIL D	ASIL C	ASIL B	ASIL A
ASIL D	1	0.833333	0.666667	0.5	0.5	0.333333	0.166667	0	0	0	0	0	0	0	0	0
ASIL C	0	0.166667	0.333333	0.5	0.5	0.5	0.5	0.5	0.5	0.333333	0.166667	0	0	0	0	0
ASIL B	0	0	0	0	0	0.166667	0.333333	0.5	0.5	0.5	0.5	0.5	0.5	0.333333	0.166667	0
ASIL A	0	0	0	0	0	0	0	0	0	0.166667	0.333333	0.5	0.5	0.666667	0.833333	1

Other road users

Traffic cont...	Sophisticated						Partly developed						Poor					
Day of week	Weekend			Weekday			Weekend			Weekday			Weekend			Weekday		
Traffic rules...	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low	High	Medium	Low
Nerver-rarely	1	0.9175	0.835	0.7525	0.67	0.5875	0.505	0.4225	0.3333	0.3333	0.2475	0.165	0.0825	0	0	0	0	0
Occasionally...	0	0.0825	0.165	0.2475	0.33	0.33	0.33	0.33	0.3333	0.3333	0.33	0.33	0.33	0.33	0.2475	0.165	0.0825	0
Often-always	0	0	0	0	0	0.0825	0.165	0.2475	0.3333	0.3333	0.4225	0.505	0.5875	0.67	0.7525	0.835	0.9175	1

Fig. 3.9: a & b: the NPTs for 'hardware reliability' and 'other road users' in Hugin.

In order for the automated NPT calculations to be performed, it may be mandatory to assign weights to applicable parent/child node combinations (Fenz, 2012; Rohmer, 2020). While this can turn to a very time-consuming task (depending on the topology of the model), it allows the domain experts to attach weights to different parent nodes and influence the NPT computation (Fenz, 2012). To extract those weights, a survey was designed and experts of relevant fields (e.g., robotics and extreme environments, HMI, urban traffic and AV development) took part in the survey.

3.8.3. Expert knowledge elicitation

Experts knowledge elicitation has played a key role in decision-making, particularly where the aftermaths of an event or activity are unknown (O'Hagan *et al.*, 2006, p.9). The process of eliciting opinions from one or more experts to constrain uncertainties of one or more influential variables feeds straight into the decision itself (O'Hagan *et al.*, 2006, p.9). The probabilities required in a BBN are quantified with data and expert opinion, mostly the latter (Mohaghegh, Kazemi and Mosleh, 2009). There are numerous studies (e.g., Cooke, 1991, p.19; Bedford, Quigley and Walls, 2006; Fenton, Neil and Caballero, 2007; Fenton and Neil, 2012, p.260; Pibouleau and Chevret, 2014; Verdolini *et al.*, 2020) which advocate the use of experts' beliefs in case of missing or imperfect data.

The utilisation of expert opinions in probabilistic risk assessment as a source of data became popular in the second half of twentieth century and has been reported in several fields including but not limited to breeder nuclear reactors, seismic risks, and fire hazards in nuclear powerplants (Cooke, 1991, p.29). Bedford, Quigley and Walls (2006) investigated the importance of expert opinions in a broader context termed as 'assessing the reliability of engineering system design processes'. In recent years, the applications of expert knowledge elicitation are witnessed in a wider range of disciplines such as insurance (e.g., Mkrtchyan *et al.*, 2022), oil and gas (e.g., Dimaio *et al.*, 2021), health care (e.g., Bojke *et al.*, 2022) ecosystem and environment (e.g., Kaikkonen *et al.*, 2021), food safety risks (e.g., Lachapelle *et al.*, 2021), and structure failure (e.g., Verzobio *et al.*, 2021).

Similar to the topology of a BBN model, the CPTs can be derived from several sources including experts (or stakeholders) knowledge (Fenton and Neil, 2012, p.260; Groth and Mosleh, 2012; Pibouleau and Chevret, 2014). O'Hagan *et al.* (2006, pp.185-187) and O'Hagan (2019) suggested two approaches for aggregating the elicited judgements. *Mathematical aggregation* approach (aka pooling) advises separate elicitations in which experts do not have interaction with each other, and a pooling rule is used aggregate the results. In contrast, *behavioural aggregation* allows experts to exchange their opinions and reach a consensus over a given query, then a distribution is fitted to represent the aggregated outcome. Since each block of the model aggregates the risks from different sources (i.e., environment, vehicle, traffic conditions and onboard drivers) and the selected experts for informing them were from diverse backgrounds, reaching consensus on the queried weights was not guaranteed. For this reason, mathematical aggregation was preferred over the latter approach. Assigning weight to experts' judgements based on their competence/performance is a widely discussed method in expert elicitation (e.g., Cooke, 1991, pp.147-157; O'Hagan, 2019). Nevertheless, O'Hagan *et al.* (2006, p.185) concluded that the best combination (i.e., pooling rule) is simple average of the two most experienced experts.

3.8.3.1. Survey

Although BBNs are being used widely to solve real-world risk and uncertainty problems, their use still entails the difficulty of populating their CPTs. A key challenge is to construct relevant CPTs using the expert elicitation in an efficient manner, recognising that often it is not time (or cost) effective, or even viable, to elicit complete sets of probability values for a network (Fenton, Neil and Caballero, 2007; Perkusich, Perkusich and de Almeida, 2013). There are several methods and tools to elicit the knowledge of experts. Interview, (online) surveys and expert panel discussion are among popular means. Although the main method for this study was to run a workshop and form an expert panel to inform the model, due to the COVID-19 pandemic, time restrictions and insufficient budget, we have run an Internet-based survey. There are several advantages of performing an online survey, such as (Perkusich, Perkusich and de Almeida, 2013): low cost to send questionnaire and pertinent documents including participant information sheet, saving time, reaching participants worldwide, may encourage participants to participate by providing an interactive survey process and can effectively reduce errors from transcription and coding in comparison with panel discussions.

Perkusich, Perkuich and de Almeida (2013) propose surveys to collect information from domain experts and with the collected data populate the network's NPTs. There are also several studies (e.g., Pibouleau and Chevret, 2014) that practically used a survey to extract judgements of domain experts. Nevertheless, a limitation of using surveys can be the scarce number of domain experts for some fields of study. Small population of experts can lead to small sample sizes and subsequently biased or imprecise estimates (Hertzog, 2008). Notwithstanding, there are studies (e.g., Yin *et al.*, 2015; Rietbergen *et al.*, 2016) that used limited number of experts (three and four) to take part in Bayesian analyses. Brito and Griffiths (2016) used a panel consisting of ten experts in a BBN model to assess collision risks for AUVs. In a research conducted by the US Environmental Protection Agency (2015, cited in Verdolini *et al.*, 2020), 38 expert elicitation studies were reviewed and reported that 60 percent used 6-8 experts and 90 percent of the studies had less than 12 experts.

In this research, nine experts were invited to attach appropriate weights to the links across the block in the model. The composition of the expert group and how they informed the links are discussed in the following section. The extracted weights were effected in the NPTs of child nodes. By doing this, a weight (out of 100%) was assigned to every parent of each child node in the model in a way that the sums of weights are equal to 1.

Two approaches were singled out for designing the survey. First, asking experts to distribute weights (out of 100%) among the parents of a node. Second, using a Likert scale to evaluate the strength of every node. Considering the drawbacks of Likert method, the second option was adopted for designing the survey (please see Appendix B). The drawbacks include the potential ambiguities over the definition of each option in the Likert system, lack of any feasibility for drawing a comparison between the parents of a node when answering every question, and higher number of questions for eliciting weights. In the next step, an ethical approval (ERGO No.: 63032) was obtained for the survey and ethical considerations were taken into account. The information sheet and the consent forms are attached in Appendix C. After receiving the ethical clearance, the experts were contacted via email and offered to take part in the study. The results of this survey are presented in section 4.3.

3.8.3.2. The composition of the expert group

Nine experts from different backgrounds were surveyed and their judgments on the weights of each parent node on its child(ren) were elicited. The weights of links in human and traffic blocks were informed by two experts, whereas environmental and technical blocks which three experts apprised the weights of their links. One of the experts (i.e., Expert 1) filled the surveys for two blocks. For the sake of privacy and due to ethical considerations, the survey was run anonymously. The expert panel comprised of six males and three females. The experts were selected based on their publication records and research relevance to the field of AVs and their safety implications. The background and research areas of the experts are as follows:

- **Expert 1:** his expertise falls within the field of *Cognitive Approaches for Multimodal Sensor Data Perception* and has eight years of forensic experience, investigating road traffic accidents. His PhD revolved around the technologies used in AVs and their impacts on traffic safety.
- **Expert 2:** is currently PhD candidate at a German university and his research centres on motion prediction of AVs in the context of intelligent infrastructure systems. He also has been involved in a project aiming to build an intelligent infrastructure system on German highways.
- **Expert 3:** is currently a post-doctoral researcher with wide expertise in the *human-swarm interaction and swarm robotics*. His current research is on the trustworthiness of autonomous systems in extreme environments.
- **Expert 4:** is a Professor of Computer Science and has many peer-reviewed publications in the field of AVs and robotic. Some of his papers have won the best paper prize from publishers and journals.
- **Expert 5:** is an Associate Professor in Urban Planning. She also has had ample publications on transport politics and infrastructure planning. Her research is currently targeting the contemporary models of urban governance and transportation planning which are extendable to the area of autonomous driving.
- **Expert 6:** being an Associate Professor in Human Factors and Sociotechnical Systems, her research covers potential safety risks that AVs can pose, particularly in the initial introductory phase. Her expertise also includes approaches based on complexity and systems theory to improve safety of transportation systems.
- **Expert 7:** holds a PhD degree and one strand of his research aims to develop an international comparative comprehension of the urban impacts of novel mobility technologies such as AVs.
- **Expert 8:** is an Assistant Professor in Smart and Sustainable Urbanism at an Irish University. His current research is to address questions about impact that artificial intelligence can have on urban design. He is also involved in a practical project intending to investigate the *sustainability potential* of self-driving cars in urban environments.
- **Expert 9:** is a PhD candidate in Urban Mobility Systems. Her research contributes to coordination and trajectory planning of CAVs on freeway segments. She is also involved in a project infrastructure planning for CAVs.

Apart from the questions for the assigned blocks to the experts, all experts answered the question concerning the impacts of KPIs (i.e., road condition, reaction time, traffic condition, and technical reliability) on the collision risk. The average of the allocated percentages to each link by the experts was calculated and used as the weighting scale. The results of the survey are presented in section 4.3.

3.9. Underlying assumptions

An important attribute of a *well-defined* research problem is the articulation of its constraints that narrow down the scope of research and indicate data, materials and research methods required to solve it (Fortus, 2009). With all the involved variables/risk factors and dynamic environment that AVs are expected to operate in, it is almost impossible to build a risk model without making any assumptions and free from constraints. Fortus (2009) also maintains that making constraining subject assumptions can confine the solutions space and turn a broad problem into "more" defined problem. This section, therefore, is dedicated to reflecting the assumptions about technological specifications, environmental and traffic characteristics, and variable interdependencies in the BBN model.

In section 2.1.4 different levels of automation for AVs were presented and it was discussed that the embedded technologies and level of human intervention vary accordingly. These differences can shift the risk of collision to dissimilar levels for each of automation levels under identical circumstances. To avoid ambiguities over functionality and system specifications it was necessary to decide on the automation (autonomy) scale for modelling. Delineating the automation level is also essential for expert knowledge elicitation phase of this study as it certainly impacts the judgement of experts in evaluating the influence of variables on the collision risk. To settle this issue the automation level was decided to be SAE 4 which includes sophisticated autonomous driving technologies and still human interventions may be required in cases such as disengagement or hazardous situations that an AV cannot deal with.

The results of the literature review in this study (appendix A) reveal that the notion of connectedness and communication with other traffic participants in addition to infrastructure is attracting considerable attention in academic literature. There is a consensus that timely and secured communication between traffic participants and infrastructure can reduce collision risks. The connected and autonomous vehicle (aka CAV) term is also being now broadly used in academic and non-academic literature. The establishment of connection and communication between agents in urban traffic ambience, however, requires adequate infrastructure, customised protocols, and security measures in place. After all, this possibility is assumed to be available for AVs to communicate through V2V, V2I and V2X channels and receive/send information.

Demographic characteristics including gender, age and education are extensively studied in traffic and accident analysis mainly because the impact of these factors on driving behaviour and risk taking is undeniable. Nonetheless, demographic characteristics were not included in the model, and it was assumed that they do not affect collision risk at SAE 4 level. Likewise, driver impairment as a result of alcohol or drug consumption was omitted and it was assumed that the behaviour of road users (i.e., traffic safety culture) is homogenous across a society.

Among academics and technical communities there is debate on whether AVs must be strictly programmed to comply with the traffic rules, or they may be allowed to break traffic laws under certain conditions, for instance, where there is an immediate risk of loss of life or injury. If that is the case, several questions remain to be answered. For example, it must be delineated *who* can permit the vehicle to break traffic laws and how such risks are evaluated and by whom. To avoid those ambiguities the assumption here was that all traffic participants must be compliant with traffic rules and regulations and non-compliance will have adverse effect on traffic safety.

Various forms of cyber-attacks on connected AVs can disturb different functionalities and paralyse one or more components of an AV. Correspondingly, the consequences on traffic safety can be manifold. Sheehan *et al.* (2019) used a Bayesian Network to classify cyber-related risks for CAVs and discussed different types of attacks and their potential severities. Katrakazas *et al.* (2020) reviewed safety implications of cybersecurity for CAVs and investigated the probable scenarios for a compromised CAV. These consequences can vary depending on type of attack, intention of attacker(s), duration of attack, its magnitude and dozens of other factors. In this study, it was assumed that any cybersecurity breach will only degrade the communication channels of a CAV posing Denial of Service (DoS) threat (Katrakazas *et al.*, 2020).

The term ‘collision’ limits accidents to a scenario that a CAV collides with one or more traffic participant(s) (e.g., vehicles, bikes, pedestrians, animals, etc.) and/or obstacles. There can be other safety incidents presumed for CAVs such as a data privacy breaches, injuries to occupants due to discomforting driving styles or compromised safety measures, and fire that are not led to collisions. Non-collision accidents are therefore excluded from the keywords in database searching and emphasis was placed on collision risks.

In assessing the influences of selected variables on collision risk, the current level of technological progress for CAVs was set as a benchmark and experts were required to answer the questions of survey based on the state-of-the-art technologies available for CAVs. In that elicitation process the existing infrastructure was assumed to be the benchmark and expected advancements were disregarded.

3.10. Summary of methodological discussions and conclusions

To summarise, this chapter put forward a set of criteria for qualifying relevant publications for thematic analysis and identification of risk factors. Integrative literature review and its protocols were discussed to regulate the selection and review of the publications. A framework for thematic analysis was provided to . It was discussed and justified why BBN is a fitted platform for synthesising qualitative and quantitative data in this research. A comparison with other potential modelling techniques (e.g., ANN) was drawn. The step-by-step development of the BBN model including construction of the network and filling in the CPTs was explained. A new and efficient method was introduced to populate CPTs. The proposed method is efficient in saving time during the elicitation process and simplifies the that for the domain experts. The process for expert judgement elicitation was described. A survey was designed to gather expert opinions on the weights of parent nodes on their child(ren). Finally, the major assumptions in designing frameworks and modelling were clarified.

The main conclusion from the methodological discussions and comparisons is that BBN has a proven capability to handle large number of variables and serves as a competent platform for integrating qualitative and quantitative data, particularly in risk analysis. The outcome (i.e., probability distribution) provides a base for performing scenario analysis and classifying risks to answer research questions in this study. Those features make BBN a powerful tool to address research questions specified in section 1.5. The unique elements in research method design in this study are adopting a socio-technical approach towards collision risks in urban environments and employing ILR to construct a BBN model.

Chapter 4

4. Results and analysis

This chapter presents the findings of ILR and TA (i.e., 53 risk factors) which formed the skeleton of the BBN model. A description for every identified risk factor is provided to support their selection and inclusion in the BBN model. The results of the expert elicitation are exhibited and incorporated into the model. The outcomes of scenario and sensitivity analyses are also demonstrated.

4.1.Results of the integrative literature review and thematic analysis

Among the main results of this project is the classification of the reviewed papers and documents which attribute the collision risk to environmental, human, traffic and technical causes. 594 papers were reviewed and the table in appendix A presents the main theme in each paper as well as the subordinate themes. A summary is provided for every paper to spotlight the topic and key points related to causes of safety degradations in AVs. These themes were converted into 'ranked nodes' (Fenton, Neil and Caballero, 2007; Laitila and Virtanen, 2016) to form the topology of the BBN model. In constructing the CPTs, labelled states which represent qualitative variables that are abstractions of some essential continuous quantities were used (Fenton, Neil and Caballero, 2007). Ranked nodes are especially helpful when modelling relationships in NPTs involving variables that are (near) continuous (Fenton, Neil and Caballero, 2007; Perkusich, Perkusich and de Almeida, 2013; Laitila and Virtanen, 2016). The states were likewise derived from the literature. In this section a brief explanation for every node in the model and justification for composition of states are presented as follows:

Time of day: in accident reports involving AVs (Favarò *et al.*, 2017) and analysis of datasets assessing the *driveability* for AVs (Guo, Kurup and Shah, 2019) 'time of day' has a bold presence. This is because there is a causal and correlative relationship between time of day and other variables which directly affect the probability of collision and accidents. 'Traffic density', 'lighting conditions' and 'drowsiness' are found to be dependent on time of day. The states for this node are three-hour time intervals for a whole day period (00:00 – 24:00) as used in the Annual Road Traffic Estimates series published by the Department for Transport (Havaei-Ahary, 2019).

Day of week: besides time of day, the accident reports take account of 'day of week' (Vorko-Jović, Kern and Biloglav, 2006; Allen *et al.*, 2017; Favarò *et al.*, 2017; Aung *et al.*, 2018). This variable directly affects the traffic volume as well as speed of vehicles. An ANN model developed to predict the traffic flow in heterogeneous condition displayed the highest sensitivity of traffic flow (as the output) to day of week and time of day (as inputs) respectively (Kumar, Parida and Katiyar, 2015). To avoid higher number of elicitations in the BBN model the state structure for this node was decided to be Boolean with only weekdays and weekend as the states (Allen *et al.*, 2017; Verendel and Yeh, 2019).

Weather conditions: one of the major sources of threat to the safe operation of AVs is adverse weather conditions such as precipitation, fog and sun glare (Yoneda *et al.*, 2019). A literature review on the effectiveness of radars under rainy weather shows up to 45% reduction in the detection of radars (Zang *et al.*, 2019). This factor can effect change in other environmental variables such as lighting conditions and road surface conditions. The states for this node are defined as clear/sunny, windy, rainy, snowy, foggy and dusty (Chen *et al.*, 2015).

Lighting conditions: also specified as 'illumination' in the technical literature (Guo, Kurup and Shah, 2019), this factor can adversely affect the performance of visual cameras which are mounted on AVs to detect and recognise objects (Rashed *et al.*, 2019). Reviewing the preliminary report on the fatal accident in Arizona involving an Uber driverless car and a pedestrian reveals that the section where the incident happened was *"not directly illuminated by lighting"* (NTSB, 2018). Moreover, Paul and Chung (2018) drew attention to the dysfunction that direct dazzling sunlight can trigger in the *machine vision* module of the AVs. In May 2016, a Tesla Model S collided with a truck-tractor dragging a 53-foot semitrailer and took the life of its driver. While the car was on autopilot mode both driver and emergency brake system failed to notice the white truck-tractor against the brightly lit sky (Paul and Chung, 2018; Winkle, Erbsmehl and Bengler, 2018). The states for this node are daylight, dawn/dusk and dark/night (Chen *et al.*, 2015; Guo, Kurup and Shah, 2019).

Visibility: *obstructed visibility* due to bad weather conditions, poor lighting or road layout can restrict or thwart the perception and sensory module of the AVs (Bagheri, Siekkinen and Nurminen, 2016). Winkle, Erbsmehl and Bengler (2018) analysed 1,286,109 digital copies of accident reports to evaluate the role of limited visibility in accidents which occurred in the state of Saxony between 2004 and 2014. The results suggested that limited visibility is a risky scenario that must be taken into consideration for developing automated vehicles (Winkle, Erbsmehl and Bengler, 2018). Various functions in AVs such as road marking detection hinge on camera-based vision systems (Mohsen *et al.*, 2020). Inappropriate road design or landscaping may block the visibility splay of the vision systems. Poor visibility can blind these cameras or cause visual obstruction resulting in failure in detecting or recognising objects/obstacles. The states for this node are *good* and *bad* (Stroeve, Blom and Bakker, 2009; Zhang, Yau and Chen, 2013; García-Herrero *et al.*, 2020).

Road type: there are several factors that designing a road is highly dependent on them. 'Road type' has a decisive influence on the layout, geometry and design of roads. For example, Geometric Design of Roads Handbook explicitly states a link between the type of road and development of *gradeline*, *design of speed*, *horizontal and vertical alignments*, and *design of urban drainage systems* (Wolhuter, 2015). To enhance quality, preserve uniformity and provide safety design standards are defined for each functional road type (Benson and Lay, 2016). Malin, Norros and Innamaa (2019) developed a risk profile for three road types and three geographical locations in Finland. Their results affirm that the risk of accident occurrence significantly varies across different road types. Therefore, this can be concluded that road type plays a crucial rule in the frequency of road vehicle accidents and affects variables such as permitted speed, traffic flow, driver reaction time and other road design characteristics. The themes for this concept were roadway configuration, road layout and road design, however, the former was used in the model as a node representing all those aspects. The Department for Transport classifies the road types into four groups: single carriageway, double carriageway, motorway and built-up areas (DfT, 2015). This classification determines the speed limit law for each of those types of roads. Since built-up areas are considered to be a type of road but any road can pass through built-up areas, this option was excluded from the final composition of states for this node. As a result, the states for this node were narrowed down to 'single-carriageway', 'dual-carriageway' and 'motorway' (Piao *et al.*, 2004).

Roadway configuration: this factor and the variables that define its complexity have been discussed in depth in the field of transportation and mobility. Number of lanes (Malin, Norros and Innamaa, 2019), road curvature and slope (or gradient) (Yagar and Van Aerde, 1983), and road type (Intan Suhana *et al.*, 2014) are found to be determining characteristics of roads as far as safety is at stake. A´lvarez *et al.* (2020) performed a case-control study to locate urban road configurations in Valladolid that may needed redesigning to alleviate the *odds of a run-off crash*. In their study they found geometric design factors such as number of lanes, presence of traffic lights and length of curves to be influential up to twelve times in the odds of a run-off crash (Álvarez *et al.*, 2020). Wang *et al.* (2019) outlined the road geometric parameters as curvature, number of lanes, gradient, and ramp type. To capture the impact of these factors a node with categorical states was incorporated into model. The states are appropriate, challenging and complex. These states can specify how the combination of the discussed factors above can provide a driving road environment for the vehicle.

Number of lanes: reviewing the literature on the accident causes for both conventional and autonomous vehicles reveals that larger number of lanes exert influence on the increase of the likelihood for accident occurrence. Analysis of 1606 accidents over a three-year period in Central Florida shows that narrower lane width and larger number of lanes simultaneously heighten the risk of accident for both female and male drivers (Abdel-Aty and Radwan, 2000). Further, Zurlinden, Baruah and Gaffney (2020) reported that the number of conflict points for two-lane, three lane and seven-lane roads are 2, 7 and 77 respectively. By the same token, safe lane departure for AVs is indispensable as lane-departure collisions between the ego vehicle and other traffic participants is a likely scenario (Olofsson and Nielsen, 2020). The states for this node are *one lane, two lanes* and *multiple lanes*.

Road infrastructure: Milakis, van Arem and van Wee (2017) reviewed the literature to look at the policy-making and societal implications of AVs in urban areas. Among the keywords in their review, ‘road infrastructure(s)’ along with ‘road design’ and ‘road planning’ was used to search for the implications of *transportation infrastructure* in connection with the AVs. In another study Nitsche, Mocanu and Reinthaler (2014) investigated the interactions between road infrastructure and AVs. 76% respondents in the online questionnaire ranked road infrastructure as ‘very important’ while only two percent rated it as ‘not important at all’ (Nitsche, Mocanu and Reinthaler, 2014). Visibility and harmonisation of lane markings and traffic signs, road surface friction, and pedestrians/cyclists protection (e.g. shielding) at junctions were among the main listed factors with highest influence on the safety of AVs (Nitsche, Mocanu and Reinthaler, 2014).

Work zones: roadwork operations are usually undertaken to maintain a standard level of quality for road networks. Research shows that driving in work zones incurs more risk comparing to non-work zones (Weng, 2011; Genders and Razavi, 2016). The peculiarity of some work zones, forcing the vehicle to change speed and/or lane, and creating blind or visually obstructed spots for the vehicle may incapacitate the perception and planning modules of AVs. Research suggests that road work can increase the motor vehicle crashes by 26% (Meng and Weng, 2013). In 2017 alone, a total of 158,000 vehicle crashes occurred around the work zones on the US roads (Tang *et al.*, 2021). Frequent lane changing and merging manoeuvres can also add to the complication of the traffic scene (Wu *et al.*, 2020). Presence of work zones also contributes to the presence of obstacles (e.g. debris, material, barriers, temporary signs, work equipment, etc.) (Weng, 2011). This includes encroaching over the public roads by nearby construction sites. A Boolean node was therefore designed to involve this factor. The states for this node are ‘present’ and ‘not present’ refereeing to the presence of work zones in a given driving environment.

Obstacles: a large body of literature in conjunction with many industrial projects are dedicated to design and operationalisation of collision avoidance systems. One of the tasks of path planning module of an AV is to generate a trajectory for the vehicle to avoid collision with consideration of obstacles’ geometric characteristics and the kinematic constraints of the vehicle (Ji *et al.*, 2016). This task becomes even more crucially important where the ego vehicle reaches the edge of its stability limits and handling capabilities in constrained environments (Ji *et al.*, 2016). The recent accident in California between a Tesla car (allegedly in autoploid mode) with a parked police car can demonstrate how presence of (static and dynamic) obstacles on roads can delude the AVs and run into an incident (Calvert *et al.*, 2019).

Road Conditions RI: this variable compiles the impacts of the environmental nodes and creates an intermediate node between them and the *collision risk index* as the outcome of the model. It also reflects the overall suitability or complexity of road conditions including surface friction (Kim *et al.*, 2018) that an AV may face during its travel. Malin, Norros and Innamaa (2019) suggested three scales (green, amber and red) to classify road conditions. ‘Green’ denotes normal conditions, ‘yellow’ (or amber) represents poor, and ‘red’ refers to hazardous road conditions (Malin, Norros and Innamaa, 2019).

Traffic rules enforcement: to reassure the safety of AVs the enforcement of traffic regulations is an implication which needs to be recognised and dealt with ahead of mass production and adoption of the technology (Baldini and Neisse, 2020). In fact, the effects of traffic rules is highly contingent upon the enforcement of the rules (Åberg, 1998). Research shows that the level of traffic laws enforcement makes a difference in drivers’ risk perception and attitude (Åberg, 1998; Stanojević, Jovanović and Lajunen, 2013). In a study comparing the safety culture in China, Japan and the US, it is argued that the way that standards and regulations are enforced has mutual interaction with (traffic) safety culture (Atchley, Shi and Yamamoto, 2014). The safety benefits of reduction in absolute vehicle speeds are not debateable. The World Health Organisation lays heavy emphasis on traffic law enforcement to increase the safety of roads (WHO, 2009). The results of a literature review provided strong evidence for a negative relationship between *average speed enforcement* and vehicle speeds (Soole, Watson and Fleiter, 2013). To appraise the effectiveness of certain traffic laws a three-point scale defined as *low*, *medium* and *high* was used before (Wali *et al.*, 2017) and is adopted in this study too.

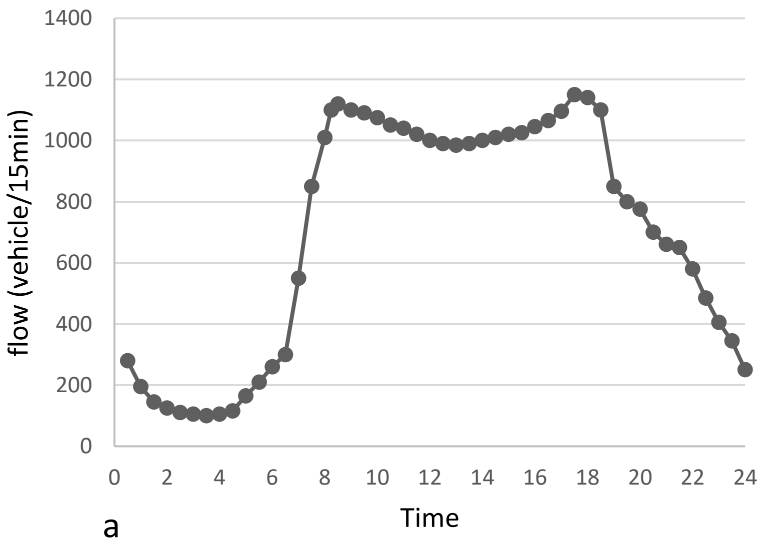
Traffic control infrastructure: investment on infrastructures is an intervention which policymakers can call for to facilitate the adoption and safe operation of AVs (Cohen and Cavoli, 2019; Soteropoulos *et al.*, 2020). Traffic control in urban environments (particularly crossroads) is a hurdle on the way of AVs and requires specific infrastructure compatible with AVs to optimise operations at traffic intersections thereby reducing the risk of accident (Rey and Levin, 2019). Inadequacy and lack of appropriate traffic control infrastructure for collecting and transferring essential real-time data to traffic control centres can potentially change the traffic scenes, congestion and complexity (Kurzhanskiy and Varaiya, 2015). The US Department of Transportation (DoT) singled out infrastructure and traffic control devices as a key source for traffic congestions which can give rise to the number of accidents (De Souza *et al.*, 2017). In a BBN model developed by Gregoriades and Mouskos (2013) to identify black spots through quantifying the collision risk index, 'traffic control' was included in the model as a node with three ordinal states. Hence, a node with three ordinal states (*sophisticated*, *partially developed* and *poor*) was embodied in the model to count the weight of varying levels of traffic control infrastructure in cities on the collision risk.

Other road users: Statistics on the fatalities (nearly 5,000 per year) and injuries (207,000) of pedestrians alone in the US (Deb *et al.*, 2018) can alone bespeak of the risk of collision between vehicles and other road users including pedestrians, cyclists, motorcyclists and animals. AVs are not exempt from this risk as the tragic accident between the Uber car and a pedestrian in March 2018 raised concerns about the safety of the technology. Having discussed earlier, elimination of humans from the driving loop can dramatically reduce the number of collisions, however, even after the rollout of CAVs still this technology will have to interact with humans on roads. While dealing with complex clutter and modelling interactions with other road users is requisite, this problem has not been completely solved for AD (Schwarting, Alonso-Mora and Rus, 2018). For that reason, the perception and planning modules must be able to recognise other road users precisely and timely, anticipate their trajectory and speed, and avoid colliding with them. Urban planners have suggested dedicated lanes for AVs (Ye and Yamamoto, 2018) or shielding (Nitsche, Mocanu and Reinthaler, 2014) to protect other road users against AVs in heterogeneous traffic flows. These solutions directly or indirectly affect the frequency that AVs must interact with road users other than AVs and HDVs. To measure this frequency, three states were defined for this node: *never-rarely, occasionally/sometimes* and *often-always*.

Traffic composition: *"Incompatibility of size between different types of road vehicles is a major risk factor"* (Mohan *et al.*, 2006). Even after the AVs become widely disseminated, mixed traffic will be a quite likely scenario for a relatively long period of time (Wagner, 2016). Since we already counted the effect of other road users such cyclists and motorcyclists, the 'traffic composition' node only concerns with the constitution of traffic in terms of AVs and HDVs. This node therefore consists of three states: *only AVs, only HDVs* and *hybrid*.

Traffic culture: Özkan and Lajunen (2011) defined an accident as "*either an independent or combined outcome of internal factors of the multilevel sociocultural and technical environment of traffic*". Ye and Yamamoto (2018) also showed that similar to varied accident rates, cities appear to have different cultures when it comes to traffic safety. Regardless of the antecedent reasons of this cultural variations, evidence confirms that establishing the highest level of traffic safety is incumbent upon the right cultural conditions (Atchley, Shi and Yamamoto, 2014). Sociotechnical approach also supports the involvement of culture in safety analysis of a system where (human) operators are having interactions with technology (Özkan and Lajunen, 2011). From these facts one can conclude that in addition to visible factors such as roadway characteristics, weather and lighting conditions, less tangible factors that contribute to forming a traffic environment (including traffic culture) are responsible for traffic safety (Shinar, 2017). *Conservative*, *moderate* and *aggressive* are the states of this node which were extracted from a study on driving style recognition (Yan *et al.*, 2019; Li *et al.*, 2021).

Traffic density: in the field of aviation the relationship between traffic density and traffic complexity under higher levels of automation was scrutinised by Kopardekar, Prevot and Jastrzebski (2008). The results indicate that traffic density and complexity have a positive relationship and increase the risk of conflict (Kopardekar, Prevot and Jastrzebski, 2008). Even more so, higher traffic density can trigger more lane changing (Zurlinden, Baruah and Gaffney, 2020) and subsequently increase the risk of collision for ground vehicles. Ultimately, it can be concluded that the risk of traffic conflict heightens with an increase in density and a reduction in velocity (Kuang, Qu and Yan, 2017). Research shows that traffic



flow and traffic density are highly correlated with time of day (Wang *et al.*, 2018b). Fig. 4.1 depicts traffic flow distribution against time in Shenyang, China. Data for other major cities suggest similar traffic flow distributions (Verendel and Yeh, 2019). Accordingly, a node is dedicated to accumulating the impacts of variations in traffic density on traffic complexity. The states are defined as *no traffic at all (free flow), light, heavy* and *jam (congested)*.

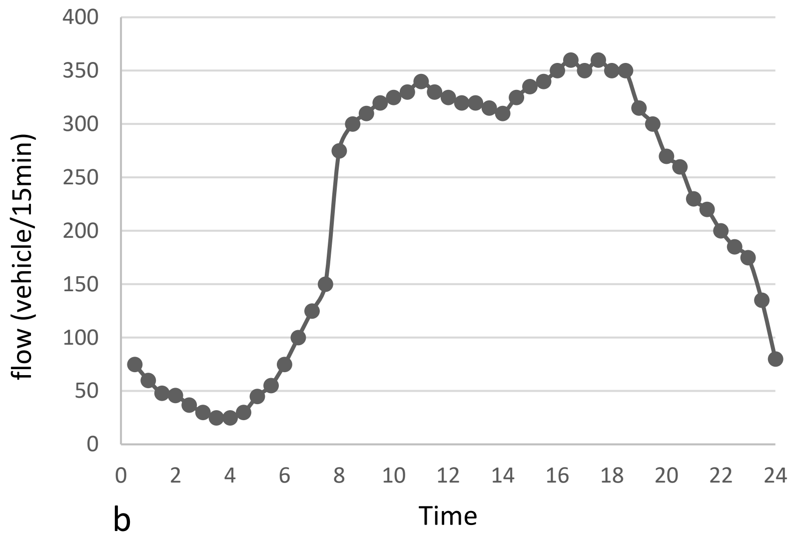


Fig. 4.1: The variations of approximate traffic flow against time at a typical intersection (a) and a road (b) in Shenyang, China (Wang *et al.*, 2018b)

Speed: besides traffic density, among the significant traffic variables are speed and speed difference (Wang *et al.*, 2019). Relative speed is also a determining variable in verifying the kinematic state of a vehicle (Wang, Yang and Hurwitz, 2019). A critical cause for traffic accidents (particularly under poor weather conditions) has been the improper speed choices (Yang, Ahmed and Gaweesh, 2019). In 2018, WHO revealed that reduction in average speed results in less road accidents (Calvi *et al.*, 2020). The common technique for measuring collision risk compares traffic measurements such as speed and flow on a certain segment of the road just before the occurrence of a collision, with the measurements from the same segment under normal circumstances (Katrakazas, Quddus and Chen, 2019). In other studies which adopted BBN approach to assess the collision risks (e.g., Simoncic, 2004; Gregoriades and Mouskos, 2013; Sheehan *et al.*, 2017), speed has a strong presence. Two states (i.e., *safe* and *unsafe*) were assigned to this node.

Kinematic state: a collision avoidance system for AVs should be responsible for continuously assessing the collision and destabilisation risks by monitoring the kinematics and dynamics of the vehicle (He *et al.*, 2019). Meanwhile, handling road dynamics and vehicle kinematics at the same time can be troublesome for the planning module and computing unit of the vehicle (Glaser *et al.*, 2010). In studying collision risks, the kinematic state of a vehicle can be defined in terms of its speed combined with longitudinal and lateral distance from the nearby vehicles (or obstacles) (Cheng *et al.*, 2019). As far as the distance between the centroids of vehicles is not less than the *safe separation distance* they are in safe mode, but when this distance is shorter that SSD the risk of collision soars and the ego vehicle will be in unsafe mode (Campos and Marques, 2018).

Traffic complexity RI: recent study conducted by Zurlinden, Baruah and Gaffney (2020) shed light on the relationship between traffic complexity (due to unstable flow or congestion) and conflict likelihoods. Katrakazas, Quddus and Chen (2019) asserted that AVs must be seen as interacting agents with the environment and other agents rather than an independent entity. In urban environments where other road users are pervasive, AVs face another dilemma to understand their intention and predict their course of actions, namely trajectory and speed (Rasouli, Kotseruba and Tsotsos, 2017). Such an interaction needs full and accurate perception of the environment as well as competent and sufficient planning capabilities to handle complex traffic scenarios. One of the challenges that technology developers are facing is to increase the capabilities of AVs to precisely perceive and interpret complex traffic situations (Winkle, Erbsmehl and Bengler, 2018). For instance, Wang *et al.* (2018) proposed a classification technique for the obtained sensory data to quantify the traffic scenario complexity on roads. Three classes (i.e. *simple, medium* and *complex*) were suggested in that research and are used as the states in this study too (Wang *et al.*, 2018a).

Training & experience: as long as humans remain in the loop, building *knowledge* and *trust* for users or those who are supposed to interact with the technology will act as a mitigator of unintended safety risks (Pradhan *et al.*, 2019). To achieve this goal in addition to familiarising the users with capabilities and limitations of the technology, *education* and *training* become momentous (Cunningham and Regan, 2015; Pradhan *et al.*, 2019). The level of trust in technology increases/decreases the level of risk that users perceive (Choi and Ji, 2015). Further, Akash *et al.* (2017) discussed the importance and yields of past experiences on forming the trust in HMI. Brinkley *et al.* (2019) reported a 20.75% increase in trust in the technology after the participants experienced interacting with a prototype self-driving car. From that, one can conclude that training and experience are influential in how individuals interact with, treat and perceive the AVs. Those constructs can, to a considerable extent, contribute to the (collective) understanding of humans on how the technology works and where it may fail to fulfil its tasks. This will lead to calibrated reliance on the technology and can prevent safety incidents by timely and apposite interventions. Thereupon, three levels of training and experience are defined for this node to act as the states of its NPT. *No training at all, basic trainings* and *extensive* can reflect the level of trainings and experience that users and interactors are supposed to receive before engaging with automated driving systems in the real-world situations.

Trust & reliance: having discussed above, experience is the fundamental issue in how much drivers trust in AVs and to what magnitude they calibrate their trust and reliance after they experience the technology (Ho *et al.*, 2017). 'Learned trust' is the accumulation of experiences with a system and influences that form the initial mindset of the individuals (Akash *et al.*, 2017). The relationship between trust and HMI (especially in automated systems) has been the focus of researchers for long time. Akash *et al.* (2017) maintained that *"to attain synergistic interactions between humans and autonomous systems, it is necessary for autonomous systems to sense human trust level and respond accordingly. This requires autonomous systems to be designed using dynamic models of human trust that capture both learned and dispositional trust factors"*. This can explain the role of trust in the quality and extent of HMI in autonomous systems. *Overtrust* and under-reliance are two symptoms of uncalibrated trust in autonomous systems that can ultimately lead to a safety risks (Hoffman *et al.*, 2013). To exemplify, Miller *et al.* (2016) reported that overtrust in the capabilities of an automated system such as AV can delay the take-over process in a hazardous situation or where the vehicle is disengaged. Therefore, three states were defined for this node as follows: *overreliance, calibrated reliance* and *under-reliance*.

Perceived risks: in AI-based (autonomous) systems perceived risk is a product of delegating control to the machine and its control mechanisms (Hengstler, Enkel and Duelli, 2016). Perceived risk(s) can further affect drivers in adapting their behaviour to the road conditions (Oviedo-Trespalacios *et al.*, 2018). Risk (or hazard) perception can be defined in terms of reaction times (as an operational KPI) that drivers record in responding to a risky situation (Sagberg and Bjørnskau, 2006; Barnard and Chapman, 2016; Sun and Hua, 2019). Drivers in order to avoid road traffic collisions need to detect an event, rate it in terms of risk, choose appropriate action(s) (or not taking any action) and finally enforce the decision(s) (Hulse, Xie and Galea, 2018). The time interval for this process may vary between drivers and must be short enough to avoid a collision. This perceptual factor, therefore, can contribute (mitigate) the collision risk in AVs under human supervision. Three states (i.e., *high, medium* and *low*) were defined for this node to measure the impact of perceived (level of) risk on the reaction times to the road dynamics (Arbabzadeh *et al.*, 2019).

Human-Machine Interactions (HMI): the current landscape of autonomous vehicles displays that passing through the semi-autonomous phase before reaching full autonomy is unavoidable (Bellet *et al.*, 2019). While the interactions between humans and AVs are essential during this phase, analysing the quality and extent of the necessary interactions is mandatory to ensure the safety of AVs (Fan *et al.*, 2018). In the recent standard (ISO 21448) created by the automotive industry for ADAS, human-machine interaction issues are highlighted to be addressed (Koopman *et al.*, 2019). Although the automotive industry has recognised the dire need to devise *verification and validation* approaches for HMI, detailed standards are still missing (Burke, 2020). Other than human drivers, other road users (e.g. pedestrians) need to have safe interactions with the AVs (Wang *et al.*, 2020a), but the focus of this thesis is upon the interactions between the AV driver and the vehicle. The transition from ‘automation’ to ‘autonomy’ requires fundamentally new approaches to reinforcing HMI in AVs. Then this can be concluded that improper or lack of HMI can be a source of risk for AVs. This node comprises of four states: *very effective, moderately effective, slightly effective* and *no interactions at all*.

Situation(al) awareness (SA): situation awareness is an ‘*emergent property*’ of a sociotechnical system (Stanton *et al.*, 2017) and closely related to the concept of risk perception, and drivers need time to develop SA when they are required to tack back the control of vehicle (Vlakveld *et al.*, 2018). Situation awareness and allowed time for taking over the control of vehicle are reported to be correlated (Vlakveld *et al.*, 2018; Vogelpohl *et al.*, 2019). For example, decreased SA is associated with delay in responding to hazardous situations (e.g. braking when faced with a failure) both in simulated and real-world driving (Jamson *et al.*, 2013). There are some factors such as involvement in secondary tasks (Jamson *et al.*, 2013; Endsley, 2018; Petersen *et al.*, 2019; Zhou, Yang and Zhang, 2020), drowsiness (De Winter *et al.*, 2014; Vogelpohl *et al.*, 2019; Kaduk, Roberts and Stanton, 2020b) and training (Schömig and Metz, 2013; Endsley, 2017) which affect the drivers' situation awareness, and reaction time lastly. Petersen *et al.* (2019) conducted an experimental study to assess the impact of SA on drivers' trust level. They manipulated SA in three levels: *no SA, low SA* and *high SA* (Petersen *et al.*, 2019). These levels were adopted for defining the states of this node in the BBN model.

Secondary task: non-driving related tasks also known as secondary tasks are supposed to be allowed in highly AD (e.g., SAE Level 3 and above), but its influence on drivers' takeover performance especially with a limited time budget, has to be taken into account to avoid collisions (Zhou, Yang and Zhang, 2020). Longer reaction times (Lu, Coster and De Winter, 2017; Mok *et al.*, 2017; Minhas *et al.*, 2020) and higher collision rates (Metz, Schömig and Krüger, 2011) are specified as the consequences of being engaged in secondary tasks while driving semi-autonomous vehicles. Depending on the autonomy level, technology capabilities and local law, the driver of an AV may or may not be allowed to divert his/her attention to one or a combination of secondary tasks for safety reasons. For instance, following the fatal crash of a Tesla car in 2016 which led to the death of its driver while the autopilot mode was active, Tesla imposed further restrictions on *hands-off driving* (BBC, 2017). Based on the above discussion, a Boolean node was inserted into the model to capture the (conditional) effect of involvement in secondary tasks on SA and reaction time.

Drowsiness: drivers are generally more prone to drowsiness in AD and are expected to show slower reactions comparing to manual driving (De Winter *et al.*, 2014; Vogelpohl *et al.*, 2019). Moreover, sleepiness can have crucial impacts on the time that drivers need to (re)gain SA to handle a takeover safely (Lu, Coster and De Winter, 2017). In semi-autonomous driving where human supervision and control might be required at some point, drowsiness can potentially affect drivers' situation awareness (Lee *et al.*, 2019). Kaduk, Roberts and Stanton (2020b;a) observed that drowsiness, driving performance and time of day are strongly related (figure 4.2). Karolinska Sleepiness Scale (KSS) has been widely used to investigate drowsiness (sleepiness) in myriad contexts. This scale is adopted here as well to shape the states for the drowsiness node. *Extremely alert, alert, neither alert nor sleepy, sleepy* and *extremely sleepy* are the ordinal states for this node (Åkerstedt and Gillberg, 1990).

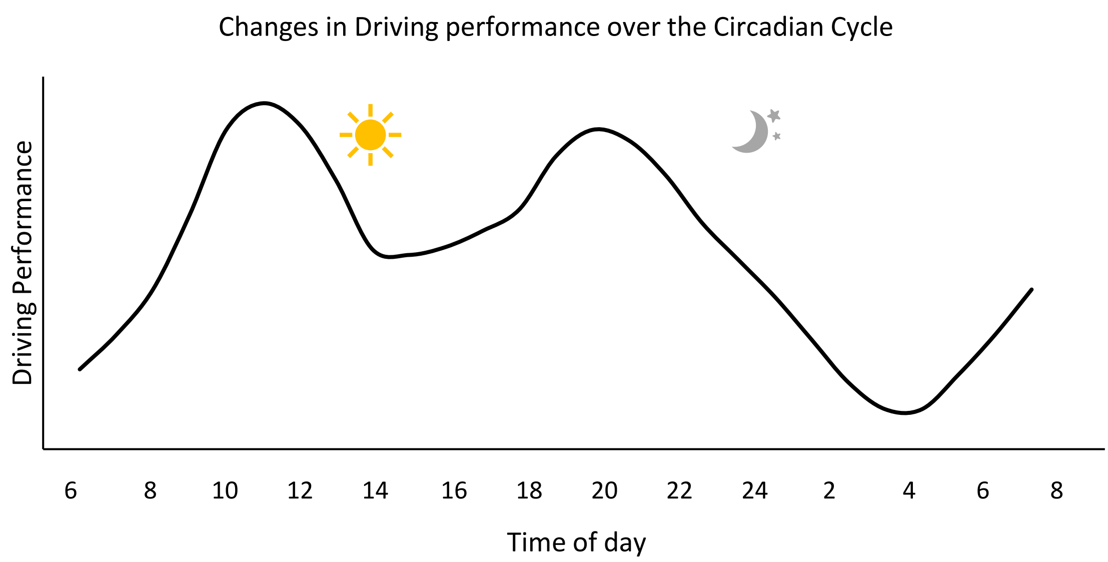


Fig. 4.2: Changes in driving performance over a 24-hour period (circadian cycle) (Kaduk, Roberts and Stanton, 2020b;a)

H-M interfaces: in general, human-machine interfaces are platforms designed to facilitate *cognition* and *communication* between human and machine (Gong, 2009). There is a strong link between HMI and H-M interface in the technical literature. Designing and integrating interfaces that promote calibrated trust in AVs is exceptionally vital for the safe operation of semi-autonomous vehicles, and this will rely upon a valid understanding of whether those interfaces are capable to build trust and improve SA (Dixit, Chand and Nair, 2016; Miller *et al.*, 2016; Wintersberger and Riener, 2016). Users have expressed their concerns about the competence of human-machine interfaces to maintain their SA and satisfy their location verification needs (Brinkley *et al.*, 2019). Minhas *et al.* (2020) also emphasised that appropriate design of H-M interfaces is critical to ensure that takeover message is properly and timely conveyed to human driver. Using right interface can have profound impact on the reaction time in emergency scenarios (Petermeijer *et al.*, 2017). Depending on the type, design and ease of use this impact can vary. To assimilate the effectiveness of the H-M interface(s) on the HMI and reaction time into the model a five-point Likert scale form *extremely effective* to *not effective at all* was used to set up the states for this node.

Reaction time RI: one of the determining factors in collision likelihood and collision avoidance in manual driving is the timing of driver reaction to traffic dynamics and conditions on the road (Hugemann, 2002). Even with AVs, driving scenarios with short-time headways and unstable vehicle dynamics might emerge and lead to unpredictable extreme events (Roche, Thüring and Trukenbrod, 2020). In AD, particularly where humans are kept in the loop (i.e. SAV), this variable has yet decisive influence on collision risk. In a recent study, Shangguan *et al*. (2020) quantified the *auto-drive* vehicle collision risk by the Time-to-Collision frequency. Russo *et al.* (2016) in a BBN model which was developed to assess the risk levels for AVs, included a separate module in the model to specifically measure reaction time. Some other researchers similarly estimated collision risk based on TTC (Russo *et al.*, 2016). This variable can also act as a fitting KPI for human performance while required to intervene and avoid a collision (Greenlee, DeLucia and Newton, 2018; Roche, Thüring and Trukenbrod, 2020). Several scholars such as Arbabzadeh *et al.* (2019) and Dixit, Chand and Nair (2016) used a 0-8 second interval with a two-second step to analyse the driver reaction times. These intervals (i.e., 0-2, 2-4, 4-6 and 6-8) formed the states for this node.

Perception accuracy: a combination of localisation systems (e.g., GPS), sensory systems, mathematical and intelligent algorithms shape the skeleton of the perception module of fully AVs (Marzbani *et al.*, 2019). A wide range of the algorithms which have been developed for autonomous control of AVs and searching in unknown, rely on vision systems and sensors (Marzbani *et al.*, 2019). However, *deficiency of perception* will occur when the artificial perception components of the vehicle fail to accurately sense the immediate surroundings of the vehicle and supply enough details to the processing and planning modules for deciding on the most legitimate (re)action in a timely manner (Lipson and Kurman, 2016). Many of these technical failures occur due to the uncertain environment in which AVs operate like road and weather conditions, inaccuracy in perceiving the environment and generating inadequate or imprecise sensory data (Khonji, Dias and Seneviratne, 2019). Sensor and algorithm limitations, high dynamism of the environment and hardware defects are just a few causes to name. Sensory system of AVs is yet unable to discern the subtle social aspects of driving and traffic volatility in the way that human drivers do (Vinkhuyzen and Cefkin, 2016). Inaccurate or inadequate perception of the environment dramatically increases the likelihood of collision particularly in highly dynamic and cluttered urban environments. The main sensory equipment installed in AVs consists of vision sensors (e.g. cameras), LiDAR and radar (Kocić, Jovičić and Drndarević, 2018; Schwarting, Alonso-Mora and Rus, 2018; Zhao, Liang and Chen, 2018; Novickis *et al.*, 2020). Therefore, these sensors were set as the parent nodes of 'perception reliability' in the model. The states for the technical nodes are defined based on *Automotive Safety Integrity Level (ASIL)* (Koopman and Wagner, 2016) except for 'system integration' and 'cybersecurity'.

Safety requirements in automotive industries may vary depending on the criticality of functions and local/regional standards. ISO 26262 defines detailed quantitative techniques and risk classification methods for verification and validation of vehicle safety (da Silva Azevedo *et al.*, 2013; Sanguino, Domínguez and de Carvalho Baptista, 2020). Safety Integrity Levels (SILs) were originally stemmed from the UK Health and Safety Executives guidelines and serve as indicators of the level of safety of a function in safety-critical systems (Papadopoulos *et al.*, 2010). ASILs are an automotive industry adoption of SILs for the functional safety of Electrical/Electronic/Programmable (E/E/PE) Safety-Related Systems in road vehicles (e.g., AVs) (Gheraibia, Djafri and Krimou, 2018). They range from least stringent (ASIL A) to most stringent (ASIL D) (Mader *et al.*, 2012; Mariani, 2018). da Silva Azevedo *et al.* (2013) adopted ASILs for software and systematic failures too. According to ISO 26262, the acceptable probability (i.e., target values) for hardware or software failures for each class of ASILs are as follows (Lu and Chen, 2019; Török, Szalay and Sághi, 2020):

- ASIL D: $<10^{-8}h^{-1}$
- ASIL C: $<10^{-7}h^{-1}$
- ASIL B: $<10^{-7}h^{-1}$
- ASIL A: $<10^{-6}h^{-1}$ or hardware metric calculation not required

$*$ h stands for hour (time)

Sensor fusion: in addition to the deployed sensors, 'sensor fusion' plays a critical role in feeding accurate information to the processing and planning module to augment scene recognition (Kato *et al.*, 2015). Sensor fusion entails simultaneously fusing various data coming from an array of sensors in order to reinforce the vehicle's perception as well as the reliability of the system (Campbell *et al.*, 2018). Sensor fusion is a basic method to overcome challenges such as limited sensing range, diversity of dynamic obstacles and large number of false positives and/or negatives (Zheng *et al.*, 2018). The reliable function of sensor fusion component is crucial for autonomous control, navigation and planning (Patel *et al.*, 2019), but any failure in this component can have similar consequences to sensor failures. Disengaged or faulty sensor fusion unit will result in uncertain and noisy information and the deficiencies associated with every single sensor will not be compensated (Lamkin-Kennard and Popovic, 2019).

Software reliability: assuring safe operation of an autonomous system is conditional upon the reliable and robust operation of its critical software components (Hutchison *et al.*, 2018). Reassuring that all software pieces are working safely requires formal verification of important properties along with identification of defects which can hinder the safe operation of the system and pose safety risks (Hutchison *et al.*, 2018). Haynes and Thompson (1980) defined software reliability "*as the probability of the absence of any software-related system malfunction for a given mission*". Such errors and defects in the software subsystems of the AVs can result in inadequate control (Koopman and Wagner, 2016; Abdulkhaleq *et al.*, 2017) and cause an irregular behaviour or collision (Sheehan *et al.*, 2017). Some of these software malfunctions will happen during the operation of AVs and can have catastrophic consequences (Koopman and Wagner, 2016).

There have been four major areas in the literature with a link to the software reliability of AVs. AI performance which refers to the capability and maturity of machine learning and deep learning algorithms of the perception and planning modules of the vehicle is determining factor for a reliable software system (Khonji, Dias and Seneviratne, 2019). AVs also must be capable of generating behaviour (like human performance) based on learning potentials and this task becomes even more important in mixed urban traffic (Guo *et al.*, 2017). Behaviour generation subsystem of AVs which is designed based on data-driven rather than modelling approaches (Wolf *et al.*, 2018), has an immense role in software reliability and collision avoidance (Bernhard, Pollok and Knoll, 2019). Behaviour generation algorithms are in charge of analysing and examining the interactions between the nearby road users (Bernhard, Pollok and Knoll, 2019) and decide on the next action to achieve mission goals (Barbera *et al.*, 2004). Planning module (consisting of path, trajectory and motion planning algorithms) of the vehicle is responsible for generating a geometric path between two spatial points and it influences both kinematic and dynamic properties of the vehicle (Gasparetto *et al.*, 2015). Any abrupt motion can imperil the safety of the ego vehicle and surrounding road users (Gasparetto *et al.*, 2015). Intelligent control technologies constitute a key component of AVs (Zhao, Liang and Chen, 2018). Control and following the generated path by path and trajectory planning modules while maintaining coordination between lateral and longitudinal stability is another significant problem associated with AVs in crowded driving environments. Vehicle dynamics have strongly non-linear characteristics and complex properties that make path-following a demanding job for the control algorithms/systems of AVs (Wang *et al.*, 2020b). Figure 4.3 demonstrates the overall structure of a control system designed for AVs.

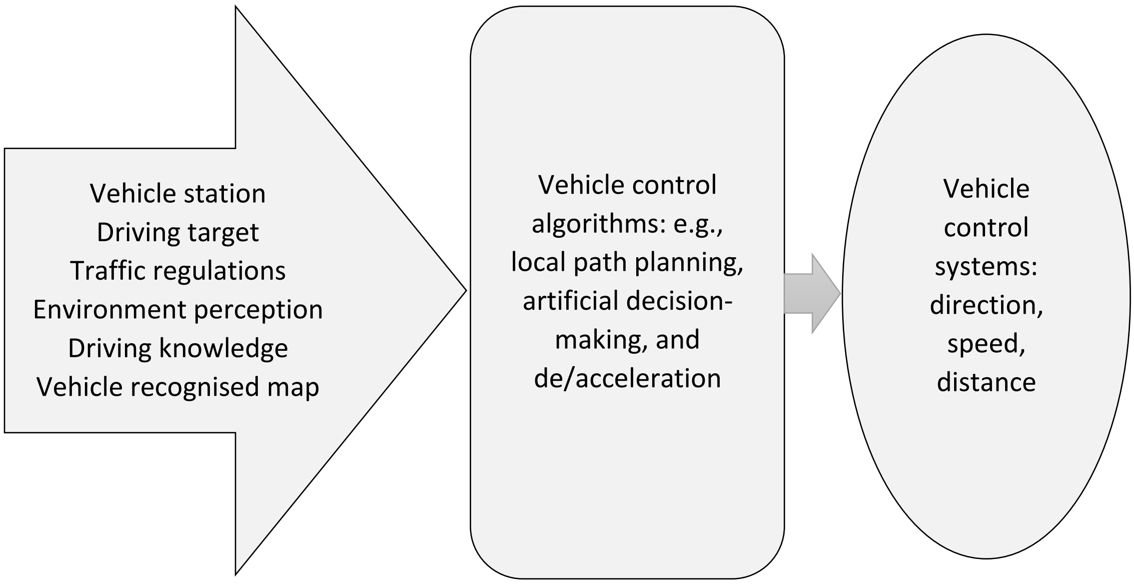


Fig. 4.3: Control system in AVs (Zhao, Liang and Chen, 2018).

Hardware reliability: every AV is a combination of hardware components and software architecture (Koopman and Wagner, 2017; Schlatow *et al.*, 2017). Collisions may occur due to both software or hardware failures (Goodall, 2020). Therefore, reliability of hardware components such as computing hardware and actuators is a risk factor in AD like conventional vehicles. The National Motor Vehicle Crash Causation Survey (NMVCCS) conducted by NHTSA between 2005 and 2007 highlighted the share of vehicle components' failures (e.g. tyres, transition, and engine-related defects) in motor vehicle crashes in the US (Singh, 2015). Similar to software reliability, hardware reliability can be "defined as the probability of the absence of any hardware-related system malfunction for a given mission" (Haynes and Thompson, 1980). Although any component or part in a vehicle can fail or become faulty at some point, not all component failures pose a collision risk. Therefore, the focus in this research will be the reliability and failure of critical components.

The concept of 'health management' stems from avionics and has been used in mission tracking for unmanned aerial vehicles (UAVs) (Valenti *et al.*, 2007). The idea is that an autonomous vehicle should be capable of actively monitoring and managing vehicle subsystems to increase mission and functional reliability through more accurate and timely system self-awareness (Valenti *et al.*, 2007). There are different definitions for *self-awareness* and *self-aware* autonomous systems e.g. in Lipson and Kurman (2016, pp.283-285), but in this research, self-awareness refers to the capacity and capability an AV to recognise its own state and limitations, feasible actions, and predict the result of these actions on the vehicle's state and the surrounding road users (Schlatow *et al.*, 2017; Ravanbakhsh *et al.*, 2018). This includes the awareness of the states of vehicle's components. Since the human driver is not fully (or at all) involved in the driving tasks, the vehicle must bear the responsibility of monitoring (or even rectifying) the state of its critical resources and components. It is urgent for an AV to decide whether to continue or halt a journey when a defect is detected. This requires the technology to be aware of the function of its components and have sufficient decision-making capacity to make such a trade-off.

According to NHTSA levels of vehicle autonomy (please see table 2.2), the main principle to distinguish the levels of autonomy in automotive industry is the share of control between the vehicle and human driver on board (Goodall, 2020). In other words, the division of control over the key controllers and actuators such as throttle, steering, brakes and acceleration between the intelligent systems and human drivers determines the level of autonomy of a vehicle. The contribution of control algorithms has been discussed above, but any control systems in AVs comprises of software and hardware including actuators, gauges and sensors. In consequence, hardware reliability in AVs depends on the reliability and function of its control components.

Communication reliability: Wilken and Thomas (2019) argue that 'data acquisition' and 'local processing' are integral features for cars to become decision-making machines (i.e. intelligent or autonomous cars). Along with the data which is gathered through the sensors and detection devices of the vehicle, AVs are expected to obtain a large volume of data from the communication channels known as V2V, V2I and V2X (Wilken and Thomas, 2019). Meanwhile, due to the high vehicle mobility, vehicular communication anomalies such as packet loss and transmission delay can negatively affect the performance of the cooperative driving system (CDS) and subsequently impair the safe operation of AVs (Jia and Ngoduy, 2016). As a result, the performance of AVs can be significantly dependent on reliable and secure communication with other road users and traffic infrastructure (Yao, Shet and Friedrich, 2020).

Cybersecurity: among the major risk factors which cause a grave concern for potential users about the safe and secure operation of AVs, cybersecurity is on the top of the list (Taeihagh and Lim, 2019). Likewise, policy-makers, regulators and insurers have amplified the same concern (Sheehan *et al.*, 2019). The risk can arise from various sources including but not limited to uncoordinated design of infrastructure and inter-vehicular systems which provide room for hackers to take advantage of these security holes and take over the control of the vehicle. AVs are cyber-physical systems that rely on imbedded data processing systems for managing control systems of activities such as steering, acceleration/deceleration, braking and lane keeping (Axelrod, 2015). Any attack on or breach of cybersecurity integrity of AVs (either infrastructure or the ego vehicle) is likely to cause disastrous collisions. Li *et al.* (2018) extensively studied the potential cyber-attacks on the communicated positions and speeds of AVs and their influence on longitudinal safety. Their results indicate that when an AV is under slight cyber-attacks, it is more hazardous if communicated positions are attacked than speeds (Li *et al.*, 2018). Form that, it can be concluded that cybersecurity risks add to the collision risks for AVs.

System integration: designing robust AVs entails coping with several integration challenges (Campbell *et al.*, 2010). Many complicated functionalities of AVs such as lane-changing manoeuvres, adopting safe speed and emergency braking require full integration of the system and sub-systems involving sensing, planning and control architecture (Lin, Juang and Li, 2014). A fundamental challenge is to ensure that the integration of the hardware and software is designed and implemented at a level that provides adequate robustness and redundancy against component failures (Campbell *et al.*, 2010). It is not unlikely that researchers and vehicle manufacturers may design and implement disparate control structures, but they need to ensure that at least the following four layers are well integrated to avoid any collision: environment perception, trajectory planning, trajectory execution and driver interface (Szalay *et al.*, 2018). The states for this node were extracted from the Systems Integration Technical Risks (SITR) assessment framework and are as follows: *critical*, *significant*, *moderate* and *low* (Loutchkina *et al.*, 2013).

Collision RI: the objective of this research is to measure the collision risk in urban environments, then the outcome of the model should be the collision risk index (classifier) under the influence of the outcome of four blocks (environmental, human, traffic and technical factors) which were defined based on sociotechnical theory. The importance of collision avoidance in AVs was discussed in section 2.2.2. This node has therefore four parents (i.e. road condition RI, reaction time RI, traffic complexity RI and technical reliability RI). The states for this node were extracted from a research designed for classifying traffic scenarios for AVs based on ANN risk estimation (Dávid, Láncz and Hunyady, 2019). These states are *Minimal, low, medium, high and extreme*.

4.2. The BBN Model

The final topology (structure) of the BBN model is presented and discussed in this section (figures 4.4 and 4.5). The network is divided into four blocks with distinct colours. The nodes in blue colour are dedicated to environmental factors that can affect road conditions. White nodes capture and accumulate the influence of human factors which can affect reaction times of human drivers on board. The factors concerning with the traffic layout are represented in amber. These variables and the risk index measure the complexity of traffic conditions that AVs must be capable of handling them. Green was used for the technical factors that are influential in avoiding collisions by AVs. Finally, the collision RI as the outcome of the model and an indication of the collision risk is displayed in red. The outcome of each block is an RI node which is also one of the four parents of the ultimate outcome of the model (i.e., collision RI) and they act as intermediate nodes to aggregate the impacts of the observable nodes (Brito and Griffiths, 2016). Collision RI node categorises (minimal to extreme) the risk of colliding with an object or other road users for an AV based on the evidence that can be inserted at any node(s) of the model. The links also denote conditional relationships between the nodes.

Furthermore, in assessing the mission success for AUVs Thieme and Utne (2017) asserted that any overall risk model for AUV operation should encompass aspects related to the technical system, environmental conditions, and HOFs (human and organisational factors), that is, human-autonomy collaboration (HAC) (Thieme and Utne, 2017). Regulations imposed by authorities, stakeholder requirements, and societal expectations are issues that can come along later and future work remains to integrate all these aspects into one model. The HAC and inclusion of traffic conditions can be a major contribution of this thesis, since several works have already focused on the technical system performance and environmental conditions, as mentioned in 2.2.

In addition to Socio-technical Theory, SoTeRiA framework and the human-autonomy collaboration conceptual framework also support the four-block structure for assessing risks. The World Health Organisation (WHO) training manual for preventing road traffic injuries (Mohan *et al.*, 2006, p.23) clearly suggests that "*road traffic crash results from a combination of factors related to the components of the system comprising roads, the environment, vehicles and road users, and the way they interact*". In this research, human factors represent operators, technical factors concern with the competence and reliability of AVs, and environmental factors are the variables that appraise the impact of the surrounding environment on the collision risk. However, the environment surrounding AVs (or other road users) consists of physical characteristics as well as dynamic traffic conditions that vehicles face during their travel on roads. Along with that, Socio-technical Theory places a special emphasis on the inclusion of organisational factors in the risk analysis for complex technical equipment and assessing technological risks (Mohaghegh, Kazemi and Mosleh, 2009; Mohaghegh and Mosleh, 2009; Ashrafi, Davoudpour and Khodakarami, 2015; Pence *et al.*, 2019). The main reason for this emphasis is the relevance and significance of behavioural aspects (e.g., safety culture) to the notion of risk (Pence *et al.*, 2019). The extensive research (e.g., Wiegmann, von Thaden and Gibbons, 2007; Atchley, Shi and Yamamoto, 2014; Edwards *et al.*, 2014) on traffic safety culture and its effect on collective safety-related behaviours in different cities and countries also can support this. For this purpose, the fourth block in the model was dedicated to the 'traffic condition' factors and variables which have influence on the collision risks.

Links between the identified variables and assigned weights can define the way that they interact with each other. The links (arcs) in the BBN model are drawn based on the findings of the ILR and thematic analysis and the logical relationships (Marcot and Penman, 2019) between the identified factors. Those findings were merged, in order to construct the network. Some variables have a reciprocal relationship with each other. This sometimes is a hard task to define clearly these arcs. Since BBNs are acyclic, it is not possible to model mutual influences (Thieme and Utne, 2017). In order to resolve mutual influences, the most frequently mentioned/cited direction of influence were taken to determine them.

When considering links between the nodes, it can be truly argued that, for example, 'weather conditions' have usually influence on the speed that drivers/vehicles adopt, or poor visibility adversely affects the performance of visual cameras of the CAVs. As discussed in 3.8.1.5 inter-block links were omitted to avoid overcomplicating the model and curbing the exponential growth of NPTs. Lack of inter-block links will not significantly damage the accuracy of the model, but represents conditional independence assumptions (Pearl, 1988; Hänninen, 2014). Nonetheless, some inter-block links were still essential. For example, there is a very strong relationship between 'time of day' and driver 'drowsiness' (please see figure 4.2) (Kaduk, Roberts and Stanton, 2020b). Similarly, in many cities around the world, traffic density is highly correlated with time of day (please see figure 4.1). In areas except near North and South poles, the lighting condition is also a function of time. Moreover, although this node is in blue and placed under the category of environmental blocks, can be a universal variable in this model. Therefore, the links between time of day and those aforementioned variables cannot be neglected.

The NPTs were populated in a way to generate uniform distributions for JDPs (except for a few nodes that their distributions cannot be uniform e.g., drowsiness and lighting conditions). In this stage it is assumed that all parents of each child have equal influence on it and all the prior probabilities except for drowsiness and lighting conditions were assumed to be uniform. The NPTs with uniform distributions are exhibited in figure 4.4. From there we can insert the weight of each variable on its child node through multiplying the elicited weights by the corresponding values in the table.

In section 3.5, it was explained that observations (evidence) can be entered at any node when they become available. For example, the reliability of sensors in different types of AVs, weather conditions across the world or even countries, and situation awareness among drivers can vary significantly. Depending on the AV models, geographical and urban locations, human factors and traffic environments the values for each input node (based on the observations) can therefore vary significantly and result in substantially dissimilar collision risks distributions. Figure 4.6 shows an instantiation based on inserted evidence at only one node in every block (i.e. visibility, HMI, sensor fusion and other road users) and the collision risk distributions for each instantiation.

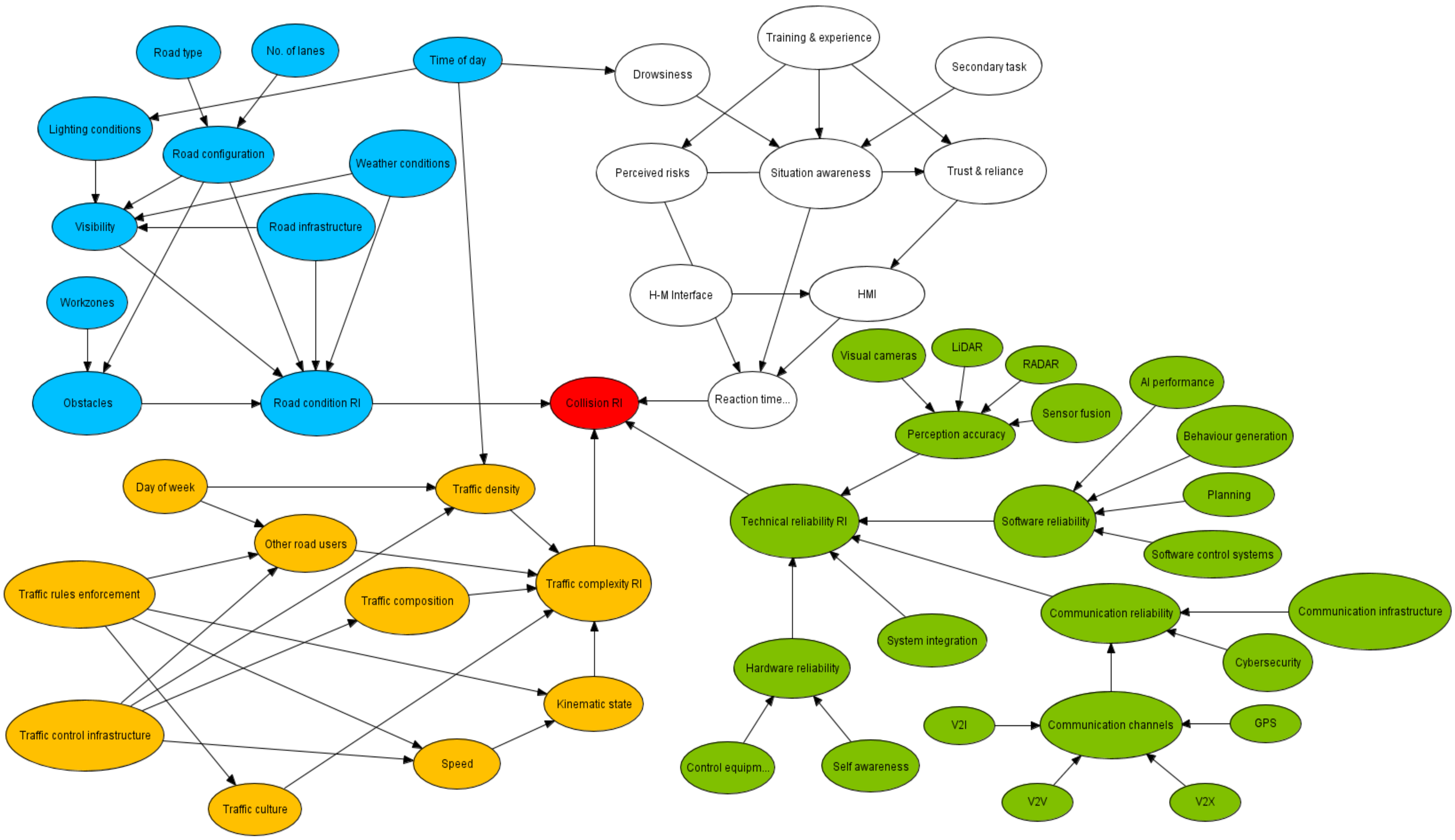


Fig. 4.4: illustrates the developed BBN in Hugin Lite for assessing risks of AVs in urban environments.

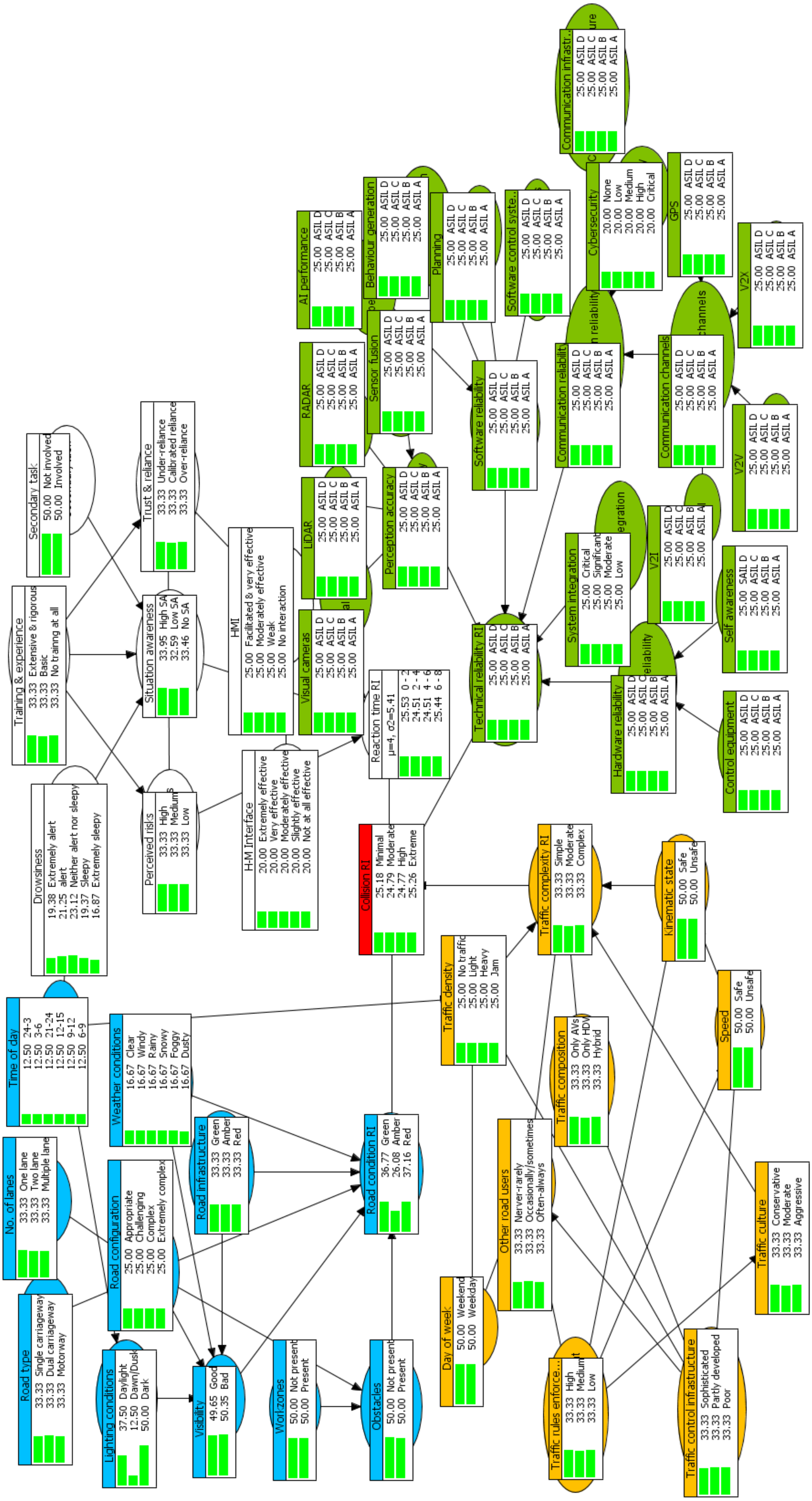


Fig. 4.5: The CPTs and JPDs of the nodes with uniform distributions (before instantiation).

It has been discussed that evidence and observations can be fed into the model at any node in BBN models. A scenario is devised to show how inference works and JDPs change in the model when new observations (or significant amount of hard data) become available. It is assumed that the visibility is 'good' for a given location and time, HMI is 'facilitated and very effective', the presence of other road users is 'never-rarely' and the reliability of sensor fusion is at 'ASIL D level'. These assumptions (imaginary observations) were incorporated into the model and figure 18a shows how the JPDs update themselves based on the new information. In the same manner, figure 18b demonstrates the instantiation on the same nodes but with assuming the other extreme ends this time. For this instantiation, the visibility is presumed to be 'bad', HMI is set on 'no interaction', presence of other road users is set to be 'often-always' and the reliability for sensor fusion is set as 'ASIL A level'. The probability distribution for the collision RI was as follows:

Table 4.1: JDPs of risk indices after insertion of new evidence.

<table>
<tr><td rowspan="4">Input</td><td colspan="2">Visibility: good=1.00; bad=0.0</td><td colspan="2">Visibility: good=0.0; bad=1.00</td></tr>
<tr><td colspan="2">HMI: facilitated & effective=1.00; moderately effective=0.0; weak=0.0; no interaction=0.0</td><td colspan="2">HMI: facilitated &effective=0.0; moderately effective=0.0; weak=0.0; no interaction=1.00</td></tr>
<tr><td colspan="2">Other road users: never/rarely=1.00; occasionally/sometimes=0.0; often/always=0.0</td><td colspan="2">Other road users: never/rarely=0.0; occasionally/sometimes=0.0; often/always=1.00</td></tr>
<tr><td colspan="2">Sensor fusion: ASIL D=1.00; ASIL B=0.0; ASIL C=0.0; ASIL D=0.0</td><td colspan="2">Sensor fusion: ASIL A=0.0; ASIL B=0.0; ASIL C=0.0; ASIL A=1.00</td></tr>
<tr><td rowspan="14">RI JDPs</td><td rowspan="3">Road condition RI</td><td>Green=0.6702</td><td rowspan="3">Road condition RI</td><td>Green=0.0484</td></tr>
<tr><td>Amber=0.2814</td><td>Amber=0.2815</td></tr>
<tr><td>Red=0.0484</td><td>Red=0.6701</td></tr>
<tr><td rowspan="4">Reaction time RI</td><td>0-2 sec=0.4518</td><td rowspan="4">Reaction time RI</td><td>0-2 sec=0.1222</td></tr>
<tr><td>2-4 sec=0.2061</td><td>2-4 sec=0.2221</td></tr>
<tr><td>4-6 sec=0.2208</td><td>4-6 sec=0.2065</td></tr>
<tr><td>6-8 sec=0.1212</td><td>6-8 sec=0.4492</td></tr>
<tr><td rowspan="3">Traffic condition RI</td><td>Simple=0.7322</td><td rowspan="3">Traffic condition RI</td><td>Simple=0.0091</td></tr>
<tr><td>Moderate=0.2587</td><td>Moderate=0.2587</td></tr>
<tr><td>Complex=0.0091</td><td>Complex=0.7322</td></tr>
<tr><td rowspan="4">Technical RI</td><td>ASIL A=0.2549</td><td rowspan="4">Technical RI</td><td>ASIL A=0.2451</td></tr>
<tr><td>ASIL B=0.2500</td><td>ASIL B=0.2500</td></tr>
<tr><td>ASIL C=0.2500</td><td>ASIL C=0.2500</td></tr>
<tr><td>ASIL D=0.2451</td><td>ASIL D=0.2549</td></tr>
</table>

Changes in the probability distributions of reaction time and traffic complexity RIs are apparent. Although the judgement of expert(s) has not been incorporated into the model, still we can witness the influence of selected nodes on the overall risk JPD for collision risk index and other four risk indices. Backward propagation can also be seen in those figures. Having discussed earlier, one benefit of BBN technique is the backward propagation when an observation is entered at output or intermediate nodes and may change the state probabilities in the parent nodes (Ghabayen, McKee and Kemblowski, 2006).

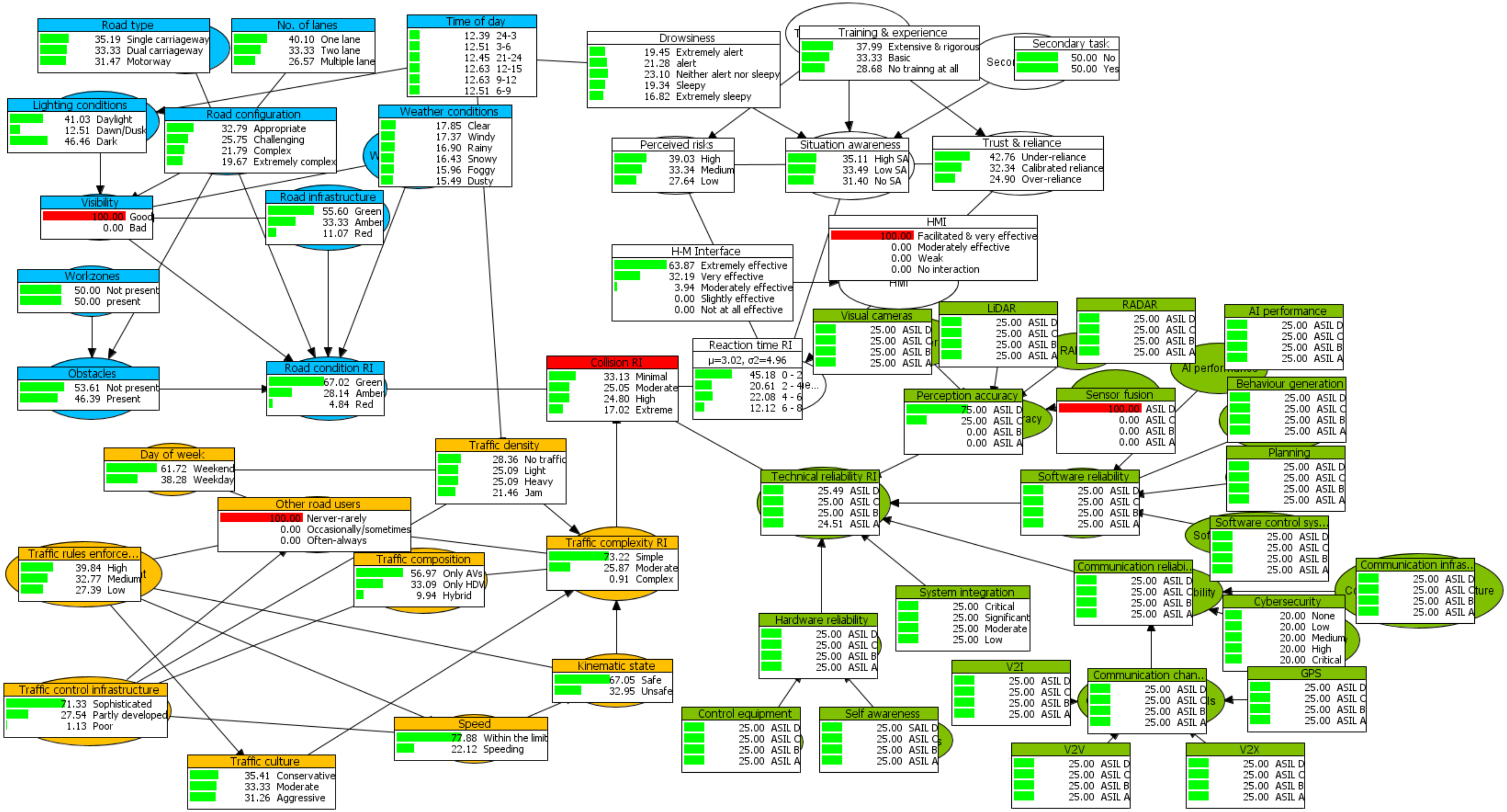


Fig. 4.6 a: shows the CPTs and JPDs of the selected nodes after new evidence is inserted.

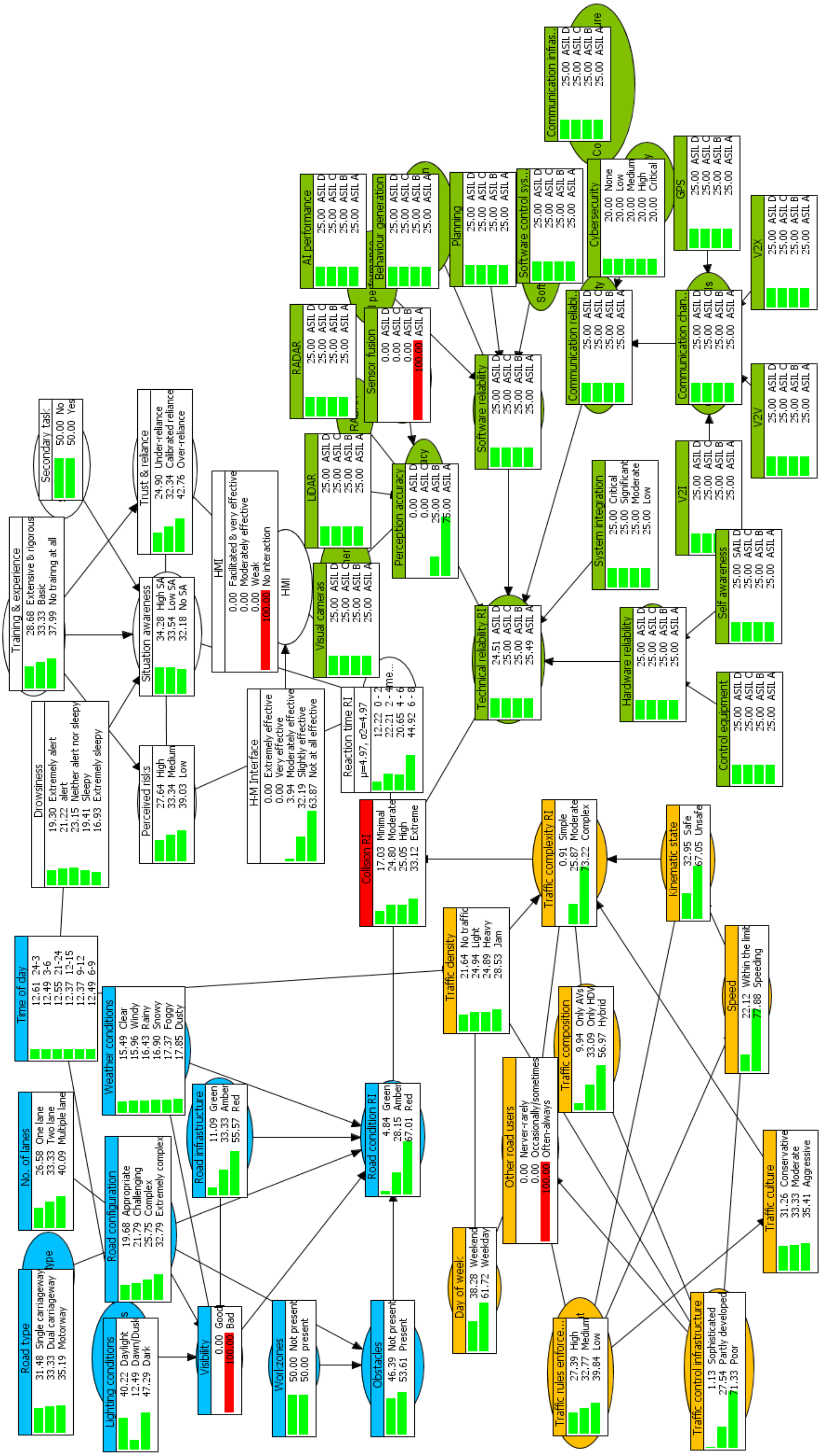


Fig. 4.6 b: shows the CPTs and JPDs of the selected nodes after new evidence is inserted.

4.3. Results of the survey (expert judgements)

The table below show the average of the weights elicited for every parent node in the model. The standard deviation (SD) for each weight is reported next to it. Lower SD values (e.g., for the impact of traffic control infrastructure on the adoption of safe speed) indicate convergence in opinions and larger SDs (e.g., for the impact of software reliability on technical reliability) reflected controversy among the domain experts. The relatively low SDs for the weights of road condition, reaction time, traffic complexity and technical reliability RIs on the collision RI are mainly due to larger number of respondents as all the participants were asked to provide their opinions on them.

Table 4.2: the average and SD of elicited weights for child nodes.

Child node	Parent nodes	Weight	SD
Situation awareness	Drowsiness	0.1500	0.0500
	Training & experience	0.4500	0.1500
	Secondary task	0.4000	0.2000
Trust & reliance	Perceived risks	0.6000	0.1000
	Training & experience	0.4000	0.1000
HMI	Trust & reliance	0.4500	0.0500
	Human-machine interfaces	0.5500	0.0500
Reaction time RI	Perceived risks	0.2667	0.0665
	Situation awareness	0.3167	0.0165
	HMI	0.4166	0.0835
Perception accuracy	Vision cameras	0.2000	0.0500
	LiDAR	0.2667	0.0288
	RADAR	0.2833	0.0288
	Sensor fusion	0.2500	0.0500
Software (reliability)	AI performance	0.4834	0.1040
	Behaviour generation	0.2000	0.0866
	Planning	0.2333	0.1607
	Software control systems	0.0833	0.0577
Communication channels	GPS	0.1000	0.0707
	V2V	0.3750	0.0353
	V2I	0.3250	0.0353
	V2X	0.2000	0.0707
Communication reliability	Communication infrastructure	0.4667	0.1365
	Cybersecurity	0.3500	0.0500
	Communication channels	0.1833	0.1401
Hardware reliability	Control equipment	0.3000	0.2291
	Self-awareness	0.7000	0.2291
Technical reliability RI	Perception accuracy	0.2433	0.1913
	Software reliability	0.4000	0.4358
	Communication reliability	0.1567	0.1209
	System integration	0.1233	0.1167
	Hardware reliability	0.0767	0.0404
Other road users	Day of week	0.3500	0.3536
	Traffic rule enforcement	0.2500	0.0707
	Traffic control infrastructure	0.4000	0.2828
Traffic density	Day of week	0.5000	0.0000
	Time of day	0.3000	0.1414
	Traffic control infrastructure	0.2000	0.1414
Speed	Traffic rule enforcement	0.3000	0.0000
	Traffic control infrastructure	0.7000	0.0000

Kinematic state	Traffic rule enforcement	0.3000	0.0000
	Speed	0.7000	0.0000
Traffic complexity RI	Traffic density	0.1500	0.0707
	Other road users	0.2000	0.0707
	Traffic composition	0.4000	0.0707
	Traffic culture	0.1500	0.0707
	Kinematic state	0.1000	0.1414
Road configuration	Road type	0.6333	0.1528
	No. of lanes	0.3667	0.1528
visibility	Lighting conditions	0.2780	0.1070
	Road configuration	0.2167	0.0289
	Weather conditions	0.2833	0.1041
	Road infrastructure	0.2220	0.0381
Obstacles	Work zones	0.4667	0.0577
	Road configuration	0.5333	0.0577
Road condition RI	Obstacles	0.1980	0.0035
	Visibility	0.2557	0.1261
	Road configuration	0.1742	0.0652
	Road infrastructure	0.1408	0.0707
	Weather conditions	0.2313	0.0595
Collision RI	Road condition RI	0.2500	0.0850
	Reaction time RI	0.2100	0.1125
	Traffic complexity RI	0.3100	0.0699
	Technical reliability RI	0.2300	0.0949

The *ranked node* technique proposed by Fenton, Neil and Caballero (2007) was used to incorporate elicited weights into the model. In ranked node technique, experts are asked to assign weights to nodes (Rohmer, 2020). For example, if there are n parent nodes and each of them has m states, then there will be only n parameters to elicit, while in full elicitation $n \times m$ parameters are required to fill up the whole table. Parent nodes are defined in an interval from 0 to 1 and accumulated weights for all parents of a node must make up to 1. This gives ground for representing unequal influence of multiple factors and the functional representation of NPTs can be traced since uncertainties in the relationships become more explicit (Rohmer, 2020). Figure 4.7 shows the BBN after the incorporation of weights and the strengths of links between the nodes.

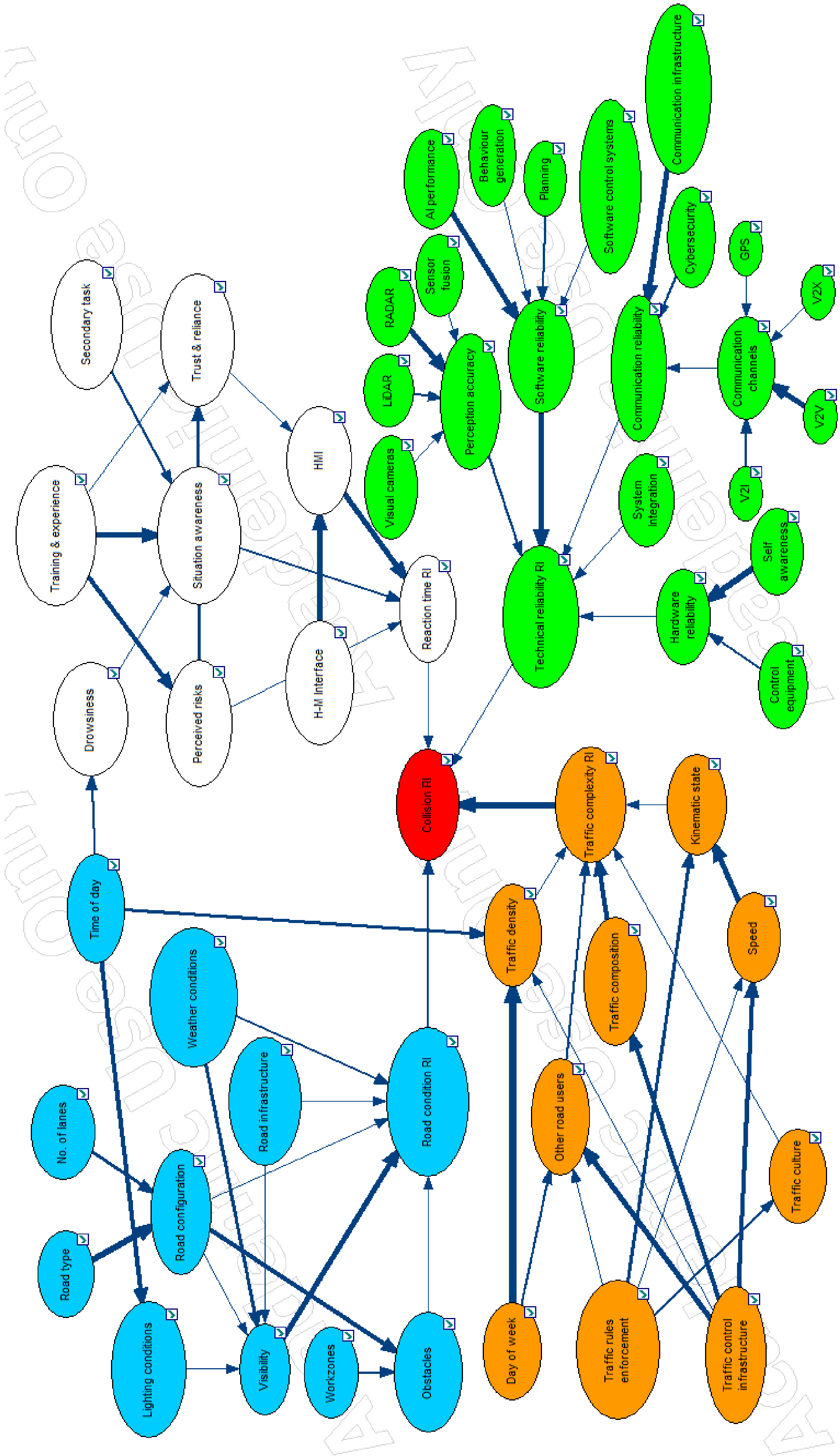


Fig. 4.7: Bayesian network with weighted links (this depiction was generated in GeNIe Modeler)

4.4. Scenario-based risk analysis

Scenario analysis is an effective tool for (strategic) decision-making in the presence of uncertainty (Postma and Liebl, 2005). Across different disciplines it is a common practice to quantify uncertainty in model output based on a set of formulated scenarios. Ambiguities over the behaviour of the model output can be reduced and trends can be detected by comparing them under unlike circumstances. Scenario analysis is not intended for generating forecasts; it projects conceivable images of the future development due to the changes in input variables (Postma and Liebl, 2005). In this section, the aim is to nominate a number of functional scenarios and study changes in the outcome.

A scenario describes a situation by determining the state of every input variable of the model at a certain or over a period of time. Six (four extreme and two random) scenarios are designed to provide a basis for comparison between risk distributions. First and fourth scenarios represent the situations that all 29 input variables in the model are in their least safe and safest states, respectively. Second and third scenarios represent the in-between situations. For instance, the input variables for the technical block were in ASIL A in the first scenario, ASIL B in the second scenario and so forth. For input nodes with three states, it was set on the least safe state in the first scenario, on the middle in the second and third scenarios, and on the safest state in the fourth scenario. For the input nodes with two states, it was substantiated on the unsafe state in the first and second scenarios, and on the safe state in the third and fourth scenarios. Finally, the risk distributions for these six scenarios were observed and compared.

The risk distributions (please see figure 4.8) indicate a shift in collision risk from extreme to minimal when we move from the worst-case scenario towards a scenario in which all variables are in their most desirable (i.e., safest) conditions. The corresponding exponential PDF drawn through the histogram of JPDs for collision RI in scenarios 1 and 4 are almost symmetrical along the line $x = a$. The fitted trends in scenarios 2 and 3 are almost straight lines with inverse slopes and symmetrical along the line $x = b$. Those trends in risk reduction from scenario 1 to 4 in addition to the sensitivity analysis in the following section can indicate the areas that have higher priorities in safety aspects of CAVs.

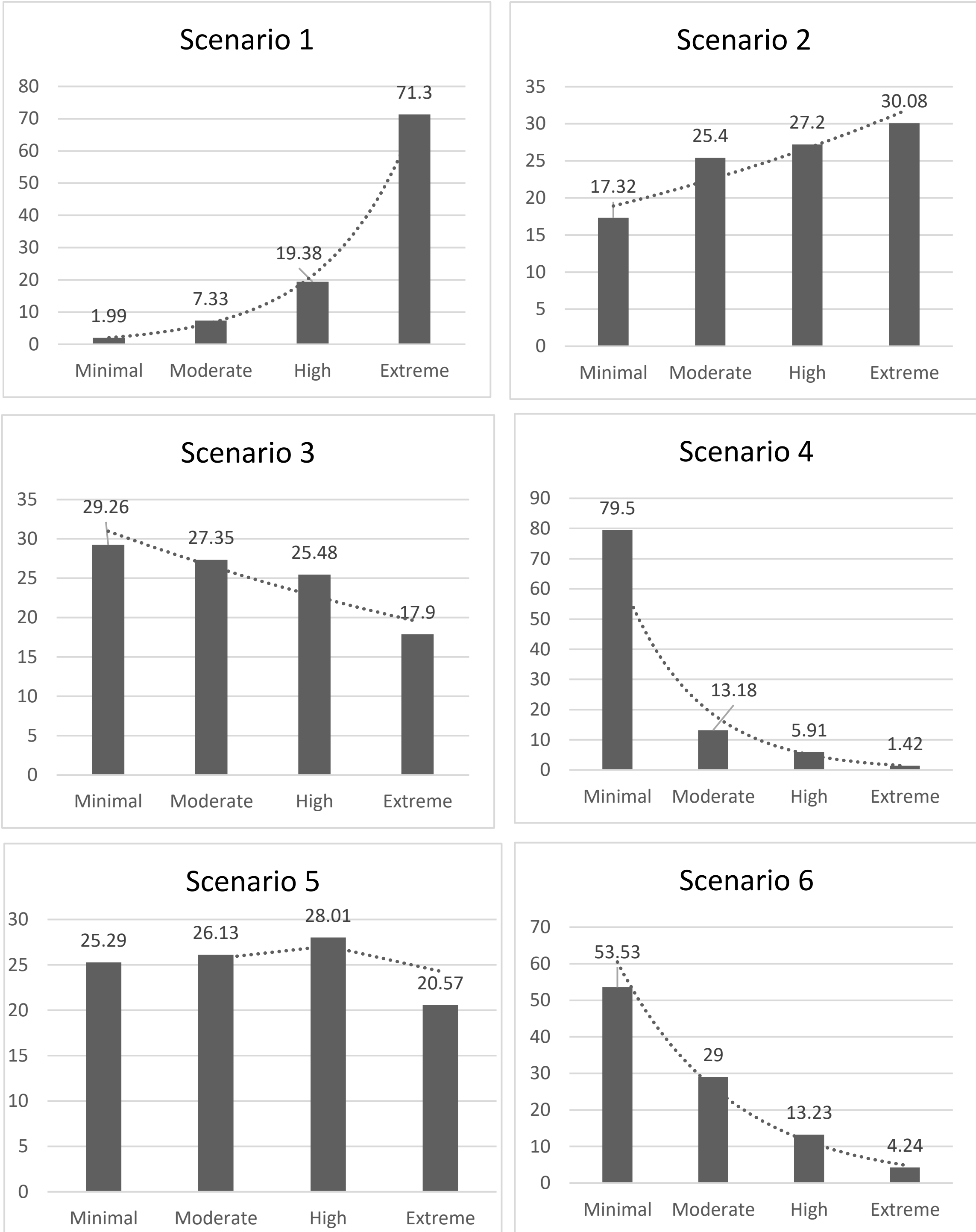


Fig. 4.8: Results of scenario analysis. Y axis represents probability.

4.5. Sensitivity analysis

Saltelli (2002) defines that "*sensitivity analysis* [...] *is the study of how the uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input*". In other words, sensitivity analysis enables us to observe which nodes have greatest or weakest influence on any target node (Fenton and Neil, 2012, p.264). The sensitivity analyses conducted by BBN tool can help to rank the uncertainties and then prioritise data collection for further research (Kabir *et al.*, 2015). Sensitivity analysis should be ideally run after uncertainty analysis (Saltelli *et al.*, 2008, p.1). Uncertainty analysis, in this thesis was carried out in the form of scenario analysis in section 4.4.

Nodes coloured in red in figure 4.9 are the variables that are important for the calculation of the posterior probability distributions in collision risk since it was set the target in sensitivity analysis. The intensity of red colour has a direct relationship with the sensitivity of the target node to the coloured nodes. The nodes in grey colour do not contain any parameters that are used in the calculation of the posterior probability distributions over the collision risk. Sensitivity of any of these nodes is zero and are determined qualitatively based on GeNIe relevance computation layer before any computation is initiated. It is important to caveat that the sensitivity analysis algorithm generates context-dependent results. The values of calculated derivatives depend on the current target(s) and the set of observations made in the network. Further observations or any changes in either CPTs, links between the nodes or assigned weights to links will prompt the algorithm to recalculate the derivatives and recolour the nodes.

A decision or in broader terms, a policy, may involve political, environmental, commercial, technical, financial and other types of input variables. To plan for a range of optimal outcomes, an essential task is to determine the most ‘contributing’ variables among risk-model input variables (Koller, 1999, p.169). In a risk model, as a decision-making tool, the quantity of risk can change by making any change to input variables. Hence, to determine the influence of a single input variable on the outcome (i.e., risk) all variables are held constant except one that is allowed to vary (Koller, 1999, p.171). The range of changes in the output variable is recorded. The result of sensitivity analyses is commonly presented in the format of a ‘tornado’ diagram (e.g., Fenton and Neil, 2012, p.265; Ashrafi, Davoudpour and Khodakarami, 2015). Figure 4.10 illustrates the tornado diagrams for the target node in BBN model in this study. It demonstrates the reachable ranges for the ten most influential combination of node states on the collision RI’s Extreme state. This can be analysed for other states such as Moderate or Minimal and any child nodes other than collision RI can be set as the target.

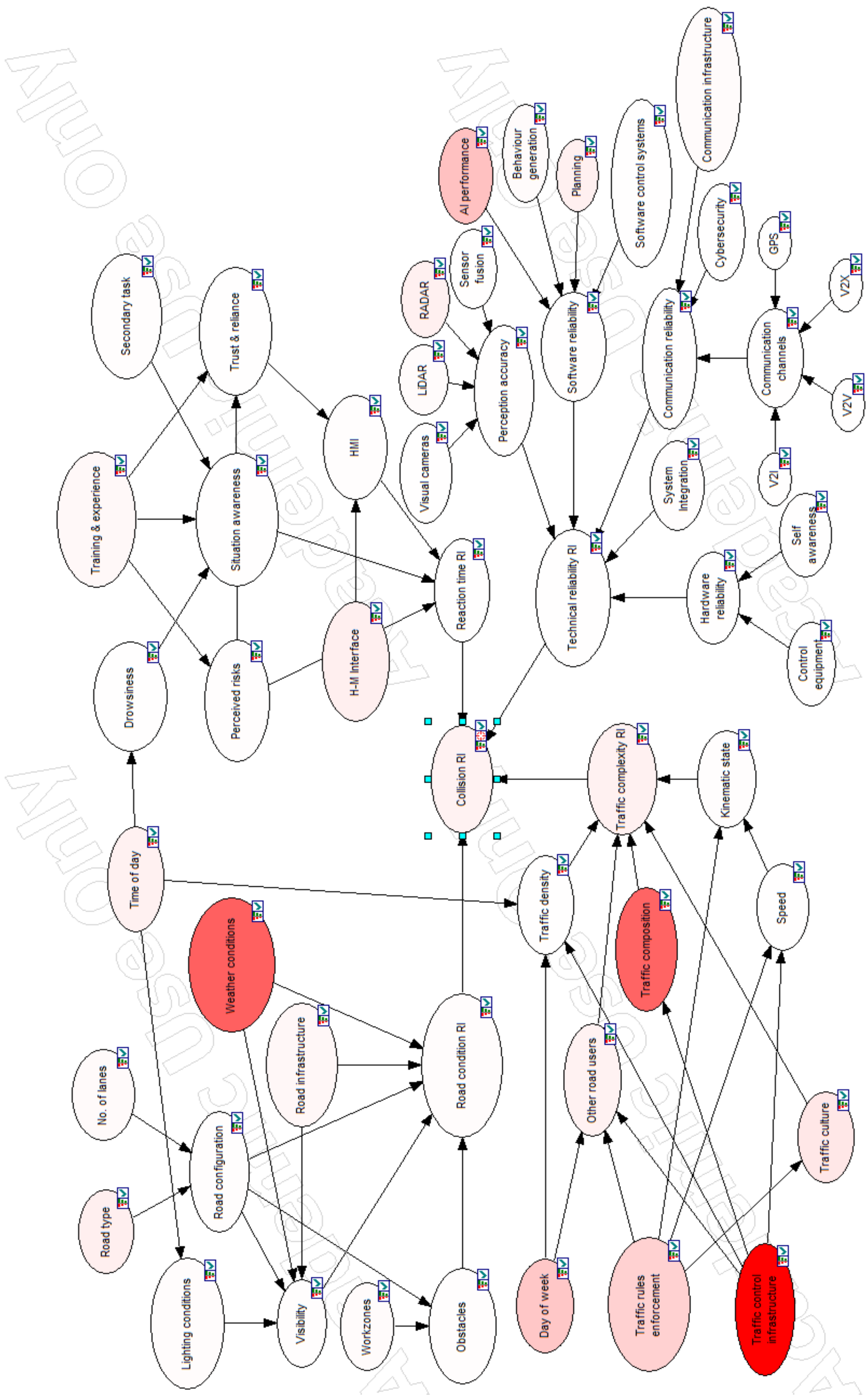


Fig. 4.9: Sensitivity analysis performed in GeNIe Modeler

Figure 4.10 depicts the tornado sensitivity diagram for the four states (i.e., Minimal, Moderate, High, and Extreme) of collision RI in GeNIe software. Label represents observed state, length of each bar corresponds to the magnitude of influence on model outcome achieved by changing specified state. The green side of bars denotes the resulting probability that $P(collision\_risk\_index) = Minimal\ or\ Moderate\ or\ High\ or\ Extrem$ for the states presented. The red bars represent the probability after reversing the observed states. The bars are sorted from the most to least sensitive parameters for a selected state of the target node.

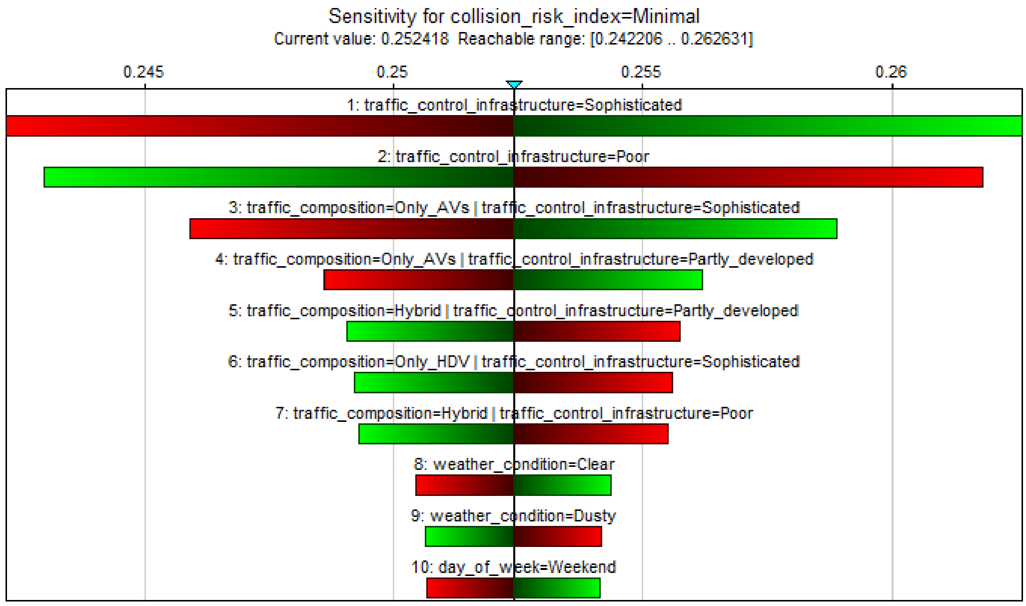


Fig. 4.10 a: Tornado diagram for $P(collision\_risk\_index) = Minimal$

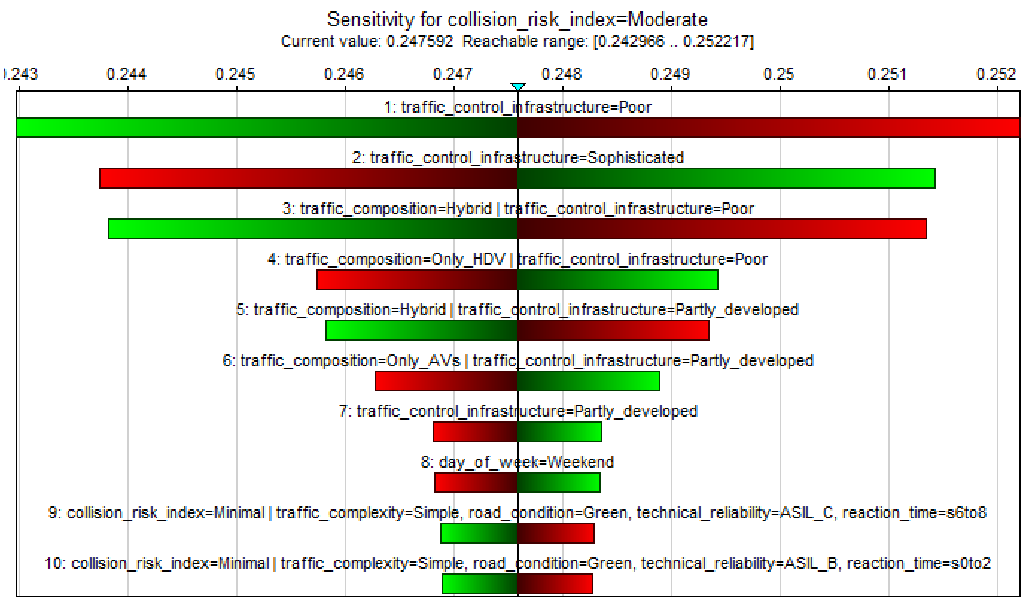


Fig. 4.10 b: Tornado diagram for $P(collision\_risk\_index) = Moderate$

Fig. 4.10 c: Tornado diagram for $P(collision\_risk\_index) \ = High$

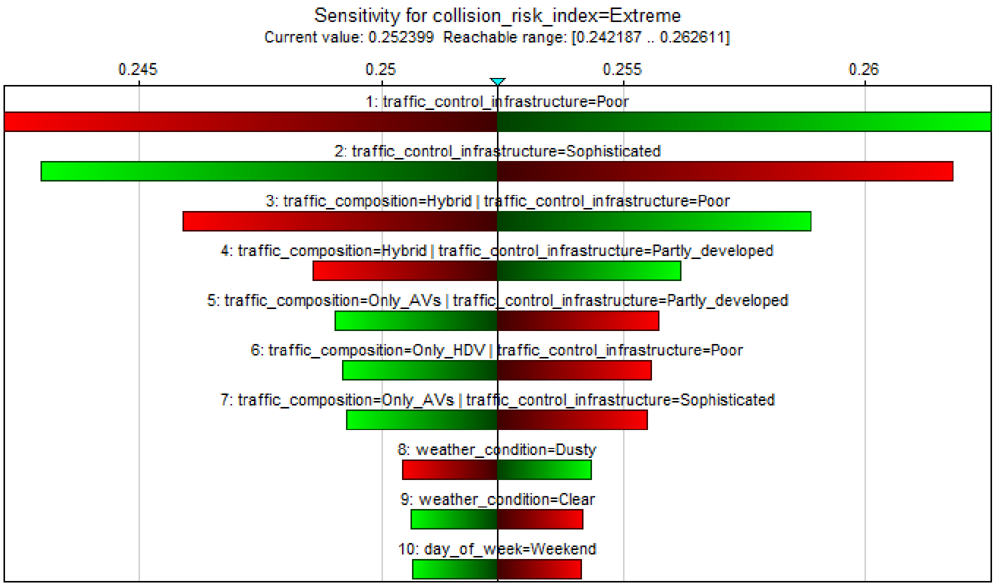


Fig. 4.10 d: Tornado diagram for $P(collision\_risk\_index) \ = Extreme$

Table 4.3 ranks 19 nodes of the model across the four blocks based on the highest maximum sensitivity. The target node for the sensitivity analysis was set on the ‘collision risk RI’ node. The average sensitivity and minimum sensitivity for the nodes in that table are presented too. This table together with the scenario analysis in previous section form the main foundation of policy implication in following section (i.e., section 5.3).

Table 4.3: results of sensitivity analysis while collision RI was set as target

Node		Max sensitivity	Avg. sensitivity	Min sensitivity
1	Traffic control infrastructure	0.306	0.074	0
2	Weather conditions	0.118	0.02	0
3	Traffic composition	0.114	0.021	0
4	AI performance	0.04	0.008	0
5	Day of week	0.035	0.013	0
6	Traffic rule enforcement	0.029	0.007	0
7	Traffic culture	0.014	0.003	0
8	H-M Interfaces	0.01	0.002	0
9	Road type	0.009	0.002	0
	Planning (path, trajectory and motion)	0.009	0.002	0
10	RADAR	0.009	0.002	0
11	Time of day	0.008	0.002	0
12	Traffic complexity	0.008	0.001	0
	Other road users	0.008	0.001	0
13	Road infrastructure	0.004	0.001	0
	Training & experience	0.004	0.001	0
14	LiDAR	0.002	0	0
	Communication infrastructure	0.002	0	0
	Behaviour generation	0.002	0	0

In the next step, the RIs (i.e., road conditions, reaction time, traffic complexity, and technical reliability) were set as target and sensitivity analysis was iterated. The only node that appeared among influential nodes but was not captured in the first round of sensitivity analysis was HMI. The results are summarised in table 4.4.

Table 4.4: results of sensitivity analysis while the outcome node for each block was set as target

Risk Index	Rank	Antecedent node	Max sensitivity
Traffic complexity	1	Traffic control infrastructure	0.465
	2	Traffic composition	0.174
	3	Day of week	0.053
Road conditions	1	Weather conditions	0.595
	2	Road types	0.042
	3	Time of day	0.034
Technical reliability	1	AI performance	0.500
	2	Radar	0.105
	3	Planning	0.095
Reaction time	1	H-M interfaces	0.499
	2	Training and experience	0.173
	3	HMI	0.043

4.6. Summary of results and conclusions

This chapter reported the results of ILR which were used to form the structure of BBN model. The results indicate that there are a relatively large number of variables that can pose a risk to safe operation of CVAs. A socio-technical approach allows us to categorise those variables and construct a BBN model with four blocks (environment, human operators, traffic conditions, and technical reliabilities). The outcome of expert elicitation phase was also provided and incorporated into the model. The experts placed a heavy emphasis on the role of traffic conditions in collision risk, and the least emphasis was attached to human reaction capacity in highly autonomous driving.

The results of scenario analysis demonstrate an exponential relationship between the states of input variables and collision risk distribution for the outcome node in a way that deterioration of input variable states collision risk increases and while input variables are in their safest states a probability for collision risk tends to be minimal. Furthermore, the findings of sensitivity analysis suggest that only 17 nodes out of 53 appear to have a considerable influence on CAV collision risk and impact of other variables are trivial. It can be concluded that in large BBN models not every variable can have a meaningful influence on the outcome of the model, although this depends, to a substantial extent, on the topology of the model and how CPTs are composed.

The sensitivity analysis also revealed that the most decisive impact on collision risk comes from traffic control infrastructure. This opens up further avenues for exploration with regards to policy making endeavours to mitigate collision risk of autonomous driving. Among the technical variables, AI algorithms maturity (performance) appeared on the top of the list. This highlights the criticality of decision making in AVs. A sophisticated, mature and agile software system will eliminate the risk factors from the human block. If an AV is fully capable of handling every driving scenario (i.e., SAE level 5) no handover to (or reaction form) human driver will be required. As a consequence, with the current pace of advancements and technological progress some of the identified risk variables in 4.1 may not remain relevant in long term.

Chapter 5

5. Discussions and policy implications

The following chapter is divided into three sections. Section 5.1 reviews the main challenges in developing a BBN model for the purpose of assessing risks in complex systems. Section 5.2 provides a critical review of the current autonomy classification approaches and their impact on safety of CAVs. Policy implications are discussed in section 5.3. Lastly, the major research limitations are recognised in section 5.4.

5.1. Pitfalls in developing a BBN model for complex systems

Identifying the variables and causal linkages between them was among the primary dilemmas (Korb and Nicholson, 2003, p.30; Pearl, 2009, pp.43-44; Groth and Mosleh, 2012). Some of the variables are dependent and this can result in double counting (Li *et al.*, 2012; Landuyt *et al.*, 2014). Such dependencies also exacerbate the difficulty of finding causal links and their directions. This challenge becomes even worse while developing a modular BBN. For example, it is supported by literature (e.g., Yoneda *et al.*, 2019; Vargas *et al.*, 2021) and there is ample evidence that perception accuracy of an AV depends on (or is affected) by weather conditions. In other words, adverse weather conditions can obstruct sensing of the environment through sensors and impair perception accuracy for an AV. Another example can be the causal link between visibility and reaction time of a human (supervisor) driver. These inter-block links, however, were omitted to avoid myriad links in the model. Inclusion of such links can significantly change the results of sensitivity analysis.

Aside from the above challenges, there were a number of others that needed to be overcome to ensure the quality of the research. Finding a balanced point between the qualitative and quantitative methods, trade-off between the comprehensiveness and simplicity of the BBN model and deciding on the knowledge elicitation methods and techniques were among the major challenges experienced during the modelling process. It is crucial for the model to consolidate major factors influencing the risk and avoid oversimplification, but it is also necessary to avoid complicating the model with redundant nodes (Fenton and Neil, 2012, p.162). Complicated structures with redundant nodes are likely to cause confusion for experts and slow down the elicitation process.

Eliciting expert judgements for CPTs is inherently a tiering and time-consuming task for experts. Reducing the workload of experts in dealing with large CPT entries while ensuring the quality of results is a challenge to address (Rohmer, 2020). Two solutions were adopted to circumvent an exhausting elicitation. Firstly, the modular design which helped to divide the burden between domain experts. Secondly, using a new method to only elicit experts' opinions on the weight of parent nodes on their children. Ranked node method was also used to incorporate the weights into the model. There are still some caveats to the combination of these methods. There is a possibility that the generated values for the CPTs (using the method developed in section 3.8.2) do not result in uniform distributions and therefore bring about unequal weights for parent nodes. A scaling factor can be used to equalise the weight of variables.

Absence of BBN validation due to lack of real-world data poses a real challenge to assess the accuracy and validity of the model (Farmani *et al.*, 2012; McDonald, Ryder and Tighe, 2015; Pütz, Murphy and Mullins, 2019). Growth and Mosleh (2012) also recognised this problem and maintained that since BBNs are used when data are scarce, finding a benchmark to validate human reliability assessment (i.e., expert elicitation) is impossible, although diversifying the sources of data and verifying experts can add to the robustness of the model. Lack of a benchmark or case study, prevents knowledge engineers to test the model against real-world results and calibrate the parameters of the model. It is noteworthy that a risk model is not supposed to completely capture the essence of a complex system and provide accurate estimates (Haimes, 2018), particularly when the uncertainty is deep. Rather, it can be seen as a supportive tool for decision making under uncertainty (Chen and Pollino, 2012; Farmani *et al.*, 2012).

5.2. Autonomy: discrete or fuzzy?

The Law Commission of England and Wales and the Scottish Law Commission developed the concepts of '*user-in-charge (UIC)*' and '*no user-in-charge (NUIC)*' for laying a foundation to define a legal accountability system for AVs (Law Commission of England and Wales, 2022). Some automated driving systems (ADS) may be authorised NUIC mode which are referred to as NUIC features. This implies that some other features will still need a user to take charge of them. Therefore, H-M Interaction as one of the main sources of risk is not entirely eliminated at least from the legal perspective. With the current state of the technology, it may not be practical to draw a bright line between features that still need user's attention during driving and those that do not need it. A large body of academic literature (e.g., Schömig and Metz, 2013; Mackenzie and Harris, 2015; Mok *et al.*, 2017; Van Dam, Kass and VanWormer, 2020) is concerned with the problem of passivity in driving where drivers have to shift from passively monitoring tasks to performing them actively.

A few widely adopted taxonomies for automation or autonomy levels in the context of vehicle automation were provided in section 2.1.4. To avoid a sheer scope, the focus of this research for collision risk analysis was set on SAE level 4 where the technology has more capability to handle more driving scenarios (comparing to level 2 and 3) and the possibility for human intervention is not completely ruled out yet. According to the definition provided by SAE, all aspects of the dynamic driving tasks during driving *mode-specific* performance are handled by an automated driving system, even though a human driver does not respond appropriately to an intervention request (SAE International, 2016). This raises some practical problems for implementation of autonomous driving and most importantly for regulators and legislators. The Law Commission joint report declares that even their recommendations heavily rely on SAE taxonomy (Law Commission of England and Wales, 2022). This indicates the importance of investigating the implications of that taxonomy on the safety of AVs.

Firstly, the ‘mode-specific’ attribute needs to be disclosed. One can envisage hundreds if not thousands of combined driving functions and traffic scenarios for road vehicles. It is not clear under what circumstances and in which driving scenarios the technology will reliably and safely navigate a vehicle and perform all dynamic driving tasks. This definition may be referring to vehicles similar to shuttles (without steering wheel and pedals) that traverse predefined routes at low speed and have no or limited interaction with other vehicles. Then the question will be who can intervene and how an intervention can be made in case the vehicle requests one?

The second challenge in that definition arises from ambiguities around intervention requests and ‘appropriate’ responses to them. It appears obscure if a level 4 AV can still operate safely without an appropriate response from a human driver to a take-over request issued by the vehicle, then why such a request is necessary to be made? That definition assumes that the vehicle is fully capable to drive itself safely even without human interventions. However, there can be situations that there is a failure in the system (either software or hardware). For example, imagine that the sensor fusion module of an AV stops working and at the same time the vehicle is receiving contradictory data from its sensors regarding a surrounding vehicle’s trajectory. Is the vehicle still competent to decide on a chain of appropriate (re)actions in a timely manner? What happens when the vehicle issues a take-over request to the driver in this situation, but the driver decides not to respond to the request because his/her assumption is that the vehicle can still operate without any intervention?

Answering the above questions will be critical to developing and enforcing regulations as well as licensing users. If a level of human interventions is still required for level 4 AVs it needs to be clarified what interventions, under what conditions, in what driving scenarios, and through which interfaces are going to be requested from human drivers. Furthermore, more delineation is still needed to distinguish level 4 from level 3 and 5. The ambiguities and multiplicity of aspects of autonomous driving suggest that drawing a clear-cut border between autonomy levels is not straightforward. Apart from theoretical frameworks and general taxonomies for autonomy in AVs, it appears to be rather a fuzzy concept than discrete. A fuzzy approach towards measuring autonomy in road vehicles not only allows for more variability in the interval between *non-automated* and *fully-automated*, but also facilitates measuring autonomy of processes instead of output (Godin, 2002).

5.3. Policy implications for safety of CAVs

Policies are prerequisite for promoting and regulating a disruptive technology on a wider scale (e.g., societal level). Thus, ITS cannot be governed and become functional without effective and coherent policies in action. Johnson (2017) maintains that the nature of policy decisions (both nationally and internationally) will drive how CAVs will be accommodated and what form of vehicle autonomy will be permitted. Among the primary aims of this research was to use the results for elaborating on policy implications and providing further insights for stakeholders.

Autonomous riding is now becoming more feasible than ever before, and policymakers need to address potential concerns without overly burdening taxpayers and confining its promised benefits. A legitimate and immediate concern that policymakers are facing is the safety of CAVs, especially in complex environments (Anderson *et al.*, 2014, p.6; Kalra and Paddock, 2016; Koopman and Wagner, 2017; Khonji, Dias and Seneviratne, 2019; Koopman *et al.*, 2019). The scenario and sensitivity analyses in previous sections in addition to the existing literature can shed light on the areas that have more decisive influence on collision risk in urban environments. Six major areas are highlighted which need special attention when it comes to the safety of CAVs. Those areas are discussed in the rest of this section.

The mass adoption of CAVs is predicted to introduce new requirements and standards for the design of infrastructure to pave the way for their safe operation as well as ensuring the safety of other road users (Gavanas, 2019). In fact, enabling infrastructure plays a critical role in reaping the benefits of socio-technical autonomous systems (Gopalswamy and

Rathinam, 2018; Manivasakan *et al.*, 2021; Ramchurn *et al.*, 2021). The BBN model in this study includes three nodes that require infrastructural requisites. Traffic control and management, road condition and communication reliability (e.g., V2I) majorly depend on sophisticated infrastructure. These three types of infrastructure and their roles in autonomous driving are also highlighted in the work of Maurer *et al.* (2016).

5.3.1. Traffic management systems

The efficiency of road traffic systems hinges on the capacity of the traffic infrastructure (Maurer *et al.*, 2016). For instance, a pedestrian at the side or in the middle of a road may present higher risk than one who is commuting on a separate and shielded pedestrian pavement along the road. Advanced traffic control devices and technologies such as loop detectors or magnetic sensors that spot the presence of vehicles at a stop bar in addition to conventional devices that can estimate the velocity and turn movements of vehicles enhance managing traffic flow at intersections (Guanetti, Kim and Borrelli, 2018). Traffic congestion and presence of too many agents with no or low organisation can confuse the path planning and object recognition algorithms of CAVs and increase the risk of collision. Therefore, upgrading and adapting the traffic control and management infrastructure can mitigate that risk. Effective traffic management systems reduce traffic complexity and improve traffic efficiency which directly affect traffic rule enforcement.

Designated lane(s) for CAVs is among widely discussed solutions for safety and traffic management considerations (e.g., Johnson, 2017; Ye and Yamamoto, 2018; Ivanchev *et al.*, 2019; Ma and Wang, 2019; Saeed, 2019; Manivasakan *et al.*, 2021; Mirzaeian, Cho and Scheller-Wolf, 2021). Dedicated CAV lanes are believed to significantly reduce the probability of encountering unpredictable random behaviours triggered by human drivers (Ivanchev *et al.*, 2019). The negative impacts of mixed traffic state can be alleviated to a large extent too. Although this seems to have safety benefits for CAVs and other traffic participants, the feasibility of that solution needs to be assessed. Road type, geometric constraints of existing roads, road capacity, merging segments, and proportion of CAVs to the total number of vehicles are important factors that need to be taken into consideration. While the capacity of motorways and highways can allow for those lanes, typical urban roads with two lanes may need extension to accommodate a dedicated lane for CAVs.

The existing traffic signs and lights are designed for human drivers and are expected to remain in place at least until conventional vehicles dominate the roads. Recognising traffic signs and signals can turn into a challenging task for CAVs in real world. That might be due to lighting and traffic conditions, cluttered background, occlusion, motion blur or deformity

(Yang *et al.*, 2015; Lengyel and Szalay, 2018). Improving the capabilities of the perception and processing modules of CAVs can mitigate this challenge to some extent, but adjustments at infrastructural levels are still requited to augment the safety of roads and reducing collision risks. Uniform and well-maintained road signs is recommended by Liu *et al.* (2019) to address this issue. In addition, one of the main applications of V2I communication is proposed to be in traffic control and management by transmitting real-time traffic situations to CAVs (Li and Liu, 2020). Installation of RSUs (Liu *et al.*, 2019; Kim *et al.*, 2021), autonomous intersection management (AIM) (Manivasakan *et al.*, 2021), and cellular interfaces (Bouk *et al.*, 2018) facilitate V2I and provides a supplementary means for assessing traffic situations and following traffic rules.

5.3.2. Secure and reliable communication platforms

The role of communication channels (i.e., V2V, V2I, and V2X) in facilitating autonomous driving was discussed in sections 2.1.7 and 4.1. Those channels, however, will not have a palpable safety effect if the existing infrastructure is not upgraded (McAslan, Gabriele and Miller, 2021). Gopalswamy and Rathinam (2018) label three levels of communication that enable V2I. Level 1 consists of close rage wireless communication between *Multiple-Sensor Smart Packs* (MSSPs) and nearby vehicles. Examples for this category of communication can be dedicated short range communications (DSRC), Wi-Fi, cellular, and 5G. Level 2 establishes communication between neighbouring MSSPs. Fibre optics technology is suggested for this level. Lastly, level 3 connects MSSPs and cloud-based computing.

While more cyber connectivity expands vehicle and traffic control capacities, real-time data transfer, and diagnostic functions, it increases vehicles' and transportation systems' exposure to higher risks of cyberattacks (Zou, Choobchian and Rozenberg, 2021). Cyber security has been identified as a dilemma and major source of risk not only for CAVs, but also for other components of ITS such as Internet of Vehicles (IoV). Although cybersecurity did not appear among the most influential nodes of the BBN model, there is ample literature (e.g., Johnson, 2017; Parkinson *et al.*, 2017; Bouk *et al.*, 2018; Li *et al.*, 2018; Lim and Taeihagh, 2018; Gavanas, 2019; Sheehan *et al.*, 2019; Katrakazas *et al.*, 2020, p.73; Török, Szalay and Sághi, 2020; Kim *et al.*, 2021) that emphasises the criticality of this factor when it comes to safety considerations of CAVs. Connectivity attribute of cyber-physical systems stipulates sophisticated and integrated cyber-attack deterrence. The findings in the work of Kim *et al.* (2021) also confirms this.

Classification of cyber threats, as Sheehan *et al.* (2019) suggest, is a fundamental step to contemplate their likely consequences and adopt appropriate measures to prevent or tackle them. Kim *et al.* (2021) extensively reviewed and classified the potential cyberattacks on CAVs at vehicular level and recommended defence measures for vehicle on-board architecture. Nevertheless, security measures at network and infrastructural levels must be resilient, up-to-date and under perpetual revision. Strategies for enhancing *cyber resilience* must be evolved to mitigate the impact of any future cyberattacks on transportation cyber-physical systems (Zou, Choobchian and Rozenberg, 2021). Cyber resilience is responsible to adapt and mobilise the system to resist cyberattacks and remain operational during the disruption (Bouk *et al.*, 2018). The systematic literature review conducted by Katrakazas *et al.* (2020, p.95) suggests that *certifications* and *audits* in compliance with standards and regulations developed for CAV cybersecurity is an active field of research.

5.3.3. Urban design and planning

Weather condition appeared in the second place in the sensitivity analysis. Furthermore, the surveyed experts ranked road condition RI as the second influential among the four IRs specified in the BBN model. Alongside augmenting technical and technological capabilities of CAVs, interventions in urban design and planning are necessary to improve road conditions and provide a more CAV-friendly environment. Thompson *et al.* (2020) found that the risk ratio for road transport injury in the best performing city type is approximately as half as the poorest performing city type. Determining and eliminating blind zones (e.g., the corner edge of intersections), severe curvatures and irregular patterns (Yoo, Jeong and Yi, 2021), improving lane markings and illumination conditions at night (Johnson, 2017; Ye, Hao and Chen, 2018; Liu *et al.*, 2019; Saeed, 2019; Carrignon, 2020), reducing the number of speed bumps (Liu *et al.*, 2019), and repairing potholes (Johnson, 2017) are the main remedies for mitigating the safety risks arising out of inappropriate road design and conditions.

5.3.4. Regulation, standardisation and certification

It was explained in section 2.1.8 that perhaps the most significant distinction between CAVs and HDVs is delegating the tasks that are performed by human drivers in HDVs to AI algorithms. In sensitivity analysis, AI performance node of the BBN model was ranked as the fourth factor affecting the collision risk. Along with that, there are many academic papers (e.g., Scherer, 2015; Abduljabbar *et al.*, 2019; Cunneen, Mullins and Murphy, 2019; Khonji, Dias and Seneviratne, 2019; Cummings, 2021) that underline the risks and limitations of AI in autonomous driving. Commensurate and sector-specific regulations, as emphasised in the UK's National AI Strategy, allows the risks to be addressed effectively (Office for Artificial Intelligence, 2021). In spite of that, technology developers and car manufacturers seem to be way ahead of the regulatory bodies and legislators which might be impacting them in a way that does not best serves public interests. This can be overcome by active engagement with the relevant industry sectors, academic communities, and other stakeholders to develop a more in-depth understanding of the risks and safety implications. Recent research projects such as Societal Level Impacts of Connected and Automated Vehicles (LEVITATE, 2019), Trustworthy Autonomous Systems (TAS Hub, 2020) and HumanDrive (UK Government, 2020) are intended to shorten the gap and support policy-making processes with evidence.

Standardisation of CAV systems and determining the degree to which CAVs must be standardised are among the policy options for responding to safety concerns (Johnson, 2017). Uniform standards for vehicle design and operation will contribute to overall system integration (Straub and Schaefer, 2019) and user experience as well. Incorporation of steering wheel and pedals (Hanna and Kimmel, 2017), software safety (Koopman *et al.*, 2019), testing methodologies (Silva *et al.*, 2021), H-M interfaces (Straub and Schaefer, 2019), and communication protocols (Johnson, 2017; Khonji, Dias and Seneviratne, 2019; Straub and Schaefer, 2019) are just a few examples of the areas that standardisation can ensure the safety of CAVs.

Vendor-specific hardware equipment and algorithms plus lack of recognised standards hinder data sharing across different transport/non-transport systems and geographies (Nur and Gammons, 2019). On the other side, Khonji, Dias and Seneviratne (2019) argue that transparency and explainable algorithms are a public request and vital for explaining the reasonings behind individual safety incidents. Still there are practical questions to be answered. Fagnant and Kockelman (2015) raised five questions about the data sharing, ownership and usage: who should own or control a CAV's data? What types of data will be collated and retained? Who will have access to these data? In what ways will such data be made available? And, for what purposes will they be used? Data-sharing, along with privacy and security policies, make data a core element of policy-oriented transportation planning (Glassbrook, 2017, pp.77-80; McAslan, Gabriele and Miller, 2021).

The importance of certification for CAV cyber security was pointed out earlier. With more open road trials, the absence of safety certifications becomes more evident and increases risks to public safety. Rapid pace of developments and heterogeneous software and hardware configurations pose a challenge to developing uniform verification standards and so the consistent certification framework that encircles all variants of CAVs (Dia *et al.*, 2021). A major safety certification concern arises from the self-adaptiveness (or real-time learning) ability of CAVs (Koopman and Wagner, 2017). The self-adaptiveness feature might engender a different behaviour pattern after interacting with other traffic agents than what was observed during testing and certification. Currently, certification frameworks have inadequacies to handle that uncertainty, because they require analysing almost all possible system behaviours up-front in the design, validation, and verification processes.

In automotive industries, certification of vehicles depends on an ability to pass rigorous testing of components for durability and reliability in case of an accident or failure (Martin *et al.*, 2015). Testing for certification of CAVs should further verify how the underlying software and hardware components perform under various degrees of uncertainty that can jeopardise safety of passengers and other traffic participants (Cummings, 2019). In this sphere, policymakers and regulators should have an active role to ensure that stringent and transparent certification tests for consistent evaluation of CAVs will secure the safety benefits for public in first place (Dia *et al.*, 2021). Yun *et al.* (2016) predicated that Google has leveraged the establishment of a certification system for autonomous driving in the US and that can sound the alarm for other countries. This is not to say that technology developers must not be involved in testing, regulatory and certification processes, but those processes must be governed by regulatory bodies and legislation.

The notion of licensing can be extended to users of CAVs. There are still ambiguities about the nature and level of interventions required from human drivers at higher automation tiers (i.e., SAE 3 to 5). According to the taxonomy developed by SAE, the driver in a level 4 CAV is not going to be called for intervention, but can still take over the control of vehicle if wishes to. Since July 2014, state legislations in Florida, Michigan, California, Washington DC, and Nevada demand that all drivers involved in AV testing on public roads must be licensed and prepared to take over vehicle operation (Fagnant and Kockelman, 2015). This raises urgent questions about the competence and driving skills required to safely respond to a wide range of traffic situations and how those skills and competence are going to be certified. The driver licensing issue is one of the major policy implications for CAVs that needs careful deliberation (Lari, Douma and Onyiah, 2015; Johnson, 2017). Next question relates to the licensing of elderly drivers and those with special needs whose cognitive and physical abilities for using incorporated interfaces must be examined (Hancock *et al.*, 2020). This may discount the pledged benefits of CAVs for those groups unless fully autonomous vehicles (i.e., level 4 & 5) become available.

5.3.5. Enabled and facilitated interaction between CAVs and humans

Even after CAVs are commercialised and largely adopted, we will still have a mixture of CAVs, HDVs, and pedestrians in urban traffic scenes. In addition to CAV riders, it is not clear yet how other road users such as pedestrians are going to interact with CAVs. There are several studies (e.g., Rasouli, Kotseruba and Tsotsos, 2017; Hulse, Xie and Galea, 2018; Rasouli and Tsotsos, 2019) that acknowledge the complexity and essentiality of interactions between CAVs and other road users. Whether through interfaces, communication channels (i.e., V2X) and/or other innovative means, timely and facilitated interactions between other traffic participants and CAVs will improve the traffic flow and safety (Rasouli and Tsotsos, 2019). To increase the effectiveness of the interactions, uniformity of interfaces and familiarity of other road users with them must be promoted. Even though the influence of that form of interaction on safety considerations is undeniable, we are not yet hearing a consistent strategy about increasing public awareness, standardising interfaces, and amending current traffic laws based on new safety requirements and standards.

As the control of vehicles are gradually transferred to autonomous technologies, the law must be altered in both its code and implementation (Ilková and Ilka, 2017). The responses to the *Consultation on the rules on use for Automated Lane Keeping Systems* initiated an amendment to Rule 150 of The Highway Code which relieves the requirement for the drivers in AVs (in automated mode) of maintaining proper control of the vehicle at all times (UK Government, 2021). More revisions of driving legislation are underway to expedite the safe deployment of AVs on the UK roads (UK Government, 2021). Such revisions and amendments seem to be unavoidable, but the key question here is how the new rules are going to be enforced? According to the sensitivity analysis in this study, traffic rule enforcement is the sixth influential factor affecting the collision risk. More embedded technologies and capabilities of CAVs can certainly assist authorities in detecting any breach of traffic rules. For example, Ilková and Ilka (2017) put forward the idea of self-report function for CAVs which automatically reports any traffic law breach to authorities.

The above policy discussions are aligned with the six key questions stated by Anderson *et al.* (2014, p.6) and fall within the three major areas that are highlighted by Johnson (2017) for policymaking: 1) connected and autonomous technology; 2) the provision of suitable infrastructure; and 3) licensing of drivers. After pinpointing the areas that need further evidence for policymakers, the main question is who should bear the likely costs? Taxpayers, private sector, or both? There are on-going debates in academic and political forums about which parties should bear the costs of enabling infrastructures. Many ethical dimensions of CAVs also are open questions that need contemplation.

One of the overarching decisions for policymakers is a *conceptual* choice with significant implications that will touch almost every aspect of CAVs. The choice is between assigning all driving tasks to the vehicle while a human driver is either not supposed to intervene at all or taking over control in certain circumstances, and keeping the human driver in charge with ADAS at his/her disposal to provide additional support (Johnson, 2017).

5.4. Research limitations

Similar to other research projects, this study has a number of limitations. The first and main limitation here comes from the assumptions that we are making to be able to build the BBN model. The most fundamental assumption in BBN modelling is *conditional independence* which is seen as a crucial factor facilitating distributed computations (Pearl, 1982). It is assumed that each variable is independent from its non-descendent parents in the graph given the state of the parents. This property sometimes cuts the number of parameters that are required to characterise the JPD of the random variables (Ben-Gal, 2008). Depending on the research questions, availability of data and in order to avoid unnecessary complexity in the model it is inevitable for a researcher to make further assumptions which may limit the scope of research. Other major assumptions are discussed in 3.9 in detail.

Next limitation of this research is the scope of the ILR for identifying the influential variables (i.e. nodes). Due to the variety of terms used to refer to AVs, it is not technically possible to include all those terms in the search criteria. Therefore, a few keywords were used to search for papers in the databases: a) autonomous vehicles; b) automated vehicles; c) autonomous cars; d) automated cars; e) self-driving; and f) driverless. Exclusion of other names that are used to refer to self-driving vehicles (e.g., robotic cars, intelligent vehicles, smart vehicles, etc.) might have limited the scope of literature review.

Another factor that can be considered as a limitation is the number of databases accessed to conduct the literature review and collect qualitative data for identifying risk factors. Including more databases can possibly affect the replicability of the search. DelphiS database may not be a well-known to many, but it is a richer pool of papers comparing to Web of Science. Although searching “autonomous vehicle*” in Scopus generates slightly higher results comparing to DelphiS (the results checked on 24/02/2022: 72,890 for Scopus and 67,276 for DelphiS), the accessibility of documents through DelphiS was more facilitated. This is perhaps because this database is internal to the University of Southampton. In identifying risk factors the top priority was set to be breadth of search and variety of publications over type and quality of publications. This was the main reason for opting integrative literature review approach which in some papers is referred to as 'scouping review'(e.g., Munn *et al.*, 2018a; Munn *et al.*, 2018b).

It has been discussed in this thesis that when epistemic uncertainty is present, a way to make reliable predictions on the performance of a complex system is eliciting experts' judgments (please refer to section 3.8.3). Nonetheless, judgements of individuals, regardless of the level of expertise, is subject to some degrees of bias. Although the literature on minimising the bias and managing heuristics through applying methods and design techniques is rich (e.g., Renooij, 2001; O'Hagan *et al.*, 2006; Tredger *et al.*, 2016; Werner *et al.*, 2017), it is plausible that different groups of experts may come up with contradictory opinions. Hence, biases can be another limitation for this project. Diversifying surveyed experts (e.g., Keeney and Von Winterfeldt, 1991; Verdolini *et al.*, 2020) in terms of their domain expertise was an effective way to control the biases to some extent. The application of expert opinions in PRA is not free of challenge either. The *reproducibility* of the results and divergence of expert beliefs are two main problems in applying expert elicitation in PRA (Cooke, 1991, p.27). The large standard deviations for some of the elicited weights can be an indication of bias.

The number of participants (i.e., nine experts) in the survey was relatively low for rigorous quantitative analysis. Experts were predominantly from academic backgrounds, although several of them have had extensive industrial experience. Given the difficulties in finding and persuading domain experts to take part in the study, nine is a justifiable number since some other studies have used lower number of experts to inform their models. The external validity of expert judgements cannot be assessed yet because there is currently no sufficient conclusive evidence on the influence of identified risk factors in this study on collision risk. Nevertheless, higher number of experts could have strengthened the quality of elicitation and validity of results.

5.5. Summary of discussions and conclusions

Especial care needs to be taken when constructing a BBN model to assess risks of complex systems to avoid misleading or outlying results. The major challenges in that way are identification and inclusion of risk variables, defining causal relationships, filling CPTs and capturing expert knowledge in a model. Studying autonomous systems requires a deep appreciation of autonomy as well as a non-mechanical classification system. Appropriate and timely policy interventions are essential to safeguard public interest and ensure a safe and viable transition towards CAVs. Among the research limitations noted in the previous section, limited number of surveyed experts can hinder the generalisability of findings.

Chapter 6

6. Conclusions and future research

This chapter presents a summary of this thesis in four sections. Section 6.1 highlights the motivations, research problems and employed research methods. The results, findings and policy recommendations are summarised in section 6.2. The main contributions are underscored in 6.3. Finally, the future research pathways are outlined in 6.4.

6.1. Research problem, design and methods

Connected and autonomous vehicles and their enabling technologies are facing an unprecedented development especially in the last decade. The trial and road testing of these vehicles have started in several countries and car manufacturers as well as IT and technology corporations such as Apple have showcased their prototypes. Waymo, the Google brand for self-driving cars, seems to be leading in this transdisciplinary field and its AV taxi fleet is now operational in a few states in the US. The amount of investments and interest expressed by academic communities, industries, and local authorities indicate that we should consider autonomous driving as a reality. AV technology can offer enormous potentials to tackle many challenges in several areas such as transportation safety, environment, and inequality in transport. Realisation of the promised benefits, however, all depends on safe and reliable operation of the technology.

CAVs, akin to other complex and disruptive technologies, will have their own limitations and have to operate within technical and environmental constraints. The uncertainties over the performance and constraints of these vehicles are even more grave. Several reasons were mentioned for the intensity of the uncertainties. Complexity and novelty of the embedded technologies, integration of sheer number of hardware and software pieces, enormity of traffic situations that CAVs may encounter, socio-technical nature, insufficient real-world data, and absence of adequate well-established regulations for verifying/validating the reliability deepen the uncertainties over reliability of CAVs. When we take the human out of the loop, we risk losing reasoning ability in obscure scenarios. The reported fatal accidents, collisions, and the disengagement history of AVs legitimise the functional safety concerns.

Although the results of testing and simulation scale down the uncertainties to some extent, modelling tools can aid further with uncertainty and risk analysis and shed light on obscure aspects of a safety problem. The usefulness of risk modelling becomes even more each the real-world data and testing are more limited. Developing risk models to measure (or at least classify) safety risks before deployment of AVs in large scales is one of the pathways to safety analysis and of paramount importance. Risk models can support decision making under uncertainty and facilitate scenario-based analysis. This study adopted a socio-technical perspective to evaluate safety of CAVs in various environmental and traffic conditions. To measure the risk, collision probability was selected as the risk index.

Ample published literature on safety implications and the criticality of collision avoidance systems in AVs give grounds for an extensive textual analysis to identify causes of collision (i.e., risk factors) in autonomous driving. 594 documents including journal article, conference papers, working papers, white papers, technical reports, policy documents, accident reports, patents, and news articles were reviewed, and after applying thematic analysis, 53 risk factors were discovered. The identified factors were used to construct a BBN model. The choice of BBN for modelling risk has multiple reasons. Firstly, it allows for PRA and is effective tool for informing decision making under deep uncertainties regarding the behaviour of a system, phenomenon, or external conditions. Secondly, it can be used for both diagnostic and prognostic reasoning. Thirdly, sensitivity analysis can be run using a BBN model to quantify the influence of variables on a target node. Fourthly, BBNs provide a platform for meta inference and synthesising qualitative and quantitative data. Finally, BBN is capable to handle large multivariate and multi-dependable models.

Hugin was used to construct the topology of the model. The CPTs were generated in Microsoft Excel and then transferred into Hugin. Later, GeNIe Modeler (another BBN tool) was utilised to demonstrate the strength of links between nodes and sensitivity analysis diagrams.

Besides the advantages, there are some challenges in building a BBN model. Populating CPTs, especially when there are more than a few non-binary nodes in the network, is a demanding and cumbersome task. A new technique was invented to overcome this difficulty. The CPTs are populated in a manner allowing all the JPDs (except lighting conditions and its children) to have uniform distributions before any of the nodes is instantiated. A probability of 100 percent was assigned to the best (most desirable) state of a child node when all it parents were in their best states. Likewise, a probability of 100 percent was assigned to the worst (most undesirable) state of a child node when all its parents were in their worst states. An incremental transition of probabilities filled the blank cells in between, thereby creating a symmetric matrix to the centre of the tables.

A survey was designed to elicit expert opinions on the influence of each parent node on its child(ren). For that purpose, nine experts with expertise in at least one of the major domains (i.e., environmental, technical, traffic and human) in the context of CAVs and/or robotics took part in the survey. The average of the assigned percentages to each parent node was taken as the weight of that node and was incorporated into the model. GeNIe Modeler facilitated incorporation of weights by the Noisy-Adder feature.

6.2. Findings and policy recommendations

The preliminary results of the integrative literature review revealed a new set of themes (i.e., risk factors or causes of collisions) that necessitated a second round of search in databases with the latter themes as keywords. At the end, 53 risk factors were identified and categorised into 4 major groups. The overarching theme of each paper besides the peripheral themes are summarised in a table (appendix A). The risk factors were allocated to the four major modules (blocks in the model) that constitute a socio-technical system. Since defining 'organisation' and pinpointing 'organisational factors' in the context of autonomous driving is not straightforward and given that traffic conditions (ranked as the highest influential by the experts) exert direct effect on probability and severity of road collisions, organisational factors were replaced with traffic factors.

The literature review and identified factors provided a foundation for building the BBN model. Four overall themes (i.e., road condition, traffic condition, reaction time, and technical reliability) were selected to represent the aggregated risk and impacts of each block on collision risk for CAVs. Those overall themes acted as intermediate nodes in the model to avoid exponential growth in the number of CPTs. After running the model, the probability distributions for all the nodes (except the lighting condition's children) were found to be uniform before any instantiations and insertion of expert opinions on the degree of influence for each parent node.

The results of the expert elicitation (i.e., the survey) suggested a considerable convergence of expert opinions in weighting some nodes (e.g., traffic control infrastructure, SD=0) and a wide divergence over the influence of other nodes (e.g., software reliability, SD=0.43). The main reason behind these variations is the limited number of experts took part in this study. The lower standard deviations for four RIs comparing to other nodes can prove this. Another reason presumably was that the experts did not have a chance to exchange ideas and make a collective decision on the influence of each node on its children. Perhaps organising an expert panel discussion or running a focus group could have mitigated that problem to some extent. The average of the percentages assigned by the experts to each node were taken as the weight for that node. Using the noisy-adder (based on noisy-max) feature, the extracted weights were incorporated into the model.

Four extreme scenarios (1-4) were envisaged to demonstrate changes in collision risk distributions while the states of input variables shift from the least risky to the highest (figure 4.8). Then, 29 input nodes were randomly instantiated (scenarios 5 and 6) to generate cases for comparative analysis. The fitted trends to the distributions vary substantially based on the changes in input variables. The risk distributions in the worst- and best-case scenarios (1 and 4) were exponential while in moderate scenarios (2 and 3) resembled more like a linear trend. The random scenarios (5 and 6), however, had very unsimilar distributions. In scenario 5, we witnessed a normal distribution skewed towards the Extreme end and High collision risk represented the peak.

Sensitivity analysis was conducted to measure the sensitivity of collision risk to every 53 risk factors, in isolation. The results suggest that ‘traffic control infrastructure’, ‘weather conditions’, and ‘traffic composition’ are the most influential risk factors. Assigned weights by the experts and topology of the model are two main determinants of the influence that a node effects on the output (i.e., collision risk). The scenario and sensitivity analyses served as a basis for the policy implications to promote safe operation of CAVs.

The policy recommendations were extracted from the literature and focused on five overarching areas. Infrastructural upgrade and adaptations are among key requirements for introducing AVs on a vast scale. Traffic control and management has a significant role in traffic safety, particularly in mixed traffic scenarios. One of the main features of CAVs that is believed to contribute to collision avoidance is connectedness and the ability to send and receive real-time data. Exchanging real-time information of weather, traffic and road conditions will assist the planning unit of CAVs to safely plan and navigate the vehicle. Establishing secure and effective communication between vehicles (V2V) and connecting AVs to infrastructure (V2I) will need designing tailored communication platforms or expanding the existing infrastructures. While more connectivity helps to draw a clearer map for traffic controllers and traffic participants including CAVs, higher cyber threats will be the likely aftermath.

Environmental factors such as weather conditions are often beyond the control of policy makers. Consolidating technical competence of AVs to sense their surroundings more accurately and react to hazards and risky situations timely is always an option for overcoming the challenges that poor weather conditions pose to AVs. Along with technical and technological enhancements, CAV-friendly design and planning of roads and highways will mitigate the collision risk. Improving the quality of lane markings, visibility of traffic signs (especially in absence of V2I), and lighting conditions will assist AVs in identifying objects, other road users, road boundaries and traffic signs.

Public education will increase awareness about interacting with and driving AVs. Since driver interventions might be still necessary to avoid a collision (particularly in SAE level 3 and 4), licensing procedures and processes must include assessment of driving and interacting with CAVs. New interfaces, additional features and mixed traffic mandate a revision in training and licensing criteria for both CAV and non-CAV drivers. The topic of standardisation becomes the hard nut to break in this context. Disparities in interfaces and their functions will be a major challenge to establishing unified training and licensing schemes (at least at national level).

Similar to other safety-critical systems, regulatory requirements, certification and standardisation must govern the development and deployment of CAVs. Safety standards are compulsory in automotive sector to ensure functional safety. ISO 26262 shorts fall in verifying and validating all functional safety aspects of CAVs especially because exhaustive testing under all operational circumstances is impractical. Moreover, some functions such as cyber-security are difficult to test. Therefore, designing comprehensive safety standards that detail safety requirements at component, software, and system integration levels will be required to validate and verify a sufficient level of safety throughout a vehicle lifecycle.

6.3. Contributions to literature and practice

The prime contribution of this research is the review of vast and diverse literature across multiple disciplines which led to identification of 53 collision risk factors in highly autonomous vehicles. The risk factors were categorised into four overarching groups. The aim of this project was to prioritise the breadth of literature review over depth. The identification of those risk factors can provide insight for designers, regulators, researchers and policy makers and trigger further research to test the relationship between those variables applying rigorous quantitative methods. The summary of reviewed literature (appendix A) can also assist researchers for finding relevant papers/documents in a specific context (e.g., H-M interfaces, traffic culture/style, road geometry/configuration/layout, etc.) in relation to functional safety of CAVs.

Assessing the causal influences of the parent nodes in the BBN model on their children from the perspective of experts provides an indication of their ranks and importance in safety analysis. In addition to informing the BBN model in this research, the results of expert elicitation can provoke further research questions and test hypothesis about the strength of relationships between the identified risk factors. Expert knowledge can be relied on in the absence of real data, but a more detailed quantitative analysis can provide more reliable estimates.

The BBN model itself is a risk assessment tool that helps to classify RIs and collision risks based on a given set of spatio-temporal conditions of urban roads. Such a tool will support designers, insurers, policy makers, regulators and urban planners to rank roads according to the state of input variables. In case any evidence on the state of a node becomes available, uncertainty in other nodes can be reduced through inserting observations into the model and backward/forward propagation. Observations can be either deterministic or probability distributions. The model has the capability of running sensitivity analysis and enable comparison between collision risk levels in different scenarios. The results of scenario and sensitivity analyses formed the foundation for policy implications.

A new method was implemented to accelerate the process of populating CPTs. The values in each node's table (except lighting conditions) are symmetrical to the centre of the table and a transition of risk is reflected in children's JPDs by moving from the worst towards the best states. This method can save a lot of time and energy in constructing a BBN model. However, the pitfalls of this method (discussed in section 5.1) must be taken into account to avoid ending up with unequal weights for the parents of a child node.

The overarching policy recommendations were compiled to mitigate the risks from major sources (nodes with the highest sensitivity values). Sensitivity analysis provides an evidence base for prioritising policy measures in dealing with the safety concerns associated with the rollout of CAVs. Safety is currently one of the top priorities for the policy makers. Thereupon, the focal point of policy recommendations in this research was safety only. Nevertheless, coordination between safety and other policies that are designed to address other aspects (e.g., liability and environmental) is vitally important. Further research delineated in the next section can complement the contributions of this research.

6.4. Future research

Two strands of research can be built on the results of this project. Firstly, linking the BBN model to big data (when become available) and developing learning algorithms to refine the model (Lam and Bacchus, 1994). Learning Bayesian Networks is a established approach in constructing BBN by extracting the structure of the model from large data sets. The BBN in this research is a *multiply-connected* network that makes reasoning a difficult task. Refinement of the topology will therefore optimes the reasoning process. Some of the nodes may even become redundant as the selection process was based on the literature review and expert elicitation. When real data is accumulated, some of the variables may not prove to have a significant correlation with the RIs including collision risk. Likewise, the input for CPTs can be derived merely from data or in combination with prior expert knowledge (Rohmer, 2020). This will improve the robustness of CPTs and JPDs.

Secondly, with realisation of real-world data during and after testing phase of CAVs it will become possible to turn the current model into a Dynamic Bayesian Network (DBN) to estimate the probability of a collision by receiving real-time traffic dynamics data (Katrakazas, Quddus and Chen, 2019). Static BNs fail to capture dynamic nature. Traffic conditions are dynamic in nature and a DBN model will better represent temporal relationships. Indeed, DBN is an extension of Bayesian network. Three main steps need to be undertaken for converting a static BN to a DBN (Amin, Khan and Imtiaz, 2019): 1) reconfiguring the structure to accommodate process dynamics; 2) redesigning the states of nodes to capture temporal relationships between time slices; and 3) repeating the static BN with time if all the variables exert influence on the reasoning process and update the belief of time intervals. Another possible extension to BBN is influence diagram (ID). Incorporation of decision and utility nodes (in addition to the existing chance nodes) will evolve it to a decision-making tool which adds on decision components and their relationships (Sedki, Polet and Vanderhaegen, 2013; Landuyt *et al.*, 2014).

Appendix A

No.	Main theme	Other themes	Summary	Author(s) and source
1	**Situation awareness**	Autonomy level, reaction time, secondary task, driving style, longitudinal and lateral control, traffic density, HMI, trust, roadwork, obstacle, speed	This study looked into the behaviour of drivers and drivers' take-over after highly automated driving and the links into the situation awareness.	Zeeb, Buchner and Schrauf Accident Analysis and Prevention, 2015
2	**Situation awareness**	Autonomy level, HMI, reaction time, roadwork, lateral and longitudinal controls, H-M Interfaces, speed, technical factors	The aim of this research was to develop and validate an assessment framework for driver-interaction concepts in semi-autonomous vehicles where the interaction between a human driver/supervisor and automation is still required. It also introduces an assessment framework to measure gained situation awareness in partially automated driving systems.	Van den Beukel and van den Voort Applied Ergonomics, 2017
3	**Situation awareness**	Autonomy level, secondary task, response times, HMI, H-M Interface, driver experience, longitudinal and lateral control, trust, fatigue, cognitive workload, situation awareness, other road users, driving behaviour, trust	A thematic analysis of video data was carried out to assess the effects of partially automated systems on drivers' sustained monitoring task. The findings revealed that drivers are not being properly supported in adhering to their new monitoring tasks and instead show behaviour indicative of complacency (i.e., over-trust in the reliability of the system). These attributes may encourage drivers to take more risks whilst engaged in semi-autonomous driving.	Banks *et al.* Applied Ergonomics, 2018
4	**Situation awareness**	Autonomy level, other road users, complacency, path planning, driving behaviour, road infrastructure	Human factors must be considered to ensure the safe and efficient operation of semi-autonomous systems. This simulator study investigated the effects of automating vehicle steering and implement control and monitoring task automation on the situation awareness of drivers. The findings are in line with the hypothesis that a highly automated agricultural vehicle would reduce the operator's SA when compared to the semi-automation scenarios.	Bashiri and Mann Biosystems Engineering, 2014
5	**Situation awareness**	Autonomy level, time to collision, overreliance, trust, road conditions, traffic situations, HMI, traffic intensity, speed, NDRT, perceived risk	This paper examined the effects of vehicle automation and failures due to automation on driving performance and monitoring. The results suggest that driving performance degrades in higher automation levels. In addition, it is indicated that car drivers are worse at handling complete than partial deceleration failures.	Strand *et al.* Transportation Research Part F, 2014
6	**Situation awareness**	Level of automation, workload, lateral and longitudinal motion, secondary task, other road users, visibility conditions, traffic conditions, traffic density, road infrastructure, reaction time, experience, speed, risk perception	This study investigated the effects of adaptive cruise control (ACC) and highly automate driving (HAD) on drivers' workload and situation awareness through a meta-analysis and narrative review of simulator and on-road studies. Drivers of a highly automated vehicle, and to a lesser extent, ACC drivers are likely to engage in secondary tasks. Both ACC and HAD can result in improved situation awareness compared to manual driving, if drivers are motivated or instructed to monitor the environment and detect objects.	de Winter *et al.* Transportation Research Part F, 2014
7	**Situation awareness**	Autonomy level, perceived risk, HMI, Human-Machine Interface, reaction time, secondary task, roadworks, traffic density, number of lanes,	This paper evaluated the possibility of using a real-time assessment system to monitor the drivers' attention to the roadway in automated driving (AD). Another aim of this study was to investigate how quickly drivers were able to take over the control of vehicle after AD, when it was required, by analysing observable driving performance and eye tracking metrics.	Merat *et al.* Transportation Research Part F, 2014
8	**Situation awareness**	Autonomy level, NDRT, reaction time, HMI, H-M Interface, drowsiness, traffic density, training 9and experience, traffic flow, workload, driver behaviour,	This paper proposes a framework and surveys the literature on human factors (mental underload/overload and situation awareness) of transitions in automated (autonomous) driving. It also discusses two concepts: monitoring transition and control transition.	Lu *et al.* Transportation Research Part F, 2016

9	**Situation awareness**	Workload, secondary task, situation awareness, HMI, H-M Interface, reaction time, traffic flow, driving style, autonomy level, trust in automation, longitudinal and lateral control	An empirical study was conducted to investigate the secondary task engagement and disengagement in the context of highly automated driving. The findings suggest that participants demonstrated a clear preference for task engagement during highly automated compared to manual driving. Furthermore, drivers avoided more demanding tasks prior to the situations which may trigger take-over request when they had the opportunity to anticipate them (predictive HMI).	Wandtner, Schömig and Schmidt Transportation Research Part F, 2018
10	**Situation awareness**	NDRT, longitudinal and lateral acceleration, traffic laws, traffic density, time of day, day of week	This study investigates the impact of peripheral visual information in alleviating motion sickness when engaging in non-driving tasks in fully automated driving.	Karjanto *et al.* Transportation Research Part F, 2018
11	**Situation awareness**	Trust, HMI, road conditions, reaction time, secondary task, control, experience, perceived trustworthiness, drowsiness, other road users, traffic composition	The issue of trust in AVs is pinpointed in this article. The main factors (including *situational awareness*) affecting collision risks in urban environments are discussed. The interactions between the technology and human driver that can impact the reactions times in responding to a hazard are assessed as well.	Olaverri-Monreal Nature Electronics, 2020
12	**Situation awareness**	Secondary task, number of lanes, traffic conditions, traffic flow, reaction time, speed, weather conditions, time of day, visibility	The aim of this paper was to evaluate the impact of a group of distracting activities on drivers' performance. To this end, a driving simulator experiment was designed to collect data on several driver performance measures while engaged in different non-driving activities.	Farah *et al.* Advances in Transportation Studies an international Journal, 2016
13	**Situation awareness**	Autonomy level, workload, control, algorithms, HMI, H-M Interfaces, speed, reaction time, trust, complacency	This study assesses the effects of automation levels on human-system performance, situation awareness and workload in a dynamic control task.	Endsley and Kaber Ergonomics, 1999
14	**Situation awareness**	Other road users, computational power, traffic behaviour, kinematic state	This paper presents a novel approach to artificial situation awareness for an autonomous vehicle operating in complex dynamic environments populated by other agents.	McAree, Aitken and Veres IFAC-PapersOnLine, 2017
15	**Situation awareness**	HMI, secondary tasks, H-M Interfaces, weather conditions, sensors, self-awareness, construction zones, pedestrians, traffic density, blind spots, control, training and experience, response time	This study investigated the impacts of auditory alerts (i.e. speech alert) on situation awareness of drives in autonomous vehicles. It further highlights the need for a cooperative effort between humans and the automation technology whereby human drivers will still have to maintain situation awareness during automated driving.	Nees *et al.* Human Factors and Ergonomics Society, 2016
16	**Situation awareness**	Software, sensors, radar, LiDAR, GPS, pedestrians, machine learning, AI maturity, hardware, computing power	In order for a self-driving car to work at all, the vehicle's software needs to be provided with situation awareness at all times. To continuously sense its 360-degree surroundings, it uses multiple sensors: colour-aware visible light cameras, radar transceivers, LiDAR, GPS, etc.	Cerf Communications of the ACM, 2018
17	**Situation awareness**	Autonomy level, software, HMI, traffic congestion, interface, trust, over-reliance, pedestrians, traffic composition, hardware, road conditions, secondary task, AI, traffic conditions	This paper suggests an oversight model (HASO) which is believed to facilitate human-autonomy design for semi-autonomous vehicles thereby improving safety which is dependent on maintaining situation awareness.	Endsley International Ergonomics Association, IEA 2018
18	**Situation awareness**	Autonomy level, HMI, road conditions, traffic conditions, trust, secondary tasks, over-reliance, speed, vehicle control, path planning,	The research was designed to examine and reveal potential issues associated with the use of semi-autonomous systems, exploring impacts on willingness to engage in secondary non-driving related tasks, and driver allocation of visual attention while operating under LAADS.	Llaneras, Salinger and Green Driving Assessment Conference, 2013
19	**Situation awareness**	Weather conditions, control, HMI, cybersecurity	This paper investigates impacts of AVs form a Traffic Engineering Perspective and enlighten trends and challenges surrounding this technology and related infrastructure developments.	Tettamanti, Varga and Szalay Periodica Polytechnica Transportation Engineering, 2016

20	**Situation awareness**	Sensors, LiDAR, cameras, algorithms, V2V, other road users, road infrastructure, work zones, road geometry	Situational awareness is crucial in AVs. This research went beyond the traditional functions of situation awareness in robotic an autonomous driving, such as traffic signal recognition, lane departure warning, lane detection, etc. and suggested a method to model complexities of road surfaces and dynamic environments. This further contributed to stretching of semantic understanding and situation awareness in AVs.	Mathibela PhD thesis, 2014
21	**Situation awareness**	Reaction time, hazard perception, trust, H-M Interfaces, road conditions, traffic conditions, other road users, speed, visibility, obstacles, secondary task, system failure, traffic density, demographics, construction zone, autonomy level	The present study suggests that situation(al) awareness for latent hazards is not immediately present while drivers have to resume manual driving after a taking over the control of vehicle and when they were not previously engaged in driving activities since the vehicle was operating in autonomous mode. A simulator was deployed to determine whether drivers could spot latent hazards in a traffic scenario immediately after manual driving had become obligatory (i.e., after a take-over request). The findings indicate that drivers need time to construct a mental representation and activate picture that allow them to recognise latent hazards.	Vlakveld *et al.* Transportation Research Part F, 2018
22	**Situation awareness**	Trust, traffic rules, communication, speed, self-awareness, vehicle control, sensors, H-M Interface, perception limitations, V2V, V2X, weather conditions, task planning	The objective of the paper is to investigate the problem of safety assurance for autonomous systems where external events and interaction with the environment and other systems have essential influence on safety. This also links the concept of *situation awareness* with trust and risk perception in the context of autonomous robots.	Wardziński 25th International Conference SAFECOMP, 2006
23	**Weather conditions**	Sensors, perception accuracy, localisation, V2V, V2I, path planning, vehicle control, road conditions, fatigue, algorithms, vehicle state, road infrastructure, other road users, obstacle, road layout, cameras, lighting conditions, sensor fusion, software, LiDAR, Radar, speed limit, H-M interfaces, HMI, drowsiness, traffic conditions, traffic rules	This article provides up-to-date information about the advantages, disadvantages, limits, and ideal applications of specific AV sensors. It also highlights crucial areas which developers needed to focus on incl. poor weather conditions and complex urban scenarios. Perception accuracy is one the main themes in this study.	Van Brummelen *et al* Transportation Research C, 2018
24	**Weather conditions**	Visibility, reaction time, traffic condition, traffic control, visibility, speed, traffic flow, algorithms, road conditions, road geometry, density, interface, traffic control	The primary objective of this study was to develop a control strategy of variable speed limits (VSL) to reduce the risks of secondary collisions during inclement weathers. The VSL strategy is proposed to dynamically adjust the speed limits according to the current traffic and weather conditions.	Li *et al.* Accident Analysis and Prevention, 2014
25	**Weather conditions**	Traffic conditions, traffic density/volume, speed, visibility, road type, number of lanes, road conditions, temperature, geometrical characteristics, sensors,	This paper investigated the impact of weather and traffic conditions on the road safety. Various variables/metrics were discussed and analysed.	Theofilatos and Yannis Accident Analysis and Prevention, 2014
26	**Weather conditions**	Lighting conditions, sensors, software, LiDAR, radar, cameras, road conditions, situation awareness, AI, SLAM, algorithms, traffic conditions, obstacles, road infrastructure, GPS, AI	The contribution of multimedia technologies to autonomous driving is recognised in this article (EIC message). The multimedia technology is capable to overcome conventional computer vision limitations namely under adverse weather and lighting circumstances.	Chen IEEE Computer Society, 2019
27	**Weather conditions**	Regulations, cybersecurity, control, other drivers' behaviour, planning, perception accuracy, software and hardware reliability,	This study proposes innovative methods to calculate the number of miles of driving that would be needed to provide clear statistical evidence of autonomous vehicle safety. It concludes that AV's regulations are adaptive and evolutionary.	Kalra and Paddock Transportation Research Part A, 2016
28	**Weather conditions**	Visibility, reaction time, radar, sensors, road conditions, V2V, communication, road geometry, speed, algorithms, automated perception, car-following behaviour, control	This article evaluated the impacts of different longitudinal driver assistance systems (i.e. FCW, AEB, ACC, CACC) on reducing multi-vehicle rear-end collisions during small-scale adverse weather.	Li *et al.* Accident Analysis and Prevention, 2017

29	**Weather conditions**	Speed, traffic conditions, road conditions, lighting conditions, traffic flow, driver response	This paper surveys empirical literature on the effects of climate change and weather conditions on the transport sector. It considers factors such as temperature and precipitation.	Koetse and Rietveld Transportation Research Part D, 2009
30	**Weather conditions**	Visibility, lighting conditions, cameras, vehicle navigation, hardware, road geometry, algorithms, sensors	Light scattering due to bad weather conditions affects outdoor images and results in poor contrast and faded colours. These effects can be critical in applications such as video surveillance, driving assistance or perception accuracy autonomous driving. This study proposes a novel algorithm to restore the contrast of images under inclement weather conditions (e.g., fog, mist or haze). The proposed method blends several techniques to provide an algorithm fast enough to detect colour and process grey images.	Andrade IEEE Latin America Transactions, 2017
31	**Weather conditions**	V2V, V2I, V2X, communication, work zone, sensors, roadside infrastructure, communication infrastructure, situational awareness, visibility, cameras, radar, sensor fusion, vehicle control, obstacles, perception, algorithms, AI	Handling adverse weather conditions is a challenge for AVs. On average, inclement weather causes 5,300 fatalities alone in the US. Although AVs can mitigate this figure, co-operation between the *meteorological* and transportation sector needs to be established and aimed at generating solutions for this problem. For example, advancing sensory systems and updating AVs'/drivers with accurate and timely weather conditions/forecasts could address this challenge to some extent.	Walker *et al.* American Meteorological Society, 2020
32	**Weather conditions**	Traffic conditions, road conditions, traffic volume, road capacity, road infrastructure, visibility, speed	This article examines variations in road traffic volume due to adverse weather in an arctic region as well as vulnerability of transportation systems to adverse weather affecting efficiency and reliability.	Bardal Journal of Transport Geography, 2017
33	**Weather conditions**	Sensors, LiDAR, radar, navigation, algorithms, vision, perception capabilities, speed, localisation, path planning, sonar, obstacles	The performance of different types of sensors (i.e. LiDAR, vision, sonar and UWB radar) under adverse weather is surveyed in this paper. These are prevalent sensors used in autonomous systems/robots.	Yamauchi IEEE International Conference on Robotics and Automation, 2010
34	**Weather conditions**	Visibility, sensors, software, cameras, algorithms, road geometry, image processing, lane markings	This article identifies adverse weather conditions as a degrading factor for the performance of advanced driver assistance systems (ADAS). To tackle this problem, it presents two novel approaches that aim to detect unfocused raindrops on a car windscreen using only images from an in-vehicle camera.	Cord and Gimonet IEEE Robotics & Automation Magazine, 2014
35	**Weather conditions**	Software, sensors, LiDAR, road conditions, localisation, road infrastructure, algorithms, GPS, obstacles, system integration	This paper develops on a fast-multiresolution scan matcher for vehicle localization in urban environments for self-driving vehicles. 3D light detection and LiDAR can often fail when facing adverse weather conditions. Then a novel scan matching algorithm that leverages Gaussian mixture maps to exploit the structure in the environment. This is important for detecting lane markings, traffic signs, etc.	Wolcott and Eustice IEEE International Conference on Robotics and Automation, 2015
36	**Weather conditions**	Localisation, mapping, software, GPS, communication, road geometry, speed, lateral and longitudinal localisation, algorithms, trajectory/path planning, traffic conditions, other road users, perception accuracy, information fusion	This paper proposes a survey of the Simultaneous Localization and Mapping (SLAM) field when considering the recent evolution of AD. Building maps in various conditions (e.g., weather) is the focus of this study. It concludes that the safety of localization algorithms is critical factor in safety analysis. Multiple sources of data should be envisaged and strategies to safely switch among them must be devised.	Bresson *et al.* IEEE Transactions on Intelligent Vehicles, 2017
37	**Weather conditions**	Sensors, radar, visibility, road conditions, software, road geometry, algorithms, sensors, LiDAR, cameras, sensor fusion, road infrastructure, road structure, speed, CAN	This study investigated radar-based technologies that collects information about road curves under undesired conditions (i.e. adverse weather) in which optical sensors can be impaired or their performance is degraded. This paper asserts that the road curvature measurement results would be more realistic and reliable if the corresponding road infrastructure, car velocity reference signal, and intelligent pre-processing as well as postprocessing algorithms are available.	Lee *et al.* IEEE Sensors Journal, 2018

38	**Weather conditions**	HMI, TOT, traffic rules, visibility, reaction time, age, road type, time of day	This study investigates the effect of age and weather on takeover control performance among drivers from Highly Automated Vehicles (HAV).	Li *et al.* IET Intelligent Transport Systems, 2018
39	**Weather conditions**	Traffic conditions, traffic flow, speed, road conditions, time of day, day of week, roadway type, visibility, control	This paper conducted literature review and considered the recent research (carried out by the Center for Transportation Research and Education) on the impacts of weather conditions on traffic demand, traffic safety, and traffic flow relationships.	Maze, Agarwal and Burchett Journal of the Transportation Research Board, 2006
40	**Weather conditions**	Work zone, reaction time, traffic conditions, speed, driver distraction, driving behaviour, roadway conditions, traffic congestion, sensors, V2V, V2I, traffic flow, environmental characteristics, traffic management infrastructure, time of day, other road users, algorithms, visibility conditions, situation awareness, human factors, road geometry, kinematic state, H-M Interface	Three simulation studies were conducted to evaluate the safety benefits of driver speed selection. Findings of these simulations provide early insights into the effectiveness of connected vehicles Traveler Information Messages (TIMs), which can facilitate developing more efficient transportation management strategies under inclement weather.	Yang *et al.* Accident Analysis and Prevention, 2020
41	**Weather conditions**	Visibility, software, cameras, algorithms, sensors, pedestrians, obstacles, speed	This paper proposes an extended algorithm for camera-based ADAS which better handles road images and enhances visibility under heterogeneous fog.	Tarel *et al.* IEEE Intelligent Vehicles Symposium, 2010
42	**Weather conditions**	Driver behaviour, speed, road conditions	This study addressed the effects of adverse weather and traffic weather forecasts on driver behaviour in Finland. The results suggest that the on-road driving behaviour is predominantly affected by the prevailing observable conditions.	Kilpela¨inen and Summala Transportation Research, 2007
43	**Weather conditions**	Software, road conditions, sensors, visibility, cameras, hardware, obstacles	In this paper, a solution is proposed thanks to a contrast restoration approach to tackle the impact of adverse weather on Free space detection is a primary task in autonomous navigation.	Hautière *et al.* Machine Vision and Applications, 2014
44	**Weather conditions**	Visibility, software, AI, lighting conditions, road infrastructure, time of day, traffic rules	This news article discusses the struggles autonomous cars encounter in spotting traffic signs in rain and surveys a computer programme (machine-learning algorithm) to overcome this obstacle.	Brewster News article on sciencemag.org, 2017
45	**Weather conditions**	Sensors, software, GPS, visibility, road conditions, LiDAR, time of day, lighting conditions, sensor fusion, algorithms, obstacles, path planning, road infrastructure, speed, V2X, hardware, road geometry, perception accuracy, CAN	In this paper, it is suggested to equip autonomous cars with sensor fusion algorithms able to operate in various weather conditions (e.g., rain). The proposed algorithm was used in testing the self-driving car EureCar (KAIST) to assess its applicability for real-time use. The vehicle accomplished self-driving task by using GPS, cameras, and LiDARs in addition to vehicle information. Path information improved the lane estimation performance.	Lee *et al.* International Journal of Automotive Technology, 2018
46	**Weather conditions**	Speed, road conditions, driver behaviour, traffic volume, lighting conditions, time of day, speed, visibility,	This paper assessed trends in motor vehicle fatalities associated with adverse weather and presents spatial variation in fatality rates by state in the US.	Saha *et al.* Environmental Health, 2016
47	**Weather conditions**	Autonomy level, visibility, software, traffic conditions, lighting conditions, sensors, cameras, algorithms, radar, sensor fusion, road configuration, traffic density, road condition, perception accuracy	This article proposes a using a fuzzy system and line segment algorithms to overcome various illumination problems which can be caused by internal and external factors such as road quality, occlusion, weather conditions, and illumination.	Hoang *et al.* Sensors, 2017
48	**Weather conditions**	Infrastructure, time of day, visibility, sensors, software, other road users, cybersecurity, LiDAR, obstacles, time of day, communication, road configuration, communication infrastructure	The authors investigated the changes and uncertainties about timing, scale, and nature of AVs which can present substantial challenges for the city planners, traffic engineers, and other public officials. This paper suggests focusing efforts around policy making when it comes to AVs.	Guerra and Morris Planning Theory & Practice, 2018

49	**Weather conditions**	Sensor, autonomy level, situation awareness, self-awareness, velocity, distance from other vehicles, control, actuators, V2I, drivers' state, traffic conditions, road infrastructure, traffic regulations, algorithms, software architecture, obstacles, kinematic state, communication, lighting conditions, road configuration, road type, time of day, HMI, drowsiness, localisation	This study proposes an ontology-based model to determine the automation level of an automated vehicle for co-driving. It discusses main challenges in achieving fully automation in all situations (adverse weather or traffic conditions, etc.). several factors including human, environmental and traffic variables are discussed and evaluated in terms of their influence on the performance of AVs in different automation levels.	Pollard, Morignot and Nashashibi 16th International Conference on Information Fusion, 2013
50	**Weather conditions**	Fatigue, velocity, traffic density, VANET, road infrastructure, time of day, day of week, speed, lighting conditions, road conditions, road type, communication channels, sensors and cameras, pedestrians, traffic control, traffic composition	To ensure the safety of road commuters in a mixed traffic environment, it is crucial to advance the performance of ADAS. This paper proposes an accident prediction system for Vehicular ad hoc networks (VANETs) in urban environments, in which the crash risk is seen as a latent variable that can be observed using multi-observation such as velocity, weather condition, risk location, nearby vehicles density and driver fatigue.	Aung *et al.* Information, 2018
51	**Weather conditions**	LiDAR, sensor, control, speed, software, V2X, data fusion, planning layer, hardware, radar, road-side units, road conditions, environment perception, algorithms, traffic density	This article concentrated on developing a baseline for novel LIDAR which can be deployed in future autonomous cars. Such detector requires perception not only in clear weather, but also under adverse weather conditions such as fog, rain and snow. Development of automotive laser scanners is bound to the following requirements: maximise sensor performance, assess the performance level and keep the scanner component costs reasonable (i.e., less than 1000 €) even if more expensive optical and electronic components are still required.	Kutila *et al.* IEEE 19th International Conference on Intelligent Transportation Systems, 2016
52	**Weather conditions**	Sensors, pedestrians, malicious activity by other road users, traffic control, pedestrians, technical failures, traffic composition, perception, traffic density, HMI, speed, traffic rules, visibility, roadwork, type of road, time to collision, traffic participants experience, actuator control, longitudinal and lateral safety distances, autonomy level	This article provides a definition for *safe state* in the automated (autonomous) driving context. Several events are identified which can influence the risk and the capabilities of the vehicle guidance system. Change in environmental conditions (e.g. rain and/or fog) are among these events.	Reschka and Maurer IT: Information Technology, 2015
53	**Weather conditions**	Sensors, radar, GPS, cameras, sonar, pedestrians, traffic infrastructure, time of day, visibility, perception accuracy, obstacles, algorithms,	A systematic literature review was conducted to characterise and evaluate the effect of adverse weather conditions on different types of sensors such as radar, visual cameras and LiDAR which typically compose the perception hardware in AVs. The results suggest that adverse weather can reduce the detection range of radars up to 45%.	Zang *et al.* IEEE Vehicular Technology Magazine, 2019
54	**Weather conditions**	Lighting conditions, LiDAR, cameras, sensors, radar, traffic conditions, control, static/dynamic obstacles, visibility, road type, road structure, road conditions, other road users, traffic rules, traffic density, speed, V2X, surrounding perception, algorithms	The ability to assess various traffic conditions/scenarios and navigate safely is a serious challenge for AVs. Another important challenge is the development of a robust recognition system that can account for adverse weather conditions. Sun glare, rain, fog, and snow are the weather conditions that can occur in the driving environment and affect the performance of AVs. This paper summarised research focused on AD technologies and discussed challenges to recognition of adverse weather by vehicle and other situations that increase the risk, thus complicating the introduction of automated vehicles to the market.	Yoneda *et al.* IATSS Research, 2019

55	**Weather conditions**	Software, road conditions, traffic conditions, traffic compositions, road type, vehicle controller, speed, reaction time, driving style, traffic density, traffic infrastructure, algorithms, kinematic state	This paper demonstrates the applicability of a reconfigurable vehicle controller agent for AVs that adapts the parameters of a used car-following model at runtime, so as to maintain a high degree of traffic quality (efficiency and safety) under different weather conditions. The results suggest that as the intensity of the rain builds up, vehicle acceleration was reduced up to 25.96% and time headway rose up to 78.95% under heavy rain, which are very close to the expected variations for human drivers with decrements in acceleration up to 20.86% and increments in time headway up to 77.50%.	Horcas *et al.* Journal of Software: Evolution and Process, 2017
56	**Urban design**	traffic conditions, traffic culture, software, road conditions,	This news article considers different obstacles, challenges and impacts in respect to test, launch and prevalent use of self-driving cars in developing cities.	Waddell www.wired.com, 2017
57	**Urban design**	Sensors, software, traffic conditions, traffic culture	In this paper, authors propose a real time genetic algorithm with Bezier curves for trajectory planning. The main contribution is the integration of vehicle following and overtaking behaviour for general traffic as heuristics for the coordination between vehicles in the absence of speed lanes.	Kala and Warwick Applied Soft Computing, 2014
58	**Urban design**	Communication, sensors, software, traffic conditions/culture, trust, inter-vehicle interactions, traffic rules	This paper briefly summarises the approaches that different teams used in the DUC, with the goal of describing some of the challenges that the teams faced in driving in urban environments.	Campbell *et al.* Philosophical Transactions of the Royal Society A, 2010
59	**Urban design**	Sensors, traffic conditions, road conditions, communication	This article examines how large metropolitan planning organizations (MPOs) are preparing for autonomous vehicles. Uncertainties about the new technology have kept mention of self-driving cars out of nearly all long-range transportation plans.	Guerra Journal of Planning Education and Research, 2016
60	**Urban design**	Traffic conditions/rules, speed	This paper studies “Caroline”, an autonomous car which participated in Urban Challenge competition in 2007 and later was adopted to master the challenge of realising autonomous driving in the domain of Braunschweig’s inner ring road.	Wille, Saust and Maurer IEEE Intelligent Vehicles Symposium, 2010
61	**Urban design**	Software	This paper presents an autonomous driving test held in Parma on urban roads and freeways open to regular traffic. It also reviews other Intelligent Vehicles Tests including their scenarios, sensors used in the vehicle and adopted approaches.	Broggi *et al.* IEEE Transactions on Intelligent Transportation Systems, 2015
62	**Urban design**	Sensors, communication, autonomy level	This study surveys the mutual impacts of AVs and different aspects of urban design, urban infrastructure and vehicle form.	Durate and Ratti Journal of Urban Technology, 2018
63	**Urban design**	Collision avoidance, car dynamics, software	The author considers an extension of *Multi-lane Spatial Logic* (MLSL) for autonomous cars to deal with urban traffic scenarios, thereby focusing on crossing manoeuvres at intersections.	Schwammberger Theoretical Computer Science, 2018
64	**Urban design**	Traffic conditions/culture, integration	This paper reflects on how the relationship between traffic, people, and places might be otherwise. It tries to define the relationship of traffic engineering and urban design which might offer possibilities for reconciling the competing and conflicting demands for safe, efficient movement with the quality and legibility of the built environment.	Hamilton-Baillie Urban Technology, 2004
65	**Urban design**	Community design, Traffic conditions	This study investigates the relationship between community design/urban planning and traffic safety.	Dumbaugh and Rae JAPA, 2009
66	**Urban design**	Traffic conditions/culture, speed, road types	Starting from Alker Tripp's seminal ideas about city design, street morphology, and accident risk, this article summarises results from an increasingly sophisticated line of enquiry at the boundaries between transport geography, network modelling, urban geography, and planning.	Sarkar, Webster and Kumari International Journal of Sustainable Transportation, 2018

67	**Urban design**	Traffic rules/culture, speed, software	This paper addresses the problem of motion planning of an autonomous vehicle amidst other vehicles on a straight road is considered. Challenges include assessing a possible overtaking opportunity, cooperating with other vehicles, partial driving on the "wrong" side of the road and safely going to and returning from the "wrong" side.	Kala and Warwick Electronics, 2015
68	**Urban design**	Software, sensor, traffic conditions/culture, speed, communication	The paper describes the current status of and main trends in automated vehicles, a preliminary vision of the future city with mobility supported mainly by automated vehicles, and freight distribution.	Alessandrini *et al.* Transportation Research Procedia, 2015
69	**Urban design**	Speed, traffic conditions,	Sprawl has been studied in relation to many topics from residential energy use to social capital. This work studies direct and indirect relationship between sprawl and fatal/non-fatal crash rates	Ewing, Hamidi and Grace Urban Studies, 2016
70	**Urban design**	Speed, traffic conditions, pedestrians, sprawl	This paper considers the rise of traffic accidents in the creation of the modern city. The notion of accidents is deconstructed. It also reviews a range of recent papers that explore the causal connections between urban design and traffic accidents.	Short & Pinet-Peralta Mobilities, 2010
71	**Urban design**	Visibility, collision avoidance, visibility	This paper deals with accidents between reversing vehicles and pedestrians occurring on public roads and other places open to the public in France. It also analyses the accident cases to contribute to reflections on possible preventive measures, notably in the field of urban planning and design.	Brenac and Fournier The Open Transportation Journal, 2018
72	**Urban design**	Infrastructure, traffic conditions, communication, software	This work describes two phases of a project designed to adapt an existing commercial traffic simulation package and use the simulation model to develop and demonstrate the operation of a new automatic incident detection algorithm based on these messages.	Waterson, Cherrett and McDonald Journal of the Operational Research Society, 2005
73	**Urban design**	Infrastructure	This article indicates in which ways Autonomous Vehicles can be disruptive and further highlights the major barriers to adopting AVs in urban area.	Cox D/SRUPTION (disruptionhub.com), 2017
74	**Urban design**	Motion planning, algorithm, traffic conditions, speed and road type	The purpose of this paper is to present the numerous extensions made to the standard RRT algorithm that enable the on-line use of RRT on robotic vehicles with complex, unstable dynamics and significant drift, while preserving safety in the face of uncertainty and limited sensing.	Kuwata *et al.* IEEE/RSJ International Conference on Intelligent Robots and Systems Intelligent Robots and Systems, 2008
75	**Urban design**	Speed, time of day, car type, weather conditions, road design, traffic conditions	To analyse various factors influencing the accident severity of urban river-crossing tunnels, twelve influence factors were chosen according to the three traffic elements of vehicle, road, and environment. These factors were based on the historical data of 14 urban river-crossing tunnels in Shanghai.	He *et al.* Journal of Engineering Science and Technology Review, 2018
76	**Autonomy level**	Trust, UA, UX, HMI interactions, control	This study surveys the relationship between the degree of autonomy in cars, User Acceptance (UA) and User Experience (UX).	R¨odel *et al.* 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 2014
77	**Autonomy level**	Sensors, software, urban design, control	Section 6 of this paper describes a low-level reactive subsystem empowered to respond to exceptions often due to failures in higher level autonomy layers.	Kelly *et al.* The International Journal of Robotics Research, 2006
78	**Autonomy level**	Software, perception	This paper reviews a framework for Autonomy Levels for Unmanned Systems (ALFUS) which has been developed by a group at NIST to address the autonomy issues.	Huang *et al.* Proceedings of the AUVSI's Unmanned Systems North America, 2005
79	**Autonomy level**	Control, software, H-M interactions	This research explores the notion of adjustable autonomy. It also discusses a porotype system which allows human users to interface with a remote robot at various levels of autonomy.	Goodrich *et al.* American Association for Artificial Intelligence, 2001

80	**Autonomy level**	Control, communication, liability, software	This paper addresses some of the early policy concerns about "connected cars" and driverless vehicles and challenges the concept of full autonomy in such vehicles. It also categorises car automation into 5 levels and addresses risk factors.	Thierer and Hagemann Mercatus working paper, 2014
81	**Work zones**	Road geometry, road conditions, weather conditions, traffic rule enforcement, speed, road infrastructure, control, sensors, algorithms, weather conditions, visual cameras	To be deployed in real-world driving environments, AVs must be able to detect, recognise and handle exceptional road conditions, such as highway work zones as such peculiar events can alter previously known traffic rules and road geometry. These events can be challenging for AVs and pose safety risks. For example, the line of sight between a sign and a camera perceptually and computationally changes the colour of a work zone sign from that of the sign template. This can make it difficult for the vehicle to recognise the signs.	Seo *et al.* IEEE Transactions on Intelligent Transportation Systems, 2015
82	**Work zones**	Road geometries, traffic conditions, speed, reaction time, road conditions, traffic flow, longitudinal and lateral	Transition taper length has crucial effect on work zone safety since too short a transition taper length can result in higher collision risks and if the transition taper length is too long can lead to longer traffic delays. This paper evaluated the effect of taper length on the longitudinal lane changing distance and emergency stopping distance which are determinants of collision in work zones. Various traffic conditions and road geometries are taken into account for that purpose.	Weng Transportation Planning and Technology, 2011
83	**Work zones**	V2V, V2I, communication infrastructure, GPS, traffic network, algorithms, velocity, weather conditions, traffic conditions, roadside unites, path planning, time of day, day of week, driving behaviour, traffic control, traffic volume, situation awareness, obstacles	The primary objective of this research was to evaluate the potential safety benefits of deploying connected vehicles on a traffic network in the presence of a work zone. A relationship was observed between the safety benefits of rerouting around work zones and the detriments of longer average trip distances, which increased safety risks.	Genders and Razavi Journal of Computing in Civil Engineering, 2015
84	**Work zones**	Velocity, traffic flow, lane changing, longitudinal and lateral distance, other road users, traffic conditions, traffic congestion, traffic capacity, reaction time, time to collision, trajectory planning	Presence of work zones can affect the freeways' traffic metrics in a negative way (e.g., traffic delays, emission and speed variations). This research proposed a cooperative cellular automata model (CCAM) to be incorporated into CAVs as a collaborative component.	Zou and Qu Journal of Intelligent and Connected Vehicles, 2018
85	**Work zones**	Motion control, lane-changing control, traffic flow, traffic composition, speed limits, traffic conditions, V2I, algorithms, traffic density, traffic control infrastructure, number of lanes, weather conditions, road section, road conditions, motion planning	This paper aimed to simulate and assess the traffic performance around work zone under the CAV-based coordinated control of variable speed limits (VSL) and lane-changing (LC) strategies in mixed traffic flow. The simulation consisted of: a) a multi-layer control structure is applied in work zone traffic control; b) the work zone traffic simulation model is constructed based on cellular automata; and c) the six CAVs-based control strategies composed of NC, VSL, LC and their coordinated control strategies are simulated.	Wu *et al.* International Journal of Modern Physics B, 2020
86	**Work zones**	Speed variation, traffic conditions, traffic volume, other road users, actuators, V2V, GPS, software, hardware, traffic control, obstacle, environmental conditions, lateral and longitudinal positions, control, driving behaviour	Road maintenance operations such as bridge flushing and pothole patching are essential for safety of roads and highways. Nevertheless, it is vital to consider the hazards for the maintenance workers and public. This research can help transportation agencies that may consider deploying autonomous vehicles and to apply knowledge gained in transportation modelling and simulation practices. This paper developed a methodology for evaluation of an autonomous truck-mounted attenuator (ATMA) system and the results of field tests performed in April 2019 in Sedalia, Missouri.	Tang *et al.* Transportation Research Record, 2021

87	**Work zones**	Environmental conditions, traffic conditions, perception accuracy, planning algorithms, system integration, vehicle control, infrastructure, weather conditions, lighting conditions, component failure, other traffic participants, visibility, type of road, number of lanes, road geometry	It is held that to ensure the robustness of an AV architecture, dimensioning the parameters related to functional scenarios is of high importance. In this paper, a risk analysis approach is developed which intends to qualitatively identify hazardous patterns and by this way the underlying critical situations including work zones.	De Galizia, Bracquemond and Arbaretier Safety and Reliability – Safe Societies in a Changing World, 2018
88	**Work zones**	Road geometry, traffic control infrastructure, traffic flow, communication, weather conditions, speed, V2V, V2I, V2X, traffic composition, GPS, sensor, reaction time, LiDAR, lighting conditions, driver behaviour, path planning, algorithms, RSU, cameras, road conditions, obstacles	Due to increase in construction and maintenance activities, work zones are becoming common areas on highways. Work zones can expose both conventional and autonomous vehicles to a sudden and complex geometric change in the roadway environment and subsequently speed change which may challenge many of CAV navigation and control capabilities. To avoid collision, CAVs should be able to reliably traverse work zone geometry. This paper investigates the key concepts of deploying CAV systems at work zones focusing on mobility, safety, and infrastructure considerations.	Dehman and Farooq Working paper, 2021
89	**Work zones**	Number of lanes, V2X, V2I, mixed traffic, traffic control, driving state, traffic flow, road infrastructure, road geometry, obstacles, traffic congestion, trajectory planning	When it comes to CAVs lane changing is seen as a risky activity as it can cause lateral collisions when coordination is not appropriately performed. Nevertheless, in many traffic scenarios such as work zones, changing the lane is inevitable for the vehicle. This study developed a risk function to estimate the risk of a collision between a pair of vehicles, and then a predictive control model was used to solve the resulting constrained nonlinear optimisation problem.	Xu *et al.* Transportation Research Part C, 2020
90	**Work zones**	V2V, V2I, traffic flow, level of autonomy, mixed traffic, traffic conditions, communication, speed, algorithm, data fusion, tome-to-collision	The recent advent of CAVs is believed to pose an additional risk to traffic flow performance and safety around highway work zones. This paper developed a novel and utilised existing vehicle-driver models to simulate manual driving, mixed traffic and infrastructure-assisted highly automated traffic around highway work zones.	Mintsis *et al.* IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), 2020
91	**Work zones**	HMI, sensors, actuators, communication buses, radar, control structure, obstacles, vehicle environment, other traffic participants, weather conditions, vehicle dynamics	This study centred the “Automated Unmanned Protective Vehicle for Highway Hard Shoulder Road Workers” (aFAS). It aimed at designing unmanned protective vehicles to address the risk of injuries due to accidents for road maintenance staff in Germany. This paper applies a new method based on system theory and System-Theoretic Process Analysis (STPA).	Bagschil, Stolte and Maurer 4th European STAMP Workshop, 2016
92	**Work zones**	Motion control, environment perception, H-M Interfaces, HMI, obstacles, traffic rule enforcement, other traffic participants, road geometry, speed, longitudinal control, communication, sensors	This paper conducted hazard analysis for an unmanned protective vehicle operating without human supervision for motorway hard shoulder roadworks.	Stolte *et al.* IEEE Intelligent Vehicles Symposium (IV), 2017
93	**Cybersecurity**	Weather conditions, control, H-M interaction, and situation awareness	This paper investigates impacts of AVs form a Traffic Engineering Perspective and enlighten trends and challenges surrounding this technology and related infrastructure developments. It further highlights the cyber vulnerabilities of Autonomous Vehicles.	Tettamanti, Varga and Szalay Periodica Polytechnica Transportation Engineering, 2016
94	**Cybersecurity**	V2V & V2I, H-M interactions, traffic laws, weather, road type, speed	The Federal Automated Vehicles Policy includes vehicle cybersecurity in a framework for evaluating performance guidance of Highly Automated Vehicles (HAVs). It provides guidance on minimising safety risks due to Cyber-security threats and vulnerabilities.	US Department of Transportation NHTSA, 2016
95	**Cybersecurity**	Liability, ethics, communication	This study provides a review of the strategies formulated by multiple countries to govern the development of AVs.	Taeihagh and Lim Transport Reviews, 2018

96	Cybersecurity	Communication, VANET, IDS, V2V & V2I	It is emphasised that VANETs (a network of wireless links which are used to connect mobile vehicles) are exposed to security threats in communication systems. This paper focuses on two types of attacks (i.e. "control of a vehicle's resources" and "jamming the communication channels") and adopts a new approach to secure external communication.	Alheeti, Gruebler and McDonald-Maier IEEE 12th Consumer Communication and Networking Conference, 2015
97	Cybersecurity	Situation awareness, H-M interactions, reaction time, speed, communication	Some major concerns over the adoption of autonomous cars are highlighted in this article. It considers cybersecurity as one of the safety components of AVs and relates this to the vulnerability of on-board computers.	Elbanhawi, Simic and Jazar IEEE Intelligent Transportation Systems Magazine, 2015
98	Cybersecurity	RSU, AI, sensors, VANET, infrastructure, RSU, other road users, V2V, algorithms	This paper proposes a four-layer IDS for VANETs used in self-driving cars to detect potential threats and secure communication networks.	Straub *et al.* 12th System of Systems Engineering Conference, 2017
99	Cybersecurity	IoT, software, infrastructure, V2V & V2I, communication, traffic rules,	It is discussed that uncoordinated evolution of complex systems-of-systems while they are interconnected and integrated can expose a multitude of vulnerabilities and pose cyberattack threats. Main reasons are seen to be lack of standards and inadequate design. Then, cybersecurity requirements are proactively introduced to mitigate such risks.	Axelrod IEEE Long Island Systems, Applications and Technology Conference, 2017
100	Cybersecurity	VANET, software, communication, sensors, speed,	Security of driverless cars and the catastrophic fallouts which may be imposed on the society due to security issues are centred in this paper. Current communication technologies (VANET & ANN) which are used for driverless cars in addition to possible attacks on these systems are explored as well.	Ydenberg, Heir and Gill IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC), 2018
101	Cybersecurity	Software, hardware reliability, CAN, bus, communication, V2V, V2I, V2X, infrastructure, regulation, sensors	In this study, autonomous and unmanned vehicles are examined in terms of their cybersecurity vulnerabilities. Threats and attacks which may exploit these susceptibilities are identified and categorised.	Yağdereli, Gemci and Aktaş Journal of Defense Modeling and Simulation: Application, Methodology, Technology, 2015
102	Cybersecurity	Communication, V2V, V2I, HMI, infrastructure, regulations, trust	This journal article finds the privacy and cybersecurity risks of AVs as crucial and examines the measures taken by several governments around the world to mitigate these risks. The implications of AVs' cybersecurity for safety are highlighted too.	Lim and Taeihagh Energies, 2018
103	Cybersecurity	Communication, software, integration, regulation, standardisation, bus	This report was presented to the congressional requesters to investigate the vulnerabilities of modern vehicles (including autonomous vehicles and self-driving cars) to cyberattacks and the impacts they can have on passengers' safety. Key vehicle interfaces can be exploited through *direct access*, *short-range wireless* and *long-range wireless*.	GAO United States Government Accountability Office, 2016
104	Cybersecurity	Communication, V2V, V2I, bus, recovery	The security issues arising from external wireless communication in connected vehicles (V2V & V2I) are investigated. A defence-in-depth strategy is adopted to address these issues.	Larson and Nilsson 4th Annual Cyber Security and Information Intelligence Research Workshop, 2008
105	Cybersecurity	Communication, V2V, V2I, RSU, situation awareness, self-awareness, CAN, LIM, MOST	This journal article underlines the wireless gateway (as an entry point to the automobile in-vehicle network) to compromise cybersecurity of the vehicles and networks. The requirements and prerequisites for an in-vehicle forensic investigation system are proposed and discussed.	Nilsson and Larson International Journal of Digital Crime and Forensics (IJDCF), 2009
106	Cybersecurity	Communication, bus, CAN,	Prominent and established communication systems in vehicles besides potential attacks and exposures are investigated in this study. Cryptographic mechanisms are proposed to provide secrecy, prevent manipulation and mitigate the bus security issues of vehicles.	Wolf, Weimerskirch and Paar Workshop on Embedded IT-Security in Cars, 2004
107	Cybersecurity	Communication, CAN, bus, V2V	The authors analyse the potential security risks and their repercussions on safety measures when vehicles are equipped with and IP based protocol.	Lang *et al* 26th International Conference, SAFECOMP 2007
108	Cybersecurity	Software, hardware. ECU, communication, V2V, V2I, organisational structure, DES, autonomy level, infrastructure, integration, HMI	This study recognises IT security as one of the pivotal technologies for the next generation of vehicles. It further reflects on an interrelation technical failure (safety issue) and malicious attack (security issue).	Wolf, Weimerskirch and Wollinger EURASIP Journal on Embedded Systems, 2007

109	**Cybersecurity**	ECU, communication, software, BUS,	This paper raises concerns over the reliability and robustness of computer codes embedded in the highly automated and computerised vehicles. Any failure or deficiency can provide the possibility for attackers to obtain *remote code execution* on the electronic control units (ECU) and take control over steering, braking, acceleration and display. These attacks are deemed to potentially endanger the physical safety.	Valasek and Miller IOActive technical white paper, 2014
110	**Cybersecurity**	Autonomy level, regulation, H-M interface, communication, V2I, V2V, machine learning, HMI, traffic culture, traffic control infrastructure, GPS, control	The author critiques the current developed self-driving cars (e.g. Oxford University's RobatCar) to be fully and truly autonomous and defines an autonomous car as *self-contained*, *self-determining*, *self-correcting*, *self-healing*, and ultimately *self-aware*. Therefore, any engagement in communities can give rise to the cybersecurity risks due to security breaches, hacking and privacy violations.	McBride Computers & Society, 2015
111	**Cybersecurity**	Communication, design, software, hardware	This document is an overview of the SAE Cybersecurity Guidebook for Cyber-Physical Vehicle Systems (SAE J3061). The motivations and necessities (e.g. lack of common principals, processes, and terminologies between OEMs and Tier 1 suppliers) for developing such a practice as well as the link between System Safety and System Cybersecurity are defined.	Boran, Czerny and Ward SAE International, 2016
112	**Cybersecurity**	Communication, sensors, GPS, radar. LiDAR, ECU, CAN, V2V, V2I	The author maintains that cyber threats are among main concerns of AV developers and draws a positive (direct) relationship between the level of autonomy and the possibility of cyber-attacks.	Raiyn Transport and Telecommunication, 2018
113	**Cybersecurity**	V2V, V2I, V2X, software, CAN, ECU, LIN, sensors, LiDAR	The advent of connected vehicles (including AVs) has of necessity called for protection methods against cyber-attacks to circumvent such attacks and secure connected services. This paper surveys recent trends in cyber-attacks and cybersecurity countermeasures.	Takahashi IEICE Transactions on Information and Systems, 2018
114	**Cybersecurity**	Communication, V2V, V2I, hardware, software, design, integration, standardisation	The rise in inter-vehicle connections as well as networking with non-vehicle entities (which is a prominent feature of AVs) impose new challenges to the assurance of dependability for Cyber-Physical Systems (CPS).	Macher *et al* 24th European Conference, EuroSPI, 2017
115	**Cybersecurity**	AI, machine learning, deep learning, neural networks, hardware	Due to the exponential increase in deployment of Cyber-Physical Systems and machine learning (ML) techniques (e.g. AVs), new cybersecurity vulnerabilities are introduced into these systems. This work provides a brief overview of security threats in ML-based systems (during training and inference) and their threat models.	Khalid *et al* International Conference on Frontiers of Information Technology, 2018
116	**Cybersecurity**	IoT, communication, V2V, integration,	This paper scrutinises the V2V communication in CPSs and acknowledges the issue of network security in V2V connections.	Wan *et al* Computer Science & Information Systems, 2013
117	**Cybersecurity**	CAN, bus, WiFi	The link between cyber-attacks and safety physical repercussions in CPSs and AVs due to their mobility is indicated. To facilitate the automatic detection of cyber-attacks on those systems, the authors have developed a detection mechanism to oversee large amount of real-time data form various sources such as sensors and networks.	Bezemskij *et al* 15th International Conference on Ubiquitous Computing and Communications and 2016 International Symposium on Cyberspace and Security
118	**Cybersecurity**	Traffic, communication, VANET,	This paper investigates the reaction of traffic flaw to *false-accident* attacks (a form of cyber-attack) in connected vehicles. The experimental results show that this class of cyber-attack may or may not significantly affect the traffic congestion and traffic perturbation. The extent of impact varies depending on the initial conditions, behavioural assumptions, and attacking parameters.	Jin *et al* International Conference on Connected Vehicles and Expo (ICCVE), 2013

119	**Cybersecurity**	Physical safety, collision	The mounting integration of autonomous systems (e.g. parcel delivery and driverless cars) with publicly available networks, ad-hoc wireless and satellite networks and other remote operators can potentially expose them to cybersecurity threats. Therefore, designing security mechanisms is integral CPSs.	Xu and Zhu IEEE 54th Annual Conference on Decision and Control (CDC), 2015
120	**Cybersecurity**	Trust, V2X, infrastructure, hardware, ECU, cloud, software, traffic infrastructure	With the advancement of V2X technologies and assimilation of AVs into the intelligent traffic infrastructure, remote interaction between safety-critical components becomes investable. Although the realisation of such an integrated system is appraised to have benefits, the main challenge with AVs and their interconnectivity is their vulnerability to cyber-physical attacks. In this study, a *remote testimony architecture* is proposed to receive/send testimony of correctly executed programmes without "integrity violation".	Alesiani and Gajek IEEE 83rd Vehicular Technology Conference (VTC Spring), 2016
121	**Cybersecurity**	ECU, software, hardware, integration, CAN, firmware,	This paper takes security implications of on-board network of ECUs into account and develops an automated, quantitative, probabilistic method and metric for attack surface and vulnerability assessment automation. The focus is mainly on *injecting malicious code* which can exploit the vulnerabilities of the actual implementation.	Salfer and Eckert 12th International Joint Conference on e-Business and Telecommunications (ICETE), 2015
122	**Cybersecurity**	Communication, V2X, CAN, VLAN	With V2X communication and distributed connected nature of AVs, security becomes a focal issue of future automotive systems. The security, safety and their interactions in Ethernet-based automotive networks are discussed in this study.	Lin and Yu 53rd ACM/EDAC/IEEE Design Automation Conference (DAC), 2016
123	**Cybersecurity**	IoT, CAN, integration, VIMP	Considerable increased attack surface, complexity, heterogeneity and number of interconnected resources are major challenges in securing and protecting advanced information services in interconnected smart vehicles as a result of IoT realisation. A framework (ISDF) is therefore developed by the authors to build secure and trustworthy AV networks.	Pacheco *et al* IEEE Conference on Intelligence and Security Informatics (ISI), 2016
124	**Cybersecurity**	Communication, hardware, software, infrastructure, V2I, V2V, V2X, CAN, bus, FlexRay, sensors, integration, GPS, autonomy level, infrastructure, cloud	In this paper, interconnectivity is seen as a factor which can heighten the risk of a cybersecurity breach. Higher automation (autonomy level) can exacerbate the consequences of any breach or attack. This paper presents a review of publicly accessible literature and categorises the vulnerabilities in CVs and AVs.	Parkinson *et al* IEEE Transactions on Intelligent Transportation Systems, 2017
125	**Cybersecurity**	Software, hardware, communication, V2V, V2I, V2X, situation awareness, sensors, CAN, ECU, GPS	This study develops a *proactive* cybersecurity risk classification model (Bayesian Network) and by incorporating known software susceptibilities into the model tries to overcome this issue in CAVs.	Sheehan *et al* Transportation Research Part A: Policy and Practice, 2019
126	**Cybersecurity**	Pedestrian, software, AI	It is shown that if the decision-making processes and functions of an autonomous vehicle are transparent and perfectly known, then the risk of manipulation caused by malicious, opportunistic, terrorist, criminal and non-civic individuals increases. This manipulation can be either physical or cyber.	Osório and Pinto International Journal of Human-Computer Studies, 2019
127	**Cybersecurity**	IoT, systemic collapse,	Extreme automation until ''everything is connected to everything else'' can pose vulnerabilities that have not raised too much concerns until now. For example, highly integrated systems are susceptible to *systemic risks* such as total network collapse in the event of failure of (or glitch in) one of its parts, for instance, by hacking or computer viruses or malwares that can put integrated systems at serious risks.	Özdemir and Hekim Journal of Integrative Biology, 2018
128	**Cybersecurity**	Human factors, trust, communication, infrastructure, standardisation, training and experience	Human factors are seen to be the most common contributor to successful cyberattacks. In this paper, the role of human factors in AVs' cybersecurity is studied and recommendations are made to strengthen the security of this technology.	Linkov *et al*. Frontiers in Psychology, 2019

129	**Cybersecurity**	Communication, V2X, V2I, V2V,	Although ample amount of generated and transferred data play a pivotal role in data-driven economies of scale as far as AVs are concerned, privacy and integrity-dependent scenarios can pose a challenge. The concept of 'hyperconnected vehicle' as well as security techniques are developed in this paper to tackle these challenges. There are some safety risks identified in this paper such as wrong information fed into the navigation module of the car or security and safety issues due V2I.	Karnouskos and Kerschbaum Proceedings of IEEE, 2017
130	**Cybersecurity**	Communication infrastructure, V2V, other road users, hardware and software reliability, traffic composition, sensor reliability	Several factors that can affect the adoption of AVs and users' trust are discussed in this article. Among them, there are some risks and concerns about the performance of the technology. Security, hardware/software reliability, sensor reliability and network security are identified to have impact on the safe performance of the vehicle. For example, it is asserted that any failure of the sensors can cause a fatal accident.	Kaur and Rampersad Journal of Engineering and Technology Management, 2018
131	**Cybersecurity**	Traffic conditions, sensors, actuators, kinematic state, speed	AVs are inherently cyber-physical systems. This means such vehicles will have novel security vulnerabilities that entail both the cyber aspects of the vehicle including the on-board computing software and any communication channel, with the physical nature and hardware of the vehicle including its sensors, electronics and actuators.	Mascareñas, Stull and Farrar Mechanical Systems and Signal Processing, 2017
132	**Cybersecurity**	Communication, connectivity, V2I, V2V, RSU, traffic flow, traffic conditions, position and speed, congestion, reaction time, road capacity, control, number of lanes	The impacts of cyber-attacks on CAVs based on the proportion of attacked vehicles, cyber-attack severity and attack range are evaluated in this research. Four indicators including safety were singled out to analyse the performance of transportation system in case any cyber-attack occurs. The findings of this study provide useful insights for the prediction and mitigation of cyber-attacked traffic system in future.	Dong *et al.* IEEE Access, 2020
133	**Communication**	Infrastructure, collision avoidance	This study evaluates Carcel on a state-of-the-art autonomous driving system which can facilitate communication between AVs and roadside infrastructure to reduce the average time vehicles need to detect obstacles such as pedestrians.	Kumar, Gollakota and Katabi Association for Computing Machinery, 2012
134	**Communication**	Infrastructure, traffic, and speed	This research tries to answer whether V2V and V2I communication platforms in self-driving vehicles can efficiently improve travel quality while reducing the risk of collisions. To this end, the researchers developed a simulation software to visualise traffic flow.	Gora and Rüb Transportation Research Procedia, 2016
135	**Communication**	Sensors, control, processing, situation awareness, traffic, security, infrastructure	This study provides a summary on the Internet of Vehicles (similar to IOT) as well as vehicular cloud and explains implications of V2I and V2V in autonomous driving scenarios.	Gerla *et al* IEEE World Forum on Internet of Things, 2014
136	**Communication**	Security, traffic, speed, autonomy level, control, sensors	This study presents a first look at the effects of security attacks on the communication channel as well as sensor tampering of a connected vehicle stream equipped to achieve CACC.	Amoozadeh *et al* IEEE Communications Magazine, 2015
137	**Communication**	Sensors, GPS, infrastructure, traffic, vulnerability, software	To increase the security of VANET which are deployed in self-driving cars, the authors propose an intrusion detection mechanism using Artificial Neural Networks to detect Denial of Service.	Alheeti and Gruebler and McDonald-Maier IEEE 12th Consumer Communication and Networking Conference, 2015
138	**Communication**	Infrastructure, situation awareness, speed	This paper reviews traditional comfort measures and proposes autonomous passenger awareness factors. It also highlights some concerns with autonomous cars (e.g. road safety, software reliability and cybersecurity).	Elbanhawi, Simic and Jazar IEEE Intelligent Transportation Systems Magazine, 2015
139	**Communication**	Situation awareness, speed, sensor	This paper develops a conceptual model to assess the situation risks for autonomous motion planning in urban environments.	Wardziński 1st International Conference on Information Technology, 2008

140	**Communication**	Cybersecurity, VANET, RSU, DSRC, type of road, infrastructure, sensors, V2I	Vehicular Ad hoc Network (VANET) enables inter-vehicular communication as well as communication between vehicles and various road side units (RSU). This work proposes a novel message authentication scheme that protects cars from bogus messages and makes VANET resilient to Denial-of-Service (DoS) attacks.	Abueh and Liu Symposium on Technologies for Homeland Security (HST), 2016
141	**Communication**	Platooning, car-following strategies, control, mixed traffic	This study presents a car-following strategy for mixed traffic stream which involves platoon development in a connected automated vehicle (CAV) environment. The study also explores various platoon configurations to determine platoon parameters at different traffic states to obtain utmost benefits.	Seraj, Li and Qiu Journal of Advanced Transportation, 2018
142	**Communication**	V2V, cybersecurity, path planning, sensors, VANET, RSU	This paper investigates the security risks of vehicle to vehicle communications. Further it proposes an intrusion detection system for the self-driving car network system-of-systems.	Straub *et al* 12th System of Systems Engineering Conference (SoSE), 2017
143	**Communication**	VANET, Cybersecurity, RSU, software, control, security protocols, integrity	This study applies Artificial Neural Networks (ANN) to tackle the security problems with Vehicle Ad Hoc Networks (VANET). It divides the attacks into two groups with different purposes: 1) take the control of a vehicle's resources and 2) jam the communication channels.	Ydenberg, Heir and Gill IEEE 8th Annual Computing and Communication Workshop and Conference (CCWC), 2018
144	**Communication**	Software, sensor, regulations, pedestrians, self-awareness, V2V, V2I, traffic congestion	This paper provides an overview and short history of self-driving vehicles. It also reviews different levels of autonomy and divides the technology into four basic components: sensor, mapping, perception and communication.	Lutin, Kornhauser and Lerner-Lam ITE Journal, 2013
145	**Communication**	Infrastructure, sensors, cameras, road conditions	This article mainly focuses on liability and insurance risks of autonomous cars. It highlights the facilitated communication between vehicles and infrastructure as a potential risk factor.	Stankard Aon Risk Solutions, 2017
146	**Communication**	Ethics, Cybersecurity, regulations, standardisation	This study adopts a broader perspective (than just complexities arising from a single vehicle) and analyses the impacts and interactions that AVs can have on each other and the socio-technical systems. The discussion includes the apprehensions that need to be addressed to implement V2V communication successfully.	Borenstein, Herkert and Miller Science and Engineering Ethics, 2017
147	**Communication**	Situation awareness, collision avoidance, control, pedestrian, V2V, V2I and V2X	This paper reviews the evolution of technologies which facilitate the communication between vehicles and between vehicles and infrastructure. It also emphasises the benefits of such technologies in collision avoidance, increasing situational awareness and detecting threats.	Narla ITE Journal, 2013
148	**Communication**	Self-awareness, take over control and cybersecurity	This paper addresses some of the early policy concerns about "connected cars" and driverless vehicles.	Thierer and Hagemann MERCATUS Working Paper, 2014
149	**Communication**	V2V, V2I, V2X, HMI, VANETs, H-M interface, situation awareness, traffic environment,	The role of V2X and V2I in design and improvement of HMI and reduction in accidents is highlighted in this study.	Olaverri-Monreal and Jizba IEEE Transactions on Intelligent Vehicles, 2016
150	**Communication**	Control, sensors, LiDAR, cameras, weather conditions, other road users, algorithms, V2X, V2V, V2I, road infrastructure, speed, visibility, work zones, road conditions, communication infrastructure	This paper sees communication as an additional sensor feeding traffic/road information to the vehicle. For example, under adverse weather conditions that the sensors and LiDAR can be impaired, communication channels (e.g., V2I) can relay information.	Uhlemann IEEE Vehicular Technology Magazine, 2018
151	**Communication**	Big data, infrastructure, cybersecurity, regulations, software, sensors	This article investigates the challenges and opportunities pertaining to transportation policies that may arise as a result of emerging Autonomous Vehicle (AV) technologies.	Bagloee et al Journal of Modern Transportation, 2016
152	**Communication**	V2X, algorithm, traffic congestion, traffic control infrastructure, VANET, communication, vehicle control, traffic regulation, RSU, traffic flow, traffic condition, vehicle velocity, traffic complexity	A *vehicle-to-everything* V2X is combined with AI algorithms to enhance traffic management efficiency. This proposed concept can be applied to intersections and assist with collision avoidance.	Xu *et al.* IEEE Internet of Things Journal, 2021

153	**Communication infrastructure**	Communication, cybersecurity, V2I, V2V, IoT	The evolution of smart automobiles and vehicles within the Internet of Things (IoT) - particularly as that evolution leads toward a proliferation of completely autonomous vehicles - has sparked considerable interest in the subject of vehicle/automotive security. While the attack surface is wide, there are patterns of exploitable vulnerabilities. As vehicles become more connected, road infrastructure components become an intrinsic part of these growing transportation computing networks.	Brewer and Dimitoglou International Conference on Computational Science and Computational Intelligence (CSCI), 2019
154	**Communication infrastructure**	Communication, cybersecurity, V2I, V2V, V2X, RSI, RSU, H-M interface	In this paper, the authors developed a communication model for autonomous vehicles and identified threats to the security of the fully autonomous vehicle communication infrastructure.	Oham, Jurdak and Jha arXiv preprint, 2019
155	**Communication infrastructure**	Traffic flow, communication, regulations, V2I, V2V,	This article explores and investigates possible interventions and their impacts which can be made by governments to manage congestion or protect accessibility in the AV scenarios. AV is seen as an emerging technology which offers both benefits and poses risks which must be governed.	Cohen and Cavoli Transport Reviews, 2019
156	**Communication infrastructure**	Communication, V2I, V2V, V2X, control, speed, regulation, road geometry, traffic flow, time of day,	The results of this research could provide valuable insights to policy makers regarding the reconfiguration of existing infrastructure to accommodate CAVs, the trustworthiness of existing connected AV equipment and the optimal platoon size that should be enforced according to the market penetration rate.	Papadoulis Doctoral thesis, 2019
157	**Communication infrastructure**	Road infrastructure, integrity, cybersecurity, V2I, V2V, V2X, control, human factors, other road users,	This study identifies cybersecurity risks as a result of 'uncoordinated design and development', particularly of supporting infrastructure systems. It is also concluded that if infrastructure systems, both physical and cyber, do not receive the attention required to achieve sufficient levels of cybersecurity and safety, AV developers will hit a roadblock.	Axelrod 13th International Conference and Expo on Emerging Technologies for a Smarter World (CEWIT), 2017
158	**Communication infrastructure**	Communication, V2V, road infrastructure, traffic density, traffic conditions, sensors, LiDAR	Changing lanes can be risky in some traffic scenarios. This paper proposes two protocols to reduce this risk for CAVs when performing lane change. These protocols are designed to increase the safety of lane changing to the highest level.	Hodgkiss, Djahel and Hadjadj-Aoul 16th IEEE Consumer Communications & Networking Conference, 2019
159	**Communication infrastructure**	Self-awareness, situation awareness, communication, sensors, LiDAR, RADAR, V2I, V2V, GPS, vehicle dynamics, road design, RSU	The concept of 'infrastructure enabled autonomy' is developed in this study. A Bayesian Network Model-based framework is proposed for assessing the risk benefits of such a distributed intelligence architecture. It is believed that in the context of AVs, infrastructure plays a critical role.	Gopalswamy and Rathinam IEEE Intelligent Vehicles Symposium, 2018
160	**Communication infrastructure**	Traffic composition, V2V, traffic flow, RSU, road infrastructure, reaction time	This study highlights the role of V2V communication in collision avoidance and reaction time to hazardous situations.	Li *et al.* Transportation Research Part C, 2020
161	**Communication infrastructure**	Cybersecurity, software failure, trust, HMI	A system dynamic (SD) model is simulated to assess the risks and opportunities of adopting AVs from the insurance perspective. Several factors are identified to have impact on the 'crash rate', 'loss rate' and 'loss ratio'.	Liu, Rouse and Belanger IEEE Systems Journal Systems Journal, 2020
162	**System integration**	Path planning, control, software, algorithms, LiDAR, Visual cameras, actuators, sensors, sensor fusion, motion planning, GPS, speed, kinematic state	System integration besides perception, planning and control is seen to have a key role in development of AVs. The robustness and reliability of an AV depends on the integration of all sub-systems. This report provides an overview of the system architecture of AVs and develops a real-time path planning and speed control algorithm for autonomous vehicles to avoid obstacles.	Chu, Kim and Sunwoo SAE technical paper series, 2012
163	**System integration**	Other road users, traffic culture, traffic regulation, road infrastructure, regulation, visibility, time of day, weather conditions, HMI	'System integration' can be a challenge with serious consequences in diverse disciplines. Improper system integration can lead to risks and loss of lives and/or assets. Further, 'integration' can be a key performance indicator of cost, quality and time. This study suggests consideration of both technical and non-technical factors in *system integration* and develops a theoretical foundation for properly integrating (engineering) systems.	Rajabalinejad, van Dongen and Ramtahalsing Safety and Reliability, 2020

164	**System integration**	system complexity, hardware & software components, human and environmental factors	System integration technical risk assessment is a challenging task particularly in large complex engineering systems with both software and hardware components. A BBN model is proposed to tackle this challenge. Several risk exposure variables are determined, and states are qualitatively defined: critical, significant, moderate, and low.	Loutchkina *et al.* Journal of Intelligent & Fuzzy Systems, 2013
165	**System integration**	Trajectory generation, V2I, V2V, other road users, work zone, AI, sensors, localisation, radar, cameras, H-M Interfaces, control, actuators, motion planning, path tracking, software infrastructure, algorithms, hardware, velocity, vehicle kinematic models, communication, perception, GPS, LiDAR, sensor fusion, work zone, obstacles	The Carnegie Mellon University (CMU) autonomous vehicle research platform has been tested extensively on public roads to evaluate its safety and reliability. Various AD capabilities of this platform e.g. lane changing, intersection handling and trajectory planning are discussed in this paper.	Wei *et al.* IEEE Intelligent Vehicles Symposium (IV), 2013
166	**Sensor fusion**	Weather conditions, sensors, target perception, cameras, LiDAR, tracking algorithms, control systems, radar, other road users, relative velocity, vehicle intelligence, roadside infrastructure, obstacles, perception accuracy	This study discusses the increasing risk of using single sensor for detecting obstacles by AVs and advocates the installation of an array of sensors. To achieve an integrated perception system, a multi-sensor fusion and tracking algorithm are proposed in this paper.	Yi, Zhang and Peng Journal of Automobile Engineering, 2019
167	**Sensor fusion**	Other road users, traffic density, dynamic object perception, traffic conditions, speed, trajectory tracking, time-to-collision, kinematical state, sensors, LiDAR, radar, traffic rules, road conditions, traffic control, human-vehicle-environment interactions, object type, AD algorithms	A risk assessment method based on multi-sensor fusion is developed to integrate 4 states of track life into a generic fusion framework thereby improving the performance of multi-object perception by AVs. The results of the testing reflect low false and missing tracking.	Zheng *et al.* Journal of Intelligent and Connected Vehicles, 2018
168	**Sensor fusion**	Traffic laws, LiDAR, sensors, radar, HD cameras, GPS, control system, obstacles, perception, path planning, redundancy of software/hardware components, number of sensors	Relying merely on LiDAR sensors even in low-speed AVs (LSAV) carries risk and can lead to collision. Therefore, sensor fusion system is requited to verify the authenticity of the information provided by sensors. “In this paper, an observer system is present for fault detection of automated sensor fusion system for a LSAV, which functions based on octree fusion”.	Raouf *et al.* IEEE 91st Vehicular Technology Conference, 2020
169	**Sensor fusion**	Obstacles, sensors, environmental conditions, speed, laser scanner, depth cameras, plausibility algorithm, latency	In order for AVs to avoid collisions, it is essential to detect small-size obstacles accurately and in a timely manner. This study investigates the distance detection fusion of a target away from two uncorrelated, different sensors (i.e., depth camera and laser).	Khesbak 18th International Multi-Conference on Systems, Signals & Devices, 2021
170	**Sensor fusion**	Environment perception, sensors, wireless communication, other road users, trajectory prediction, V2X, longitudinal and the lateral motion control, weather conditions, radars, cameras, lidars, lighting conditions, V2I, V2N, V2V, matching algorithms, CAN, RSU, relative speed, localisation, position accuracy, time-to-collision, road configuration, traffic signals	This study presented a configuration for environment perception based on the fusion of vehicular wireless communications and remote sensors. A *track-to-track fusion* of high-level sensor data and vehicular wireless communication data were collected and analysed to locate the remote target in the vehicle radios and predict their future trajectory. The proposed approach was implemented and tested in vehicle on vehicles.	Baek *et al.* Sensors, 2021

171	**Sensor fusion**	Wireless communication, velocity, acceleration, V2V, radar, risk assessment algorithm, other traffic participants, road geometry, kinematic state, traffic flow, vehicle trajectory, traffic behaviour models	To avoid collisions and increase ride comfort it is vital for AVs to monitor and predict the behaviour of other traffic agents in nearby. This paper derives desired steering angle and longitudinal acceleration to pinpoint a safe kinematic state for the ego vehicle based on the probabilistic prediction of other traffic participants using radar or radar/V2V information fusion.	Shin *et al.* IEEE 18th International Conference on Intelligent Transportation Systems, 2015
172	**Sensor fusion**	Perception, traffic conditions, camera, LiDAR, sensor tolerances, radar, dynamic sensors, plausibility sensors, software algorithms, trajectory prediction, geometry of the vehicle, weather conditions, lighting conditions, V2X, obstacles, speed, driver behaviour	This paper developed a novel method for evaluating collision risk in the precrash phase based on information fusion using camera and LiDAR for bullet vehicle detection together with *physical motion model-based* collision detection.	Lugner *et al.* IEEE 3rd Connected and Automated Vehicles Symposium, 2020
173	**Sensor fusion**	5G, radar, LiDAR, sensors, V2X, V2V, V2I, IoT, cameras, RSU, communication infrastructure, ML algorithms	A collision avoidance system is proposed which uses data fusion to predict potential collision events. The performance of this system was evaluated within a testbed.	Lee, Yang and Moessner International Conference on Information and Communication Technology Convergence (ICTC), 2020
174	**Sensor fusion**	Parked cars, traffic participants behaviour, trajectory planning, other traffic participants, machine learning, perception, mapping, localisation, object tracking, weather conditions, time of day, cameras, sensors, vehicle specification, radar, lane characteristics, construction sites, obstacles, traffic density, visibility, road topology	This paper focuses on the challenge of parked vehicles for AVs and introduces a list of features as *candidate predictors* to classify parked cars on urban roads. To detect objects sensor fusion becomes crucial to achieve a more realistic perception of the environment including parked vehicles. For this purpose, the information from every individual sensor are combined to generate a more accurate map of the surrounding for AVs.	Behrendt *et al.* IEEE Intelligent Vehicles Symposium, 2019
175	**Sensor fusion**	Data integrity, V2X, sensors, cyber-attacks, control algorithms, LiDAR, cameras, radar, perception, road boundaries, speed, lighting conditions, deep learning	Connectedness of AVs exposes them to cybersecurity risks including compromised sensors and/or manipulating sensory data. One of the possible ways to construct an array of sensors for AVs is the *centralised data fusion architecture.* In this structure, multiple sensors are linked to the decision-making (perceiving and planning) module through different interfaces. In this paper, a *3D QIM based data-hiding techniques* to safeguard data from LiDAR sensors.	Changalvala and Malik IEEE Symposium Series on Computational Intelligence (SSCI), 2019
176	**Sensor fusion**	Path planning, monocular cameras, LiDAR, obstacles, localisation, radar, vision sensors, algorithms, sensor modalities, objection detection	This study develops a framework for detecting and tracking objects for AVs using LiDAR sensors, cameras, and a fusion of range and vision sensors.	Rangesh and Trivedi IEEE Transactions on Intelligent Vehicles, 2019
177	**Sensor fusion**	Sensors, data alignment, path planning, obstacles, other roadway users, communication infrastructure, LED radar, ultrasonic sensors, LiDAR, stereovision, relative velocity	Autotaxi is a safety critical sensory system which is proposed in this paper to perceive surrounding environment for an AV. To address the *multiple-sensor multiple-target* tracking data fusion problem, a decentralised structure known as *sequential pair-wise track-to-track fusion* is proposed.	Escamilla-Ambrosio and Lieven 7th International Conference on Information Fusion (FUSION), 2005
178	**Sensor fusion**	Control, laser range finder, GPS, trajectory planning, obstacles, radar, velocity, kinematic model, curvature	Two major research areas in the field of AD are road-following and collision avoidance. A sensor fusion system is proposed for electric AVs' navigation and control. It is designed to integrate signals of laser range finders, magnetometers and inertial measurement units (IMUs).	lee, chen and Li IEEE International Conference on Systems, Man, and Cybernetics, 2011
179	**Sensor fusion**	Localisation integrity, gyro, smart cameras, HD maps, GNSS, GPS, LiDAR, trajectory planning, road curvature	To bound the estimation errors with low probability risk for AVs, the classical Kalman filter is substituted with a *Student's t filter*. Besides, a novel real-time adaptive computation of the degree of freedom is suggested to utilise the *heavy tailored property* of t distribution.	Al Hage, Xu and Bonnifait 22th International Conference on Information Fusion (FUSION), 2019

180	**Sensor fusion**	Other road users, object tracking, trajectory estimation, sensory systems, algorithms, localisation, environmental perception, LiDAR, GNSS, cameras, system integration, hardware limitations, software, motion planning, cybersecurity, vehicle control, weather and lighting conditions, obstacles, radar, ultrasonic, exteroceptive sensors, relative velocity, visibility	The emphasis is placed on the objection detection criticality for AVs especially when dynamic elements such as pedestrians and cyclists are present in the scene. Different sensory systems were tested and scrutinised to evaluate their advantages, limitations and applications in AVs. Sensor fusion and its role in overcoming limitations of individual sensors are broadly discussed in this paper.	Khatab *et al.* Integration, 2021
181	**Sensor fusion**	Sensors, obstacles, algorithms, perception, vision cameras, LiDAR, radar, software, vehicle control, weather conditions, other road users, system integration, planning, V2X, actuators, IoT, localisation, path planning, ultrasonic sensors, environment mapping, road infrastructure, traffic conditions, lighting conditions, visibility	This paper reviews recent multi-sensor fusion algorithms for detecting on-road object in AD. The challenges that can hurdle fusing information from different sensors are highlighted.	Yeong *et al.* Sensors, 2021
182	**Self-awareness**	Cameras, GPS, sensors, machine learning, algorithms, actuators, planning, control, perception, obstacle, radar	One of the fundamental challenges in the field of robotics is how to systematically integrate self-awareness (SA) capabilities into artificial agents. This paper presented "a bio-inspired framework for generative and descriptive dynamic models that supports SA computationally and efficiently". This is expected to contribute to the evolution of autonomous systems.	Regazzoni *et al.* Proceedings of the IEEE, 2020
183	**Self-awareness**	Trajectory planning, pedestrian, obstacles, velocity, algorithms, animal crossing, weather conditions, driving style, perception, machine learning, communication capabilities, environmental conditions, sensors, HMI	Self-awareness is necessary for autonomous vehicles as an element of Intelligent Transportation Systems. This study introduced an original method to achieve self-awareness in AVs. A data-driven Dynamic Bayesian Network was developed to use multi-sensory data to detect anomalies.	Kanapram *et al.* Robotics and Autonomous Systems, 2020
184	**Self-awareness**	Machine learning, control, sensors, planners risk analysis modules, HMI, reinforcement learning, hardware components, actuators, system integration, control algorithms, environmental perception, system architecture	This paper offers an overview of building self-aware autonomous systems and how self-aware behaviour can be verified. This framework is based on a modular architecture where key autonomous decision making takes place. It is deemed that self-awareness is crucial for safety, reliability, and verifiability of autonomous systems.	Dennis and Fisher Proceedings of the IEEE, 2020
185	**Self-awareness**	Machine learning, system configuration, control cycle, algorithms	This paper offers a solution for incorporating self-awareness principles in electronic design automation (EDA) for autonomous systems such as autonomous cars. The Information Processing Factory (IPF) metaphor was used as an exemplar to demonstrate how self-awareness can be realised across multiple abstraction levels.	Sadighi *et al.* Design, Automation & Test in Europe Conference & Exhibition (DATE), 2018
186	**Self-awareness**	Visual perception, system integration, sensors, cameras, algorithms	This study proposed a novel approach for learning self-awareness models and integrating it into AVs. This proposed technique relies on the availability of synchronised multi-sensor dynamic data.	Ravanbakhsh *et al.* 21st International Conference on Information Fusion (FUSION), 2018
187	**Self-awareness**	System integration, machine learning, communication, sensors, hardware/software platform, other traffic participants, CAN controller, cameras, LiDAR, radar, control algorithms, actuators, hardware reliability, weather conditions	The notion of *self-awareness* has been intertwined with autonomy of computing systems. In automotive systems, self-awareness mechanisms of all layers need to be coherent and integrated to avoid *conflicting decisions* and subsequent catastrophic consequences.	Schlatow *et al.* Design, Automation & Test in Europe Conference & Exhibition (DATE), 2017

188	**Self-awareness**	Maintenance, sensors, software, processing, communication, mission planning, component failure, control, HMI, sensors, perception,	This study investigates the costs and benefits of integrated system health management and autonomous control in autonomous and robotic exploration. Intelligent Self-situational awareness refers to the ability of a system to autonomously assess its health and condition and to interpret the impact of its current and future health and condition on current mission objectives.	Reichard *et al.* 1st Space Exploration Conference, 2005
189	**Road infrastructure**	Traffic density, traffic flow, speed, algorithms, traffic control infrastructure	This paper analyses numerical results to explore insights from the introduced modelling framework for AV network equilibrium. This is because a reliable estimation of network traffic pattern serves as the foundation of system assessment and governmental policymaking for infrastructure development.	Zhang, Liu and Waller Computer-Aided Civil and Infrastructure Engineering, 2019
190	**Road infrastructure**	Communication, hardware, software, system integrity	A question is raised about how the current road infrastructure must be changed to accommodate AVs and achieve the desired performance.	Maurer *et al.* Autonomous Driving, 2016
191	**Road infrastructure**	Road configuration, communication, V2V, V2I, traffic flow, V2X	The main goal of this study is to design a microscopic traffic simulation model for AVs, including a robust protocol for exchanging information. The question arises as to whether such communication system may efficiently improve travel quality while reducing the risk of collisions. The transport infrastructure in this work includes multiple junctions, optionally equipped with traffic lights, and roads with varying number of travel lanes. Each vehicle is assigned a fixed route leading to a randomly chosen destination point.	Gora and Rüb Transportation Research Procedia 14, 2016
192	**Road infrastructure**	Traffic control infrastructure, traffic congestion, other road users, positioning,	This report emphasises the need for investment in Finnish road infrastructure to host self-driving and electric cars.	Hyytinen, Määttänen and Vihriälä The Research Institute of the Finnish Economy, 2018
193	**Road infrastructure**	Other road users, vehicle dynamics, static and dynamic obstacles, road geometry, road type, environmental factors, traffic conditions, motion control	Several risk factors to the trajectory planning for AVs are identified in this study. Static road infrastructure (e.g. roadside trees) are mentioned among factors which can affect the path planning systems of AVs.	Wei *et al.* Transportation Research Part C: Emerging Technologies, 2019
194	**Road infrastructure**	Cybersecurity, other road users, GPS, regulation,	This report discusses the benefits and costs of AVs and predicts their likely development and implementation based on experience with previous vehicle technologies. It also highlights the need for additional roadway infrastructure for AVs.	Litman Victoria Transport Policy Institute, 2014
195	**Road infrastructure**	Road conditions, traffic density, speed, human factors, road geometry	This paper investigates the impacts of road infrastructure on drivers' behaviour and collision risks. A new method based on field strength is developed to assess the risks of road infrastructure.	Li and Chen Journal of Advanced Transportation, 2018
196	**Road infrastructure**	Speed, traffic flow, traffic control, road configuration	Historical data are used to develop a BN model to quantify the risks of accidents. The BN model was mainly developed using machine learning through combination of accident data from the Cyprus Police and traffic data generated with VISTA. The enriched dataset, enabled the specification of the BN variables' causal relationships and the corresponding CPTs.	Gregoriades and Mouskos Transportation Research Part C, 2013
197	**Road infrastructure**	Communication, visual cameras, lighting conditions, work zones, HMI, H-M interface, reaction time, other road users, AI maturity, objects, weather conditions, regulatory requirements, V2V, V2I, RSU, speed, traffic rules	This article identifies main challenges ahead of mass adoption of self-driving cars and requirements to increase their safety while operating in complex environments such as urban areas. It is seen to be necessary to standardise the driving environment and invest in road infrastructure.	Oliver, Potočnik, and Calvard Harvard Business Review, 2018

198	**Road infrastructure**	Road configuration, regulatory requirements,	The author argues that several changes other than technical aspects, for example in road configuration and infrastructure, must take place to facilitate the introduction of AVs to public roads.	Sclar Financial Times, 2018
199	**Road infrastructure**	Road type, road surface, weather conditions, lighting conditions, work zones, traffic control, traffic composition, traffic flow, other road users,	This paper provides a taxonomy of infrastructure related factors which have impact on accident risks in urban areas. Then, it ranks those risk factors based on a colour coding system to assess their influence on the safety of roads (accidents risk, frequency, etc.)	Papadimitriou *et al.* Accident Analysis and Prevention, 2019
200	**Road infrastructure**	Communication, traffic composition, V2X, V2V, autonomy level, traffic congestion, navigational software, time of day, sensors, LiDAR, radar, cameras, fatigue, driving behaviour, distracted driving, reaction time, adverse weather, regulations, public perception, cybersecurity, blind spots, speed, control	After the introduction of AVs, the risk ecosystem is expecting to change and pose new challenges and opportunities for primary insurers. Although the economic benefits are anticipated to arise, they will be offset by the economic detriment incurred by emerging risks and the increased scrutiny attached to current risks. In this study, four plausible scenarios are designed to analyse the rate of injury claims after the introduction of CAVs. Risk factors associated with CAVs and traffic dynamics are discussed.	Shannon *et al.* Risk Management and Insurance Review, 2021
201	**Road infrastructure**	Human factors, lateral and longitudinal motion controls, LiDAR, radar, other road users, motion planning, sensors, vehicle dynamics constraints, drowsiness, path planning, trajectory system, actuator, obstacles, traffic rule enforcement, V2V, V2X, road infrastructure	This paper reviewed advances in collision mitigation technologies for ADAS as a prelude platform for fully autonomous vehicles. AVs can facilitate vehicle platooning strategy thereby reducing congestion on public roads. Nevertheless, implementation of this strategy is still a challenging concept due to the needs to modify/strengthen existing road infrastructures.	Zamzuri *et al.* PERINTIS eJournal, 2016
202	**Path planning**	Obstacles, algorithms, sensors, actuators, control, trajectory generation, road geometry, number of lanes, other road users, velocity, driving behaviour	A novel method is introduced for AVs to plan a safe path and follow the front vehicle safely in highway environment.	Arrigoni *et al.* 24th International Symposium on Dynamics of Vehicles on Roads and Tracks, 2015
203	**Path planning**	Obstacles, speed, road type, perception, control, algorithms, vehicle dynamics, traffic rules, localisation, sensors, cameras, radars, number of lanes, road topology	The aim of this paper is to develop a local path planning approach for AVs. This methods id real-time and dynamic that allows AVs to avoid both static and dynamic obstacles.	Hu *et al.* Mechanical Systems and Signal Processing, 2018
204	**Path planning**	Time-to-collision, perception, algorithms, obstacles, sensors, localisation, kinematic state, control architecture, traffic regulations, traffic conditions, other traffic participants, velocity, reaction time	This paper develops a *multi-level Bayesian decision-making* for AD in highway environments. In the proposed multi-controller architecture, path planning is one of the critical and determining modules.	Iberraken, Adouane and Denis IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018
205	**Path planning**	Sensors, mixed traffic, other road users, algorithms, computer vision, LiDAR, radar, infrared sensors, ultrasonic sensors, sensor fusion, localisation, control, kinematic state, pedestrian density, road geometry, weather conditions, obstacles, reaction time, cameras, behaviour prediction	To avoid collision in AD, it is critical for an AV to monitor the behaviour of surrounding traffic participants and detect any potential unusual maneuverers. This paper proposes two indices (i.e., lane-index and lane-change-index) in addition to position and velocity to detect lane-changing maneuverers of nearby agents (including human-driven vehicles).	Wang *et al.* 22nd International Conference on Information Fusion, 2019
206	**Path planning**	Weather conditions, road conditions, obstacles, communication, V2V, V2I, V2X, algorithms, sensors, LiDAR, other road users, visibility, regulation, vehicle dynamics	In this work, a system architecture is proposed for risk-aware AVs to enable them to deliberately bound the risk of collision below a given threshold, defined by the policymaker. Several key components and factors that can be a source of risk to the performance of AVs are discussed.	Khonji, Dias and Seneviratne Working paper, Cornell University Library, preprint, 2019
207	**Path planning**	Path planning, traffic conditions, speed, road configuration, localisation, road map, traffic regulations, other road users	This paper investigates the relationship between AD system configuration and safety.	Zhang *et al.* IEEE 31st International Symposium on Software Reliability Engineering (ISSRE), 2020

208	**Path planning**	Algorithms, visibility, mapping, environment, perception, motion control, sensors, localisation, obstacles, AI	This research intended to evaluate algorithms that enable semi-autonomous vehicles to search an object in a known environment and avoid colliding with them.	Marinheiro and Bianchini Proc. of the 2nd International Conference on Electrical, Communication and Computer Engineering (ICECCE), 2020
209	**Path planning**	Path planning, obstacles, vehicle dynamics, algorithms, motion planning, road geometry, kinematic states, road condition, other road users	This paper presented a vehicle lane change system applying model predictive path planning (MPPP) built on the artificial potential field (APF) for speeding vehicles. The simulation results suggest that the MPPP algorithm is highly effective in high-speed lane change scenarios while avoiding dynamic obstacle vehicles.	Lin *et al.* 20th International Conference on Control, Automation and Systems (ICCAS), 2020
210	**Path planning**	Obstacles, other road users, algorithms, velocity, road infrastructure, motion planning, traffic conditions, kinematic state, number of lanes, road configuration, road conditions, sensors	A risk estimation model is proposed to evaluate potential risks by considering nearby vehicles' relative positions, velocities, and accelerations. This model uses a predictive occupancy map (POM) to choose the safest path with the minimum risk values.	Shen *et al.* 0 IEEE Intelligent Vehicles Symposium (IV), 2020
211	**Path planning**	Control, system integration, obstacles, algorithms, perception, vehicle dynamics, relative velocity, motion planning, road boundaries	This work utilises *Model Predictive Control* to develop an *integrated Path Planning* for AVs to select a collision-free path.	Ko *et al.* 20th International Conference on Control, Automation and Systems (ICCAS), 2020
212	**Trajectory planning**	Training and experience, trust, other road users, control, velocity, traffic conditions, longitudinal and lateral distance	The possibility of teaching AVs by drivers to choose their preferred trajectories (and manoeuvres) in real traffic is put forward in this study.	Nagahama *et al.* IEEE Transactions on Intelligent Transportation Systems, 2020
213	**Trajectory planning**	Control algorithms, other road users, traffic conditions, traffic complexity, traffic rules, road geometry, road limits, vehicle limits, kinematic state, cameras, sensors, driver's psychology, driving style, obstacles, V2X, V2V, V2I, mixed traffic, GPS	This paper is concerned with the overtaking scenario in highways under mixed traffic conditions. the proposed solution is developed based on *quadratic programming optimization* and assesses traffic situation online and performs an overtaking manoeuvre safely by selecting a safe trajectory.	Coskun Engineering Science and Technology, an International Journal, 2021
214	**Trajectory planning**	Road geometry, surrounding vehicles, motion predictor, velocity, mixed traffic, cameras, radar, algorithms, vehicle dynamic, actuator limit, vehicle control	AVs need to adjust their performance to road geometry and other vehicles' behaviour. This paper suggests a trajectory planner that can predict motions of surrounding vehicles exploiting *artificial potential field method.*	Song, Kim and Huh International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS), 2019
215	**Trajectory planning**	Algorithms, traffic complexity, road geometry, perception, control, driving behaviour, velocity, obstacles, GPS, radar, cameras, path generation, vehicle kinematic constraints, actuator limitations, road conditions	This work presents a trajectory planning algorithm using the quartic *Bézier curve* and dangerous potential field for AVs. To generate collision-free trajectories, potential field functions are developed to weigh the collision risk of available paths.	Zheng *et al.* IET Intelligent Transport Systems (the Institute of Engineering Technology), 2020
216	**Trajectory planning**	Algorithms, traffic rules, kinematic state, H-M Interface, path planning, obstacles, perception, vehicle control, actuators, weather conditions, sensors, traffic conditions, traffic density, speed, sensor fusion, road geometry, reaction time, system integration, number of lanes, HMI	This study presents the development and initial test in a simulator of a trajectory-planning algorithm for highly automated vehicles and discusses hoe it enables AVs to adapt to traffic on a structured road environment such as highways. That algorithm is designed to run on a *fail-safe* embedded environment with low computational power e.g. an engine control unit, to be feasible for mass produced AVs.	Glaser *et al.* IEEE Transactions on Intelligent Transportation Systems, 2010

217	**Trajectory planning**	Obstacles, visibility, perception, motion planning, environmental complexity, algorithms, motion planning, driving style, vehicle state, behaviour planning, velocity error, blind spots, vehicle control, kinematic models, sensor coverage, LiDAR, other traffic participants, road type, traffic rule enforcement, traffic conditions, road boundaries, time-to-collision	This paper presents a trajectory generation method for AVs to overtake unexpected obstacles in a dynamic urban environment. The possibility and implications of perception impairment dur to occlusion is also taken into account.	Andersen *et al.* IEEE Transactions on Intelligent Vehicles, 2020
218	**Trajectory planning**	Sensor malfunction, environment perception, weather conditions, vehicle control, other traffic participants, behaviour planning, V2X, algorithms, trajectory planning, velocity, vehicular dynamic, driving behaviour, LiDAR, sensors, radar, stereo cameras, obstacle	Collision probability and accident severity assessment are incorporated into an approach that considers environment uncertainties in planning a safe trajectory for AVs.	Hruschka *et al.* IEEE International Conference on Vehicular Electronics and Safety (ICVES), 2019
219	**Motion planning**	Visibility, weather conditions, occlusion, perception, sensors, sensor fusion, localisation, other road users, behaviour planning, road infrastructure, velocity, reaction time	Inclement weather and occlusions in urban environments can impair perception. The uncertainties are handled in different modules of an AV, ranging from sensor level over situation prediction until motion planning.	Sahin Tas and Stiller IEEE Intelligent Vehicles Symposium (IV), 2018
220	**Motion planning**	Traffic control infrastructure, perception, vehicle control, other road users, LiDAR, front camera, localisation, algorithms, V2V, machine learning, GPS, V2X, velocities, sensors, number of lanes, road geometry, perception reaction time, time-to-collision	This paper proposes a motion planning framework for AVs operating in urban environments with uncontrolled intersections. Computer simulation a well as vehicles tests were conducted to evaluate the effectiveness of the presented framework. The results suggest that it is reliable at uncontrolled intersections generating a human like driving pattern.	Jeong and Yi IEEE Transactions on Intelligent Transportation Systems, 2021
221	**Motion planning**	Control, localisation, perception, obstacles, velocity, algorithms, traffic conditions	One of the major problems in AD is collision-free motion and trajectory planning.	Banzhaf *et al.* 21st International Conference on Intelligent Transportation Systems (ITSC), 2018
222	**Motion planning**	Other road users, sensor noise, blind zones, trajectory planning, mixed flow, dynamic obstacles, vehicle dynamics, control mechanisms, road boundaries, behaviour generation, speed, path planning, kinematic constraints, road geometry, drivers' behaviour, traffic complexity, radar, LiDAR, weather conditions, traffic rules	Handling a *mixed-flow* intersection while interacting with other traffic participants (e.g., pedestrian and other motorised vehicles) is a challenging task for AVs. Sensor noise and blind spots can add to the complexity of that scenario too. This paper presents a hierarchical framework that splits the driving function into a decision, planning and action layers. This segregation makes motion planning feasible for that scenario.	Zhou, Ma and Sun IEEE Transactions on Intelligent Vehicles, 2020
223	**Motion planning**	Control, road conditions, sensory system, trajectory planning, algorithms, obstacles, vehicle model, Vehicle Kinematics, driver's risk perception, speed, road edges	This paper proposes an advanced driver assistance system (ADAS) for AVs with a focus on motion planning and control. The motion planning algorithm for collision avoidance is formulated utilising artificial potential field approach based on perceived risk by human drivers.	Wahid *et al.* IEEE International Conference on Mechatronics (ICM), 2017
224	**Behaviour generation**	Traffic composition, other road users, traffic environment, algorithms,	This study focuses on the importance of behaviour generation in AVs (beyond SAE 3) in dealing with risks arising from uncertain traffic environment.	Bernhard, Pollok and Knoll IEEE Intelligent Vehicles Symposium, 2019

225	**Behaviour generation**	Traffic composition, stereo cameras, path planning, speed, kinematic state, pedestrian, reaction time, environmental perception, sensors, traffic conditions, perception accuracy	In order for AVs to safely operate in mixed urban traffic, it is crucial for them to perceive the surrounding traffic participants and interact with them harmoniously. To achieve harmony in the mixed traffic, this paper proposes a vision-based approach to implement the humanlike autonomous driving function along a predefined lane level route in the complex urban environment with daily traffic.	Guo *et al.* IEEE Transactions on Intelligent Vehicles, 2018
226	**Behaviour generation**	Software reliability, path planning, speed, situation awareness, traffic rules, vehicle control, algorithms, road layout, AI maturity, trajectory planning, traffic conditions, number of lanes, vehicle characteristics, longitudinal control, types of road	This paper developed a risk-aware multi-objective decision-making algorithm to choose between the optimal behaviour to execute a successful navigation mission. In that manner it is necessary for the autonomous vehicle to be able to perceive its surrounding and understand scenario context.	Rodrigues *et al.* IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), 2017
227	**Behaviour generation**	Perceived risk, mixed traffic, control algorithms, time to collision, safe distance, reaction time, speed, weather conditions, road type, number of lanes, trust, driver's experience, GPS	Lane changing is inevitable in driving and can increase the risk of collisions. This paper developed a *lane-change decision model* for AVs that conforms to a driver's risk perception and safely change lane.	Wang *et al.* Sensors, 2020
228	**Behaviour generation**	Traffic density, learning algorithms, traffic complexity, trajectory planning	The behaviour generation methods must be capable of handling complex real-world traffic. To this end, data-driven approaches can be used to train the algorithms. In this paper, reinforcement learning is combined with local optimisation to generate safe and reliable behaviour for AVs.	Hart, Rychly and Knoll IEEE Intelligent Transportation Systems Conference (ITSC), 2019
229	**Behaviour generation**	Algorithm, neural network, traffic density, other road users, trajectory planning, GPS, V2X, radar, LiDAR, sensor fusion, velocity, traffic conditions, perception, kinematic state	Analysing an AV's decision-making algorithm that plan a series of manoeuvres is the aim of this paper. The focus is on machine-learning algorithms (e.g., neural networks) for risk estimation. A BBN is also developed for behaviour planning.	Dávid, Láncz and Hunyady Design, 2019
230	**Behaviour generation**	Traffic density, other traffic participants, kinematic state, sensors, actuator control, visibility, reaction time, weather conditions, predictive risk, obstacles, number of lanes, risk awareness	This study proposes a risk-aware Responsibility Sensitive Safety (RSS) layer for AVs to increase vehicle's situation awareness, reduce *safety margins* and achieve a desired balance between safety and usefulness.	Oboril and Scholl IEEE Intelligent Vehicles Symposium (IV), 2020
231	**H-M Interfaces**	Situation awareness, urban areas, trust, human-machine communication, road surface, other road users, road infrastructure, experience, traffic rule enforcement, obstacles, weather conditions, road conditions, road type, speed, traffic conditions, V2I, pedestrian density, road layout	Urban areas are challenging AVs, since even highly reliable systems may face traffic situations that need agile driving manoeuvres in hard-to-predict. This can adversely surprise the driver and cause discomfort, anxiety or loss of trust. To tackle that challenge, this paper proposed an interface benefiting from augmented reality (AR) to maintain situation awareness of drivers during a ride.	Lindemann, Lee and Rigoll Multimodal Technologies and Interaction, 2018
232	**H-M Interfaces**	Time to collision, localisation, environmental conditions, secondary tasks, situation awareness, algorithms, longitudinal control, sensors, road infrastructure, radar, LiDAR, cameras, weather conditions, visibility, road configuration, traffic conditions, control, sensor fusion, perception, traffic law, other road users	This paper investigates appropriateness of human-machine interfaces for each phase of autonomous driving. The objective here is to establish accurate situation awareness.	Debernard *et al.* IFAC Papers Online, 2016

233	**H-M Interfaces**	Vehicle control, HMI, trajectory planning, sensors, traffic regulations, traffic flow, speed limit, V2I, V2V, traffic control infrastructure, human-machine cooperation (HMC), weather conditions, road conditions, reaction time, trust, obstacle, traffic complexity	This paper proposes a cooperative approach to the control issue of AVs which may require human interventions to avoid collisions in real-world traffic. A cooperative interface is supposed to eliminate the need for full handover when human input is necessary. 32 participants took part in a simulation study and were tasked to choose how the system should handle traffic situations.	Walch *et al.* Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 2016
234	**H-M Interfaces**	Vehicle control, takeover, sensors, traffic law enforcement, situation awareness, HMI, demographics, reaction time, weather conditions, trust, road conditions, road type, other road users, traffic conditions, traffic flow, driving experience, obstacle	The topic of adjusting Human-Machine Interfaces to older users of highly autonomous vehicles has been around for a while. This paper developed three Human-Machine Interface concepts based on older drivers' needs and conducted a driving simulator investigation with 76 drivers (39 old and 37 younger drivers) to investigate the effectiveness and relative merits of these interfaces on drivers' takeover performance, workload and attitudes.	Li *et al.* Transportation Research Part F, 2019
235	**H-M Interfaces**	other traffic participants, control, weather conditions, construction sites, static and dynamic objects, road infrastructure, driving behaviour, sensors, reaction time, road type	This paper examined the possibility of using augmented reality (AR) in designing interfaces for semi-autonomous vehicles (i.e., level 3). The participants took part in simulation experiment and faced unplanned short-notice take-over request (TOR). The results show that VR can be effective in reducing driver workload and improving take-over performance in a subset of possible of TOR.	Lindemann, Muller and Rigoll IEEE Intelligent Vehicles Symposium (IV), 2019
236	**H-M Interfaces**	Driver distraction, road conditions, demographics, NDRT, HMI, traffic conditions, reaction time, traffic density, visibility, road geometry, weather conditions, algorithms, cameras, sensors, drivers' experience, construction sites, speed, actuators, kinematic state, obstacles, trust, mental workload, driving style, road type	Machine learning techniques and a simulation experiment were used to assess the predictability of driver's reaction to major hazards during take-over of vehicle control in HAVs.	Alrefaie PhD Thesis, 2019
237	**HMI (Human-Machine Interaction)**	Communication, trust	This study investigates the interactions between pedestrians/bicyclists and driverless cars. A vehicle was designed to appear to have no driver and a driver was trained to emulate an autonomous system. Then, observations were made to learn about the interactions of pedestrians and cyclists with the vehicle at a crosswalk.	Rothenbücher *et al.* 25th IEEE International Symposium on Robot and Human Interactive Communication, 2016
238	**HMI (Human-Machine Interaction)**	Software	The AV-AV, human-human and AV-human interaction on the roads in terms of decision making is the focus of this study. Game theory and Nash equilibrium are used to analyse these interactions.	Harris Annual Conference Towards Autonomous Robotic Systems, 2017
239	**HMI (Human-Machine Interaction)**	Communication, V2V, sensors, algorithms	AVs and human drivers are expected to coexist for a long time. Thus, it is important to consider their interactions. the implicit and complex states and behaviours of human drivers like distractions and fatigue, which are hard to detect by the AVs, may result in sudden brakes and subsequent accidents because of the late alert to the following AVs.	Yan *et al.* IEEE-INST Electrical Electronics Engineering INC., 2019
240	**HMI (Human-Machine Interaction)**	Weather conditions, visibility, road conditions, road user behaviour, lighting conditions, time of day, sensors	This study proposes the concept of "driveability" for AVs to identify and handle driving risks. To this end, road datasets are reviewed and driveability factors are identified and categorised into majors groups: 1) environmental factors; and 2) road users' interactions.	Guo, Kurup and Shah IEEE Transactions on Intelligent Transportation Systems, 2019
241	**HMI (Human-Machine Interaction)**	Situation awareness, weather conditions, road conditions, perception and trust	This papers centres on the interactions between pedestrians and AVs. It developed a situation awareness model and included environmental as well as individual factors to describe the interaction between a pedestrian and an AV.	Rodríguez Palmeiro *et al.* Transportation Research Part F: Traffic Psychology and Behaviour, 2018

242	**HMI (Human-Machine Interaction)**	H-M Interface, Autonomy level, reaction time, situation awareness, training and experience, traffic density, trust, perceived risk, secondary task, vehicle control, speed, weather conditions, road characteristics, drowsiness, driving styles, road infrastructure, visibility, other road users, driver state, driver skills, sensors, obstacles, construction zone	There are concerns about the performance of human drivers when it comes to partially (semi) automated vehicles. This paper explores the role of human drivers and challenges that they may face in semi-autonomous driving and provides inspiration for conceptualising the driving task more completely.	Zhang, Angell and Bao Transportation Research Interdisciplinary Perspectives, 2021
243	**HMI (Human-Machine Interaction)**	Algorithms, control, speed, trust, traffic condition, traffic congestion	The results of this experiment revealed that there is significant value in evaluating human factors in a highly technological system such as an AV. Human behaviours and sentiments may complicate the development of safe algorithms for AVs.	Brown *et al.* Systems and Information Engineering Design Symposium, 2018
244	**HMI (Human-Machine Interaction)**	Other road users, algorithms, traffic conditions, speed, traffic congestion, sensors, visibility, road geometry, obstacles, vehicle dynamics, geometry, traffic culture, urban design	The primary aim of this study is to model the risk of collision at junctions and intersections and evaluate the impact of full and shared autonomous systems on safety. With respect to human drivers, collisions at intersections often occur due to inattention or misjudgement of the other cars' dynamics. This remains an open problem for autonomous vehicles, which can struggle to navigate intersections without incident or to interact naturally with cars driven by humans.	McGill et al IEEE Robotics and Automation Letters, 2019
245	**HMI (Human-Machine Interaction)**	Speed, algorithms, communication, V2V, V2X, traffic conditions,	In this study, with accurately predicted motion of a remote vehicle, a collision risk and the automated drive mode are determined by incorporating human factors. Effects of the V2V communication on a human-cantered risk assessment algorithm have been investigated through a safe triangle analysis.	Shin, Park and Park Applied Sciences, 2018
246	**HMI (Human-Machine Interaction)**	Trust, rules, risk perception, familiarity	This paper studied the attributed values and perceived safety as predictors of the intention to use autonomous vehicles. The human factor is seen central in traffic. Therefore, it is important to focus on the need of formulating strategies that might prepare the public for a *live interaction* with autonomous vehicles.	Montoro *et al.* Safety Science, 2019
247	**HMI (Human-Machine Interaction)**	Hardware, software, communication, V2X, V2V, traffic congestion, cybersecurity, drowsiness, speed, algorithms	This design study examines the trade-offs that occur in autonomous vehicle hardware and software development. It also investigates the role of humans in the car accidents and the significance of that in the *scaled vehicle construction process*.	Rowley *et al.* Systems and Information Engineering Design Symposium (SIEDS), 2018
248	**HMI (Human-Machine Interaction)**	Pedestrians, traffic conditions, human-driven cars, algorithms, road design,	The risks and risky encountering cases of pedestrian-(autonomous) vehicle interactions are classified. A list of descriptive variables is provided and the ability of ML algorithms in classification of pedestrian-car conflicts is evaluated.	Gandhi, Luo and Tian International Conference on Human-Computer Interaction, 2019
249	**HMI (Human-Machine Interaction)**	Algorithms, vehicle dynamics, collision avoidance, traffic conditions, pedestrians,	A motivational driver model is developed to design a rear-end crash avoidance system. These motivations simplify both autonomous driving algorithms and human-machine interactions. Moreover, the motivations are used as risk assessment factors for driver–machine interaction in dangerous situations.	Mozaffari and Nahvi Journal of System and Control Engineering, 2020
250	**HMI (Human-Machine Interaction)**	Sensors, weather conditions, obstacles, other road users, algorithms,	Examples for uncertainty from the environment are hidden RWM (road world model) states due to occlusions from large obstacles or sharp turns, or parameters that cannot be physically sensed such as intentions of humans participating in the environment, including other drivers, cyclists, and pedestrians.	Naghshvar, Sadek and Wiggers NeurIPS Workshop on Machine Learning for Intelligent Transportation Systems (MLITS), 2018
251	**HMI (Human-Machine Interaction)**	Pedestrians, environmental conditions, demographics, traffic conditions, HMI, traffic culture, communication, V2V, V2I, V2P, V2X, time of day	The pedestrian behaviour, as the most vulnerable road user, id discussed and influential factors as well as their interrelations are studied. This necessitate the communication between the AVs and other road users.	Rasouli and Tsotsos IEEE Transactions on Intelligent Transactions, 2019

252	**HMI (Human-Machine Interaction)**	Trust, other road users, traffic conditions, sensor, AI,	Autonomous systems in logistics provide a new level of challenge for the analysis and design of human–machine interaction concepts. A comprehensive case study regarding automated lorry driving in logistics is provided in order to test the concept concerning practical implications.	Klumpp International Journal of Logistics Research and Applications, 2018
253	**HMI (Human-Machine Interaction)**	H-M interface, situation awareness, drowsiness, reaction time, traffic conditions, driver state, traffic rule enforcement, algorithms, technical failures, trust, perceived risk	The central focus of this paper is about the Human Machine Interactions (HMI) which are progressively moving as Human Machine Transitions (HMT), according to the recent advances in AVs. Emerging risks due to *takeover/handover* of the control are also investigated.	Bellet *et al.* Transportation Research Part F, 2019
254	**HMI (Human-Machine Interaction)**	Algorithms, regulation, bias, cybersecurity, hardware, component, path planning, sensors, obstacles, control,	This article investigates the ethical and technical concerns surrounding algorithmic decision-making in AVs by exploring how driving decisions can perpetuate discrimination and create new safety risks for the public. Modelling and understanding human-vehicle interactions is essential for safe navigation in mixed traffic to build consumer trust in AVs, although this remains a challenge for decision-making algorithms.	Lim and Taeihagh Sustainability, 2019
255	**HMI (Human-Machine Interaction)**	Road geometry, visibility, lighting conditions, road infrastructure, animals, road conditions, pedestrians	This study focuses on the environmental, human and road factors influencing the car crashes in South Africa and discusses how the introduction of self-driving cars can mitigate the accident risks.	Verster and Fourie South African Journal of Science, 2018
256	**HMI (Human-Machine Interaction)**	Algorithms, perceived risk, sensor, control,	With the ever-expanding capabilities of technical systems, *user-appropriate design* issues are becoming increasingly important. That importance comes from two aspects. One is about capability of single vehicle; The other is about capability of the whole traffic system before all the on-road vehicles become capable of fully autonomous driving.	Hu *et al.* Journal of Advanced Transportation, 2017
257	**HMI (Human-Machine Interaction)**	Speed, reaction time, reliability, trust, takeover/handover, sensors, weather conditions, road configuration	This article sees this essential to consider human-vehicle interactions in order to study the reaction times in takeover/handover situations in automated driving which inherently involve the collision risks.	Kim and Yang IEEE Transactions on Human-Machine Systems, 2017
258	**HMI (Human-Machine Interaction)**	Other road users, H-M Interface, training & experience, traffic composition, road features, traffic rules, road infrastructure, vehicle shape, environment perception	This study investigates the challenges that integration of AVs into mixed traffics can pose to the safe operation of them. Four categories of information were emerged from the literature review in this paper: 1) vehicle driving mode, 2) AVs' manoeuvres, 3) AVs' perceptions of the environment; and 4) AVs' cooperation capabilities. The recommendations place a strong emphasis on HMI and H-M Interfaces.	Schieben *et al.* Cognition, Technology & Work, 2019
259	**HMI (Human-Machine Interaction)**	Sensor fusion, trust, traffic control infrastructure,	This work evaluated the future of mobility and transportation in the age of autonomous driving. Several impacts and challenges that AVs can have for the developers and users are discussed. The authors adopted a human-centric approach to analyse this technology will be experienced by human drivers.	Hancock, Nourbakhsh and Stewart Proceedings of the National Academy of Sciences of the United States of America, 2019
260	**HMI (Human-Machine Interaction)**	Road infrastructure, neighbourhood environment, other cars, bicyclists, pedestrians perceived risk, weather conditions	This paper studies the factors that influence people's views of the interactions between AVs and other road users based on a large sample from the 2015 and 2017 Puget Sound Travel Surveys. The neighbourhood environment and road infrastructure are specifically underlined in this work. Results reveal that	Wang and Akar Transportation, 2019
261	**Training & Experience**	Situation awareness, HMI, H-M Interface, V2V, V2I, overtrust, sensors	This article concentrates on the role of human behaviour in the safety of intelligent vehicles (i.e. AVs). In this study the importance of providing appropriate training for the drivers of this type of vehicle is highlighted. It is asserted that training is one of the most crucial factors to the acquisition and maintenance of safety critical hazard mitigation skills that perhaps will never be acquired if Level 3 autonomous vehicles become a reality for the a large number of drivers from the moment they try this technology for the first time.	Fisher *et al.* IEEE Transactions on Intelligent Vehicles, 2016

262	**Training & Experience**	Reliability, trust, HMI, situation awareness, handover	This project was aimed to study the 'handover problem' in HAD. In this way, it takes the effects of training and experience into account and underlines their role in handling handover situations.	Morgan, Alford and Parkhurst Project Report, Venture Project, University of the West of England, 2016
263	**Training & Experience**	Trust, HMI, system reliability, H-M interface	This study focuses on the importance of 'trust repair' in human-machine interactions especially in autonomous systems. The 'level of experience' is believed to have a considerable impact on the human-machine relationships. The experience can affect the level of trust in the capabilities of an autonomous systems.	de Visser, Pak and Shaw ERGONOMICS, 2018
264	**Training & Experience**	Secondary tasks, HMI, driving behaviour, cultural environment, situation awareness, lateral and longitudinal control, other road users, hardware and software reliability, road infrastructures	This paper highlighted the benefit of research on the role of driver 'experience' in safety of AVs. This becomes particularly important because training and experience not only contributes to apprehending system limitations, but also in reacting to complex and hazardous situations.	Demeulenaere Technological Forecasting & Social Change, 2020
265	**Training & Experience**	Overreliance, road users, MHI,	The issue of drivers' skills and enough experience to handle critical safety situations, handovers and long-term trips was studied in this work. It is argued that initial and sufficient training are crucial for drivers in taking over the control of the vehicle when facing hazards or uncertainty.	Trösterer *et al.* Proceedings of the 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 2016
266	**Training & Experience**	Trust, HMI, H-M Interface,	This study emphasises the need for modified trainings for drivers to be able to engage with AVs and benefit from their capabilities.	Kyriakidis *et al.* Theoretical Issues in Ergonomics Science, 2019
267	**Training & Experience**	Road users, age, pedestrians, obstacles, communication, handover/takeover, control	This book deals with the human factors affecting the interactions between ADSs and humans. The significance of training and experience is highlighted here: "*Many, if not most, will have no specific training in how the technology works, but will have experience interacting with human-driven vehicles. The risks are significant—getting an interaction wrong can result in injury or death. Major design problems could result in many death*".	Fisher *et al.* Handbook of Human Factors for Automated, Connected, and Intelligent Vehicles, 2020
268	**Training & Experience**	Trust, safety perception, HMI, training & experience,	125 participants take part in this survey and experienced a ride on an AV in a large clinic area in Berlin, Germany. Results show that this experience had significant impact on the trust and safety perceptions of the participants.	Zoellick *et al.* PLoS ONE, 2019
269	**Training & Experience**	HMI, trust, situation awareness, perceived reliability, Human-Machine Interface, speed limit, training and experience, trust, other road users	Concerns about interactions between humans and AVs are studied in this paper. A quasi-naturalistic study was conducted on public roads to examine to test a self-driving vehicle human–machine interface, ATLAS. The results show that following interaction with this prototyped system, participants expressed an improved trust in self-driving vehicle technology, an increased belief in its likely usability, and a decreased fear of probable operational failures.	Brinkley *et al.* International Journal of Human–Computer Interaction, 2019
270	**Training & Experience**	Trust, HMI	An expert panel was designed to discuss the implications of human factors in automated driving. The impact of trust and education on the control and usability of AVs are accentuated. This becomes crucial when we expect humans (e.g. other road users) to interact with the technology.	Pradhan *et al.* Road Vehicle Automation 5, 2019
271	**Training & Experience**	System integration, culture	Human errors are often reported as the 'root cause' of accidents in socio-technical systems. However, these errors can be due to other factors such as training machine design, or culture.	Swallom, Lindberg and Smith-Jackson Handbook of Human Systems Integration, Chapter 14, 2003
272	**Training & Experience**	Weather conditions, speed, trust, road conditions, road type, road configuration, road infrastructure, perceived risk, number of lanes, speed, perceived reliability,	The results of this study show that providing 'explanations' on the autonomous driving process for the occupants of the vehicle can improve their level of trust in the technology. The participants reported a significant increase in their trust when provided with 'attributional explanations' in diverse driving situations including adverse weather conditions, poor road conditions and high speeds.	Ha *et al.* Transportation Research Part F, 2020

273	**Training & Experience**	Perceived risk, experience, HMI, H-M interface, reaction time, control, drowsiness and fatigue, situation awareness, over-trust, weather conditions, other road users, traffic conditions, speed and distance, sensor, over-reliance, road conditions	The current study reports an improvement in technology acceptance, trust levels and perceived risks by participants in automated driving. Use of a partially automated vehicle on a public highway increased drivers' trust and perceptions of safety around AVs, consistent with greater acceptance of and intention to use AV technology.	Wilson *et al.* Safety Science, 2020
274	**Drowsiness**	Time of day, circadian factors, secondary task	This work analyses some potential aftermaths of 'sleep-related' issues in the context of autonomous driving and suggests new multidisciplinary areas for future research between social and drowsy scientists. The authors categorise the current state-of-technology as semi-autonomous vehicles (level 4) and see the issue of drowsiness still to be relevant. Therefore, sleepiness or drowsiness is believed to increase the risk of accident.	Grunstein and Grunstein International Conference on Intelligent Human Systems Integration, 2020
275	**Drowsiness**	Situation awareness, weather conditions, road characteristics, time of day, reaction time,	While there might be situations that the control transition between an AV and a driver can be initiated due to some environmental conditions or road characteristics, the states of drivers play a role in safe take-over of control.	Vogelpohl *et al.* Accident Analysis and Prevention, 2019
276	**Drowsiness**	HMI, situational awareness, non-driving tasks, control, reaction time	This research suggests that non-driving tasks can manage driver drowsiness in automated driving. 71 employees of the AUDI AG participated in this experiment. The results show that different activities such as texting, listening to music and using body exercisers can have different impacts on driver drowsiness.	Weinbeer, Muhr and Bengler Proceeding of the 20th Congress of the International Ergonomics Association, 2018
277	**Drowsiness**	Reaction times, situation awareness, secondary tasks, time of day, weather conditions, lighting conditions, work zones, road conditions, physiological factors	Evidence suggests that drivers will be more prone to falling asleep during automated driving. In higher levels of vehicle automation, the need for monitoring the state of the human driver will become vital. This study aimed to find potential physiological measures as a basis for developing systems that can detect driver drowsiness in automated driving.	Wörle *et al.* IET Intelligent Transport Systems, 2019
278	**Drowsiness**	Non-driving tasks, reaction time, system failure, situation awareness, speed, pedestrians,	Drowsiness and distraction are known as risk factors in AD. This research suggests that secondary or non-driving tasks (as major cause of distraction) can be used to prevent drivers from sleeping during automated driving. This can reduce the time requited for the driver to gain situation awareness and react to a hazardous situation.	Miller *et al.* Proceedings of the Human Factors and Ergonomics Society 59th Annual Meeting, 2015
279	**Drowsiness**	H-M Interface, reaction time, HMI, traffic situation, weather condition, driver state, other road users, take-over, speed	In the lower levels of driving automation where intervention of human driver is still required, drowsiness as a risk factor can play a crucial role and lead to dangerous situations. The findings reveal that driving time, driving mode as well as age have a significant impact on driver drowsiness. Furthermore, this study reports that the participants got drowsier in AD comparing to manual driving, with the younger participants experiencing higher levels of drowsiness.	Kundinger *et al.* Proceeding of the 25th International Conference on Intelligent User Interfaces, 2020
280	**Drowsiness**	Reaction time, secondary task, Human-Machine Interface, autonomy level, sensors, work zone,	Drowsiness and secondary tasks are reported to impair drivers' ability to safely and timely handle take-over performance. The results of this research suggest a relationship between the driver's drowsiness and non-driving related tasks (NDRT) engagement in semi-autonomous vehicles, but not in highly AD.	Naujoks *et al.* Accident Analysis and Prevention, 2018
281	**Drowsiness**	Reaction time, HMI, secondary task, work zone, driver state, speed	Due to the operational limitations of AVs, it is critical to ensure that human intervention is made in a timely manner to avoid a collision. Drowsy driving can increase the reaction time of human drivers. This driving simulator study evaluates the impact of *scheduled manual driving* on driver drowsiness and performance, as well as age differences therein. The findings reveal that driver drowsiness meaningfully declines when scheduled manual driving begins.	Wu *et al.* Accident Analysis and Prevention, 2019

282	**Drowsiness**	Reaction time, NDRT, trust, traffic density, training	This paper investigated the impact of drowsiness on different aspects of take-over performance. 31 participants took part in an experiment which was conducted on the motorway A9 in Germany. No significant influence of the drowsiness level was reported on take-over-time aspects.	Weinbeer *et al.* 8. Tagung Fahrerassistenz Conference, 2017
283	**Drowsiness**	HMI, driver state, AI algorithms, perception, navigation planning, vehicle control, H-M Interfaces, sensor robustness, V2V, V2I, behaviour planning, motion planning	This paper discusses the concept of 'shared autonomy' and the idea of 'Human-Cantered Autonomous Vehicle Systems'. The author argues that it is achievable for AI systems and humans to collaborate effectively. This can contribute to the design, development and testing of AVs. Several challenges and risk factors including driver drowsiness are discussed as well.	Fridman arXiv preprint arXiv:1810.01835, 2018
284	**Drowsiness**	Trust and reliance, driver state, sensor malfunction, response time, pedestrians, communication, V2I, V2V, V2X, training and experience	This study investigates the reliance of drivers on AD and discusses the human factors. The results show that prior knowledge about the possibility of AV failures leads to calibrated reliance on AVs and increases the awareness of drivers. Conversely, over-reliance on AV's performance can inhibit drivers to appropriately respond to system failures.	Arakawa International Journal of Innovative Computing, Information and Control, 2018
285	**Drowsiness**	Reaction time, NDRT, sensors, actuators, perception accuracy, speed, control, traffic conditions, situation awareness, driving duration, driver state, traffic density	This paper investigated the impact of durations of automated driving on the take-over performance. The findings suggest that 1 hour of automated driving affects the driver's behaviour, leading to deterioration of take-over quality, increased reaction time and increased drowsiness.	Bourrelly *et al.* IET Intelligent Transport Systems, 2019
286	**Drowsiness**	Weather and lighting conditions, reaction time, speed, vehicle control system, sensors, cameras, driver state, path planning, pedestrians, V2V, intention recognition, vehicle state, LiDAR, H-M Interface	This study defines a collaborative driving framework consisting of two elements: an automated co-pilot and a human driver. This framework is based on internal and external risk assessment. The internal risk is defined in terms of driver drowsiness and intention recognition, and the external risk comprises of a collision avoidance system to estimate the collision probability between the ego vehicle and surrounding vehicles.	Tran *et al.* IEEE Transactions on Intelligent Transportation Systems, 2019
287	**Drowsiness**	Driver's state, secondary task, traffic density, road curvature, H-M Interface, lighting conditions, situation awareness	The influence of HAD on driver's drowsiness development was studied. The findings demonstrate that the drivers experienced highest level of drowsiness when drivers proceeded driving manually as well as when in HAD mode but without being engaged in NDRT inside the vehicle.	Schömig *et al.* 6th International Conference on Applied Human Factors and Ergonomics, 2015
288	**Drowsiness**	Circadian phase, time of day, situation awareness, driver state, visibility, HMI, perceived risk, trust, mental workload, control perception, driver state, fatigue	Driving in the night is notably more hazardous and it is not merely attributed to poorer visibility or sleep deprivation. Circadian changes in human cognitive performance also play a role. This study suggests an extended, multi-period, Consensus Model of the driver that includes circadian rhythmicity during semi-automated driving. The results of the literature also support the idea that circadian rhythmicity must be taken into account when researching semi-automated driving.	Kaduk, Roberts and Stanton Theoretical Issues in Ergonomics Science, 2020
289	**Drowsiness**	Reaction time, fatigue, NDRT, weather conditions, traffic density, visibility, control	This study investigated the effect of NDRTs on drivers' fatigue on highly automated driving. Three factors were monitored to measure the participants' fatigue: percentage of eye-lid closure, blink related eye-tracking parameters and self-report Karolinska Sleepiness Scale (KSS). The results suggest that "the monotonous monitoring task induced task related fatigue after a time-on task of 25 min, which could be demonstrated by a rise of subjective KSS ratings, PERCLOS and blink related parameters".	Jarosch *et al.* Driving Assessment Conference, 2017

290	**Drowsiness**	Visibility conditions, traffic density, driving duration, fatigue, vigilance, circadian rhythm, time of day, reaction time, longitudinal/lateral control	The impact of semi-automated driving on drivers' vigilance and passive fatigue was investigated in this research. An automated vehicle was used by the participants and a vigilance task became the primary active task besides passive monitoring. The remaining eye tracking indicators for fatigue (pupil diameter, blink frequency, blink duration) except PERCLOS showed a significant increase in fatigue in course of the experimental drive. This directly affects the vigilance performance and subsequently drivers' reaction time.	Körber *et al.* 6th International Conference on Applied Human Factors and Ergonomics, 2015
291	**Reaction time**	Mixed traffic, traffic flow, demographics, road geometry, traffic complexity, road capacity, traffic rules, weather conditions, driving behaviour, traffic conditions, reaction time, speed, sensory system, traffic control	This study suggests a novel *cellular automata* model to address the issue of drivers' characteristics in mixed traffic where different AVs (e.g., cars and buses) and HDVs are compared in terms of fundamental traffic parameters.	Tanveer *et al.* Sustainability, 2020
292	**Reaction time**	Velocity, cybersecurity, machine learning algorithms, road conditions, vehicle dynamics, control, lane configuration	A data-driven tool is developed to evaluate the safety of AVs involving sensitivity analysis and Automotive Safety Integrity Levels (ASILs).	Fan, Qi and Mitra arXiv:1704.06406, 2017
293	**Reaction time**	Traffic flow, other traffic participants, traffic density, mixed traffic, control, velocity, road conditions, weather conditions, number of lanes	To test the capability of AVs in harmonising with HDVs in real traffic, thousands of vehicle-recorded data in the US was used and reaction time was chosen to be a performance indicator.	Althoff and Lösch IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), 2016
294	**Reaction time**	Sensors, communication, speed, road infrastructure, obstacles, traffic density, VANET, V2V, V2I, other road users, trajectory planning, radar, LiDAR, GPS, H-M Interface, road conditions, driving style, driver's state, weather conditions, road type, fatigue, situation awareness, driver's age, kinematic state, temperature, road geometry, traffic conditions	This paper proposes a tool for assessing collision risk for AVs. This tool includes environmental, vehicle, and driver factors and exploits a Bayesian Network to model collision risks.	Russo *et al.* IFAC Conference Paper Archive, 2016
295	**Reaction time**	Fatigue, secondary task, HMI, speed, vehicle control, driver state, training, human factors, visibility, other road users, weather conditions, traffic density	This study tested the hypothesis that monitoring roadway during AD affects driver vigilance. A 40-minute simulated drive was designed and on-board drivers were tasked to watch out the roadway for hazards. The results suggest that hazard detection rate dwindles and reaction times slows as AD carries on.	Greenlee, DeLucia and Newton Human Factors, 2018
296	**Reaction time**	Algorithms, road conditions, velocity, vehicle dynamics, software	The application of *hierarchical control* in AVs and ADAS is highlighted in this paper. It is upheld that conventional design and test methodologies are insufficient for ensuring safety of AVs. One of the variables which is used to characterise safety is reaction time.	Fan, Qi and Mitra IEEE Design and Test, 2018
297	**Reaction time**	Secondary task, perceived risk, training and experience	In case of any failure in the automation system, drivers' ability and readiness to take over the manual control play a vital role in safe performance of AVs. This article shows the results of an experimental study to test the impact of 'risk attitude' on acceptability, productivity and safety (reaction times) under failure of autonomous driving systems.	Dixit *et al.* Accident Analysis & Prevention, 2019
298	**Reaction time**	Secondary task, drowsiness, training and experience, trust, perceived risk, situation awareness	A driving simulator study was conducted to test the impact of 'time budget' and secondary (non-driving-related) tasks on take-over of control in low crash risks (LCR) against high crash risk (HCR) drivers. The results found that HCR drivers had lower risk perception in comparison with LCR participants. In addition, engagement in reading news and watching video had similar impact on the reaction time of drivers in both groups.	Lin *et al.* Accident Analysis & Prevention, 2020

299	**Reaction time**	H-M Interfaces, vehicle control, weather conditions, hardware reliability, non-driving related task, drowsiness, fatigue, time of day, obstacles, situational awareness	Takeover modality in highly automated vehicles is the focus of this research. 60 participants were required to handle a stalled park vehicle after being awoken from a light sleep. Half of participants were exposed to a peppermint odour stimulation, while the other half received a placebo (air). The results indicate that the presence of peppermint did not affect the participants' reaction time.	Tang *et al.* Human Factors, 2020
300	**Reaction time**	V2V, algorithms, communication, radar, sensors, HMI, other traffic participants, driving style, GPS, obstacle, kinematic models, velocity, road geometry, sensor fusion, driver's sensitivity	Reaction time was used to measure collision risk in AD while V2V wireless is fused with radar to anticipate motion of a remote vehicle.	Shin *et al.* IEEE Transactions on Intelligent Transportation Systems, 2019
301	**Reaction time**	H-M Interfaces, weather conditions, road conditions, traffic conditions, control, situation awareness, driving behaviour, driver distraction, training, secondary task, trust	Driver's distraction is still an issue even in semi- and highly automated vehicles. Two streams of research were conducted investigate the capabilities of Human-Machine Interfaces to address driver distraction.	Geitner University of Warwick WMG Experiential Engineering, 2018
302	**Reaction time**	Situation awareness, secondary task, hardware failures, sensor failures, obstacles, traffic density, V2X, overreliance,	This work investigated the effect of V2X communication channel on the allowed time for control transition from the autonomous system to the driver. The findings show that benefiting from V2X can add 6-7 seconds to the time allowed by local perception thereby reducing the risk of collision.	Demmel *et al.* Proceedings of the 2nd IFAC Conference on Cyber-Physical and Human Systems CPHS, 2019
303	**Road type**	Traffic conditions, speed	The effect of a specific type of ADAS (i.e. lane change driver support system) is evaluated in this study. 'Road type' is among studied variables and is categorised into five groups: European highways, highways, city roads, roundabouts, and unspecified.	Isaksson-Hellman and Lindman Journal of Traffic Injury Prevention, 2017
304	**Road type**	Road configuration, obstacle, road alignment, speed	The results suggest that "the adjusted Odds-Ratio of run-off crash was five times higher in double direction roads with median strip than in one-way urban roads". Then the authors identify urban road configurations that may need to be redesigned to reduce the odds of a run-off crash. A series of risk factors including road geometry, road layout, road width, road type and road alignment are highlighted in this study.	Álvarez *et al.* PLoS ONE, 2020
305	**Road type**	Reaction time, road characteristics, secondary tasks, other road users, environmental variables, weather conditions, lighting conditions, human factors, situation awareness, speed	This research explores the contributing factors and mechanisms of the accidents involving autonomous vehicles. The paper concludes that "*the highway is identified as the location where sever injuries are likely to happen due to high travel speed*". Other factors and causes also mentioned in this paper including environmental and human factors.	Wang and Li PloS ONE, 2019
306	**Road type**	Weather conditions, traffic density, number of lanes, visibility, time of day, road geometry	This paper investigated the effect of multiple variables such road type, weather conditions and road conditions on the accident risk.	Malin, Norros and Innamaa Accident Analysis and Prevention, 2019
307	**Road type**	Road geometry, trust, driving style, vehicle control, speed, traffic conditions, road infrastructure, traffic infrastructure, control	This study used a set of models to evaluate the effect of road environments and road elements such as road segment and road type on the speed behaviour of drivers. The results indicate the need for the design of AV controllers that can adapt their driving behaviour to the road environment.	Paschalidis *et al.* Analytic Methods in Accident Research, 2020
308	**Road type**	Driving style, traffic density, weather conditions, lighting conditions, relative speed, reaction time, secondary task, driver visual attention, training and experience, number of lane changes, kinematic state, other road users, road situation	This paper examines the relationships between the *road situational risk* and *angry driving style* on lane-changing decisions in drivers and the allocation of visual attention of angry-driving-style drivers based on video clips of driving. The findings of this research are applicable in the field of AD and development of ADAS.	Huo, Ma and Chang Transportation Research Part F, 2020

309	**Road type**	Situational awareness, GPS, cameras, sensors, road environment, traffic flow, traffic rules, weather conditions, road quality, obstacles, LiDAR, other road users, lighting conditions, self-awareness	In this thesis, a novel video-based framework for the automatic assessment of collision risk in a road scene is proposed. The proposed framework classifies road type to achieve higher accuracy than the state-of-the-art methods, for each road type separately.	Muhammad PhD Thesis, 2016
310	**Road configuration (layout/design)**	Visibility, speed, collision avoidance, pedestrian, HMI	This paper discusses the framework for a risk predictive driver assistance system that dynamically shares control authority between the elderly driver and the ADAS depending on the potential risk of the situations, in order to cope with uncertainty and complexity in urban areas.	Saito and Raksincharoensak IEEE Transactions on Intelligent Vehicles, 2016
311	**Road configuration (layout/design)**	Human factors	The aim of this research project was to analyse how precisely the drivers perceive hazardous degrees of the four common mountainous highway traffic risk factors by drawing an analogy between subjective and objective risks. Those four risk factors are sharp turns, continuous long downhills, multi-tunnel sections and dangerous roadside environment.	Xue and Wen Journal of Cognition Technology & Work, 2020
312	**Road configuration (layout/design)**	Road conditions, speed limit, V2V, V2I, traffic congestion, sensors, trust & acceptance, obstacles, weather conditions, road infrastructure, GPS	This study investigates the road design requirements required to accommodate AVs on roads. It is maintained that "*the problem of road design compatible with AVs could become the assessment of that quantity DE*".	Colonna *et al.* International Conference on Applied Human Factors and Ergonomics, 2017
313	**Road configuration (layout/design)**	Speed, other road users,	This paper explores the effects of roadside vegetation and/or cover on the probability of vehicular collisions with deer by identifying and simulating dangerous animal-vehicle interaction scenarios for autonomous driving. The methodology used in this study produces recommended safe driving speeds for vehicles employing each driver assist system given a particular road configuration.	Font and Brown Advances in Transportation Studies; Special Issue, 2020
314	**Road configuration (layout/design)**	Weather conditions, time of day, lighting conditions, road design, road conditions, vehicle parameters, width of road, traffic flow, traffic density, speed, obstacles,	Darmstadt Risk Analysis Method (DRAM) is developed in this work to deal with uncertainties and get access to the *cause-and-effect* chains of the road systems. Several factors influencing the probability and severity of traffic accidents are identified and incorporated into the chain.	Bald *et al.* Proceedings of the Transport Research Arena (TRA) Europe, 2008
315	**Road configuration (layout/design)**	Road surface friction, road geometry, weather conditions	The complications due to the vehicle status, environmental factors and road geometry are taken into account to study potential collisions involving AVs. The risk here is defined as "faster-than-expected lead vehicle braking maneuver combined with a slower-than-expected ego vehicle braking maneuver".	Koopman, Osyk and Weast International Conference on Computer Safety, Reliability, and Security, 2019
316	**Road configuration (layout/design)**	Other road users, road infrastructure, traffic composition	This paper stresses the necessity for 'appropriate street design' to mitigate the risk of collision and conflict between motorised and non-motorised travels after launch of AVs in mass number on public roads. It is believed that technological advancements are outpacing urban planning and policy. In this study a workshop was designed to gather the opinions of experts on the role of urban and road design on how AVs can be integrated into public roads.	Riggs *et al.* Automated Vehicles Symposium, 2019
317	**Road configuration (layout/design)**	Cybersecurity, physical infrastructure, digital infrastructure, AI maturity, traffic composition, other road users	This study introduces the idea of "automation readiness" in the context of urban design and mobility. It further underscores the challenges arising in the field of street redesign.	van Arem *et al.* Automated Vehicles Symposium, 2019
318	**Road configuration (layout/design)**	Traffic control infrastructure, human factors, geometric design, speed, trajectory planning, communication, algorithms, traffic flow, number of lanes, driving style	This paper looks into the safety of freeway on-ramp merging areas and the factors affecting the performance of AVs in handling the risks in those areas. Several critical factors including environmental and human ones are highlighted in this study.	Zhu and Tasic Accident Analysis and Prevention, 2021

319	**No. of lanes**	Speed, time-to-collision, road type, other road users, interface, road conditions, traffic conditions	An intelligent Speed Adaptation (ISA) was developed to reduce the number of *lane changes* and *short time-to-collision* events. Two of the main factors in this study was the road type (i.e., single-carriageway, dual-carriageway, and motorway) and the number of lanes.	Piao *et al.* IEEE Intelligent Transportation Systems Conference, 2004
320	**No. of lanes**	Traffic density, driver behaviour, speed, radar, road type, traffic conditions, other road users, reaction time	Changing lanes during driving (both conventional and automated vehicles) can contribute to the criticality of the traffic situation and subsequently causing slow traffic flow and higher collision risks.	Isaksson-Hellman and Lindman Traffic Injury Prevention, 2018
321	**No. of lanes**	Other road users, kinematic state, algorithms, secondary tasks, drossiness, path planning, obstacles, trajectory planning, motion planning, time-to-collision, road conditions	Predictive occupancy map (POM), is proposed to assess potential risks associated with surrounding vehicles based on relative position, velocity, and acceleration. In generating a risk map, environmental risks are grouped into two categories: 1) driveable regions; and 2) traffic lanes. switching to another lane in order to avoid a collision can be relatively riskier than accelerating or decelerating the vehicle in the same lane.	Lee and Kum IEEE Access, 2019
322	**No. of lanes**	AI, velocity, surrounding traffic participants, traffic rules, motion planning, camera, LiDAR, dynamic obstacles, control, sensors, kinematic state, algorithms, traffic density	A deep reinforcement learning (RL) algorithm is developed to learn drive as close as possible to a desired velocity by performing safe manoeuvres (i.e., lane changes) on simulated highways with an arbitrary number of lanes.	Mirchevska *et al.* 21st International Conference on Intelligent Transportation Systems, 2018
323	**No. of lanes**	Algorithms, traffic flow, V2V, V2I, reaction times, road conditions, path prediction, communication infrastructure, speed, other road users	Among various vehicular manoeuvres, lane changing is considered as the most challenging one. This paper presents an algorithm to minimise the disruption of traffic flow by optimising for the number of safe lane changes, which is expected to result in increasing throughput and reduction in traffic congestion.	Desiraju and Chantem IEEE Transactions on Intelligent Transportation Systems, 2015
324	**No. of lanes**	Tire friction, situation awareness, approach angle, road geometry, velocity, vehicle dynamic, control, obstacles, velocity, road curvature, sensors, computing power	It is held that the number of collisions between vehicles due to lane departure is slightly more than collisions with objects/obstacles (other than vehicles). However, in some traffic scenarios it may not practically be possible to avoid changing lane. Therefore, a safe speed needs to be adopted to reduce the risk of collision. This study developed a framework based on current historic data using numerical optimisation to predict the potential value of future autonomous vehicle manoeuvres at-the-limit of tire friction in safety-critical situations.	Olofsson and Nielsen IEEE Transactions on Intelligent Transportation Systems, 2020
325	**No. of lanes**	Other traffic participants, traffic complexity, sensors, actuators, vehicle dynamics, driving behaviour, weather conditions, traffic flow, perceived risk, lighting conditions, control	A *scene-graph augmented data-driven risk assessment* is developed to classify various driving manoeuvres for AVs. Lane change was chosen as a use case. One of the main elements to define the characteristic of a road scene is traffic lane.	Yu *et al.* IEEE Transactions on Intelligent Transportation Systems, 2021
326	**Road conditions**	Sensors, machine learning, vehicle control, other road users, LiDAR, obstacles, GPS	Adaptation to human driving style is a problem in the field of autonomous driving. This paper proposes a human-like AD system which considers *road scene perception method* and *empirical decision-making network*. It also analyses factors that can have influence in decision-making process.	Li, Ota and Dong IEEE Transactions on Vehicular Technology, 2018
327	**Road conditions**	Speed, algorithms, collision avoidance	The role of ACC in collision avoidance for semi-autonomous electric vehicles is studied in this paper. Low friction is considered to complicate the road conditions for a vehicle.	Ren *et al.* Journal of Automobile Engineering, 2019
328	**Road conditions**	Speed, dynamical characteristics, traffic conditions, obstacles	This study suggests a risk-based control framework for AVs. Direction of the road and physical characteristics are categorised as the key risk attributes for these vehicles.	Vismari *et al.* IEEE International Conference on Vehicular Electronics and Safety (ICVES), 2018
329	**Road conditions**	V2V, V2X, obstacle, algorithms, road geometry, control	This paper is objected towards developing a risk-assessment algorithm that could control a vehicle to keep the presented lane and avoid a collision that may be caused by a road object. In this manner, the vehicular dynamics and road geometries are modelled to test different scenarios.	Fahmy *et al.* 29th International Conference on Microelectronics (ICM), 2017

330	**Road conditions**	V2V, speed, collision avoidance,	Conventional autonomous emergency braking (AEB) systems consider a fixed friction coefficient without regards to different road conditions. This study proposes a control method that adjusts the automatic brake application time to road conditions. Additionally, collision risks at an intersection were calculated using various road friction coefficients and the V2V-based speed inputs from adjacent vehicles. The efficacy of the proposed AEB system was validated through tests under various scenarios, applying the road friction coefficient and vehicle speed as variables.	Jeon, Kim and Kim International Journal of Software Engineering and Its Applications, 2015
331	**Road conditions**	Traffic rules, traffic density, speed, weather conditions, communication, infrastructure	A DBN model is developed to assess the collision risks for AVs. The contextual and situational factors including traffic conditions are incorporated into the model. It is endorsed that the influence of the geometry of the road on the actions and the knowledge of the road geometry and traffic rules are crucial factors.	Katrakazas, Quddus and Chen Accident Analysis & Prevention, 2019
332	**Road conditions**	Weather conditions, road surface, vehicle dynamics,	This work proposes a simulation-based framework to assess the safety performance of vehicles under hazardous driving conditions. This study has potential applications to not only regular vehicles, but also advanced traffic management and control algorithms for connected and autonomous vehicles. Complex geometric (e.g. road curvature) and environmental conditions are simultaneously considered.	Hou, Chen and Chen Transportation Research Part C: Emerging Technologies, 2019
333	**Road conditions**	Weather conditions, visibility, HMI, road user behaviour, lighting conditions, time of day, sensors, traffic conditions	This study proposes the concept of "driveability" for AVs to identify and handle driving risks. To this end, road datasets are reviewed and driveability factors are identified and categorised into majors groups: 1) environmental factors; and 2) road users' interactions.	Guo, Kurup and Shah IEEE Transactions on Intelligent Transportation Systems, 2019
334	**Road conditions**	Situation awareness, communication, VANET, V2V, V2I, infrastructure	Vehicular networks (cloud) play a key role in enabling the realisation of AVs. Such a network can facilitate the transfer of vital data like road conditions between nearby vehicles and allow them to signal potential risks.	Olariu, Eltoweissy, and Younis ICST Transactions on Mobile Communications and Applications, 2011
335	**Road conditions**	Weather conditions, sensors, GPS, infrastructure, visibility	The impact of lane departure warning (LDW) and lane keeping aid (LKA) on passenger car injury accidents is studied based on Swedish accident data. These systems can be used in autonomous vehicles in addition to other technologies to ensure the lateral control of the vehicle.	Sternlund *et al.* Traffic Injury Prevention, 2017
336	**Sensors**	LiDAR, radar, camera, ultrasound, perception, surrounding vehicles, localisation, reaction time, speed, time-to-collision, actuators, hazardous driving behaviours	A fallback approach is presented in case senser failure occurs in AD. This approach is expected to navigate the impaired vehicle to a safe stop on the designated parking zone. A simulation was run in Simulink environment to evaluate the proposed approach in two test scenarios.	Xue *et al.* IEEE Intelligent Vehicles Symposium (IV), 2018
337	**Sensors**	Weather conditions, road conditions, mixed traffic, other road users, vehicle control, LiDAR, radar, ultrasonic sensors, 3D cameras, road curvature, obstacles, sensor fusion algorithms, localisation, communication, AI algorithms, environment configurations, V2X, cybersecurity, velocity, trajectory prediction, behaviour of road users	Challenges in the way of testing and validating AVs are reviewed. A simulation based on scenario-assessment was run for this purpose. Future questions around safe operation of AVs are further discussed.	Koné *et al.* International Conference on Complex Systems Design & Management, 2019

338	**Sensors**	Perception accuracy, motion planning, control, LiDAR, trajectory planning, algorithms, localisation, other traffic participants, dynamic traffic conditions, obstacles, GPS, vehicle dynamics, velocity, visual cameras, vehicle control	Detecting and analysing the dynamics of surrounding environment is a key component of AVs. *ObserveNet Control* is a vision-dynamics approach to address the predictive control dilemma of AVs.	Ginerica *et al.* IEEE Robotics and Automation Letters, 2021
339	**LiDAR**	Weather conditions, visibility, perception accuracy, speed, control, software, V2X, data fusion, behavioural planning, trajectory planning, vehicle integration, H-M Interfaces, radar, obstacle, cameras, RSU, road conditions	This paper studies the development baseline of a new LiDAR sensor for AVs, which require accurate perception both under clear and adverse weather conditions such as precipitation and fog.	Kutila *et al.* IEEE 19th International Conference on Intelligent Transportation Systems, 2016
340	**LiDAR**	Deep neural networks, detection accuracy, cameras, obstacles, sensors, localisation	Accuracy and integrity of the object detection module in AVs is crucial to ensure that AVs can safely handle traffic scenarios on public roads. This paper proposes a practical method to address uncertainties in a 3D vehicle detector for LiDAR point cloud.	Feng, Rosenbaum and Dietmayer 21st International Conference on Intelligent Transportation Systems (ITSC), 2018
341	**LiDAR**	Sensors, computer vision, GPS, other road users, road signs, sensor fusion, control algorithms, velocity, software, cameras, obstacles, lighting conditions, appropriate hardware	A Bayesian Network is developed to estimate quantitative probabilistic of system safety for the AVs using computer vision and LiDAR sensors.	Duran *et al.* Proceedings of the 2013 Federated Conference on Computer Science and Information Systems, 2013
342	**Radar**	Stereo vision, sensor fusion, sensors, algorithms, other road users, obstacle, environment perception, weather conditions, visibility, motion planning, system integration, traffic density, relative speed, number of lanes, space geometry	This paper presents a solution for detection and tracking of moving objects within the context of ADAS. A multisensory setup consisting of a radar and a stereo camera mounted on top of a vehicle are used in that system.	Ćesić *et al.* Robotics and Autonomous Systems, 2016
343	**Radar**	Communication, weather conditions, deep reinforcement learning algorithms, visibility, V2I, velocity, cameras, road conditions	This paper suggests an *intelligent Real-time Dual-functional Radar-Communication* (iRDRC) system for AVs. This system equips an AV with both radar and data communication functions to maximise bandwidth utilisation thereby significantly enhancing safety. The data communications function enables an AV to transmit data such as traffic information to edge computing systems and the radar function is applied to improve the reliability and reduce the collision risks of AVs.	Hieu *et al.* IEEE Wireless Communications Letters, 2020
344	**Radar**	Tracking algorithms, other vehicles, relative velocity, LiDAR, cameras, sensor fusion, path planning	This paper is concerned with objective vehicle detection in AD. A data-driven object vehicle estimation approach is developed to address the measurement uncertainty and latency problems in radars incorporated into AVs.	Choi, Yang and Chung Sensors, 2021
345	**Cameras (vision)**	Trajectory planning, perception, control, motion planning, sensors, weather conditions, lighting conditions, path planning, dynamic obstacles, GPS, sensor fusion	An *uncertainty-aware end-to-end trajectory generation* network developed in this paper can obtain spatiotemporal features from the front camera images for scene perception, and then plan collision-free trajectories several seconds into the future. The experimental results in this work suggest that under varying weather and light conditions, that network can reliably generate trajectories in dissimilar urban environments, such as turning at intersections and slowing down for avoiding collision.	Cai *et al.* IEEE Transactions on Intelligent Vehicles, 2021
346	**Cameras (vision)**	Reinforcement learning, control systems, weather conditions, velocity, algorithms, human errors, GPS, deep learning, vision-based algorithms, perception, sensors, actuators, vehicle dynamics, number of lanes, traffic rules	Vision-based robust controllers for keeping an AV in the centre of a lane coping with uncertainties and disturbances, is a challenging toping in the field of DA. This work proposes a hybrid control architecture that couples *Deep Reinforcement Learning (DRL)* with *Robust Linear Quadratic Regulator (RLQR)* to develop a vision-based lateral controller for AVs.	Morais *et al.* Control Engineering Practice, 2020

347	**Cameras (vision)**	Situational awareness, onboard sensors, dynamic objects, localisation, pedestrians, radars, GPS, other road users, infrastructure, radar, LiDAR, software, path planning, angular velocities, prediction algorithms, visibility	This paper presents a system that integrates a vision-based offboard pedestrian tracking subsystem with an onboard localization and navigation subsystem to enable warnings to be communicated and effectively extends the vehicle controller's field of view to include areas that would otherwise be blind spots. This is applicable in autonomous vehicles and can improve pedestrian detection.	Borges, Zlot and Tews IEEE Transactions on Intelligent Transaction Systems, 2013
348	**Hardware reliability**	Traffic composition, transportation infrastructure, LiDAR, radar, GPS, camera vision, communication, infrared sensor, ultrasonic sensor, backup sensor, system integration, software, algorithms, database, HMI, H-M Interfaces, driving style, other road users, weather conditions, construction zones, road conditions	A fault tree is developed to analyse AVs' risk from the vehicular component and infrastructure component perspectives. This analysis produced failure a probability of around 14% resulting from a sequential failure of the AV components solely in the vehicle's lifetime, with a focus on the components responsible for automation.	Bhavsar *et al.* Transportation Research Record: Journal of the Transportation Research Board, 2017
349	**Hardware reliability**	Trajectory tracking, software algorithms, perception, global route planning, behaviour reasoning, trajectory planning, sensors, vehicle kinematic, dynamic constraints, path planning, localisation, weather conditions, road geometry, road surface, static/dynamic obstacle, road infrastructures, cameras, speed	To avoid high costs and risks of real-world testing, this paper proposes a Hardware-in-the-Loop Scaled Platform which comprises of scaled AV, roadway, monitoring centre, transmission device, positioning device, and computing device. The results of experiments show a satisfactory effectiveness of the HiL scaled platform.	Xu *et al.* Journal of Advanced Transportation, 2017
350	**Hardware reliability**	Control algorithms, sensors, actuators, speed, localisation, sensor fusion, cameras, LiDAR, ultrasound, path planning, planning algorithms, V2V, V2I, angular velocity, radar, GPS, Inertial Measurement Unit (IMU), monocular camera, other road users, obstacle, communication, vehicle state, road structure, kinematic car model, traffic complexity, traffic rule compliance, traffic management	This work proposed a novel simulation platform with hardware-in-the-loop (HiL). This platform consists of four layers: vehicle simulation, virtual sensors, virtual environment and the Electronic Control Unit (ECU) which enable hardware control. This platform offers threefold capabilities: (1) it builds and simulates kinematic car models, various sensors and virtual testing fields; (2) it implements a *closed-loop* evaluation of surrounding perception, path planning and vehicular control algorithms, whilst running multi-agent interaction system; (3) it further allows for a rapid transition of control and decision-making algorithms from the virtual environment to real self-driving cars.	Chen *et al.* IEEE Intelligent Vehicles Symposium (IV), 2018
351	**Hardware reliability**	Sensors, obstacles, velocity, LiDAR, radar, reaction time, motion planning, software, sensor fusion, algorithms, system integration	This paper introduces criteria for intervention on braking and steering in AD evaluating the occupants' injury risk. To develop such criteria software-in-the-loop and hardware-in-the-loop are introduced.	Vangi Journal of Automobile Engineering, 2020
352	**Hardware reliability**	Software, system integration, perceptual positioning, control execution, planning, weather conditions, illumination conditions, vehicle kinematics, algorithms, control interfaces, road conditions, road gradient, sensors	A hardware-in-the-loop simulation is performed to avoid high risks and costs of real road testing. This simulation aimed to evaluate autonomous emergency braking (AEB) control algorithms. Physical hardware and software components were included in the simulation platform.	Gao *et al.* IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC) Intelligent Transportation Systems (ITSC), 2020
353	**Hardware reliability**	Cybersecurity, vehicle controllers, sensors, LiDAR, actuators, algorithms, road geometry, control reconfiguration, obstacles, communication, speed sensors, system integrity,	Cybersecurity of AVs in the focus of this paper. A security architecture is introduced and a HiL platform is developed to test that architecture. In this simulation, both hardware and software architectures are taken into account.	Potteiger, Zhang and Koutsoukos Microprocessors and Microsystems, 2020

354	**(Vehicle) control**	Obstacles, LiDAR, sensor fusion, algorithms, road structure, trajectory planning, sensors, security standards, GPS, pedestrians, road type, kinematic state, hardware	A system is proposed to avoid obstacles based on the lateral and longitudinal velocity of AVs. It was tested and validated on a three-wheel vehicle.	Hasmitha *et al.* IEEE International Conference for Innovation in Technology (INOCON), 2020
355	**(Vehicle) control**	V2I, communication, number of lanes, LiDAR, radar, cameras, system integration, obstacles, algorithms, other road users, traffic flow, velocity, vehicle trajectory, reinforcement learning, machine learning, fusion algorithms, traffic control infrastructure, sensors	A *fusion-based Q-learning* method is developed in this paper to achieve an optimal *bird-view* control for CAVs in multi-lane road scenarios. This system can assist CAVs to tackle complex traffic scenarios and crossing traffic.	Wang, Hou and Wang Computer-Aided Civil and Infrastructure Engineering, 2020
356	**(Vehicle) control**	Mixed traffic, velocity, V2I, traffic density	Model Predictive Control is applied to control AVs in intersection scenarios under mixed traffic circumstances.	Mihály *et al.* IFAC PapaersOnline (Conference Paper Archive), 2021
357	**(Vehicle) control**	Driving style, traffic environment, trajectory planning, trust, algorithms, traffic environment, obstacles, AI, speed, vehicle kinematic, other road users, number of lanes, driving behaviour, reaction time	It is discussed that AVs must adapt to human driving styles and characteristics of human driver to develop trust in automation and encourage user acceptance. This work suggested an algorithm for trajectory planning/tracking and ultimately optimised control of AVs.	Li *et al.* IEEE Access, 2021
358	**(Vehicle) control**	Stabilisation, path tracking, obstacles, trajectory following algorithms, vehicle dynamics, system integration, road conditions, road geometry, velocity, vehicle state, sensors, radar, cameras	Vehicle stabilisation plays a crucial role for AVs in emergency scenarios. This study proposes a novel control structure that integrates path tracking, vehicle stabilisation, and collision avoidance to mediate among them in case of conflicting objectives by assigning the highest priority to collision avoidance.	Funke et al. IEEE Transactions on Control System Technology, 2017
359	**(Vehicle) control**	Algorithms, V2I, cybersecurity, road type, obstacles, other road users, weather conditions, road infrastructure, cameras, velocity, time of day, GPS, lighting conditions, sensor characteristics, radar, time to collision	This paper reports the current state of AVs in Russia. It scrutinises possible road situations that AVs may encounter and must respond to them while avoiding collisions.	Ivanov *et al.* IOP Conf. Series: Materials Science and Engineering, 2019
360	**(Vehicle) control**	Sensing/perceiving, planning, traffic law, other road users, road conditions, weather conditions, unsafe speed, driving style, LiDAR, V2I, V2V, reaction time, lighting conditions, visibility, road design, roadway geometry, hardware reliability, road infrastructure	This study pinpoints the causal chain of vehicle accidents and discusses what *humanlike errors* AVs must avoid for safety. Those factors are categorised into four groups: 1) sensing and perceiving surrounding environment; 2) predicting; 3) planning; and 4) executing plans.	Mueller, Cicchino and Zuby Journal of Safety Research, 2020
361	**(Vehicle) control**	Reinforcement learning, algorithms, control policy, trajectory planning, number of lanes, velocity	Reinforcement learning can be used to improve efficiency and reduce failures in AD. The outcome is control policy that can increase efficiency and safety for AVs.	Ma, Driggs-Campbell and Kochenderfer IEEE Intelligent Vehicles Symposium (IV), 2018
362	**(Vehicle) control**	Motion planning, perception, obstacles, rout planning, radar, LiDAR, GPS, sensors, vehicle dynamics, kinematic constraints, path planning, obstacles, algorithms, trajectory planning, other road users	Robust execution of safety-critical tasks such as motion planning are key to the safe performance of AVs in dynamic environments shared with other traffic participants. This work surveys the state of planning and control algorithms by the time it was prepared (i.e., 2016).	Paden *et al.* IEEE Transactions on Intelligent Vehicles, 2016
363	**(Vehicle) control**	Sensors, obstacles, actuators, mission planning, path planning, localisation, reaction time, lighting conditions, kinematic state, perception, motion planning, speed, hardware, system integration, trajectory generation, behaviour generation	This paper adopted neural models and *biologically inspired approach* to develop a control architecture for autonomous vehicles (both ground and aerial).	Vaidyanathan *et al.* Journal of Systems and Control Engineering, 2011

364	**(Unsafe) speed**	, time of day, lighting condition, road conditions, weather conditions, algorithms, traffic environment, other traffic participants, control, sensors, kinetic energy, traffic control infrastructure, road configuration, lane type, V2X, risk perception, traffic complexity, time of day, information fusion, compliance with traffic rules	This paper tires to develop a 'crash injury severity prediction' model for autonomous decision-making under emergency situation. 14 variables including lighting conditions are selected as the impact indicators.	Liao *et al.* Electronics, 2018
365	**(Unsafe) speed**	Road geometry, motion planning, vehicle kinematic state, motion control, actuators, vehicle dynamics, weather conditions, road conditions, sensors, path planning, algorithmic failures, hardware reliability	This paper presents the theory and algorithms to formulate and test a concept for a future Automated Emergency Cornering (AEC) system. The simulation for this concept was performed in CarMaker software package. The developed *Automated Emergency Cornering* (AEC) system utilises a digital map and vehicle kinematic data to trigger and update the motion reference. It further receives friction estimation to operate in a *near-optimal* way.	Gao and Gordon IEEE Transactions on Vehicular Technology, 2019
366	**(Unsafe) speed**	Risk perception, road type, road design, traffic density, road layout, weather conditions, traffic composition, road infrastructure, other road users, road geometry, visibility, traffic conditions, compliance with traffic law	This study tested three hypotheses to evaluate the relationship between driver risk perception, compliance with speed limits and speed limit credibility. An automated driving car simulator was used to rate risk perception.	Yao *et al.* Transportation Research Part F, 2019
367	**(Unsafe) speed**	Obstacles, traffic conditions, motion planning, trajectory planning, path planning, road geometry, kinematic constraints, other road users	This paper aimed to address the optimisation problem for dynamic obstacles avoidance with smoothness, risk and efficiency variables. That problem was transformed into a path searching problem to avoid collision and build an efficient speed portfolio.	Du *et al.* International Journal of Systems Science, 2020
368	**(Unsafe) speed**	Other road users, time of the day, weather conditions, traffic load, driving behaviour, road traffic law enforcement	This article argues that setting 'mandatory speed alerts' has moral justification. 'techno-regulation' is also discussed. "Techno-regulation exploits technology and technical capabilities of a system to *regulate* and *challenge* an agent's conducts.	Smids Journal of Applied Philosophy, 2018
369	**(Unsafe) speed**	Control, sensor, cameras, other road users	"The article focuses on a preliminary National Transportation Safety Board (NTSB) report regarding the fatal crash involving Tesla in self-driving mode in July 2016, which says the car was traveling 9mph over the posted 65 mph speed limit".	Jaillet Commercial Carrier Journal, 2016
370	**(Unsafe) speed**	Algorithm, control, traffic flow, weather conditions, traffic and road conditions, obstacles, V2V, V2I, traffic control infrastructure, reaction time	A *Variable Speed Limit (VSL)* control algorithm is developed for AVs. This framework focuses on individual driver behaviour and uses a multi-objective optimisation function to find an optimum between mobility, safety and sustainability.	Khondaker and Kattan Transportation Research Part C, 2015
371	**(Unsafe) speed**	Traffic flow/density, algorithms, time of day, kinematic state, traffic conditions, reaction time, road conditions, weather conditions	This study is concerned with the relationship between traffic density, speed and likelihood of crash on freeways.	Kononov *et al.* Transportation Research Record: Journal of the Transportation Research Board, 2012
372	**(Unsafe) speed**	Fatigue, poor visibility, time to collision, weather conditions, traffic composition, algorithms, traffic conditions, dilemma zone, traffic volume, road geometry, time of day, number of lanes, secondary tasks, human factors, road conditions, reaction time	A simulation study was run to evaluate the impact of AVs on unsignalized crossroads. Two crossroads in Tehran were chosen for this purpose. Vissim software package was used to simulate the probability of collision against AV penetration rate.	Khashayarfard and Nassiri Journal of Advanced Transportation, 2021

373	**(Unsafe) speed**	Number of lanes, transportation infrastructure, lateral and longitudinal control, roadway infrastructure, traffic density, visibility, road conditions, traffic composition, environmental perception, cameras, radar, LiDAR, GPS, image processing, algorithms, road configuration, actuators, obstacles, path planning, vehicle dynamics, traffic conditions, human factors, road geometry, weather conditions	Designating an exclusive lane to AVs has been the topic of several studies. This paper scrutinised implications of including a narrow and *reversible AV-exclusive* lane to expressways. For this purpose, the I-15 expressway in San Diego was chosen. Among the primary collision factors used in this study, *unsafe speed* had the highest frequency. Besides, *improper turning* and *unsafe lane change* were the main causes of collisions.	Ghanipoor Machiani *et al.* Journal of Advanced Transportation, 2021
374	**(Unsafe) speed**	Driving infrastructure, control, other traffic participants, machine learning algorithms, V2V, sensor, lighting conditions, weather conditions, obstacles, road conditions, traffic law enforcement, traffic density, driving behaviour	Unwillingness of auto makers to share automation data can lead to unsafe decisions and ultimately accidents. This article is concerned with data sharing (including disengagements and failures) of self-driving vehicles. NHTSA has made event data records mandatory for conventional vehicles. Black boxes can capture fifteen data elements including speed.	Krompier Journal of Law, Technology & Policy, 2017
375	**(Unsafe) speed**	Other road users, obstacles, reaction time, software, situation awareness, sensors, traffic congestion, roadway type, traffic rules, road conditions, visibility, roadway infrastructure, V2I, mapping system, traffic control infrastructure, lighting conditions, construction zones, roadway design	One of the major variables affecting the likelihood and severity of accidents is vehicle velocity, which directly determines the amount of *kinetic energy* asserted during a collision. This article highlights the necessity for regulating speed in highly autonomous driving.	Leshner, Boyd and Grossman Institute of Transportation and Engineers (ITE Journal), 2020
376	**Time of day**	Algorithms, deep learning, lighting conditions, visibility, cameras, weather conditions, other traffic participants, perception, visual perception	Darkness considerable affects the quality and images of roads obtained by visual cameras mounted on CAVs. This can undermine safety of CAVs. To mitigate this risk, a *light enhancement net* (LE-net) is developed which utilises convolutional neural network.	Li *et al.* Knowledge-Based Systems, 2021
377	**Time of day**	Human factors, AI, route planning, roadway conditions, other road users, weather and light conditions, road type, reaction time, LiDAR, machine learning algorithms, visibility, traffic density	This paper examines the influencing factors of injury outcomes involving AVs based on field test data. The data were obtained from the reports of traffic accidents involving AVs in California.	Ye *et al.* Injury Prevention (BMJ Journals), 2021
378	**Time of day**	Road conditions, weather conditions, speed, lighting conditions, sensors, road type, software, cyber-attacks, fatigue, driving style, V2I, V2V, GPS, construction zones, reaction time, other road users, road geometry, traffic rule enforcement, traffic conditions	The causes and factors which can contribute to the accident of semi-autonomous vehicles are identified and used to develop a BBN model to assess pertinent risks.	Sheehan *et al.* Transportation Research Part C: Emerging Technologies, 2017
379	**Time of day**	Sensors, software, traffic control infrastructure, weather conditions, algorithms, traffic participants, LiDAR, traffic conditions, road conditions, cameras, driving behaviour, reaction time, lighting conditions, traffic density, traffic rules, path planning, vehicle dynamics, kinematic state, vehicle control, driving culture, perception, hardware, sensor fusion, speed, number of lanes	AutonoVi-Sim is a simulation platform and is suggested for testing the performance of autonomous driving under varying weather conditions and time of day to generate robust data in complex traffic scenarios. There are two variables used to define the environment: time of day and weather conditions.	Best *et al.* Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018

380	**Time of day**	Weather conditions, traffic conditions, other road users, sensors, road infrastructure, V2X, lighting conditions, traffic rules,	This paper presents an open-source simulation environment for 360-degree traffic imaging. The implemented features include self-driving vehicles, pedestrians, various weather effects, and different time of day lightings.	Niemirepo *et al.* IEEE International Conference on Connected Vehicles and Expo & IEEE Vehicular Networking Conference (VNC), 2019
381	**Time of day**	Road type, other road users, road configuration, road infrastructure, reaction time, trust, AI, algorithms	This work analyses the accident reports involving AVs in California which were filed by five manufacturers from September 2014 to March 2017. Various factors and causes of accidents in addition to the severity of these accidents are examined. The analyses revealed important information on AV accidents dynamics including the most recurrent type of accidents, the break-down of damages locations and impact forces, and calculated accident frequencies.	Favarò *et al.* PLoS ONE, 2017
382	**Time of day**	Static obstacles, road configuration, road infrastructure, weather conditions, speed, human factors, road type, other road users, road conditions	work zone safety is a critical aspect for state agencies and traffic engineers. To evaluate the impacts of various variables on the injury severity of crashes in different time periods of a day, this study a total of 10,218 crashes that occurred in highway work zones in the state of Washington for the period between 2007 and 2013 were used. Time of day is disaggregated into four subgroups: 6-11 am, 12-5 pm, 6-11 pm and 12-5 am. The results show variations in the indicators of injury severity and some of variables.	Al-Bdairi Journal of Safety Research, 2020
383	**Time of day**	Weather conditions, road type, V2V, V2I, pedestrian, traffic congestion, communication, lighting conditions, day of week	This embodiment is related to autonomous and semi-autonomous vehicles functionality and can enable risk assessment and premium determination for vehicle insurance policies for vehicles which benefit from autonomous operation features. A series of factors including *time of day* are deemed to be related to insurance risks.	Konrardy *et al.* Google Patents, 2017
384	**Time of day**	Speed limit, weather conditions, lighting conditions, road configuration, day of week	In this patent, a method is disclosed for mitigating the risks associated with operating an autonomous or semi-autonomous vehicle by evaluating computed route traversal values to select less risky travel routes and/or modify vehicle operation. Various approaches to achieving this risk mitigation are presented. Among influential factors, *time of day* is counted.	Slusar Google Patents, 2017
385	**Time of day**	Path planning, algorithms, handover, road type, road configuration, weather conditions, speed limit, spatial frequency, hardware, software, other road users, road infrastructure, HMI, cybersecurity, GPS, AI, sensors, traffic congestion, day of week, public perception	This study devised a risk-aware path planning methodology for AVs based on telematics behavioural data. Multiple risk factors including *time of day* and *day of week* are identified. A correlation between spatial frequency of events and accident frequency is demonstrated too.	Ryan, Murphy and Mullins Transportation Research Part A, 2020
386	**Time of day**	Weather conditions, lighting conditions, road conditions, road configuration, visibility, communication, V2V, V2I, day of week, speed, road type, GPS, road infrastructure, sensors	A Bayesian network is developed to assess the severity of accidents for AVs and semi-autonomous vehicles using the naturalistic driving data gathering approach. 16 variables contributing to the severity of car crashes are identified and incorporated into the BN model. The data was extracted from the Michigan Traffic Crash Facts (MTCF) website for the year 2016.	van Wyk, Khojandi and Masoud Proceedings of SAI Intelligent Systems Conference, 2019
387	**Time of day**	Speed, type of road, reaction time,	This article discusses the ‘emerging risks’ associated with new technology in the domain of insurance. UAVs and self-driving cars are examples of these technologies. This paper refers to ‘telematics’ to monitor the behaviour of drivers and other characteristics including ‘time of day’ and combine them with traditional rating factors to rate drivers and vehicles.	Barlow Claims Magazine, 2016

388	**Traffic conditions (complexity)**	Autonomy level, situation awareness, secondary tasks, vehicle design, driving style, other road users, training & experience, traffic density, longitudinal and lateral acceleration, control, take-over, number of lanes, fatigue	This study focuses on the behaviour of drivers experiencing high vehicle automation in different traffic conditions (e.g., light/heavy traffic). The aim of this paper was to provide insight for vehicle designers in balancing the control and supervisory tasks between the vehicle and human drivers. The results suggest that in light traffic, higher grades of automation increase safety margins associated with car following. In heavy traffic those margins were reduced to those measured in manual driving mode.	Jamson *et al.* Transportation Research Part C, 2013
389	**Traffic conditions (complexity)**	Speed, road geometry, traffic congestion, route planning, algorithms	This paper aimed to address the problem of optimising the routes and the speeds of autonomous lorries making deliveries under uncertain traffic conditions. several factors including speed and traffic conditions are identified to have impact on the collision risks.	Nasri, Bektas and Laporte Computers and Operations Research, 2018
390	**Traffic conditions (complexity)**	V2V, V2I, V2X, traffic control infrastructure, other traffic participants, traffic culture, LiDAR, sensors, radar, visual cameras, sonar, sensor fusion, VANET, algorithms, ML, HD maps, control systems	This paper investigates the necessary technologies required to facilitate and realise AD in cities. It is believed that communication between vehicles (V2V) can prevent collisions and provide warnings of *problematic traffic conditions*.	Seif and Hu Engineering, 2016
391	**Traffic conditions (complexity)**	Time-to-collision, vehicle configuration, vehicle control, traffic congestion, GPS, radar, sensors, type of road, weather conditions, lighting conditions, velocity, other road users, kinematic state, traffic violation	The capability of AVs to handle complex traffic environments and avoid collision is the focus of considerable public concern. This paper focuses on cut-in scenarios with time-to-collision less than three seconds. 200 cut-in events were extracted from Shanghai Naturalistic Driving Study data, and the corresponding scenario characteristics for each event was transferred into a simulation platform. The Responsibility-Sensitive Safety (RSS) model demonstrated promising performance.	Liu *et al.* Transportation Research Part C, 2021
392	**Traffic conditions (complexity)**	Environmental factors, road conditions, technological factors, other traffic participants, HMI, control, experience	This paper argues that driving/using a self-driving car involves risks and one can question the behaviour, intelligence, autonomy and 'thinking' of the car when facing various traffic scenarios. The focus here is on ethics and responsibility dilemmas of replacing human drivers with machines.	Coeckelbergh Applied Artificial Intelligence, 2016
393	**Traffic conditions (complexity)**	Traffic composition, traffic density, reaction time, weather conditions, kinematic state, road type, road conditions, road topology, sensors, behaviour generating, control, algorithms	AVs need to generate behaviours adapting themselves to the traffic conditions, as well as the weather conditions and road type, in a safely way and efficient and mixed traffic scenarios. This work demonstrates the applicability of a reconfigurable vehicle controller agent for AVs that adapts the parameters of a used car-following model at runtime, to maintain a high degree of traffic quality (efficiency and safety) under dissimilar weather conditions.	Horcas *et al.* Journal of Software: Evolution and Process, 2017
394	**Traffic conditions (complexity)**	Speed, road type, obstacles, perception, sensors, manoeuvre planning, traffic density, other road users, road geometry, traffic rules, V2V, V2I, weather and visibility conditions, LiDAR, cameras, time of the day, lighting conditions, day of the week, traffic composition, path/trajectory planning, behaviour generating, vehicle kinematics, number of lanes, road infrastructure, algorithms, cybersecurity, time to collision	In the traffic engineering, a collision can be predicted in real-time based on current data on traffic dynamics such as the average speed and flow of vehicles on a road segment. This thesis aimed to integrate vehicle-level collision prediction approaches for AVs with network-level collision prediction in the context of traffic engineering.	Katrakazas PhD thesis, 2017

395	**Traffic conditions (complexity)**	Traffic density, speed, traffic behaviour, traffic composition, vehicle density, traffic flow, number of lanes, V2V, collision avoidance, reaction time, traffic control infrastructure	One of the solutions for improving safety in mixed traffic scenarios is designating a separate lane to AVs. In this research, AVs' behaviour is modelled at the macroscopic level by modifying the fundamental diagram relating hourly traffic flow and vehicle density, a step that is justified by adjusting a parameter from Newell's car-following model at the microscopic level and reversing to a macroscopic analysis.	Vander Laan and Farokhi Sadabadi International Journal of Transportation Science and Technology, 2017
396	**Traffic conditions (complexity)**	Sensors, cameras, LiDAR, radar, road geometry/topology, obstacles, time to collision, number of lanes, visibility, communication infrastructure, speed, kinematic state, control, traffic composition	This chapter (*Probabilistic Vehicle Motion Modeling and Risk Estimation*) develops a layered approach to model behaviours of vehicles under normal traffic conditions and estimate the risk of collision. The estimated risk of collision can be further used to assist an AV in planning a suitable trajectory to minimise its risks.	Tay, Mekhnacha and Laugier Handbook of intelligent vehicles, 2012
397	**Traffic conditions (complexity)**	Road geometry, speed, weather conditions, vehicle's trajectory, time to collision, traffic control infrastructure, traffic density, control, road type, communication	There have been several real-time safety studies investigating the idea that the segment conditions, including traffic, geometric, and weather affect the occurrence of an accident. The occurrence of a collision can be due to the upstream traffic conditions where and when the vehicle travels from. On that basis, a quasi-vehicle-trajectory-based real-time crash analysis was conducted in this study.	Wang *et al.* Transportation Research Part C, 2019
398	**Traffic conditions (complexity)**	Sensors, LiDAR, cameras, radar, road geometry, road infrastructure, path planning, motion planning, behaviour generation, longitudinal and lateral control, road conditions, obstacles, other road users, weather conditions, AI	Traffic scenes have their own unique complexity and dynamics. Therefore, if a self-driving vehicle is expected to achieve fully autonomous driving in a complex traffic scene, it must have the ability to learn and make predictions. Autonomous vehicles face many different scenes and road conditions, such as high-speed scenes, low-speed urban roads, and unstructured roads. this study deeply discusses some basic scientific issues of the self-driving approach based on cognitive construction, as well as the methods, computing models and technical routes to solve adaptability to complex situations of self-driving system.	Chen *et al.* SCIENCE CHINA Information Sciences, 2019
399	**Traffic conditions (complexity)**	Traffic density, traffic control, road infrastructure, road geometry, weather conditions, traffic control infrastructure, reaction time, speed, driving behaviour, static obstacles, other road users, number of lanes, road conditions	The dynamic of the traffic flow contributes to the complexity of traffic scenes. This further gives rise to the number of crashes. This paper examined the link between traffic complexity and collision risk (number of crashes) under urban motorway conditions. It was expected that linking the number of events (exposure) such as 'harsh lane change to crash numbers can provide more insights into the relationship between causation and effect. The concepts developed for urban motorways but can also be applicable to other high-volume multi carriageway roads.	Zurlinden, Baruah and Gaffney Journal of Road Safety, 2020
400	**Traffic conditions (complexity)**	Road type, algorithms, other road users, road geometry, weather conditions, obstacles, LiDAR, road conditions, lighting conditions, sensors, cameras, speed	Comprehensive traffic data scenario is often necessary to evaluate the performance of *unmanned ground vehicles* (UGVs) and measure the scene complexity. This study developed a traffic sensory data classification paradigm based on quantifying the scenario complexity for every segment of roads. This quantification is based on road semantic complexity and traffic element complexity.	Wang *et al.* IEEE Intelligent Vehicles Symposium, 2018
401	**Traffic conditions (complexity)**	Control, kinematic state, traffic rules, path planning, obstacles, actuators, cameras, LiDAR, radar, speed, other traffic participants	This paper proposed a 'cooperative control' approach for AVs to safely perform manoeuvres in complex traffic situations such as lane changing or crossing road intersections. This model is based on a cost function and collision avoidance objective for various traffic scenarios.	Mohseni, Frisk and Nielsen IEEE Transactions on Intelligent Vehicles, 2021
402	**Traffic conditions (complexity)**	Road type, other road users, algorithms, number of lanes, speed limits, time-to-collision, static and dynamic objects, traffic volume, mixed traffic, path planning, environment perception	This study adopted scenario-based testing for the validation and verification of CAVs. 189,752 scenarios including various collision scenarios were simulated for this purpose. To evaluate the risks faced by CAVs in different traffic situations, a new criticality metric (Scenario Risk Index) was defined.	Yue *et al.* IEEE Open Access, 2020

403	**Traffic conditions (complexity)**	Algorithms, machine learning, cybersecurity, other traffic participants, motion planning, perception, trajectory generation, control, kinematic state, traffic composition, road infrastructure, time-to-collision, hardware, sensors, velocity	In this work, a "fully model-based multi-modal parallelizable" is developed to analyse and evaluate the criticality of the complex traffic scene ahead of AVs. The extension of this algorithm can include road infrastructure and mobile objects. This algorithm is capable of handling a traffic scenario with 11 objects (over 86 million pose combinations) in 21 ms.	Morales *et al.* IEEE Intelligent Vehicles Symposium (IV), 2019
404	**Traffic conditions (complexity)**	Situation awareness, velocity, perception algorithms, V2I, V2V, kinematic state, road geometry, sensors, trajectory planning	Crossroads are a complex traffic situation for autonomous vehicles. This paper proposed a system with two functionalities. First, it is capable of predicting the motion of a surrounding vehicle in general traffic situation, and second, is its ability to estimate the probability of a collision given the current ego trajectory.	Annell, Gratner and Svensson IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), 2016
405	**Traffic conditions (complexity)**	Other traffic participants, algorithms, dynamic obstacles, control, trajectory planning, radar, cameras, lighting conditions, speed, sensors, LiDAR, motion state	AVs should inevitably interact with other road users such as pedestrians while traveling in complex traffic environments. All potential collisions must be avoided during the interactive process to ensure the safety. This paper analysed the active obstacle collision avoidance algorithm.	Zhang *et al.* Journal of Intelligent & Fuzzy Systems, 2018
406	**Traffic conditions (complexity)**	Time-to-collision, vehicle dynamics, algorithms, sensors, road type, sensor fusion, V2V, V2I, control, obstacles, kinematic state, GPS, other road users, road parameters, trajectory planning, speed	An anti-collision strategy based on hazard cognition is proposed to enable AVs safely passing through intersections while interacting with other vehicles. The algorithm was built and simulation was performed in MATLAB/Simulink. The simulation results have shown that the algorithm is reliable enough to prevent collisions.	Jia *et al.* Chines Automation Congress (CAC), 2019
407	**Traffic (safety) culture**	Perceived risk, training, traffic law enforcement, speed, population density, safety culture	This study maintains that without a deeper understanding of the nature and structure of traffic safety culture, discussions regarding changes to traffic safety culture are restricted. The authors attach a high significance to the 'traffic safety culture' and its impact on traffic safety.	Edwards *et al.* Transportation Research Part F, 2014
408	**Traffic (safety) culture**	Traffic rules enforcement, speed, other road users, perceived risk, training and experience, road and traffic control infrastructure	It is asserted that traffic safety culture stems from a country's cultural norms and values. This work investigates how culture influences traffic safety standards in three countries (i.e., Japan, China and US) with very different traffic safety outcomes. The results show that due to a large population and intense competition the risk acceptance is higher. In the US, the personal freedom culture adversely affects the safety culture and law enforcement, whereas Japan which leans towards limiting drivers' freedom for the sake of safety. These may explain the significant difference between fatality rates in these countries.	Atchley, Shi and Yamamoto Transportation Research Part F, 2014
409	**Traffic (safety) culture**	Speed, rule violation, perceived risk, traffic rules enforcement	The purpose of the study was to examine the country cluster differences, based on the Culture's Consequences framework, in road traffic risk perception, attitudes towards traffic safety and driver behaviour among samples from eight countries: Norway, Russia, India, Ghana, Tanzania, Uganda, Turkey and Iran. This paper concluded that cultural factors are strong predictors of driver behaviour which can affect accident risks.	Nordfjærn, Şimşekoğlu and Rundmo Accident Analysis and Prevention, 2014
410	**Traffic (safety) culture**	Speed, traffic complexity, traffic density, road characteristics	This study draws attention to *driving style* as a very important indicator and a crucial measurement of a driver's performance and ability to drive in a safe and protective manner. It also suggests that a driving style recognition module can be incorporated into AVs, which integrates different modules to improve driving automation, safety and comfort, and then the driving safety can be increased by pre-warning the drivers or adjusting the vehicle's controlling parameters when the dangerous driving style is recognised. Driving styles are categorised into three types: Aggressive type, Moderate type, and Conservative type.	Yan *et al.* Frontiers in Psychology, 2019

411	**Traffic(safety) culture**	Risk perception, speed, demographics	The aim of this paper is to enhance the understanding of how attitudes, beliefs, and values toward driving behaviour affect different subgroups of a population in adopting driving styles. This was used as a base to assess the 'traffic safety culture' among different class of drivers (e.g., low risk or high risk).	Coogan *et al.* Transportation Research Part F, 2014
412	**Traffic (safety) culture**	Traffic rules, public perception,	This study is focused on ethical dilemmas of AVs to set the foundations of an ethics test for them. The authors suggest that daily driving scenarios can inspire "edge-case" common sense testing of AVs, both in simulation and real road tests that can assess how the software behaves in a series of expected and unexpected driving situations that are not typically encountered during a standard test, but that may eventually arise on real roads. Besides traffic rules, the authors recommend incorporating idiosyncrasies of the *local driving culture* to improve the setup of driverless dilemmas to increase their realism and relevance to actual AVs.	De Freitas *et al.* Proceedings of the National Academy of Sciences, 2021
413	**Traffic (safety) culture**	Risk perception, experience and training, secondary tasks, drowsiness, road design, traffic rules enforcement, demographics, speed	It is important and practical to understand risky behavioural habits among sub-cultures and thereby focussing on groups of drivers instead of individuals, because groups are easier to approach and drivers within sub-cultures are found to influence each other. This paper investigated the driving behaviours based on drivers' sub-cultural backgrounds in Qatar. Results suggest that acceptance of speeding is highest among the young Arabic students and acceptance of distraction and drivers' negligence such as using phone and not wearing a seatbelt is highest among male Arab drivers. Acceptance of extreme risk-taking like intoxicated driving and red-light running is highest among South-Asian business drivers.	Timmermans *et al.* Journal of Safety Research, 2020
414	**Traffic (safety) culture**	Perceived risk, demographics, situation awareness, other road users, traffic rule enforcement, secondary task, driving style	This paper validates *traffic safety climate* attitudes based on a representative sample of road users of all travel modes. Traffic safety climate is defined as "the road users' (e.g. drivers') attitudes and perceptions of the traffic in a context (e.g., country) at a given point in time". Further, traffic safety culture is defined as ''the sum of all factors that affect skills, attitudes, and behaviours of drivers as well as vehicles and infrastructure''.	Gehlert, Hagemeister and Özkan Transportation Research Part F, 2014
415	**Traffic (safety) culture**	Speed, secondary task, demographics, perceived risk, road design, training and experiment, traffic rules enforcement, other road users, drowsiness, impaired driving	This study analysed the results of a survey to test the correlations between sociodemographic factors which risk perception and other constructs shaping the traffic safety culture of road users. It was found that country-specific culture might not have a strong association with risk perception; however, culture is associated with risk behaviour and therefore a valid predictor of traffic safety.	Tazul Islam, Thue and Grekul Transportation Research Record: Journal of the Transportation Research Board, 2017
416	**Traffic (safety) culture**	Traffic composition, time-to-collision, speed, reaction time, control, algorithms, vehicles' kinematics, headway distance, hardware, traffic conditions, weather conditions, roadway type, acceleration, driving volatility	This paper aimed to quantify uncertainties in the interaction of HDVs and AVs in mixed traffic and measure main impacts of AVs on conventional vehicles as well as their drivers' behaviours. On average, a driver that follows an AV recorded lower driving volatility in terms of speed and acceleration. This can result in a more stable traffic flow behaviour and lower collision risk.	Mahdinia *et al.* Accident Analysis and Prevention, 2021
417	**Traffic (safety) culture**	Weather/road conditions, other traffic participants, traffic conditions, kinematics, reaction time, perception, motion planning, path planning, speed, behaviour generation, algorithms, controllers, number of lanes, obstacles, V2V	A decision-making algorithm is suggested to assess the risks of colliding with surrounding traffic participants for AVs. The findings advocate that the proposed method is sufficiently reliable for AVs to avoid collisions in multi-scenarios with different driving style preferences (i.e., aggressive, moderate, and conservative).	Li *et al.* Transportation Research Part C, 2021

418	**Traffic (safety) culture**	Traffic laws, traffic conditions, traffic density, obstacles, reaction time, other traffic participants, kinematic state, path planning, algorithms, weather conditions, road conditions, perceived risk	For AVs to obey the traffic laws, objective measurements of safe and cautious behaviour in normal driving conditions are essential. This study put forward the conception, implementation and primary testing of an objective scoring algorithm that matches safety indices to observed driving style, and accumulates them to provide an overall safety score for a given driving session. This method can be applied to AVs' behaviour in real traffic.	Schönera *et al.* Traffic Injury Prevention, 2021
419	**Traffic (safety) culture**	lateral and longitudinal control, algorithms, reinforcement learning, velocity, traffic flow, traffic conditions, traffic density, environmental factors, sensors, GPS, cameras, LiDAR, radar, perception accuracy, kinematic state, road geometry, weather conditions, number of lane, other traffic participants	This paper developed a 'deep deterministic policy gradient (DDPG) algorithm' to coordinate the lateral and longitudinal control of AVs in complex traffic scenes. For avoiding collisions and allowing different expected lane-changing distances that represent different *driving styles* are considered for security, and the angular velocity of the steering wheel and jerk are considered for comfort.	Hu *et al.* Sensors, 2020
420	**Trust & Reliance**	HMI	This study focuses on the effects of trust (as a fundamental factor in human-automation interaction) in AV technology. Three acceptance measures (general acceptance, behavioural intention, and WTP) and two vehicle automation levels (HAV and FAV) were considered.	Liu *et al.* International Journal of Human–Computer Interaction, 2019
421	**Trust & Reliance**	H-M Interface, experience & tech literacy, algorithms,	This paper emphasises the importance of trust in human-automation interactions and relations especially in applied AI. Trust provides a valid foundation for describing the relationship between humans and automation.	Hengstler, Enkel and Duelli Technological Forecasting and Social Change, 2016
422	**Trust & Reliance**	experience & tech literacy	The attitude structure of public towards the AVs is measured in three dimensions (i.e. cognitive, affective, and behavioural components) before and after direct experience.	Liu and Xu Technological Forecasting and Social Change, 2020
423	**Trust & Reliance**	Training, pedestrians, other road users, HMI, H-M Interface,	This paper argues that successful achievement of fully/highly automated driving hinges upon demonstrating and resolving the trust issues. Training of the potential users (and interactors) to acquaint them with system boundaries and limitation plays a crucial role in safe operation of safety-critical systems.	Wintersberger and Riener i-com, 2016
424	**Trust & Reliance**	Control, communication,	This article argues that 'trust' is essential to decreasing perceived risk. In AI-based technologies, perceived risk further stems from the delegation of control to a machine and its control mechanisms.	Hengstler, Enkel and Duelli Technological Forecasting and Social Change, 2016
425	**Trust & Reliance**	HMI, public attitude	The authors see trust as a core concept in human machine interaction as well as human-automation interaction in advanced technologies. The results show that trust and risk acceptance are correlated.	Liu, Wang and Vincent Journal of Experimental Psychology: Applied
426	**Trust & Reliance**	HMI, control	This study maintains that trust in autonomous vehicles is especially important, because driving is a risky task and may result in fatal consequences. Therefore, in order to ensure a desirable interaction between the technology and human.	Rödel *et al.* 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 2014
427	**Trust & Reliance**	Experience, HMI, component failure, hardware reliability	The results of this study demonstrate that the real-life driving experience improves trust calibration in automated cars. This paper also suggests a strong relation between user (human agent) and system performance.	Walker *et al.* Journal of Advanced Transportation, 2018
428	**Trust & Reliance**	Situation awareness, dynamic objects, traffic culture	This study maintains that 'trust' affects the use of automated systems. With overreliance (or over-trust), an interactor's trust level exceeds the system capabilities, resulting in risk.	Sonoda and Wada IEEE Transactions on Intelligent Vehicles, 2017

429	**Trust & Reliance**	HNI, situation awareness, H-M interfaces	The concept of "human-autonomy teaming" is developed in this paper and is linked to the study of human factors to address the challenges of interacting with complex and increasingly autonomous systems. It is maintained that if implemented properly, HAT can foster desired teamwork and result in increased trust and reliance on the system, which in turn will reduce workload, increase situation awareness, and improve performance.	Ho *et al.* IEEE/AIAA 36th Digital Avionics Systems Conference (DASC), 2017
430	**Trust & Reliance**	Experience, perceived risk	A survey was conducted to investigate the relation between experience and trust in automated driving systems. Trust was related to several attitudinal and behavioural factors, and experience shaped the level of trust in these technologies.	Dikmen and Burns IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2017
431	**Trust & Reliance**	Shared goals, information sharing, acceptability,	This study provide evidence that trust is important for the acceptability of smart systems. Further it shows that 'shared goal' and 'giving information' can increase the trustworthiness of smart systems.	Verberne, Ham and Midden Human Factors, 2012
432	**Trust & Reliance**	Reaction time, HMI, training and experience, perceived risk, situation awareness, H-M interface, road infrastructure	The concept of 'trust fall' is introduced to investigate trust in automated systems. This paper concludes that 'overtrust' in systems that are perceived to be safe but still prone to infrequent and hazardous failures can present a significant risk.	Miller *et al.* Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 2016
433	**Trust & Reliance**	Reliance, perceived risk, predictability, functionality, behavioural intention	This study shows a strong correlation between, perceived risk, trust and behavioural intention in the context of AVs.	Choi and Ji International Journal of Human-Computer Interaction, 2015
434	**Trust & Reliance**	Urban settings, other road users, pedestrians, human-driven cars, communication	This study cites the Nissan IDS concept which shows that human-cantered issues such as social acceptance, trust in the AV, and the evocation of emotions are of great importance when people get faced with this new technology. This further investigates the impact of	Zimmermann and Wettach Proceedings of the 9th ACM International Conference on Automotive User Interfaces and Interactive Vehicular Applications, 2017
435	**Trust & Reliance**	Training, practice, experience, reaction time, over trust, distrust	The correlation between trust and fully automated driving (FAD) performance was tested. The results show that a correlation exists between trust and reaction time in the simple practice group (i.e., higher trust meant a longer reaction time), but not in the elaborate practice group. This finding indicated that to mitigate the adverse impact of overtrust on reaction time, more appropriate practice and training may be needed for drivers.	Payre, Cestac and Delhomme Human Factors, 2016
436	**Trust & Reliance**	Environmental conditions, experience, HMI	In this article, the role of 'automation trust' in monitoring behaviour of drivers and human-machine interactions during highly automated driving is investigated. A consistent relationship between drivers' automation trust and gaze behaviour was reported. Participants reporting higher automation trust were more likely to monitor the automation less frequently. Further analyses showed that higher automation trust was associated with lower monitoring frequency of the automation during (non-driving-related task) NDRTs, and an increase in trust over the experimental session was connected with a decrease in monitoring frequency.	Hergeth *et al.* Human Factors and Ergonomic Society, 2016
437	**Trust & Reliance**	HMI, system design, experience,	This study emphasises the importance of 'operator's trust' in *fielded unmanned systems* and sees this factor as a critical factor affecting the success of these systems. It suggests a framework for assessing operator's trust based on heuristics such as 'Visibility of system capabilities & limitations' and 'Visibility of current system behaviour'.	Jackson *et al.* Proceedings of the Human Factors and Ergonomics Society, 2016

438	**Trust & Reliance**	Situation awareness, overreliance, reliability, training and experience	This article investigates the importance of situation awareness (SA) of the driver in autonomous driving and highlights three crucial factors affecting SA. These factors are Attention and Trust, Engagement and Workload and Mental Model. It is maintained that "… [SA] is affected by the level of trust in the automation and the presence of competing secondary tasks and which is mediated by the effectiveness of the vehicle displays".	Endsley Journal of Cognitive Engineering and Decision Making, 2017
439	**Trust & Reliance**	Road type, reaction time, weather conditions, road infrastructure, other road users, obstacles, construction zone, light conditions, human driven vehicles, H-M interface	This study focuses on the role of human factors in disengagements, accidents and reaction times. It is asserted that "the ultimate success of automated vehicles will depend on drivers' trust in them [AVs] and on how people choose to use and interact with them, and the ensuing safety risk". Results show a positive correlation between the cumulative vehicles mile travelled and reaction time which contributes to drivers' trust.	Dixit, Chand and Nair PLoS ONE, 2016
440	**Trust & Reliance**	Technical competence, HMI,	The role of anthropomorphism in building and enhancing trust in autonomous vehicles is investigated. Trust is seen as an 'essential condition' for accepting and relying on autonomous vehicles and successful use of the technology depends on whether people trust it or not.	Niu, Terken and Eggen Human Factors and Ergonomics in Manufacturing & Service Industries, 2018
441	**Trust & Reliance**	Communication, sensors, software, traffic conditions/culture, inter-vehicle interactions, urban design, traffic rules	This paper briefly summarises the approaches that different teams used in the DUC, with the goal of describing some of the challenges that the teams faced in driving in urban environments. The issue of inter-vehicle trust in case the traffic rules are breached is suggested as an avenue for further research.	Campbell *et al.* Philosophical Transactions of the Royal Society A, 2010
442	**Trust & Reliance**	HMI, experience, tech literacy, reliability	This study investigates the influence of 'Trust Metrics' on the employments of Autonomous Systems in high risk environments and applications. To test their hypothesis of trust in technology, the authors identified constructs that facilitate measurement of human interaction with the technology. Experience and knowledge are among these constructs.	Anderson and Mun Sixteenth Annual Acquisition Research Symposium, 2019
443	**Trust & Reliance**	Traffic rules, traffic culture, regulations, control, traffic environment, HMI, situation awareness, H-M Interface	The issue of trust in driverless cars is studied in this work. It is believed that until trust is established, the vehicle has the potential to be underutilized, misused, or even unused. In order to tackle this, the authors suggest the use of knowledge about human behaviour and the social sciences to design safer systems and interfaces between these vehicles and the people using them.	Schaefer and Straub IEEE International Multi-Disciplinary Conference on Cognitive Methods in Situation Awareness and Decision Support, 2016
444	**Trust & Reliance**	Overtrust, distrust, HMI, situation awareness,	This paper centres on the influential factors that can affect trust in automated cars. It is believed that if users have too little trust, they are less likely to rely on and take full advantage of the capabilities of the technology. On the other hand, if users trust the technology too much, they are again less likely to monitor the system in challenging environmental conditions which cause the systems to operate at the edge of their capabilities.	Carlson *et al.* The Intersection of Robust Intelligence and Trust in Autonomous Systems: Papers from the AAAI Spring Symposium, 2014
445	**Trust & Reliance**	HMI, Human-Machine Interface, control, handover	This research focuses on the importance of public opinion on design of H-M Interface. Semi-structured interviews besides focus groups were conducted to gain insights into the perception of public on AVs and requirements which needed to be considered in the design of this technology.	Langdon *et al.* International Conference on Applied Human Factors and Ergonomics, 2017
446	**Trust & Reliance**	HMI, over-trust, mistrust, perceived risk, reaction time, cybersecurity,	An acceptance model for semi-autonomous vehicles (level 3) is developed in this paper. 'Trust' is specified as a major factor determining HMI.	Zhang *et al.* Transportation Research Part C, 2019

447	**Trust & Reliance**	HMI, perceived risk, training and experience,	This paper hypothesises that "*there is a significant correlation in users' psychophysiological response when exhibiting varying levels of trust towards AVs*". Then it shows a significant correlation between users' psychophysiological responses when exhibiting varying levels of trust towards AVs' during interactions.	Ajenaghughrure, da Costa Sousa and Lamas 13th International Conference on Human System Interaction (HSI), 2020
448	**Trust & Reliance**	H-M Interface, overtrust, undertrust, situation awareness,	This paper outlines the results of a driving simulator study conducted for the European CityMobil project. The aim was to investigate the impacts of FAD and HAD on the drivers' behaviour. Situation awareness, too much trust and too little trust are among the expressed concerns about the interactions between drivers and highly automated vehicles.	Merat and Jamson Proceedings of the Fifth International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design, 2009
449	**Perceived risk**	Trust, reliance, predictability, functionality, behavioural intention	This paper investigated the importance of trust in adopting AVs. The authors argue that 'perceived risk' is an essential component of a trust model. Perceived risk is a key determinant linked to trust, particularly with regards to the decision to use an automated device, or not to use it.	Choi and Ji International Journal of Human-Computer Interaction, 2015
450	**Perceived risk**	Overreliance, situation awareness, training & experience, trust, HMI, H-M interface,	The aim of this study is to discuss human-factors issues associated with AVs, with a concentration on car following. There is more emphasis placed on human factors issues of safety, usability, and acceptance rather than technical challenges ahead of this technology. A negative relationship is demonstrated to exist between experience and perceived risk.	Saffarian, de Winter and Happee Proceedings of the Human Factors and Ergonomics Society 56th Annual Meeting, 2012
451	**Perceived risk**	Training and experience, trust,	A survey was conducted to investigate the relation between experience and trust in automated driving systems. Trust was related to several attitudinal and behavioural factors, and experience shaped the level of trust in these technologies. A strong and negative correlation was reported to exist between 'initial trust' and the level of 'perceive risk'.	Dikmen and Burns IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2017
452	**Perceived risk**	Experience, cybersecurity, hardware failure, trust, V2X, traffic environment	This study explores the risk perceptions toward connected and autonomous driving technology in comparison to conventional driving vehicles. Findings of this research show that with increased experience, the risk perception decreases. Statistically, a significant omnibus interaction effect between experience, risk area, and driving technology was found. It is also maintained that gaining understanding on 'risk perception' in autonomous driving can foster a successful implementation of AVs.	Brell, Philipsen and Ziefle Risk Analysis, 2019
453	**Perceived risk**	Other road users, public perception, vehicular parameters, weather conditions, road conditions, lighting conditions, traffic conditions, speed, law enforcement, HMI, culture, cybersecurity, training and experience, reaction time	This study surveyed almost 1000 participants on their risk perceptions, particularly with regards to safety and acceptance of AVs. The interactions between AVs and humans, other vehicles and road users are discussed in this paper.	Hulse, Xie and Galea Safety Science, 2018
454	**Perceived risk**	V2X, sensors, LiDAR, cameras, obstacles, other road users, traffic infrastructure, reaction time, trust, kinematic state, H-M Interfaces, vehicle dynamics, traffic density, number of lanes, perception accuracy, vehicle control, situation awareness, communication channels, sensor fusion	This paper analyses the role of V2X and 'collective perception' in object update rate, redundancy, and awareness. Collective perception was measured in terms of three types of performance metrics: 1) effect on the communication channel; 2) environmental; perception; and 3) safety metrics. The findings agree with other studies and suggest that collective perception affects the load of the communication channel. This highlights the need for appropriate congestion control mechanisms.	Schiegg *et al.* Sensors, 2021

455	**Perceived risk**	Communication, time-to-collision, kinematic state, traffic flow, vehicle performance, road conditions, traffic infrastructure, algorithms, traffic composition	This study proposed a new methodology for risk perception and warning strategy based on safety potential field model to minimise collision risk in AD. A novel driving risk indicator (potential field indicator) was defined to evaluate the level of driving risk. Based on that, an early warning strategy was developed to prevent collisions and its performance was tested by a series of simulations carried out in SUMO simulator.	Li *et al.* Accident Analysis and Prevention, 2020
456	**Perceived risk**	Trust and reliance, reaction time, secondary task, HMI, visibility, other road users, H-M Interface, obstacle, experience in autonomy	Lack of trust in automation is a reason for the failure of drivers to fully exploit a vehicle's autonomy. It is also stipulated that "the form of trusting belief is based on the perceived level of risk, and a lower perceived level of risk leads to higher levels of trust".	Petersen *et al.* Ground Vehicle Systems Engineering and Technology Symposium, 2018
457	**Secondary task (non-driving tasks)**	driver fatigue, control of vehicle, speed, reaction time, perceived risk, weather conditions, traffic complexity, driving experience, road layout, H-M Interface, situational awareness, other vehicles, kinematic state	A challenging topic for researchers in the field AD involves an understanding of whether a period of automated driving is likely to lessen driver fatigue rather than increase the risk of distraction, specifically when drivers are involved in a secondary task (e.g., watching a video) while behind the wheel. It is maintained that from a human factor perspective, the exclusion of drivers from the control loop caused by their engagement in non-driving-related tasks (NDRTs) can make it harder for them to take over control of the vehicle. This can further affect the reaction time to hazardous situations.	Calvi *et al.* Transportation Research Part F, 2020
458	**Secondary task (non-driving tasks)**	Longitudinal and lateral control, speed, sensors, cameras, software reliability, obstacles, other road users, road configuration, reaction time, trust, H-M Interfaces, traffic rule enforcement, traffic density, automations capacities awareness, mental control	Human interventions deem to be necessary in AD at least until the technology *functions perfectly and permanently*. This study conducted two simulator experiments to examine the impact of vehicle's autonomy level on the performance of onboard drivers in performing secondary tasks (reading a book or watching video).	de Winter *et al.* International Journal of Vehicle Design, 2016
459	**Secondary task (non-driving tasks)**	Perceived risk, take-over time, driver behaviour, situational awareness, experience, trust and reliance	AVs are still unequipped to safely handle many unexpected hazards and conditions in real-world traffic. This paper quantified changes in driver *attention allocation* before and during exposure, and after the lane keeping system was disabled. To this end, the number of secondary tasks completed by the participants, accuracy of those tasks, and eyes-off-road glance durations were measured. An important finding in this research is that drivers become more willing to take risks each they feel more comfortable with the AVs.	Miller and Boyle Transportation Research Part F, 2019
460	**Secondary task (non-driving tasks)**	Drivers' mental mode, trust, longitudinal and lateral control, trust, overreliance, situation awareness, reaction time, control loop, HMI, H-M Interface, traffic density, traffic regulation, traffic conditions, velocity, other road users, obstacles, weather conditions, technical failures	A group of 20 Tesla drivers who had relatively high experience (one to five months) with Autopilot were interviewed to pinpoint their behavioural adaptation, mental models, and trust during the period of AD. The results suggested that those who had experienced semi-autonomous driving had a very positive attitude towards the technology and drivers universally engaged in non-driving related tasks (NDRTs) during AD. They also learnt from their experiences to figure out relatively safe usage conditions and considered a safety margin to avoid exposure to excessively risky situations.	Lin, Ma and Zhang Applied Ergonomics, 2018
461	**Secondary task (non-driving tasks)**	Sensors, V2X, communication infrastructure, H-M Interface, trust, vehicular control, other road users, obstacles, road design, road conditions, user experience	A survey of 29 in-vehicle information items was conducted among 156 participants, who drove a virtual indoor simulator in both manual- and autonomous-driving modes. The findings show that in the AD mode, the drivers' preference for information about the secondary tasks of driving diminished, whereas the tertiary-task information, particularly communication-related information that was reported higher. This work is useful as it can provide a basic guideline for designers of user experiences and user interfaces.	Lee, Park and Ju International Journal of Automotive Technology, 2020

462	**Secondary task (non-driving tasks)**	HMI, reaction time, perceived risk, H-M Interfaces, velocity, weather conditions, obstacles, fatigue, situational awareness, trust, road geometry, other road users	In highly automated driving, where most of the research is focusing on SAE Level 4, take-over performance is also a key factor to ensure collision avoidance. This study aimed to examine how the immersion in NDRTs affects the take-over performance of drivers in given traffic scenarios.	Minhas *et al.* IEEE Transactions on Intelligent Transportation Systems, 2020
463	**Secondary task (non-driving tasks)**	Reaction time, situation awareness, drowsiness, speed, road infrastructure, traffic density, human factors, lateral and longitudinal vehicle control	SAE Level 3 automation allows the on-bord driver to engage in NDRTs, although the driver is still required to take over the control if the technology cannot handle a risky situation. This paper examined the impact of the type of NDRTs and the complexity of the situation on driver performance.	Dogan *et al.* Transportation Research Part F, 2019
464	**Secondary task (non-driving tasks)**	time to react, situation complexity, traffic densities, road geometry, motion awareness, obstacle	AVs with higher levels of autonomy (i.e., 3 and 4) allow the drivers to divert their attention to NDRTs (e.g., texting, reading, or watching videos) during a ride. Nevertheless, these systems can still be prone to failure. Based on that, human intervention may become inevitable in critical situations. This paper proposes a new mean of communicating take-over requests (TOR) using human actuation through proprioception.	Faltaous *et al.* 18th International Conference on Mobile and Ubiquitous Multimedia (MUM), 2019
465	**Secondary task (non-driving tasks)**	Trust, driver behaviour, H-M Interface, visibility, HMI, weather conditions, obstacle, perceived risk, experience, other traffic participants, reaction time, control, situational awareness, environmental conditions	This study investigated the relationship between AD reliability, user trust and external risk (low visibility). 37 licensed drivers participated to use a simulator as part of the experiment. Internal risk was manipulated by AD reliability and external risk by visibility, producing a 2 (ADS reliability) × 2 (visibility) design.	Azevedo-Sa *et al.* Transportation Research Part C, 2021
466	**Secondary task (non-driving tasks)**	HMI, trust, H-M Interface, situation awareness, sensors, weather conditions, construction site, time to collision, control	Each automated system makes errors. The aim of this study was to evaluate whether communicating automation uncertainty improves the driver–automation interaction. A driving simulator was conducted to allow participant interacting with a highly automated driving system under varying automation reliability levels.	Beller, Heesen and Vollrath Human Factors, 2013
467	**Secondary task (non-driving tasks)**	Trust and reliance, obstacle, perception of an automation's reliability, experience and training, time-to-collision, situation awareness, speed, Human-Machine Interface, HMI	The impact of *trust promoting* and *trust lowering* on the reported trust was measured in this study. 40 participants took part in an experiment and faced three situations in a 17-min highway drive with a SAE Level 3 vehicle. Situation 1 and Situation 3 were non-critical situations where a take-over was not necessary. Situation 2 included a risky situation where an intervention was essential to avoid a collision. Drivers were required to engage in a non-driving-related task (NDRT) between the situations to track their allocation of visual attention. Participants recording a higher trust level spent less time looking at the road or instrument cluster and more time focusing on the NDRT. The manipulation of *introductory information* resulted in medium differences in reported trust and influenced participants' reliance behaviour.	Körber, Baseler and Bengler Applied Ergonomics, 2018
468	**Secondary task (non-driving tasks)**	Fatigue, traffic flow/density, lighting conditions, weather conditions, road conditions, number of lanes, day of week, speed, driver age, road design	This paper focuses on the risk of driver distraction in partially automated vehicles. It is proposed to apply technological countermeasures in partially automated vehicles to prevent drivers from engaging in secondary tasks such as using mobile phones while driving.	Flannagan, Bärgman, Bálint Transportation Research Part F, 2019
469	**Secondary task (non-driving tasks)**	Lateral and longitudinal control, driver workload, situation awareness, road conditions, adverse weather, road infrastructure, H-M Interface, HMI, trust and reliance, reaction time, automation capability awareness	One of the main concerns in AD is that with higher levels of automation, drivers will be gradually out of the control loop. In this study, the comments of YouTube users were categorised into four main groups: 1) NDRTs; 2) automation capability awareness; 3) situation awareness; and 4) warning effectiveness. It is reported that reviewers have extreme positive and negative opinions about NDRTs than other topics	Zhou, Yang and Zhang International Journal of Human–Computer Interaction, 2020

470	**Secondary task (non-driving tasks)**	Longitudinal &lateral control, time-to-collision, perceived physical danger, trust and reliance, situation awareness, velocity, H-M Interfaces, prior experience, traffic conditions, driving styles, velocity, other road users, traffic density, number of lanes, road geometry, visibility, automation level, age	Research has shown that one implication of an increase in the degree of vehicle autonomy is the tendency of drivers to engage in secondary tasks during a ride. This paper attempted to examine the effect of autonomy level on subjective and objective driving during an on-road experiment in real-world traffic. 32 participants took part in this study which was conducted in rush-hour traffic on a highway.	Naujoks, Purucker and Neukum Transportation Research Part F, 2016
471	**Secondary task (non-driving tasks)**	Vehicle control, reaction time, road type, weather conditions, road geometry	This paper investigated the effects of takeover request (TOR) modalities on drivers' takeover performance after they engaged in NDRTs in highly automated driving (HAD).	Yoon, Kim and Ji Accident Analysis and Prevention, 2019
472	**Obstacles (static and dynamic)**	Algorithms, LiDAR, sensors, collision avoidance, speed, vehicle dynamics, traffic rules	A dynamic obstacle avoidance Model Predictive Control (MPC) method is introduced for autonomous driving that uses deep learning technique for velocity-dependent collision avoidance in unknown environments. The ultimate goal is to control an autonomous vehicle in order to perform different traffic manoeuvres in a safe way with maximum comfort of passengers, and in minimum possible time, accounting for manoeuvring capabilities, vehicle dynamics, and in the presence of traffic rules, road boundaries and static and dynamic unknown obstacles	Mohseni, Voronov and Frisk IFAC Conference Paper Archive, 2018
473	**Obstacles (static and dynamic)**	Speed, algorithms, sensors,	The presence of stationary (static) and moving (dynamic) obstacles is diagnosed as a risk factor for AVs. A polar algorithm is proposed which automatically computes the avoidable set given the dynamics.	Chen, Peng and Grizzle IEEE Transactions on Control Systems Technology, 2018
474	**Obstacles (static and dynamic)**	Sensors, LiDAR, collision avoidance,	The problem of this paper is to estimate states of unobservable free spaces and obstacles occluded by other obstacles. Knowledge about blind spots helps autonomous vehicles make better decisions, such as avoiding a probable collision risk. The proposed method can also detect blind spots ahead of vehicle as driving risks in real outdoor dataset.	Sugiura and Watanabe IEEE Intelligent Transportation Systems Conference (ITSC), 2019
475	**Obstacles (static and dynamic)**	Path planning, speed, road geometry, road type, visibility, traffic rules,	Obstacles are deemed to block the mounted detection sensors on ego vehicle by limiting the visibility. Estimating the risk of collision with moving vehicles in an occluded area is difficult because their locations and speeds cannot be detected.	Lee, Sunwoo and Jo Robotics and Autonomous Systems, 2018
476	**Obstacles (static and dynamic)**	Lighting conditions, speed, sensors, algorithms, LiDAR, radar, cameras,	In this paper, the authors discuss the obstacle avoidance context for autonomous vehicles in dynamic and unknown environments, and they develop a new method for Collision Risk Estimation based on Pearson's Correlation Coefficient (PCC).	Miranda Neto *et al.* IEEE Workshop on Robot Vision (WORV), 2013
477	**Obstacles (static and dynamic)**	Communication, V2V, V2I, sensors, LiDAR, radar, weather conditions, control	Conventional intelligent vehicles have performance limitations owing to the short road and obstacle detection range of the installed sensors. In this study, to overcome this limitation, the authors tested the usability of a new conceptual autonomous emergency braking (AEB) system that employs vehicle-to-vehicle (V2V) communication technology in the existing AEB system. This method is proposed to lower the collision risk of the existing AEB system, which uses only a sensor cluster installed on the vehicle, is realised.	Cho, Kim and Kim Journal of Applied Mathematics, 2014
478	**Obstacles (static and dynamic)**	Algorithms, control, sensor, road geometry, speed	An optimisation model is presented to assess the vehicle risk and control for lane-keeping and collision avoidance at low-speed and high-speed scenarios. The optimisation approach is also able to deal with a variety of different obstacles and the corresponding optimal smooth obstacle path.	Fahmy, Abd El Ghany and Baumann IEEE Transactions on Vehicular Technology, 2018
479	**Obstacles (static and dynamic)**	Path planning, algorithms, speed, road conditions, vehicle dynamics	A risk index is constructed and introduced into the cost function to realise collision avoidance by combining the relative position relationship between vehicle and obstacles in the predictive horizon.	Li *et al.* IEEE, 2019

480	**Obstacles (static and dynamic)**	Traffic conditions, pedestrians, HMI, speed,	This paper presents a pedestrian crossing model in congested traffic conditions, taken from mobile robotics motion planning that constructs a trajectory according to the probabilistic collision risks. The idea of finding the "best motion" for autonomous vehicles in a dynamic environment is considered in robotics by the Velocity Obstacle Space (VOS), which is a set of all relative velocities characterized by the Collision Cone (CC).	Hacohen, Shvalb and Shoval Transportation Research Part C: Emerging Technologies, 2018
481	**Obstacles (static and dynamic)**	Path planning, algorithms, cameras, LiDAR,	As mobile robots and autonomous vehicles become increasingly prevalent in human-centred environments, there is a need to control the risk of collision. A novel method is developed to compute the risk of collision for mobile robots and autonomous vehicles.	Blake *et al.* IEEE Robotics and Automation Letters, 2020
482	**Obstacles (static and dynamic)**	Algorithms, sensor, path planning, road geometry, vehicle geometry, GPS	A novel probability *navigation function* (NF) is defined to reduce the risks of collision during the AV's motion. It is assumed that the obstacles and the workspace geometries are known, while their positions are stochastic variables.	Hacohen, Shoval and Shvalb International Journal of Control, Automation and Systems, 2019
483	**Obstacles (static and dynamic)**	Traffic conditions, vehicle dynamics, traffic rules, other road users, environment, speed, sensors, cameras,	A system view of the environment is generated by data fusion and data interpretation based on data stored in the dynamic data base that represents the current scene. This system view is transformed into a riskmap representation which integrates information about the street, the relative position and speed of obstacles and traffic signs.	Reichardt and Schick Proceedings of the 94 Symposium of Intelligent Vehicles, 1994
484	**Obstacles (static and dynamic)**	Path planning, traffic rules, traffic congestion, algorithms,	This study suggests static and dynamic path planning for AVs to avoid collision. Obstacles, therefore, are divided into static or dynamic categories simulations have been run to test the effectiveness the algorithms.	Lim, Shim and Takahashi Proceedings 6th IEEE International Workshop on Robot and Human Communication, 1997
485	**Obstacles (static and dynamic)**	Algorithms, sensors, road conditions, speed, vehicle dynamics, traffic condition	Planning safe trajectories for AVs under such conditions requires both accurate prediction and proper integration of future obstacle behaviour within the planner. An autonomous vehicle can safely navigate a complex environment in real-time while significantly reducing the risk of collisions with dynamic obstacles. This paper presents a real-time path planning algorithm that guarantees probabilistic feasibility for autonomous robots with uncertain dynamics operating amidst one or more dynamic obstacles with uncertain motion patterns.	Aoude *et al.* Autonomous Robots, 2013
486	**Obstacles (static and dynamic)**	Situational awareness, visibility, sensors, traffic conditions, traffic density, traffic rule enforcement, algorithms, road configuration, speed	This paper explores a moving vehicle detection and tracking module that was developed and used for the autonomous driving robot Junior. The robot won second place in the DARPA Urban Grand Challenge, an autonomous driving race organised by the US Department of Defense in 2007. The module provides reliable detection and tracking of moving vehicles from a high-speed moving platform using laser range finders.	Petrovskaya and Thrun Autonomous Robots, 2009
487	**Obstacles (static and dynamic)**	Speed, algorithms, path planning,	This letter addresses the time-optimal risk-aware motion planning problem for curvature-constrained variable-speed vehicles in the presence of obstacles. Due to complexities of the environment, it is also critical that the time-optimal path is safe for the vehicle.	Song, Gupta and Wettergren IEEE Robotics and Automation Letters, 2019
488	**Traffic density**	Speed, obstacles, time of day, other road users, HMI, road type, training and experience, situation awareness, V2I, regulations	This paper presents a high-level safety case that identifies key factors for credibly arguing the safety of an on-road AV test program. A similar approach could be used to analyse potential safety issues for high capability semiautonomous production vehicles.	Koopman and Osyk SAE International Journal of Advances and Current Practices in Mobility, 2019
489	**Traffic density**	LiDAR, traffic composition, sensors, optical cameras, V2V, V2I, visibility, weather conditions, road conditions, GPS, speed, obstacles, road infrastructure, actuators, algorithms, pedestrians	This study a simulation approach to test AVs in urban traffic scenarios. Simulations allow testing more scenarios than those that would be possible with real world testing, in addition to testing hazardous situations involving humans. The performance of AVs under varying circumstances are analysed.	Figueiredo *et al.* Proceedings of the 12th International IEEE Conference, 2009

490	**Traffic density**	Traffic composition, speed, target, communication, time to collision	This paper investigated the impact of traffic flow optimisation on the traffic safety problem in hybrid and only-AV traffic scenarios. It is reported that the optimal control for the CAV mixed traffic flow can mitigate vehicle rear-end collision risks. For the case of traffic flow with only CAVs, the rear-end collision risks of conventional vehicles flow can be decreased by more than 85.81% when the time-to-collision threshold is less than 2 seconds. This can be reduced by 48.22% to 78.80% if the time-to-collision threshold is more than 2 seconds.	Qin and Wang China Journal of Highway and Transport, 2018
491	**Traffic density**	Traffic conditions, speed, time-to-collision, road geometry, time of day	Crash surrogate metrics were used in this study to examine the relationship between collision risks and traffic flow. It has been widely recognised that one traffic flow corresponds to two distinct traffic states with different speeds and densities.	Kuang, Qu and Yan PLoS ONE, Traffic safety fundamental diagram, 2017
492	**Traffic density**	Speed, traffic conditions, drivers' behaviour, following distance, day of week, road geometry, road type, pedestrians	It is recognised that accident risk can vary as traffic conditions change due to special events or within-day variations in traffic. Furthermore, current predictive tools are mainly statistical, and this may not well fit to the environments which host automated vehicles. This study discusses how both issues can be addressed by supplementing standard statistical modelling together with models describing collision mechanisms. Brill's random walk model of how traffic shockwaves lead to rear-end accidents is merged with a traffic flow model based on a fundamental diagram to evaluate the relation between traffic density and rear-end collision risk.	Davis *et al.* Journal of Transportation Engineering, Part A: Systems, 2021
493	**Traffic density**	Traffic conditions, speed, rules, weather conditions, trajectory planning, communication, traffic control, human factors	This paper examines traffic complexity variables under higher levels of automation where the human controller is still in the loop, but is being supported by advanced conflict detection and resolution automation. A set of variables affecting the complexity for higher traffic densities were found in this article.	Kopardekar, Prevot and Jastrzebski AIAA Guidance, Navigation and Control Conference and Exhibit, 2008
494	**Traffic density**	Control, HMI, H-M Interfaces, traffic complexity, speed, situation awareness, reaction time, takeover, demographics, other road users, number of lanes, obstacles, non-driving related tasks	This article intended to assess the effect of traffic density and verbal tasks on takeover performance in highly automated driving. 72 participants were faced takeover situations needing an evasive manoeuvre on a three-lane highway with different traffic density levels (zero, ten, and twenty vehicles per kilometre). The results suggest that the presence of traffic affects the reaction time and quality of takeover. The traffic state appears to be a major factor in the study of HMI in AVs and takeover situations.	Gold *et al.* Human Factors, 2016
495	**Traffic density**	traffic condition, traffic control infrastructure, V2V, V2I, communication, traffic composition, speed, vehicle control, driving behaviour, reaction time, perception, road conditions, weather condition, road conditions, work zone, number of lanes, sensor limitations, radar, control algorithms, mixed traffic, road geometry, situation awareness	This paper develops a framework to simulate various types of vehicles with different communication capabilities. The analyses in this study took traffic composition (mixed traffic) into account.	Talebpour and Mahmassani Transportation Research Part C, 2016
496	**Kinematic state**	Time of day, weather conditions, other road users, reaction time, perceived risk, traffic composition, traffic density, speed, road conditions	A hybrid approach is adopted in this study to determine the factors which have influence on driver reaction time in traffic safety incidents. A causal model is presented to depict the influential factors in traffic safety incidents. Based on this model, it is asserted that "*the driver reaction time is one of the parameters of the kinematic and space-state models for trajectory reconstruction*".	Arbabzadeh *et al.* Transportation Research Part C, 2019

497	**Kinematic state**	Sensors, traffic density, speed, path planning, LiDAR, perception accuracy	The aim of this study was to accurately calculate the risks which are caused by each road user (including AVs) in time. Four states of track life are integrated into a generic fusion framework to improve the performance of multi-object perception in dense traffic environments in highways and urban roads.	Zheng and Huang Journal of Intelligent and Connected Vehicles, 2018
498	**Kinematic state**	Road topology, traffic flow, vehicle density, road conditions, number of lanes, perception accuracy, human factors, LiDAR, AI, path planning	The congestion problems of traffic networks after the introduction of self-driving cars at both micro and macro levels is studied here. In the developed model, the collision avoidance equation consists of two factors: velocity and the distance from the following car/vehicle.	Ji AIP Conference Proceedings, 2018
499	**Kinematic state**	Visibility, cameras, sensors, algorithms, LiDAR, radar, obstacles, weather conditions, road geometry	Safe operation under poor visibility conditions is a requirement for AVs. In this study an algorithm is developed to exploit the vehicle dynamics from *proprioceptive sensors* and include it in sensitivity study.	Boussard, Hautiere and d'Andrea-Novel IEEE/RSJ International Conference on Intelligent Robots and Systems, 2008
500	**Kinematic state**	Road conditions, trajectory tracking, vehicle control, speed, perception, algorithms, actuator, LiDAR, cameras, sensors	This work presented a novel method for an optimisation problem which combines vehicle kinematics and trajectory tracking control of a vehicle with high speed and under complex off-road conditions.	Zhao *et al.* Mechanical Systems and Signal Processing, 2019
501	**Other road users**	Road type, planning, perception, hardware and software, control, reaction time, road conditions, weather conditions, LiDAR, radar, lighting conditions, time of day, driving culture, traffic control, environmental conditions, algorithms, road geometry	This paper considers and studies the sequence of events that can lead to a collision. '*A crash sequence of events describes the AV's interactions with other road users before a collision in a temporal manner'.* Analysing the subsequences revealed that the most prevalent pattern in AV crashes is "collision following AV stop".	Song, Chitturi and Noyce Accident Analysis and Prevention, 2021
502	**Other road users**	Environmental conditions, demographics, traffic conditions, HMI, road structure, weather and lighting conditions, V2V, V2X	This study investigates the (major and minor) factors influencing the behaviour of pedestrians in interacting with AVs. A wide range of factors including human, environmental and social factors are studied to analyse and predict the behaviour (intention) of pedestrians in dealing with autonomous vehicles.	Rasouli and Tsotsos IEEE Transactions on Intelligent Transactions, 2019
503	**Other road users**	Traffic composition, driving behaviour, control, H-M Interfaces, reaction time, road type, traffic flow, communication channels, LiDAR, vehicle kinematics	This paper claims that HDVs hitting AVs from behind account for the most of accidents involving AVs. To address this problem, a study was designed to evaluate the detection of AVs' behaviours in front of human drivers.	Stanton *et al.* Human Factors and Ergonomics in Manufacturing & Service Industries, 2020
504	**Other road users**	Environment perception, dynamic obstacles, control architecture, traffic condition, traffic rules, trajectory planning, time to collision, sensors, reaction time, number of lanes	A *probabilistic overall strategy for risk assessment* is proposed for AVs in highways. This system can assess the risks of manoeuvres and generate appropriate evasive actions to avoid colliding with dynamic obstacles.	Iberraken, Adouane and Denis IEEE Intelligent Vehicles Symposium (IV), 2019
505	**Other road users**	Road geometry, reaction time, traffic conditions, trajectory planning, sensors, static/dynamic obstacles, path planning, velocity, algorithms, traffic regulation	It is crucial for the safe path planning in AD to predict stochastic occupancy of the road by other vehicles. The prediction must consider uncertainties stemming from the measurements and the possible behaviours of other road users. Furthermore, the interaction of traffic participants, as well as the limitation of driving manoeuvres due to the road configuration needs to be considered. The result of the proposed approach in this study is the likelihood of a collision for a specific trajectory of an AV.	Althoff, Stursberg and Buss IEEE Transaction on Intelligent Transactions Systems, 2009
506	**Other road users**	Human factors, pedestrians, bicycles	This paper discusses the human preferences for moral judgments in risky and uncertain situations that AVs are subject to face when operating in urban environments. It also highlights that due to the dynamic driving environments in the real world and presence of AVs, human-operated vehicles, bicyclists, and pedestrians some collisions will be unavoidable.	Meder *et al.* Society for Risk Analysis, 2018

507	**Other road users**	Perception, algorithms, control, path planning, camera, LiDAR, ultrasonic, time to collision, sensors, road infrastructure, weather conditions, obstacles, global navigation satellite system (GNSS), velocity	A risk assessment method (decision making algorithm) is developed for AVs to 1) be predictable by other road users (drivers) and 2) to maintain a desirable level of comfort for passengers.	Mechernene *et al.* International Conference on Control, Automation and Diagnosis (ICCAD), 2020
508	**Traffic control infrastructure**	Trajectory planning, traffic flow, V2V, V2I, velocity, other road users, traffic rules, road capacity	A coordination scheme is presented for AVs which can eradicate the need for traffic lights at intersections. The optimal collision risk is worked out to choose the optimal trajectory.	Kamal *et al.* Proceedings of the 16th International IEEE Annual Conference on Intelligent Transportation Systems (ITSC), 2013
509	**Traffic control infrastructure**	Traffic composition, driving behaviour, reaction time, autonomy level, traffic flow, traffic conditions, V2I, V2V, V2X, communication, other road users, road capacity, speed, geometric characteristics,	This paper investigates the performance of signalised intersections under the mixed flow conditions and analyses the probability of conflict as well as the mitigation impacts of communication channels e.g. V2I.	Pan *et al.* Arabian Journal for Science & Engineering, 2020
510	**Traffic control infrastructure**	Communication, traffic density, weather conditions, work zones, algorithms, number of lanes, V2I, V2V, traffic congestion	This paper proposes a new traffic control system excluding traffic lights at intersections. It is assumed that vehicles are fully autonomous and infrastructure is there to eliminate collision risks completely.	Park and Lee 2011 IEEE Vehicular Technology Conference (VTC Fall), 2011
511	**Traffic control infrastructure**	Weather conditions, road conditions, visibility, sensors, communication, V2V, V2I, traffic conditions, road type, time of day, day of week, speed, control	The authors suggest that to increase the effectiveness the AVs it is necessary to transform the current human-based safety infrastructure. In this paper, they focus on accident report infrastructure and the escalation procedures required to avoid systemic risks.	Sahawneh *et al.* IEEE, 2019
512	**Traffic control infrastructure**	RSUs, V2I, communication, number of lanes, traffic conditions, speed, traffic flow, lighting condition, V2V, traffic density, road geometry, kinematic state, other road users' behaviour, reaction time	A visible light communication (VLC)-based collision avoidance system is developed to effectively coordinate AVs in roundabouts. Heavy emphasis is placed on the traffic infrastructure and readiness for managing AV traffics.	Fakirah *et al.* EURASIP Journal on Wireless Communications and Networking, 2020
513	**Traffic conditions (complexity)**	Sensors, LiDAR, cameras, radar, road geometry, road infrastructure, path planning, motion planning, behaviour generation, longitudinal and lateral control, road conditions, obstacles, other road users, weather conditions, AI	Traffic scenes have their own unique complexity and dynamics. Therefore, if a self-driving vehicle is expected to achieve fully autonomous driving in a complex traffic scene, it must have the ability to learn and make predictions. Autonomous vehicles face many different scenes and road conditions, such as high-speed scenes, low-speed urban roads, and unstructured roads. this study deeply discusses some basic scientific issues of the self-driving approach based on cognitive construction, as well as the methods, computing models and technical routes to solve adaptability to complex situations of self-driving system.	Chen *et al.* SCIENCE CHINA Information Sciences, 2019
514	**Traffic conditions (complexity)**	Traffic density, traffic control, road infrastructure, road geometry, weather conditions, traffic control infrastructure, reaction time, speed, driving behaviour, static obstacles, other road users, number of lanes, road conditions	The dynamic of the traffic flow contributes to the complexity of traffic scenes. This further gives rise to the number of crashes. This paper examined the link between traffic complexity and collision risk (number of crashes) under urban motorway conditions. It was expected that linking the number of events (exposure) such as 'harsh lane change to crash numbers can provide more insights into the relationship between causation and effect. The concepts developed for urban motorways but can also be applicable to other high-volume multi carriageway roads.	Zurlinden, Baruah and Gaffney Journal of Road Safety, 2020
515	**Traffic conditions (complexity)**	Road type, algorithms, other road users, road geometry, weather conditions, obstacles, LiDAR, road conditions, lighting conditions, sensors, cameras, speed	Comprehensive traffic data scenario is often necessary to evaluate the performance of *unmanned ground vehicles* (UGVs) and measure the scene complexity. This study developed a traffic sensory data classification paradigm based on quantifying the scenario complexity for every segment of roads. This quantification is based on road semantic complexity and traffic element complexity.	Wang *et al.* IEEE Intelligent Vehicles Symposium, 2018

516	**Traffic conditions (complexity)**	Control, kinematic state, traffic rules, path planning, obstacles, actuators, cameras, LiDAR, radar, speed, other traffic participants	This paper proposed a 'cooperative control' approach for AVs to safely perform manoeuvres in complex traffic situations such as lane changing or crossing road intersections. This model is based on a cost function and collision avoidance objective for various traffic scenarios.	Mohseni, Frisk and Nielsen IEEE Transactions on Intelligent Vehicles, 2021
517	**Traffic conditions (complexity)**	Road type, other road users, algorithms, number of lanes, speed limits, time-to-collision, static and dynamic objects, traffic volume, mixed traffic, path planning, environment perception	This study adopted scenario-based testing for the validation and verification of CAVs. 189,752 scenarios including various collision scenarios were simulated for this purpose. To evaluate the risks faced by CAVs in different traffic situations, a new criticality metric (Scenario Risk Index) was defined.	Yue *et al.* IEEE Open Access, 2020
518	**Traffic conditions (complexity)**	Algorithms, machine learning, cybersecurity, other traffic participants, motion planning, perception, trajectory generation, control, kinematic state, traffic composition, road infrastructure, time-to-collision, hardware, sensors, velocity	In this work, a "fully model-based multi-modal parallelizable" is developed to analyse and evaluate the criticality of the complex traffic scene ahead of AVs. The extension of this algorithm can include road infrastructure and mobile objects. This algorithm is capable of handling a traffic scenario with 11 objects (over 86 million pose combinations) in 21 ms.	Morales *et al.* IEEE Intelligent Vehicles Symposium (IV), 2019
519	**Traffic conditions (complexity)**	Situation awareness, velocity, perception algorithms, V2I, V2V, kinematic state, road geometry, sensors, trajectory planning	Crossroads are a complex traffic situation for autonomous vehicles. This paper proposed a system with two functionalities. First, it is capable of predicting the motion of a surrounding vehicle in general traffic situation, and second, is its ability to estimate the probability of a collision given the current ego trajectory.	Annell, Gratner and Svensson IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), 2016
520	**Traffic conditions (complexity)**	Other traffic participants, algorithms, dynamic obstacles, control, trajectory planning, radar, cameras, lighting conditions, speed, sensors, LiDAR, motion state	AVs should inevitably interact with other road users such as pedestrians while traveling in complex traffic environments. All potential collisions must be avoided during the interactive process to ensure the safety. This paper analysed the active obstacle collision avoidance algorithm.	Zhang *et al.* Journal of Intelligent & Fuzzy Systems, 2018
521	**Traffic conditions (complexity)**	Time-to-collision, vehicle dynamics, algorithms, sensors, road type, sensor fusion, V2V, V2I, control, obstacles, kinematic state, GPS, other road users, road parameters, trajectory planning, speed	An anti-collision strategy based on hazard cognition is proposed to enable AVs safely passing through intersections while interacting with other vehicles. The algorithm was built and simulation was performed in MATLAB/Simulink. The simulation results have shown that the algorithm is reliable enough to prevent collisions.	Jia *et al.* Chines Automation Congress (CAC), 2019
522	**Traffic composition**	Human factors, other road users, kinematic state, HMI, traffic flow, LiDAR, sensors, cameras, traffic conditions, road type, number of traffic lanes, weather conditions, visibility	This paper analysed traffic accidents with AVs that occurred in California between 2015 and 2017. Drivers' manoeuvres of conventional vehicles do not differ in mixed or homogeneous traffic. Drivers' errors of conventional vehicles that are more often in accidents with AVs are "unsafe speed" and "following too closely".	Petrović, Mijailović and Pešić Transportation Research Procedia 45, 2020
523	**Traffic composition**	Time-to-collision, traffic volume/flow, speed, position, cameras, sensors, radar, communication channels, control algorithms, system integration, V2V, road environment, human factors, road capacity, acceleration, number of lanes, vehicle characteristics, road conditions	We will experience periods that both CAVs and HDVs share public roads as it needs time for all vehicles on the road to upgrade to CAVs. This study analysed the stability of mixed traffic flow under different penetration rates of CAVs. This paper suggests that if communication failure occurs the Cooperative Adaptive Cruise Control (CACC) vehicles will degenerate into ACC vehicles and subsequently the safety risk of mixed traffic flow increases considerably.	Yao *et al.* Journal of Safety Research, 2020
524	**Traffic composition**	Traffic flow, control, speed, algorithms	This work focuses on the challenge of controlling AVs in mixed traffic environments. The control algorithm introduced in this paper is based on the same components of standard platoon control, but adjust them to mixed environment.	Orki and Arogeti IEEE International Conference on Connected Vehicles and Expo (ICCVE), 2019
525	**Traffic composition**	Reaction time, traffic conditions, control, communication, driving behaviour, V2V	This paper looked into the impact of vehicle connectivity on the collision risk in mixed traffic (AVs and HDVs) streams. An optimisation problem was defined to minimise the collision risk while AVs and HDVs are expected to interact with each other. This paper suggests that mixed traffics can increase the probability of traffic conflicts.	Li *et al.* Working paper, 2020

526	**Traffic composition**	Kinematic state, communication, control, traffic conditions, road design, traffic flow, reaction time	This study presents a car-following strategy for mixed traffic stream which involves platoon development in a connected automated vehicle (CAV) environment. The study also explores various platoon configurations to determine platoon parameters at different traffic states to obtain utmost benefits.	Seraj, Li and Qiu Journal of Advanced Transportation, 2018
527	**Traffic composition**	Collision avoidance, software, communication, weather conditions, HMI, sensor, speed, actuators, V2V, V2I	This paper considers the problem of controlling an autonomous vehicle that must share the road with human-driven cars and presents proactive collision avoidance algorithms which can adapted to various driving manners and road/weather conditions.	Osipychev *et al.* American Control Conference (ACC), 2017
528	**Traffic composition**	Traffic conditions, traffic flow, algorithms, communications, V2V, V2I, speed, traffic control, reaction time, control strategies, kinematic state	Constrained the one-step model predictive control (MPC) are applied to control the movement of the connected AV platoon upstream or downstream of the HDV platoon so that both transient traffic smoothness and asymptotic stability of this sample mixed flow platoon can be ensured, leveraging the communication and computation technologies equipped on connected AVs. Considering the absence of the centralised computation facilities and severe changes of the platoon topology, this study develops a distributed algorithm to solve the MPCs according to the properties of the optimisers, such as solution uniqueness, sequentially feasibility, and nonempty interior point of the solution space.	Gong and Du Transportation Research Part B, 2018
529	**Traffic composition**	Drowsiness, fatigue, traffic flow/density, perception, sensors, algorithms, lighting conditions, time of day, weather conditions, road conditions, speed, road infrastructure, time to collision, other road users, HMI, obstacles, lateral/longitudinal control, secondary task, cameras, cybersecurity	A scoping literature review on CAVs was conducted to analyse current trends in academic literature, evaluate models and anticipate future research directions. The main focus of this paper in on safety performance of CAVs.	Sohrabi *et al.* Accident Analysis and Prevention, 2021
530	**Traffic composition**	Speed, traffic rule enforcement, V2I, traffic control infrastructure, weather conditions, traffic congestion/flow, driver behaviour, communication, reaction time, algorithms	In early stages of deployment, AVs are expected to coexist with HDVs on motorways. This study explored methods to implement variable speed limits (VSL) under a mixed traffic condition where connected AVs and HDVs share public roads. VSLs can improve safety of motorway through harmonisation of traffic flow.	Li *et al.* IET Intelligent Transport Systems, 2017
531	**Software reliability**	Behaviour planning, path planning, algorithms, vehicle control, V2V, number of lanes, other road users, road layout, traffic rules, GPS, sensors, actuators, sensor fusion, cameras, LiDAR, construction zone, obstacles, localisation, kinematic state, trajectory planning	This study proposes a behaviour/path planning algorithm that is responsible for safe AD in structured environments such as urban roads.	Kim *et al.* IFAC Intelligent Autonomous Vehicles Symposium, the International Federation of Automatic Control, 2013
532	**Software reliability**	Software control, environment perception, localisation, planning, LiDAR, obstacles, other road users, algorithms, weather conditions, hardware, GPS, object recognition, trajectory tracking, velocity, lighting conditions, sensors, cameras, traffic conditions, takeover, construction zones, software infrastructure, system integration	This work looks into the integration of systems, subsystems, algorithms and hardware that enable AD in challenging urban traffic scenarios.	Levinson *et al.* IEEE Intelligent Vehicles Symposium (IV), 2011

533	**Software reliability**	Weather conditions, sensors, other road users, control loop, environmental conditions, motion planning, actuators, perception	*Robustness testing* for autonomous systems is still immature. On the other hand, AVs need novel approaches when it comes to testing. This paper presents Autonomous Stress Testing for Autonomy Architecture (ASTAA) and compares it with similar traditional robustness testing methods for software used in autonomous systems.	Hutchison *et al.* ICSE-SEIP '18, 2018
534	**Software reliability**	Algorithms, actuators, control, perception, road geometry, other road users, machine learning, visibility, weather conditions, time of day, speed, LiDAR, traffic rules, mixed traffic, road infrastructure, road type, hardware, system integration	This study highlights five major challenge areas in testing AVs based on the V model: 1) driver out of the loop, 2) complex requirements, 3) non-deterministic algorithms, 4) inductive learning algorithms; 5) and fail operational systems.	Koopman and Wanger SAE World Congress, 2016
535	**Software reliability**	Motion planning, algorithms, obstacles	An efficient and robust motion planner is essential for safe operation of AVs in real urban traffic. This paper presents a risk-aware planning algorithm that benefits from chance-constraint approximation to leverages the *asymptotically optimal property* of RRT* framework.	Liu and Ang Jr. IEEE International Conference on Robotics & Automation (ICRA), 2014
536	**Software reliability**	VANET, sensors, algorithms, AI, machine learning, acceleration sensors, LiDAR, radar, traffic density, road conditions, communication, ultrasonic sensors, speed, other agents	To tackle the dynamic and complex traffic scenarios that can result in collision, this study proposes a *Reinforced Cooperative Autonomous Vehicle Collision AvoidancE (RACE)* framework. *Co-DDPG* algorithms are also developed to train AVs. The VANET is used to protect location privacy of vehicles. These systems are supposed to reduce the collision risks for AVs.	Yuan *et al.* IEEE Transactions on Vehicular Technology,
537	**Software reliability**	Software, sensors, perception, motion planning, CAN, GPS, algorithms, behavioural execution, road blockage, number of lanes, road geometry, road infrastructure, other road users, obstacles, velocity, sensor fusion, construction zones, traffic density, radar, LiDAR, traffic rules	This article provides a summary on Urban Challenge competitions and studies Boss which was announced as the winner and analyses different aspects of that autonomous car such as software architecture and performance.	Urmson *et al.* Association for the Advancement of Artificial Intelligence, 2009
538	**Lighting conditions**	Visibility, road infrastructure, road conditions, traffic congestion, speed	The focus of this study is on perceiving the environment by AVs and in particular recognising the road signs and markings. The situations which can cause difficulty for the sensors and increase the risk are identified and classified based on the *quality, status, quantity, visibility, perception, recognisability, clarity, and interpretability of the boards at the permitted speed*.	Lengyel and Szalay International Conference on Manufacturing, 2018
539	**Lighting conditions**	Cameras, sensors, weather conditions, algorithms,	This paper, proposes and evaluates DeepTest, a systematic testing tool for automatically detecting erroneous behaviours of DNN-driven vehicles that can potentially lead to fatal crashes. In this paper, the cause of a fatal accident involved the Tesla autopilot mode, is diagnosed as 'image contrast' and failing to detect the white truck against a bright sky.	Tian *et al.* ACM/IEEE 40th International Conference on Software Engineering, 2018
540	**Lighting conditions**	Time of day, algorithms, sensors, visual cameras,	This paper offers an algorithm to tackle the challenges and risks arising from the direct dazzling sun light. This problem can blind the *machine vision* in AVs as well as human drivers. The fatal accident between a Tesla Model S and a white tractor trailer serves as a notable example to signify the risk.	Paul and Chung Computers in Industry, 2018
541	**Lighting conditions**	Road infrastructure, pedestrian, sensors, time of day, obstacles	*Road environmental recognition* is seen as a key ability for AVs. This paper presents the test results of various object detection algorithms using single monocular camera for autonomous vehicle in real driving conditions. Pedestrian detection, traffic sign and traffic light recognition under various lighting conditions are three main issues this study covers.	Jeon *et al.* 13th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), 2016

542	**Lighting conditions**	Integration, communication, sensors, GPS,	ForeSight is developed to integrate the observations coming from an array of devices (sensors) in AVs. Bad light conditions is diagnosed as an influential factor in the performance of on-board cameras.	Li *et al.* IEEE Conference on Computer Communications, 2014
543	**Lighting conditions**	Cameras, sensors, algorithms, obstacle, weather conditions	In railway scenarios a camera in front of the train can aid drivers with the identification of obstacles or strange objects that can pose danger to the route. Image processing in these applications is not easy of performing. The changing conditions create scenes where background is hard to detect, lighting varies, and process speed must be fast.	Uribe, Fonseca and Vargas 46th Annual IEEE International Carnahan Conference on Security Technology, 2012
544	**Lighting conditions**	Obstacles, cameras, hardware, algorithms, time of day, infrastructure, visibility, perception, planning, control	This paper developed a method based on the shadow of objects to detect static and dynamic objects and avoid collision for mobile robots and AVs.	Naser *et al.* 21st International Conference on Intelligent Transportation Systems (ITSC), 2018
545	**Lighting conditions**	Sensors, cameras, traffic conditions, obstacles, pedestrians, road design, algorithms, GPS	This US patent considers risks in active sensing for autonomous vehicles. Light detection by on-board cameras is one of the main discussions of this document.	Teller *et al.* United States Patent, 2014
546	**Lighting conditions**	Weather conditions	This work classifies the types of collisions AVs may encounter. According to this research, unlit roadways and adverse weather conditions increase the risk of rear end collision.	Parkin *et al.* VENTURE, 2016
547	**Lighting conditions**	Environmental conditions, demographics, traffic conditions, HMI, road structure, weather and lighting conditions, V2V, V2X, lighting conditions	This study investigates the (major and minor) factors influencing the behaviour of pedestrians in interacting with AVs. A wide range of factors including human, environmental and social factors are studied to analyse and predict the behaviour (intention) of pedestrians in dealing with autonomous vehicles.	Rasouli and Tsotsos IEEE Transactions on Intelligent Transactions, 2019
548	**Lighting conditions**	Sensors, weather, visibility, component failure, human factors, algorithms, traffic conditions	This paper surveys the challenges of testing autonomous vehicles. Five different categories of reasons for exposure to accidents were identified: component failure, environmental conditions and failing to perceive the environment accurately, algorithms, behavioural factors and rule compliance, and HMI.	Schöner International Stuttgart Symposium, 2018
549	**Lighting conditions**	Visibility, weather conditions, sensors, speed, CAN, V2I, V2V, pedestrian, infrastructure	This US patent develops a method for assessing risks of automated vehicles. This method has been implemented in an electronic processing system that includes a memory and one or more processors, includes receiving, at the electronic processing system, operational data indicative of when a vehicle is driven according to an automated control mode.	Binion *et al.* United States Patent, 2015
550	**Lighting conditions**	Sensors, cameras, algorithms	This experimental work evaluated the performance of an autonomous grand vehicle in bad environmental situations (e.g. rain and low lighting). The negative impact of low visibility conditions on the system is among limitations of the proposed system in this study.	Foresti and Regazzoni IEEE Transactions on Vehicular Technology, 2002
551	**Lighting conditions**	Weather conditions, GPS, sonar, radar, LiDAR, information fusion, algorithms, cameras	AVs operating in urban environments need to detect traffic lights and recognise their states (i.e., red, amber or green). This work proposes a vision-based traffic light structure detection which can work under various lighting and weather conditions.	Saini *et al.* IEEE Intelligent Vehicles Symposium (IV), 2017
552	**Lighting conditions**	Weather conditions, visibility, HMI, road user behaviour, time of day, sensors, traffic conditions	This study proposes the concept of “driveability” for AVs to identify and handle driving risks. To this end, road datasets are reviewed and driveability factors are identified and categorised into majors groups: 1) environmental factors; and 2) road users' interactions.	Guo, Kurup and Shah IEEE Transactions on Intelligent Transportation Systems, 2019
553	**Lighting conditions**	Weather conditions, speed, road configuration, time of day, other road users, traffic composition, traffic control, road conditions	This paper identifies significant factors contributing to rear-end accidents and incorporates them into a BBN model to assess the collision risk under varying weather and lighting conditions.	Chen *et al.* Accident Analysis and Prevention, 2015

554	**Lighting conditions**	Weather conditions, radar, camera, dynamic/static obstacle, reaction time, hardware reliability, algorithms, time of day,	Whether in manual or automated driving, detection and recognition of brake lights are essential to avoid collisions and accidents in urban traffics. The experiments in this research were conducted on real video road in various sequence on roads under various weather and lighting conditions. the result showed that the proposed mobile decision-making system warning against traffic risks is highly effective.	Małecki and Wątróbski Procedia Computer Science, 2017
555	**Visibility**	Dynamic obstacles, weather conditions, traffic flow, communication, lighting conditions, road conditions, takeover, HMI	Poor visibility is identified as a risk factor in developing and operationalising AVs. 374 accidents mainly due to bad weather conditions were analysed. Adverse weather conditions are believed that impacted the perception and caused 'visual obstruction'.	Winkle, Erbsmehl and Bengler European Transport Research Review, 2018
556	**Visibility**	Weather conditions, obstacles, other road users, communication infrastructure, time of day, traffic density, road type	This patent offers methods for determining fault for collisions/accidents involving a vehicle encompassing one or more autonomous or semi-autonomous features. Several influencing factors are identified to contribute (or cause) theses faults. Namely, pedestrians, weather conditions (e.g. rain, fog and wind), road conditions and road infrastructure (e.g. road signs, lane marking and traffic signals) are mentioned to have impact on the sensor functionality.	Konrardy *et al.* United States Patent (US 9,805, 423 B1), 2017
557	**Visibility**	Weather conditions, lighting conditions, time of day	One of the crucial and challenging tasks for AVs is to detect the road boundaries and lanes using vision systems (i.e. visual camera). This paper adopts an approach to address this problem despite lighting change and shadows.	Assidiq *et al.* Proceedings of the International Conference on Computer and Communication Engineering, 2008
558	**Visibility**	Obstacles, sensors, visible and infrared spectrum camera), radar, laser-scanner, sonar, lighting conditions, weather conditions, algorithms, speed, GPS, other road users, time of day, sensor fusion, lateral and longitudinal distance	Obstacle detection is critical to mobile autonomous systems and too many obstacle detection systems have been developed so far. This study classified the main types of sensors. For a reliable solution, such a system must operate under varying range of visibilities, lighting and weather conditions.	Discant *et al.* 30th International Spring Seminar on Electronics Technology (ISSE), 2007
559	**Visibility**	Communication, obstacle, algorithms, motion planning, velocity, kinematic state, sensors, control, cameras	An algorithm is proposed to tackle the challenge of cooperative motion coordination of nonholonomic mobile robots facing visibility and communication constraints in obstacle environments.	Panagou and Kumar IEEE Transactions on Robotics, 2014
560	**Visibility**	Optical sensors, road geometry, cameras, algorithms, CAN, weather conditions, object detection, radar, LiDAR, sensor fusion, machine learning, vehicle dynamics, algorithms, kinematic state, control software, time of day, road infrastructure, hardware	This study focuses radar-based technologies that can gather and transfer road geometry information (i.e., curvature) to the driver while the optical sensors are impaired. Optical sensors are widely used in AVs, but they are sensitive to weather conditions such as fog poor visibility conditions (e.g., nigh illumination).	Lee *et al.* IEEE Sensors Journal, 2018
561	**Visibility**	Sensors, cyber-attacks, V2V, communication, time-to-collision, speed control, human errors, lateral and longitudinal control, other road users, traffic conditions, vehicle dynamic, traffic flow, weather conditions	Under the low-visibility conditions (due to inclement or fog), the sensing distance of adaptive cruise control (ACC) will be shorter, which may be from 25 to 250 meter. If the visibility drops to 25m the collision risk will slightly increase.	Tu *et al.* Journal of Safety Research, 2019
562	**Visibility**	Path planning, motion planning, perception, path geometry, kinematic constraint, obstacles, algorithms, speed	Motion planning is one of the main drivers of the moving efficiency for an autonomous agent. It defines how the agent (i.e., vehicle) moves and interacts with other surrounding agents. This paper offered a new approach to exploit Visibility Diagrams and plan the optimum *holonomic paths*.	Sedighi *et al.* IEEE Intelligent Transportation Systems Conference (ITSC), 2019

563	**Visibility**	Behaviour generation, occlusion, obstacles, sensors, other traffic participants, road curvature, reaction time, velocity, trust,	This paper presents an approach that assists AVs to drive efficiently in scenarios with occlusions, ensuring safety and comfort. The visibility risk (VR) represents the collision risk with possible hidden obstacles in occlusions and anticipate the predictive VR. This metric is quantified by forecasting the scene in the short-term.	Wang, Lopez and Stiller IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), 2020
564	**Visibility**	Perception accuracy, weather conditions, sensors, obstacle, radar, LiDAR, ultrasonic, cameras, far-infrared, sensor fusion, localisation, planning, control, GPS, V2V, V2I, road infrastructure, speed, machine learning, other road users, road geometry, road conditions, road type, traffic volume, traffic lanes, lighting conditions, hardware and software architecture, integration, actuators	This paper investigates the impact of weather conditions on visibility and subsequently on the perception accuracy of Intelligent Ground Vehicles. A fusion perspective is proposed to augment the reliability and robustness of the perception module of such vehicles.	Mohammed *et al.* Sensors, 2020
565	**Visibility**	Weather conditions, time headway, speed, situation awareness, other road users, driver experience	Reduced visibility (due to bad weather conditions e.g. fog) generally led to a shift in comfortable following distances towards larger headways. These results have implications for the introduction of highly automated vehicles and their time headway adjustments, which will need to be adaptive to speed and visibility in the road environment. It was reported that while there was no significant difference of comfort ratings between the fog and the truck condition, there was a significant interaction of visibility and speed.	Siebert and Wallis Transportation Research Part F, 2019
566	**AI performance**	Software reliability, time of day, algorithms, HMI, control, speed, type of road, traffic density, computing hardware reliability	The reliability of AI-based systems is comprehensively analysed in this paper. It is asserted that reliability of such systems needs to be appraised. However, the availability of reliability data for AI systems is currently sparse posing challenge to rigorously evaluating system reliability.	Hong *et al.* Working paper, 2021
567	**AI performance**	Other road users, obstacles, vision algorithms, machine learning, perception, sensors, weather conditions, hardware reliability, LiDAR, radar, cameras, consumer expectation	Applications of AI in safety-critical systems are most concerning due to any failure can result in deadly consequences. Transportation is one of those fields that requires high safety standards. An example cited in this work is the fatal collision between a pedestrian and an Uber self-driving car in Arizona, in 2018.	Cummings AI Magazine, 2021
568	**AI performance**	Machine learning, deep learning, algorithms, hardware reliability, maintenance, other traffic participants, obstacles, road boundaries, sensor fusion, temperature, lighting conditions, weather conditions	Soft Error Rate (SER) is a critical element of safety-critical autonomous systems. With AI algorithms in charge of decision making in these systems, an essential requirement is to test and model vulnerabilities of these system and assess their reliability. This paper is concerned with soft errors affecting the reliability of ground/air autonomous systems.	Athavale et al. 50th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN-W), 2020
569	**AI performance**	Weather conditions, speed, traffic, Human-machine interactions, public perception	The AI decisionality in AVs and its differences with human driving decision-making is the focus in this article. The authors maintain that pure statistics are inadequate and impotent to justify the superiority of AI decisionality over humans.	Cunneen, Mullins & Murphy Applied Artificial Intelligence, 2019
570	**AI performance**	Trust, reliance, algorithms, compliance with traffic rules	This paper centres on the issue of AI trustworthiness. It is discussed that AI cannot be trusted with common dominant definitions of trust.	Ryan Science and Engineering Ethics, 2020

571	**AI performance**	Hardware failure, traffic conditions, control, AI, software reliability, road type, road conditions, roadworks, traffic density, algorithms	This study centres on the problem of using operational testing to demonstrate high reliability for AVs. One of the main challenges to the reliability of AVs is that they rely on machine learning (ML). "*There is an expectation that AV safety improves as the AV evolves (i.e. its ML-based core systems "learn") with driving experience, or that the AV is deployed in different environments with different road/traffic conditions, and both kinds of change will affect the frequency of failures*".	Zhao *et al.* Journal of Information and Software Technology (IST), 2020
572	**AI performance**	Software, sensors, control, HMI, localisation, deep learning, perception, trust, interfaces, V2V, V2I, V2X, road geometry, sensor fusion, LiDAR, radar, visual sensors, infrared, obstacles, route planning, motion planning, algorithms, reaction time, weather conditions, visibility, perceived risk	It is maintained that AVs must be capable of considering the failures or errors of each component as well as their ultimate impact on the performance of the whole system. This paper discussed open challenges for research within the safety, compliance and trust themes in the context of AV safety.	McAllister *et al.* Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, 2017
573	**AI performance**	Driving behaviour, dynamic traffic environment, other road users, path planning, velocity	Decision-making for AVs can be challenging under complex urban environments. This study developed a rough-set artificial neural network to be trained and learn from highly competent human drivers. Findings of this work can be adopted to address the problem of car-flowing under complex traffic circumstances.	Chen *et al.* Journal of Central South University, 2017
574	**AI performance**	Weather conditions, objects, control, lighting conditions, time of day	One of the major obstacles for systems which benefit from deep learning techniques is acquiring data to train those systems. However, for self-driving cars, it takes a lot of time and cost to get real world driving data. Lack of enough training data can expose the vehicle to unforeseen situations and impact its perception and planning power.	Kim *et al.* International Conference on Artificial Intelligence in Information and Communication (ICAIIC), 2019
575	**Traffic rules & regulations (enforcement)**	Speed, road type, takeover	This issue of traffic laws and regulations is raised by the author as a challenge for the performance and adoption of AVs. Besides liability and insurance dilemmas, contradictions in the Highway Code and Road Traffic Act/Motorway Traffic Regulations when comes to AD are highlighted.	Kilpatrick Car magazine, 2020
576	**Traffic rules & regulations (enforcement)**	Traffic composition, static obstacles, traffic conditions, road conditions, control software, kinematic state, number of lanes, speed, sensors, algorithms, other road users	This study focuses on *automatic synthesis of provably correct controllers* for AVs operating in urban environments with presence of static obstacles and real-world traffic. The traffic rules are taken into account. For example, collision avoidance, vehicle separation, speed limit, lane following, passing, merging and intersection precedence requirements are the rules that traffic participants including AVs are supposed to comply with.	Wongpiromsarn, Karaman and Frazzoli 14th International IEEE Conference on Intelligent Transportation Systems, 2011
577	**Traffic rules & regulations (enforcement)**	RSU, traffic density, weather conditions, traffic conditions, road conditions, technical standards, road infrastructure, sensors, control, speed, other road users	One the main requirements for AVs that is specified in this report is compliance of AVs with the road traffic law. One of the actions for the Government (No. 14) is to "consider appropriate measures to ensure that automated vehicles are designed to respect road traffic law".	DfT, 2015
578	**Traffic rules & regulations (enforcement)**	Algorithms, traffic conditions, traffic composition, time-to-collision, sensors, other road users, hardware platform, speed	A probabilistic collision threat assessment algorithm for AD at road intersections is proposed to assess a traffic situation for AVs even if the traffic rules are violated by other vehicles. Human drivers may not obey traffic rules and this can be problematic particularly at intersections.	Noh IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018
579	**Traffic rules & regulations (enforcement)**	Pedestrian, infrastructure, LiDAR, radar, ultrasonic sensors, mixed traffic, velocity, weather conditions	It is maintained that the law needs to keep up with the technology when it comes to self-driving vehicles.it is deemed possible to change the law as well as infrastructure to treat the driverless cars as a benchmark rather than exceptions. Current legal system leaves a lot of room for uncertainty and this can cause confusion for developers and users.	Greenblatt IEEE Spectrum, 2016

580	**Traffic rules & regulations (enforcement)**	Traffic control infrastructure, driving style, time of day, socio-demographic characteristics, road type, road conditions, lighting conditions, speed, other road users, weather conditions, traffic volume, road infrastructure	This PhD thesis investigated the effectiveness of police enforcement on Road Traffic Accidents. Results indicate that the trend linking increased police enforcement with declining 'Killed and Seriously Injured' (KSI) accident rates. This can be applied to the mixed traffic environment that hosts AVs as both human drivers and AVs will be required to obey with the traffic rules.	Scott PhD Thesis, 2010
581	**Traffic rules & regulations (enforcement)**	Speed, types of road, traffic flow, traffic control infrastructure, road characteristics	This study investigated the effect of speed enforcement cameras on the quantity of road accidents in the UK. A significant decrease in the number of accidents (at all severity levels) was recorded in the areas covered by speed cameras. Speed cameras were reported to be most effective in reducing collisions up to 200 meters from camera sites and no evidence of accident migration was found.	Li, Graham and Majumdar Accident Analysis and Prevention, 2013
582	**Traffic rules & regulations (enforcement)**	Traffic composition, vehicle control, software control	This article discusses the need for changes in traffic law enforcement after the AVs hit public roads in mass. It is maintained that adoption of AVs entails significant implications for law enforcement.	Cowper and Levi FBI Law Enforcement Bulletin, 2018
583	**Traffic rules & regulations (enforcement)**	Sensors, HD mapping, network connectivity, speed, human factors, other road users, cybersecurity, GPS, obstacles, control, weather conditions, road conditions, time of day, traffic volume, driving style	There are serious worries around the law enforcement in the era of autonomous vehicles. Still policymakers and scholars can work on this and consider how AVs will affect police work so that the technology can develop in ways that mutually benefit officers and civilians during police encounters. Several risk factors together with consequences of lack an adapted law enforcement system are further discussed in this work.	Wood Northwestern University Law Review, 2019
584	**Traffic rules & regulations (enforcement)**	Communication, infrastructure, cybersecurity, other road users, trust	As socio-technical agents, AVs will have important consequences for law enforcement and significant upsides for traffic safety. One is the compliance of AVs with traffic rules.	Lyakina *et al.* Contemporary Readings in Law and Social Justice, 2019
585	**Traffic rules & regulations (enforcement)**	Other traffic participants, motion planning, traffic behaviour, trajectory planning, traffic complexity, kinematic variables, velocity, lateral and longitudinal dynamics, vehicle control, obstacles, environmental constraints, road configuration, perception accuracy, occlusion, traffic behaviour	One challenge for AVs to plan their motion without colliding with other road users is that the behaviour of other traffic participants cannot be predicted since traffic participants are often hidden due to occlusions. A legal specification is therefore necessary for defining which behaviours are considered to be acceptable. It explicitly represents our assumptions based on traffic rules, while the degree of conformity to traffic rules can be parameterised by the road user. Based on formalized traffic rules and nondeterministic motion models, the authors performed reachability analysis to predict the set of possible occupancies and velocities of vehicles, pedestrians, and cyclists.	Koschi and Althoff IEEE Transactions on Intelligent Vehicles, 2021
586	**Perception accuracy**	Sensors, V2I, V2V, radar, laser scanner, obstacles, algorithms, other road users, GPS, actuators, sensor fusion, traffic conditions, kinematic state, road geometry, road type, visibility,	The need for further research and improvements on current perception systems for AVs is highlighted. The possibility of transmitting the collected data from the sensor arrays through the wireless communication channels is put forward. The criticality of accurate perception system is even more for detecting obstacles and assess the risks that they may pose to the ego vehicle. For this purpose, it is discussed how AVs can generate digital maps to locate obstacles, estimate their velocity and indicate their directions.	Jiménez, Naranjo and Gómez Sensors, 2012
587	**Perception accuracy**	Visibility, software, weather conditions, sensors, lighting conditions, radar, LiDAR, cameras, sensor fusion, road infrastructure, GPS, path planning, obstacles, road type, road, drowsiness, road attributes, traffic density, algorithms, hardware, software, system integration, speed regulation, communication, autonomy level, control, HMI, H-M Interface, situation awareness	This paper provides an overview on reliability and robustness implications of sensors data processing and perception. To ensure a desired level of safety for autonomous driving, it is vital to guarantee a reliable level of quality for the perception mechanisms. To this end, this paper detailed critical perception stages and provided a presentation of applicable sensors. To process the information gathered and/or generated by an array of sensors, the multi-sensors data fusion algorithms constitute a mandatory step. Furthermore, the human factors must be taken into account in the design of automated driving systems, as it is suggested in the SAE classification.	Gruyer *et al.* Annual Reviews in Control, 2017

588	**Perception accuracy**	Localisation, planning, control, software, LiDAR, sensor, V2V, actuator, behaviour planning, motion planning, path planning, trajectory planning, road conditions, other road users, algorithms, GPS, road rules enforcement, road geometry, speed, traffic conditions, radar, ultrasonic sensors, sensor fusion, system integration, obstacles, time to collision, computing power, lighting conditions	The notion of '*time integration*' is discussed in this study which focuses on perception, planning, control and coordination for AVs. It is contended that perceiving the surrounding is a fundamental function which is essential to enable AD.	Pendleton *et al.* Machines, 2017
589	**Perception accuracy**	Sensors, perception accuracy, weather conditions, algorithms, LiDAR, AI, static/dynamic obstacles, pedestrians, vehicle control, cameras, time of day, road geometry, radar, ultrasonic, hardware architecture, concurrency,	This paper briefly summarises the recent progress on visual perception algorithms and their corresponding hardware implementations for the emerging application of AD. Algorithm design, hardware design, and system validation are the main areas discussed in this study.	Shi *et al.* INTEGRATION, the VLSI journal, 2017
590	**Perception accuracy**	Integration, actuators, path planning, obstacles, sensors, control, AI, computer vision, GPS, algorithms, map matching, localisation, road infrastructure, traffic control, road layout, lane type, road conditions, communication infrastructure, LiDAR, radar, vision sensors, velocity, vehicle conditions, weather conditions, urban environment, hardware and software, data fusion, mixed traffic	This paper identifies and discusses the key technologies which pave the path for AVs to operate in public traffic. Especial emphasis is placed on the criticality of perception module to detect and recognise objects, signs, road users, etc.	Zhao, Liang and Chen International of Intelligent Unmanned Systems, 2018
591	**Perception accuracy**	Machine learning, sensory data, path planning, road agents, lighting conditions, weather conditions, localisation and mapping, LiDAR, cameras, radar, sonar, algorithms, occlusion, obstacles, time of day, sensor configuration, sensor fusion, V2X, road infrastructure, GPS, road geometry, visibility, vehicle control,	Accurate perception is vital for AVs to function reliably. Object detection is central to the perception module in AVs and it is crucial to avoid collisions. This paper surveys a 3D object detection method which is fed by sensors and datasets. Fusion methods are discussed too.	Arnold *et al.* IEEE Transactions on Intelligent Transportation Systems, 2019
592	**Perception accuracy**	Sensors, radar, LiDAR cameras, ultrasonic, actuators, planning, control, localisation, motion planning, behavioural planning, motion planning, path trajectory, trajectory tracking, V2V, GPS, road type, weather conditions, road conditions, other road users, traffic law, traffic conditions, kinematic states, integrity of system, system integration	A systematic review of the perception systems for AVs is presented in this paper. It discusses the physical fundamentals, principle functioning, and electromagnetic spectrum applied in the most common sensors embedded in AVs' perception systems (ultrasonic, RADAR, LiDAR, cameras, IMU, GNSS, RTK, etc.).	Rosique *et al.* Sensors, 2019
593	**Perception accuracy**	Sensors, radar, LiDAR, weather conditions, GNNS, GPS, infrared, prebuilt maps, ultrasonic, camera, sensor fusion, software, algorithms, obstacles, lighting conditions, speed, visibility, road infrastructures, traffic control, V2I	This paper examined the effects of diverse weather conditions on an array of sensors (e.g., radar, LiDAR, and cameras) used in AVs. It concluded that despite breakthroughs in the field of sensory, severe weather circumstances can obstruct on-board visibility and adversely affect the performance of sensors, thereby increasing the probability of accident.	Vargas *et al.* Sensors, 2021

594	**Perception accuracy**	Control, weather conditions, road infrastructure, construction zone, other road users, obstacles, hardware reliability, communication, software reliability, sensors, cameras, motion planning, localisation, operator takeover, reaction time, HMI, traffic flow, road geometry, traffic control infrastructure, training of operators, speed limit, situational awareness, time of day, trust	This article analysed the around 160,000 disengagement and accident reports involving AVs in the California Department of Motor Vehicle's repository. The disengagements are classified into six categories. The contributing factors for each category are highlighted and discussed.	Boggs, Arvin and Khattak Accident Analysis and Prevention, 2020

Appendix B

Questionnaire:

First of all, I would like to sincerely thank you for agreeing to take part in this short survey and I appreciate your valuable time. Before starting the survey there are some definitions provided for the terms used in the survey. Some of those terms are used interchangeably with other terms and some of them may encompass more than one concept or variable. Therefore, the following definitions can provide a better insight and clarify the variables used in this questionnaire. In the meantime, if you feel unsure about what exactly is tried to convey by the terms and words used in the survey, you are more than welcome to contact the researcher (s.toliyat@soton.ac.uk) and discuss your concerns.

Please note that all the questions are designed with respect to SAE Level 4 of automation in urban environments, so please adjust your answers to that level when answering the questions. The sum of assigned weights in each question must add up to 100%. There are also a set of assumptions:

- Autonomous vehicles (AVs) must comply with the traffic rules.
- AVs are sharing the roads with other road users (e.g. pedestrians, cyclists, etc.) and can encounter any obstacles (e.g. temporary road signs like cones) that human drivers may do while driving.
- We are assessing the risks based on the current level and maturity of available technologies deployed in AVs.
- It is also assumed that main communication channels for AVs (i.e., V2V, V2I and V2X) are enabled.

Definitions:

Road configuration: this refers to the geometric characteristics (e.g. length of curves, slop or gradient and ramp type) as well as the layout of road infrastructure such traffic signs and lights, curbs, humps and roadside vegetation.

Visibility: this variable concerns with the quality of visibility for both human drivers and vision cameras mounted on AVs and quantity (length and splay) which can be affected by several factors such as adverse weather conditions, time of day, geometric characteristics of a road and road infrastructure (lights).

Lighting conditions: the lighting conditions of any given road can vary depending on the time of day. This variable is designed to convert time of day to quality of light (e.g. daylight, dark and dawn) for any roads.

Weather condition: comprises of 6 different states: *clear (sunny), windy, rainy, snowy, foggy, dusty*.

Road infrastructure: the equipment and facilities which are essential for safe driving in urban areas including road signs, traffic lights, lane markings, lighting equipment, appropriate surface etc.

Obstacles: dynamic and static obstacles can appear on the way of both conventional and autonomous cars and pose a risk to the operation of the vehicle. A moving trolly, flying plastic bag or big waste bin can be examples.

Work zones: areas designated to road maintenance or construction sites which encroach and occupy some areas of roads,

Road condition Risk Index (RI): this variable is aimed to capture the risk that may arise from the environment (public urban roads) that AVs are supposed to travel.

Reaction time RI: time is a critical factor for human drivers to (re)act and avoid a collision when facing a hazardous situation. There are number of factors which can affect this variable as the outcome of human factors affecting the safety of AVs.

Traffic complexity RI: the more complex traffic scenarios can increase the probability of collision and affect the safe operation of AVs. This variable was therefore designed to aggregate the effect of the human factors which can influence the risk of collision for SAE Level 4 AVs.

Technical reliability RI: this variable refers to both software and hardware competence and reliability of AVs to operate in urban environments. Reliability of components such as sensors, algorithms, data processors, control systems and equipment, actuators and communication channels, etc. is called into question here.

Situation(al) awareness: the situation awareness of human drivers is of concern here. Although in SAE level 4 the majority of driving tasks are performed by the AV, drivers may be required to take over the control while the AV is disengaged.

Trust and reliance: the level of trust that a user (i.e., human driver) has in the safety of AVs and subsequently adjusts his/her reliance on the vehicle.

Perceived risk: the level of safety risk perceived by the users (human drivers on board).

Human-machine interaction (HMI): lack of appropriate and timely HMI can lead to accidents. This variable was incorporated into the model to measure the quality and ease of interactions between the human drivers and AVs through embedded interfaces.

Other road users: includes pedestrians, human driven vehicles (HDVs), cyclists, motorcycles, animals, etc.

Day of week: weekdays or weekends

Kinematic state: the kinematic state of vehicles in this research is defined in terms of their speed, longitudinal and lateral distance from the nearby vehicles (or obstacles).

Traffic composition: the mixture of AVs and HDVs (hybrid), only AVs, or only HDVs

Traffic culture (style): this varies from country to country and city to city. In different areas (according to research) drivers mostly adopt conservative, moderate or aggressive driving styles.

AI performance: refers to the capability and maturity of machine learning, deep learning algorithms, artificial neural networks and other AI-based algorithms used in the perception and planning modules of the vehicle.

System integration: since the components, parts and pieces of software may come from different OEMs or software developers, integration of these elements plays a substantial role in preventing failures and minimising errors. As a result, this variable was inserted in the model to assess the level of integration between those components and measure their influence on the technical reliability of AVs.

Environmental factors:

1. Assign a respective weight (out of 100%) to the following factors regarding their influence on the 'road configuration' suitability for the AVs. The sum of weights must add up to 100%.

Road type (single carriageway, dual carriageway and motorway) ………………………..

Number of lanes (one, two, and multiple) ………………………

2. Assign a respective weight (out of 100%) to the following factors regarding their impact on the 'visibility' index (sight quality) of AVs.

Lighting conditions ………………………..

Road configuration ………………………..

Weather conditions ………………………..

Road infrastructure ………………………..

3. Assign a respective weight (out of 100%) to the following factors regarding their impact on the probability of presence of an (disruptive) 'obstacle' on the way of AVs in urban environments.

Work zones (e.g., construction or road maintenance) ………………………..

Road configuration ………………………..

4. Assign a respective weight (out of 100%) to the following factors regarding their impact on the 'road condition RI' for AVs.

Presence of obstacles ………………………..

Visibility ………………………..

Road configuration ………………………..

Road infrastructure ………………………..

Weather conditions ………………………..

5. Assign a respective weight (out of 100%) to the following factors regarding their impact on the 'collision RI'. Reaction time refers to the average time that takes for a human driver to react to a potential hazard.

Road condition RI ………………………..

Traffic complexity RI ………………………..

Reaction time RI ………………………..

Technical reliability RI ………………………..

Human factors:

1. Assign a respective weight (out of 100%) to the following factors regarding their influence on the drivers' 'situation awareness' in SAE 4 automated driving. The sum of weights must add up to 100%.

Drowsiness ………………………..

Training & experience ………………………..

Engagement in secondary (non-driving) task ………………………..

2. Assign a respective weight (out of 100%) to the following factors regarding their impact on the 'trust & reliance' level of AV users.

Perceived risks ………………………..

Training & experience ………………………..

3. Assign a respective weight (out of 100%) to the following factors regarding their influence on 'human-machine interaction (HMI)' in the context of AVs.

Trust & reliance ………………………..

Human-machine interfaces ………………………..

4. Assign a respective weight (out of 100%) to the following factors regarding their influence on 'reaction time RI'.

Perceived risks ………………………..

Situation awareness ………………………..

HMI ………………………..

5. Assign a respective weight (out of 100%) to the following factors regarding their impact on the 'collision RI'. Reaction time refers to the average time that takes for a human driver to react to a potential hazard.

Road condition RI ………………………..

Traffic complexity RI ………………………..

Reaction time RI ………………………..

Technical reliability RI ………………………..

Traffic factors:

1. Assign a respective weight (out of 100%) to the following factors regarding their influence on the probability of encountering 'other road users' (e.g., pedestrians, HDVs, cyclists and buses) for an AV. The sum of weights must add up to 100%.

Day of week ………………………..

Traffic rule enforcement ………………………..

Traffic control infrastructure ………………………..

2. Assign a respective weight (out of 100%) to the following factors regarding their influence on 'traffic density'.

Day of week ………………………..

Traffic control infrastructure ………………………..

3. Assign a respective weight (out of 100%) to the following factors regarding their influence on 'speed' adopted by drivers.

Traffic rule enforcement ………………………..

Traffic control infrastructure ………………………..

4. Assign a respective weight (out of 100%) to the following factors regarding their influence on 'kinematic state' of AVs.

Traffic rule enforcement ………………………..

speed ………………………..

5. Assign a respective weight (out of 100%) to the following factors regarding their influence on 'Traffic complexity RI' for AVs.

Traffic density ………………………..

(Presence of) other road users ………………………..

Traffic composition ………………………..

Traffic culture ………………………..

Kinematic state ………………………..

6. Assign a respective weight (out of 100%) to the following factors regarding their impact on the 'collision RI'. Reaction time refers to the average time that takes for a human driver to react to a potential hazard.

Road condition RI ………………………..

Traffic complexity RI ………………………..

Reaction time RI ………………………..

Technical reliability RI ………………………..

Technical factors:

1. Assign a respective weight (out of 100%) to the following factors regarding their influence on the probability of failure in the ‘perception’ module (e.g., detecting/recognising an object, estimating the distance/velocity/direction, detecting road signs, etc.) for SAE level 4 AVs. The sum of weights must add up to 100%.

Vision cameras ………………………..

LiDAR ………………………..

RADAR ………………………..

Sensor fusion ………………………..

2. Assign a respective weight (out of 100%) to the following factors regarding their share in the ‘software’ module failures for SAE level 4 AVs.

AI (e.g. machine learning) performance ………………………..

Behaviour generation ………………………..

Planning ………………………..

Software control systems ………………………..

3. To what extent each of the following communication and data transferring channels feed data to the AVs. Assign a respective weight (out of 100%) to each of the following channels.

GPS ………………………..

V2V ………………………..

V2I ………………………..

V2X ………………………..

4. Assign a respective weight (out of 100%) to the following factors regarding their influence on the ‘reliability of communication’ in SAE level 4 AVs.

Communication infrastructure ………………………..

Cybersecurity ………………………..

Communication channels ………………………..

5. Assign a respective weight (out of 100%) to the following factors regarding their influence on the ‘hardware reliability’ in SAE level 4 AVs.

Control equipment ………………………..

Self-awareness ………………………..

6. Assign a respective weight (out of 100%) to the following factors regarding their influence on the ‘technical reliability’ of AVs at SAE level 4.

Perception accuracy (and reliability) ………………………..

Software reliability ………………………..

Communication reliability ………………………..

System integration ………………………..

Hardware reliability ………………………..

7. Assign a respective weight (out of 100%) to the following factors regarding their impact on the 'collision RI'. Reaction time refers to the average time that takes for a human driver to react to a potential hazard.

Road condition RI ………………………..

Traffic complexity RI ………………………..

Reaction time RI ………………………..

Technical reliability RI ……………………….

Appendix C

Consent form

I, the undersigned, confirm that (please tick box as appropriate):

1	I have read and understood the information about the project, as provided in the Information Sheet dated ( ).	
2	I have been given the opportunity to ask questions about the project and my participation ( ).	
3	I voluntarily agree to participate in the project ( ).	
4	I understand that I can withdraw at any time without giving reasons and that I will not be penalised for withdrawing nor will I be questioned on why I have withdrawn ( ).	
5	The procedures regarding confidentiality have been clearly explained (e.g. use of names, pseudonyms, data, etc.) to me ( ).	
6	If applicable, separate terms of consent for interviews/surveyees, audio, video or other forms of data collection have been explained and provided to me ( ).	
7	The use of the data in research, publications, sharing and archiving has been explained to me ( ).	
8	I understand that other researchers will have access to this data only if they agree to preserve the confidentiality of the data and if they agree to the terms I have specified in this form ( ).	
9	Select only **one** of the following: • I would like my name used and understand what I have said or written as part of this study will be used in reports, publications and other research outputs so that anything I have contributed to this project can be recognized ( ). • I do not want my name used in this project ( ).	
10	I, along with the Researcher, agree to sign and date this informed consent form ( ).	

Participant:

Name of Participant: …………………… Signature ………………… Date ………………

Researcher:

Name of Researcher: …………………… Signature ………………… Date ………………

Participant Information Sheet

Study Title: Assessing safety risks for autonomous vehicles in urban environments

Researcher: Seyed Mohammad Hossein Toliyat

ERGO number: 63032

You are being invited to take part in the above research study. To help you decide whether you would like to take part or not, it is important that you understand why the research is being done and what it will involve. Please read the information below carefully and ask questions if anything is not clear or you would like more information before you decide to take part in this research. You may like to discuss it with others, but it is up to you to decide whether to take part or not. If you are happy to participate you will be asked to sign a consent form.

What is the research about?

This research is undertaken by Seyed Toliyat, a PhD candidate at the University of Southampton as a PhD thesis.

This research is about developing a risk assessment model to estimate associated safety (collision) risks that autonomous vehicles (AVs) may encounter while operating in urban environments. The objectives are:

▪ Identify variables that can influence the collision risks of AVs in urban environments.

▪ Integrate the identified variables into a risk (uncertainty) quantification model.

▪ Extract expert knowledge and judgements to inform the model in terms of the strengths of links between the variables.

▪ Evaluate the sensitivity of the outcome (collision risk) to the identified variables.

All participants will receive an electronic copy of the questionnaire via email.

Why have I been asked to participate?

As data for the performance of autonomous vehicles in urban environments are scarce, incomplete, and unavailable due to the commercial nature, knowledge of experts is required to inform some aspects of the model developed in this study. All participants should be domain experts in the relevant contexts e.g. human-machine interactions, artificial intelligence, urban traffic, etc. Participants are required to assign respective weights to the relationship between influential variables in the model.

What will happen to me if I take part?

All participants will receive an electronic copy of the questionnaire via email. All communications will be via email. There are four questionnaires designed for each area of expertise. Every expert will be required to answer only questionnaire which will not take more than 10 minutes. Each questionnaire includes 5-7 questions (depending on the expertise domain).

This survey will last at least two months. However, there will be a one-week allowance for the participants to return completed questionnaires since they receive them. There will be no harmful, stressful or private questions and information being collected. There will be no negative consequences in any forms.

Are there any benefits in my taking part?

This research is expected to contribute to the safety of autonomous vehicles (AKA driverless and self-driving cars) and provide insights for policymakers, insurers, urban designers and planners, technology developers and traffic planners. You will also be provided with the findings of the research upon your request.

Are there any risks involved?

This research contains no risk in any forms.

Will my participation be confidential?

The experts will remain anonymous and their identities will be kept strictly confidential.

Only members of the research team and responsible members of the University of Southampton may be given access to data about you for monitoring purposes and/or to carry out an audit of the study to ensure that the research is complying with applicable regulations. Individuals from regulatory authorities (people who check that we are carrying out the study correctly) may require access to your data. All of these people have a duty to keep your information, as a research participant, strictly confidential.

Do I have to take part?

No, it is entirely up to you to decide whether or not to take part. If you decide you want to take part, you will need to sign a consent form to show you have agreed to take part.

What happens if I change my mind?

You have the right to change your mind and withdraw at any time without giving a reason and without your participant rights being affected.

If you withdraw from the study, we will keep the information about you that we have already obtained for the purposes of achieving the objectives of the study only.

What will happen to the results of the research?

Your personal details will remain strictly confidential. Research findings made available in any reports or publications will not include information that can directly identify you without your specific consent.

Where can I get more information?

If there is any questions, doubts and further information you would like to acquire about this research, you can contact via Email: s.toliyat@soton.ac.uk or via MS Teams.

What happens if there is a problem?

If you have a concern about any aspect of this study, you should speak to the researchers who will do their best to answer your questions. You can contact via Email: s.toliyat@soton.ac.uk or via MS Teams.

If you remain unhappy or have a complaint about any aspect of this study, please contact the University of Southampton Research Integrity and Governance Manager (023 8059 5058, rgoinfo@soton.ac.uk).

Data Protection Privacy Notice

The University of Southampton conducts research to the highest standards of research integrity. As a publicly-funded organisation, the University has to ensure that it is in the public interest when we use personally-identifiable information about people who have agreed to take part in research. This means that when you agree to take part in a research study, we will use information about you in the ways needed, and for the purposes specified, to conduct and complete the research project. Under data protection law, 'Personal data' means any information that relates to and is capable of identifying a living individual. The University's data protection policy governing the use of personal data by the University can be found on its website (https://www.southampton.ac.uk/legalservices/what-we-do/data-protection-and-foi.page).

This Participant Information Sheet tells you what data will be collected for this project and whether this includes any personal data. Please ask the research team if you have any questions or are unclear what data is being collected about you.

Our privacy notice for research participants provides more information on how the University of Southampton collects and uses your personal data when you take part in one of our research projects and can be found at http://www.southampton.ac.uk/assets/sharepoint/intranet/ls/Public/Research%20and%20Integrity%20Privacy%20Notice/Privacy%20Notice%20for%20Research%20Participants.pdf

Any personal data we collect in this study will be used only for the purposes of carrying out our research and will be handled according to the University's policies in line with data protection law. If any personal data is used from which you can be identified directly, it will not be disclosed to anyone else without your consent unless the University of Southampton is required by law to disclose it.

Data protection law requires us to have a valid legal reason ('lawful basis') to process and use your Personal data. The lawful basis for processing personal information in this research study is for the performance of a task carried out in the public interest. Personal data collected for research will not be used for any other purpose.

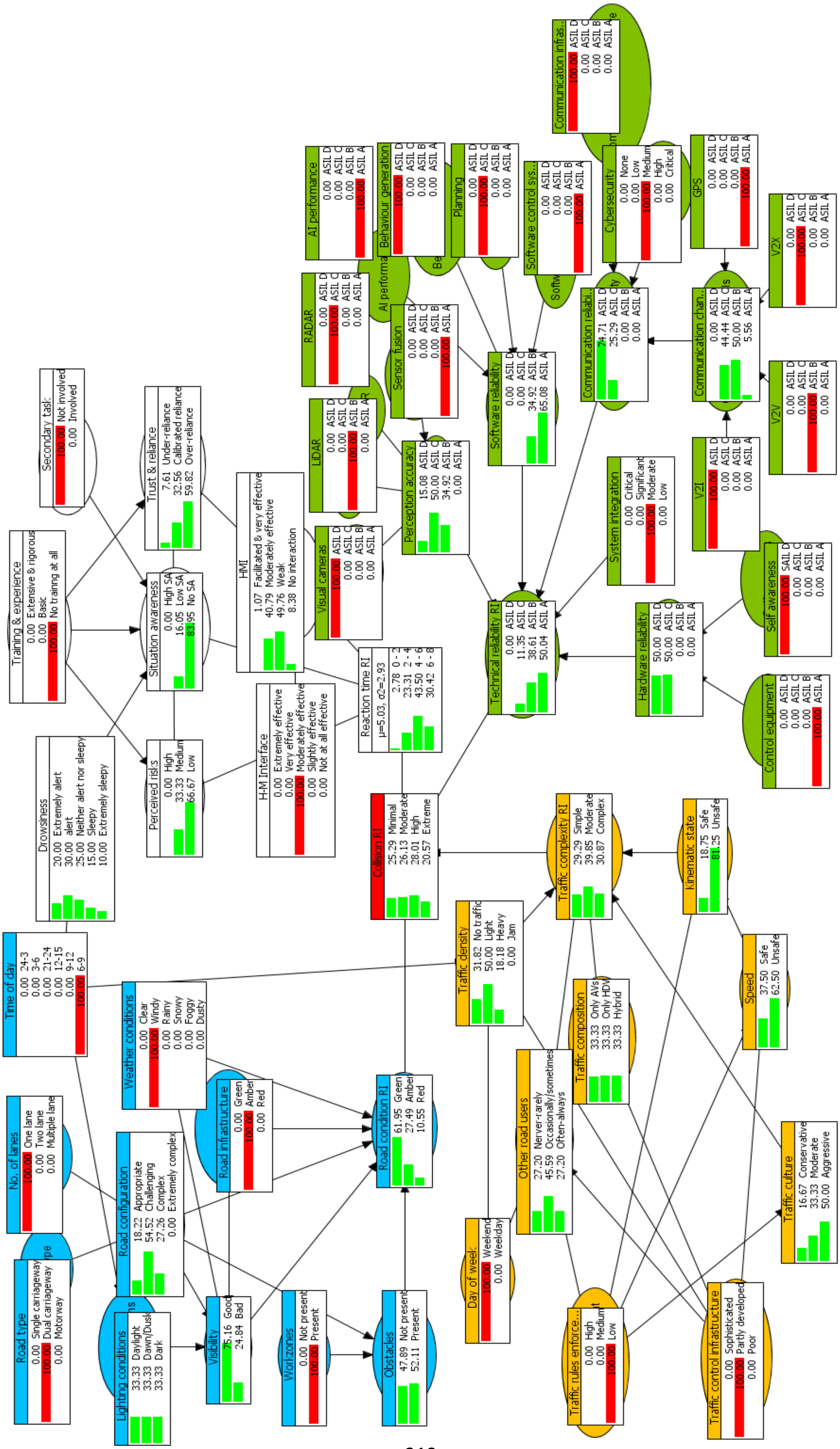
For the purposes of data protection law, the University of Southampton is the 'Data Controller' for this study, which means that we are responsible for looking after your information and using it properly. The University of Southampton will keep identifiable information about you for 1 year after the study has finished after which time any link between you and your information will be removed.

To safeguard your rights, we will use the minimum personal data necessary to achieve our research study objectives. Your data protection rights – such as to access, change, or transfer such information - may be limited, however, in order for the research output to be reliable and accurate. The University will not do anything with your personal data that you would not reasonably expect.

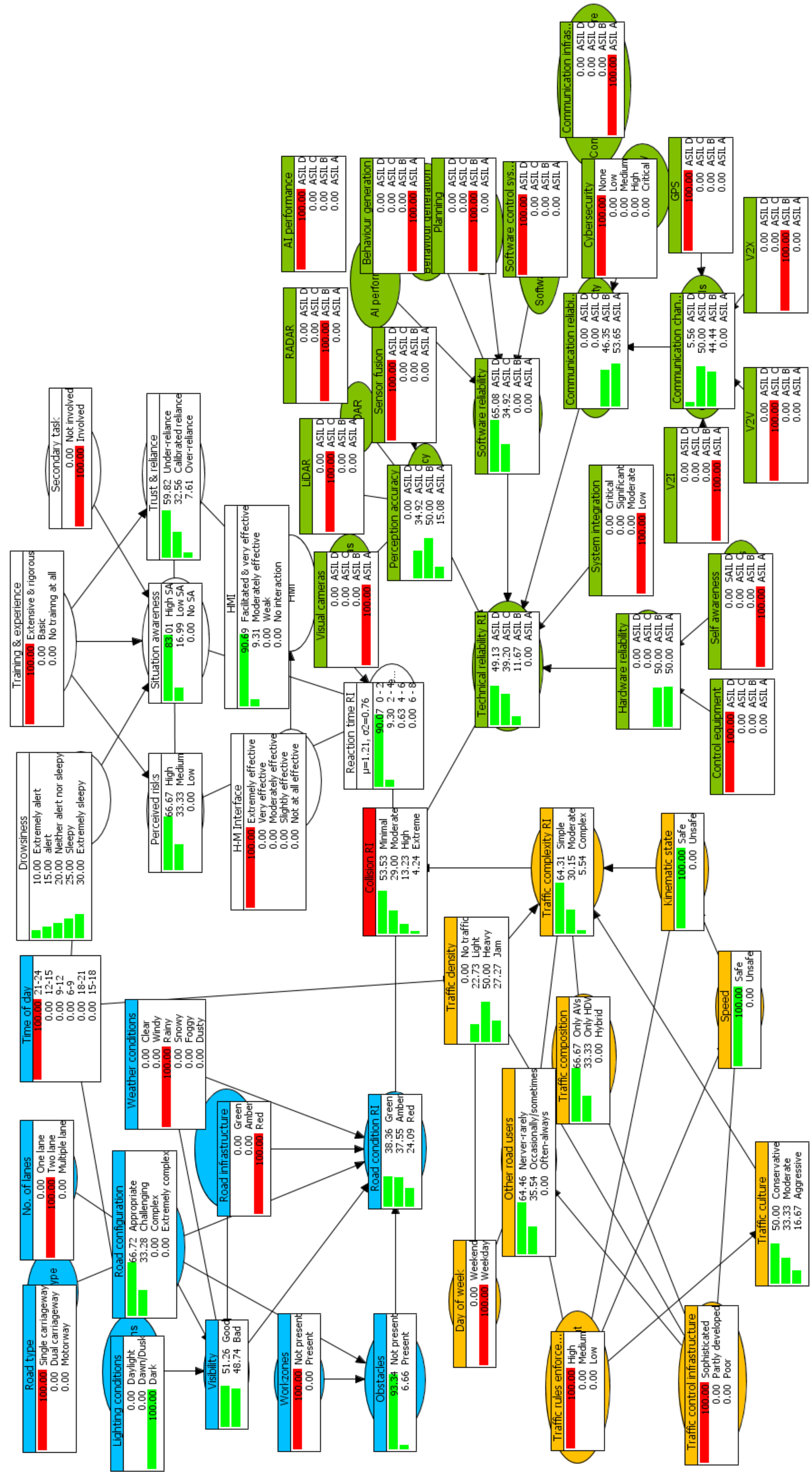
If you have any questions about how your personal data is used, or wish to exercise any of your rights, please consult the University's data protection webpage (https://www.southampton.ac.uk/legalservices/what-we-do/data-protection-and-foi.page) where you can make a request using our online form. If you need further assistance, please contact the University's Data Protection Officer (data.protection@soton.ac.uk).

Thank you.

Appendix D



Instantiated nodes and JDPs for scenario 5



Instantiated nodes and JDPs for scenario 5

References:

Abdel-Aty, M.A. and Radwan, A.E. (2000) 'Modeling traffic accident occurrence and involvement', *Accident Analysis & Prevention*, 32(5), pp. 633-642.

Abduljabbar, R. *et al.* (2019) 'Applications of artificial intelligence in transport: An overview', *Sustainability*, 11(1), p. 189.

Abdulkhaleq, A. *et al.* (2017) 'Using STPA in Compliance with ISO 26262 for Developing a Safe Architecture for Fully Automated Vehicles' [Working Paper]. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=edsarx&AN=edsarx.1703.03657&site=eds-live.

Åberg, L. (1998) 'Traffic rules and traffic safety', *Safety science*, 29(3), pp. 205-215.

Acheampong, R.A. *et al.* (2021) 'Can autonomous vehicles enable sustainable mobility in future cities? Insights and policy challenges from user preferences over different urban transport options', *Cities*, 112, p. 103134.

Agli, H. *et al.* (2016) *International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems*. Eindhoven, The Netherlands. Springer.

Agrawal, A., Gans, J. and Goldfarb, A. (2019) *The Economics of Artificial Intelligence: An Agenda*. University of Chicago Press.

Aguiar Noury, G. *et al.* (2019) 'User-defined challenges and desiderata for robotics and autonomous systems in health and social care settings', *Advanced Robotics*, 33(7-8), pp. 309-324.

Ahmad, M. *et al.* (2021) 'Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential', *Frontiers of Structural and Civil Engineering*, 15(2), pp. 490-505.

Akash, K. *et al.* (2017) 'Dynamic modeling of trust in human-machine interactions', *2017 American Control Conference (ACC)*. Seattle, WA, USA. IEEE, pp. 1542-1548. doi: 10.23919/ACC.2017.7963172.

Åkerstedt, T. and Gillberg, M. (1990) 'Subjective and objective sleepiness in the active individual', *International Journal of Neuroscience*, 52(1-2), pp. 29-37.

Alheeti, K.M.A., Gruebler, A. and McDonald-Maier, K.D. (2015) *2015 12th Annual IEEE Consumer Communications and Networking Conference (CCNC)*. IEEE.

Allen, T. *et al.* (2017) 'Contributing factors to motorcycle injury crashes in Victoria, Australia', *Transportation research part F: traffic psychology and behaviour*, 45, pp. 157-168.

Allouch, A. *et al.* (2019) 'Qualitative and Quantitative Risk Analysis and Safety Assessment of Unmanned Aerial Vehicles Missions Over the Internet', *IEEE Access*, 7, pp. 53392-53410.

Almalki, S. (2016) 'Integrating Quantitative and Qualitative Data in Mixed Methods Research--Challenges and Benefits', *Journal of Education and Learning*, 5(3), pp. 288-296.

Álvarez, P. *et al.* (2020) 'Geometric road design factors affecting the risk of urban run-off crashes. A case-control study', *Plos one*, 15(6), p. e0234564.

Amin, M.T., Khan, F. and Imtiaz, S. (2019) 'Fault detection and pathway analysis using a dynamic Bayesian network', *Chemical Engineering Science*, 195, pp. 777-790.

References

Anderson, J.A. (2017) *After Digital: Computation as Done by Brains and Machines*. Oxford University Press.

Anderson, J.M. *et al.* (2014) *Autonomous Vehicle Technology: A Guide for Policymakers*. RAND Corporation.

Aniculaesei, A. *et al.* (2018) *Proceedings of the 1st International Workshop on Software Engineering for AI in Autonomous Systems*. ACM.

Arbabzadeh, N. *et al.* (2019) 'A hybrid approach for identifying factors affecting driver reaction time using naturalistic driving data', *Transportation research part C: emerging technologies*, 100, pp. 107-124.

Ashrafi, M., Davoudpour, H. and Khodakarami, V. (2015) 'Risk assessment of wind turbines: Transition from pure mechanistic paradigm to modern complexity paradigm', *Renewable and Sustainable Energy Reviews*, 51, pp. 347-355.

Atchley, P., Shi, J. and Yamamoto, T. (2014) 'Cultural foundations of safety culture: A comparison of traffic safety culture in China, Japan and the United States', *Transportation research part F: traffic psychology and behaviour*, 26, pp. 317-325.

Auer, A. *et al.* (2016) *History of intelligent transportation systems* (FHWA-JPO-16-329). Washington, DC.

Aung, N. *et al.* (2018) 'Accident prediction system based on hidden markov model for vehicular ad-hoc network in urban environments', *Information*, 9(12), p. 311.

Aven, T. (2013) 'On the meaning of a black swan in a risk context', *Safety science*, 57, pp. 44-51.

Axelrod, C.W. (2015) *2015 12th International Conference & Expo on Emerging Technologies for a Smarter World (CEWIT)*. Stony Brook, NY, USA. IEEE.

Bagheri, M., Siekkinen, M. and Nurminen, J.K. (2016) 'Cloud-based pedestrian road-safety with situation-adaptive energy-efficient communication', *IEEE Intelligent transportation systems magazine*, 8(3), pp. 45-62.

Bahrammirzaee, A. (2010) 'A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems', *Neural Computing and Applications*, 19(8), pp. 1165-1195.

Baldini, G. and Neisse, R. (2020) *2020 Global Internet of Things Summit (GIoTS)*. IEEE.

Barber, D. (2012) *Bayesian Reasoning and Machine Learning*. Cambridge University Press.

Barbera, T. *et al.* (2004) 'How task analysis can be used to derive and organize the knowledge for the control of autonomous vehicles', *Robotics and Autonomous Systems*, 49(1), pp. 67-78.

Barnard, M.P. and Chapman, P. (2016) 'Are anxiety and fear separable emotions in driving? A laboratory study of behavioural and physiological responses to different driving environments', *Accident Analysis and Prevention*, 86, pp. 99-107.

BBC (2017) *Fatal Tesla crash driver 'given warnings'*. Available at: https://www.bbc.co.uk/news/technology-40340828 (Accessed: 15/12/2020).

BBC (2018) *Tesla in fatal California crash was on Autopilot* (Accessed: 30/04/2019).

BBC (2021) *Tesla Model 3: Paris' largest taxi firm suspends cars after fatal crash*. Available at: https://www.bbc.co.uk/news/world-europe-59647069 (Accessed: 18/12/2021).

Bedford, T., Quigley, J. and Walls, L. (2006) 'Expert elicitation for reliable system design', *Statistical Science*, pp. 428-450.

Bellet, T. *et al.* (2019) 'From semi to fully autonomous vehicles: New emerging risks and ethico-legal challenges for human-machine interactions', *Transportation research part F: traffic psychology and behaviour*, 63, pp. 153-164.

Ben-Gal, I. (2008) 'Bayesian networks', *Encyclopedia of statistics in quality and reliability*, 1.

Benson, F.J. and Lay, M.G. (2016) 'Roads and highways' *Technology*. Encyclopædia Britannica. Available at: https://www.britannica.com/technology/road.

Benzaghta, M.A. *et al.* (2021) 'SWOT analysis applications: An integrative literature review', *Journal of Global Business Insights*, 6(1), pp. 55-73.

Berger, R. (2015) 'Now I see it, now I don't: Researcher's position and reflexivity in qualitative research', *Qualitative research*, 15(2), pp. 219-234.

Bernhard, J., Pollok, S. and Knoll, A. (2019) 'Addressing Inherent Uncertainty: Risk-Sensitive Behavior Generation for Automated Driving using Distributional Reinforcement Learning' [Conference]. IEEE, pp. 2148-2155. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=edseee&AN=edseee.8813791&site=eds-live.

Berntorp, K. (2017) *2017 American Control Conference (ACC)*. Seattle, WA, USA. IEEE.

Berntorp, K. *et al.* (2018) *2018 IEEE Conference on Control Technology and Applications (CCTA)*. Copenhagen, Denmark. IEEE.

Bimbraw, K. (2015) *2015 12th International Conference on Informatics in Control, Automation and Robotics (ICINCO)*. IEEE.

Bojke, L. *et al.* (2022) 'Reference case methods for expert elicitation in health care decision making', *Medical Decision Making*, 42(2), pp. 182-193.

Bonnefon, J.-F., Shariff, A. and Rahwan, I. (2016) 'The social dilemma of autonomous vehicles', *Science*, 352(6293), pp. 1573-1576.

Borgström, Å., Daneback, K. and Molin, M. (2019) 'Young people with intellectual disabilities and social media: a literature review and thematic analysis', *Scandinavian Journal of Disability Research*, 21(1).

Bosch, J. and Olsson, H.H. (2016) *Proceedings of the 11th International Symposium on Software Engineering for Adaptive and Self-Managing Systems*. ACM.

Bouk, S.H. *et al.* (2018) 'Named data networking's intrinsic cyber-resilience for vehicular CPS', *IEEE Access*, 6, pp. 60570-60585.

Bradshaw, J.M. *et al.* (2013) 'The seven deadly myths of" autonomous systems"', *IEEE Intelligent Systems*, 28(3), pp. 54-61.

Braun, T. and Möller, R. (2016) *Joint German/Austrian Conference on Artificial Intelligence (Künstliche Intelligenz)*. Springer.

Braun, V. *et al.* (2019) 'Thematic Analysis', in Liamputtong, P. (ed.) *Handbook of Research Methods in Health Social Sciences*. Singapore: Springer Singapore, pp. 843-860.

Briganti, G. and Le Moine, O. (2020) 'Artificial intelligence in medicine: today and tomorrow', *Frontiers in medicine*, 7, p. 27.

References

Brinkley, J. *et al.* (2019) 'An open road evaluation of a self-driving vehicle human–machine interface designed for visually impaired users', *International Journal of Human–Computer Interaction*, 35(11), pp. 1018-1032.

Brito, M. and Griffiths, G. (2016) 'A Bayesian approach for predicting risk of autonomous underwater vehicle loss during their missions', *Reliability Engineering & System Safety*, 146, pp. 55-67.

Brito, M.P., Griffiths, G. and Challenor, P. (2010) 'Risk analysis for autonomous underwater vehicle operations in extreme environments', *Risk Analysis: An International Journal*, 30(12), pp. 1771-1788.

Broggi, A. *et al.* (2010) 'TerraMax vision at the Urban challenge 2007', *IEEE Transactions on Intelligent Transportation Systems*, 11(1), pp. 194-205.

Brookhuis, K.A., De Waard, D. and Janssen, W.H. (2019) 'Behavioural impacts of advanced driver assistance systems–an overview', *European Journal of Transport and Infrastructure Research*, 1(3).

Bryman, A. and Bell, E. (2015) *Business Research Methods*. Oxford University Press.

Buehler, M., Iagnemma, K. and Singh, S. (2007) *The 2005 DARPA Grand Challenge: The Great Robot Race*. Springer Berlin Heidelberg.

Burke, M. (2020) 'Human Factors Considerations in Preparing Policy and Regulation for Automated Vehicles', in Fisher, D.L. *et al.* (eds.) *Handbook of human factors for automated, connected, and intelligent vehicles*

CRC Press.

Büscher, C. (2011) 'Systemic risk as a perspective for interdisciplinary risk research', *TATuP-Zeitschrift für Technikfolgenabschätzung in Theorie und Praxis*, 20(3), pp. 4-12.

Cai, P. *et al.* (2020) 'VTGNet: A vision-based trajectory generation network for autonomous vehicles in urban environments', *IEEE Transactions on Intelligent Vehicles*.

Calvert, S.C. *et al.* (2019) 'Gaps in the control of automated vehicles on roads', *IEEE intelligent transportation systems magazine*.

Calvi, A. *et al.* (2020) 'A driving simulator study to assess driver performance during a car-following maneuver after switching from automated control to manual control', *Transportation research part F: traffic psychology and behaviour*, 70, pp. 58-67.

Cambridge Dictionary (2008).3rd edn Cambridge University Press.

Campbell, M. *et al.* (2010) 'Autonomous driving in urban environments: approaches, lessons and challenges', *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 368(1928), pp. 4649-4672.

Campbell, S. *et al.* (2018) *2018 29th Irish Signals and Systems Conference (ISSC)*. IEEE.

Campos, L.B. and Marques, J.G. (2018) 'On the Kinematics of Vehicles Relevant to Conflict Detection and Resolution', *Journal of Advanced Transportation*, 2018.

Cannella, J. (2018) 'Artificial Intelligence In Marketing'.

Carleo, G. and Troyer, M. (2017) 'Solving the quantum many-body problem with artificial neural networks', *Science*, 355(6325), pp. 602-606.

Carlson, M.S. *et al.* (2014) *2014 AAAI Spring Symposium Series*.

Carrignon, D. (2020) 'Connected and autonomous vehicles, electric scooter and their implications for road network design', *Transportation research procedia*, 49, pp. 160-169.

Chan, C.-Y. (2017) 'Advancements, prospects, and impacts of automated driving systems', *International journal of transportation science and technology*, 6(3), pp. 208-216.

Chandler, P. and Pachter, M. (1998) *American Control Conference, 1998. Proceedings of the 1998*. IEEE.

Charisi, V. *et al.* (2017) 'Towards moral autonomous systems', *CoRR*, abs/1703.04741.

Chen, C. *et al.* (2015) 'A multinomial logit model-Bayesian network hybrid approach for driver injury severity analyses in rear-end crashes', *Accident Analysis & Prevention*, 80, pp. 76-88.

Chen, S.H. and Pollino, C.A. (2012) 'Good practice in Bayesian network modelling', *Environmental Modelling & Software*, 37, pp. 134-145.

Chen, Y. and Lin, P. (2019) 'Bayesian network of risk assessment for a super-large dam exposed to multiple natural risk sources', *Stochastic Environmental Research and Risk Assessment*, 33(2), pp. 581-592.

Cheng, S. *et al.* (2019) 'Longitudinal collision avoidance and lateral stability adaptive control system based on MPC of autonomous vehicles', *IEEE Transactions on Intelligent Transportation Systems*.

Choi, E.-H. *et al.* (2008) *Sampling Design Used in the National Motor Vehicle Crash Causation Survey* (DOT HS 810 930). Analysis, N.s.N.C.f.S.a. Available at: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/810930.

Choi, J.K. and Ji, Y.G. (2015) 'Investigating the importance of trust on adopting an autonomous vehicle', *International Journal of Human-Computer Interaction*, 31(10), pp. 692-702.

Christopher Frey, H. and Patil, S.R. (2002) 'Identification and review of sensitivity analysis methods', *Risk analysis*, 22(3), pp. 553-578.

Chu, K., Kim, J. and Sunwoo, M. (2012) *Distributed system architecture of autonomous vehicles and real-time path planning based on the curvilinear coordinate system* (0148-7191).

Clark, B., Parkhurst, G. and Ricci, M. (2016) 'Introducing Driverless Cars to UK Roads'.

Clough, B.T. (2002) *Metrics, schmetrics! How the heck do you determine a UAV's autonomy anyway*.

Cohen, R.A. (2015) 'Self-driving technology and autonomous vehicles: a whole new world for potential product liability discussion', *Defense Counsel Journal*, 82(3), p. 328.

Cohen, T. and Cavoli, C. (2019) 'Automated vehicles: exploring possible consequences of government (non) intervention for congestion and accessibility', *Transport reviews*, 39(1), pp. 129-151.

Cooke, R.M. (1991) *Experts in Uncertainty: Opinion and Subjective Probability in Science*. New York: Oxford University Press.

Craig, I. and Liu, M. (2018) 'Driving force', *Property Journal*, pp. 24-25.

Cummings, M. (2019) 'Adaptation of human licensing examinations to the certification of autonomous systems', in *Safe, autonomous and intelligent vehicles*. Springer, pp. 145-162.

Cummings, M.L. (2021) 'Rethinking the Maturity of Artificial Intelligence in Safety-Critical Settings', *AI Mag.*, 42(1), pp. 6-15.

References

Cunneen, M., Mullins, M. and Murphy, F. (2019) 'Autonomous vehicles and embedded artificial intelligence: The challenges of framing machine driving decisions', *Applied Artificial Intelligence*, 33(8), pp. 706-731.

Cunningham, M. and Regan, M.A. (2015) *Proceedings of the 2015 Australasian Road safety conference*.

D'Ambrosio, B. (1999) 'Inference in Bayesian networks', *AI magazine*, 20(2), pp. 21-21.

da Silva Azevedo, L. *et al.* (2013) 'Assisted assignment of automotive safety requirements', *IEEE software*, 31(1), pp. 62-68.

Darwiche, A. (2003) 'A differential approach to inference in Bayesian networks', *Journal of the ACM (JACM)*, 50(3), pp. 280-305.

Davey, J. (2020) 'By insurers, for insurers: The UK's liability regime for autonomous vehicles', *Journal of Tort Law*, 13(2), pp. 163-188.

Dávid, B., Láncz, G. and Hunyady, G. (2019) *2019 IEEE 17th World Symposium on Applied Machine Intelligence and Informatics (SAMI)*. IEEE.

Davis, M.C. *et al.* (2014) 'Advancing socio-technical systems thinking: A call for bravery', *Applied ergonomics*, 45(2), pp. 171-180.

De Souza, A.M. *et al.* (2017) 'Traffic management systems: A classification, review, challenges, and future perspectives', *International Journal of Distributed Sensor Networks*, 13(4), p. 1550147716683612.

De Winter, J.C. *et al.* (2014) 'Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence', *Transportation research part F: traffic psychology and behaviour*, 27, pp. 196-217.

Deb, S. *et al.* (2018) 'Pedestrians' receptivity toward fully automated vehicles: Research review and roadmap for future research', *IEEE Transactions on Human-Machine Systems*, 48(3), pp. 279-290.

Dekkers, R. (2018) 'Group technology: Amalgamation with design of organisational structures', *International Journal of Production Economics*, 200, pp. 262-277.

Denaro, R.P. *et al.* (2014) 'Automated Vehicle Technology: Ten Research Areas to Follow', *King Coal Highway*, 292, pp. 19-24.

Department for Transport (2015) *Driverless vehicles: connected and autonomous technologies* Available at: https://www.gov.uk/government/collections/driverless-vehicles-connected-and-autonomous-technologies (Accessed: 14/01/2020).

Department of Transport (2016) *Federal Automated Vehicles Policy: Accelerating the Next Revolution In Roadway Safety*.

DfT (2015) *The Highway Code*. Available at: https://www.gov.uk/guidance/the-highway-code/general-rules-techniques-and-advice-for-all-drivers-and-riders-103-to-158#speedlimits (Accessed: 19/11/2020).

Dia, H. *et al.* (2021) 'Artificial Intelligence Tests for Certification of Autonomous Vehicles', *Academia Letters*, p. 3.

Dimaio, F. *et al.* (2021) 'Accounting for safety barriers degradation in the risk assessment of oil and gas systems by multistate Bayesian networks', *Reliability Engineering & System Safety*, 216, p. 107943.

Dimitrakopoulos, G. and Bravos, G. (2017) *Current Technologies in Vehicular Communication*. Springer.

Dixit, V.V., Chand, S. and Nair, D.J. (2016) 'Autonomous vehicles: disengagements, accidents and reaction times', *PLoS one*, 11(12), p. e0168054.

Douali, N. *et al.* (2014) 'Diagnosis support system based on clinical guidelines: comparison between case-based fuzzy cognitive maps and Bayesian networks', *Computer methods and programs in biomedicine*, 113(1), pp. 133-143.

Drennan, L.T. and McConnell, A. (2007) *Risk and Crisis Management in the Public Sector*. Routledge.

Druzdzel, M.J. and Simon, H.A. (1993) *Uncertainty in Artificial Intelligence*. Washington DC, USA. Elsevier.

Edwards, J. *et al.* (2014) 'A framework for conceptualising traffic safety culture', *Transportation research part F: traffic psychology and behaviour*, 26, pp. 293-302.

Eldred, M.S., Swiler, L.P. and Tang, G. (2011) 'Mixed aleatory-epistemic uncertainty quantification with stochastic expansions and optimization-based interval estimation', *Reliability Engineering & System Safety*, 96(9), pp. 1092-1113.

Endsley, M.R. (2017) 'Autonomous driving systems: A preliminary naturalistic study of the Tesla Model S', *Journal of Cognitive Engineering and Decision Making*, 11(3), pp. 225-238.

Endsley, M.R. (2018) *Congress of the International Ergonomics Association*. Springer.

Englund, C. *et al.* (2018) 'Enabling technologies for road vehicle automation', in *Road Vehicle Automation 4*. Springer, pp. 177-185.

Eskandarian, A. (2012) *Handbook of intelligent vehicles*. Springer.

Fagnant, D.J. and Kockelman, K. (2015) 'Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations', *Transportation Research Part A: Policy and Practice*, 77, pp. 167-181.

Fahmy, H.M., El Ghany, M.A.A. and Baumann, G. (2018) 'Vehicle Risk Assessment and Control for Lane-Keeping and Collision Avoidance at Low-Speed and High-Speed Scenarios', *IEEE Transactions on Vehicular Technology*, 67(6), pp. 4806-4818.

Faisal, A. *et al.* (2019) 'Understanding autonomous vehicles: A systematic literature review on capability, impact, planning and policy', *Journal of Transport and Land Use*, 12(1), pp. 45-72.

Fan, C.-F. *et al.* (2018) 'A simulation platform for human-machine interaction safety analysis of cyber-physical systems', *International journal of industrial ergonomics*, 68, pp. 89-100.

Farmani, R. *et al.* (2012) 'An evolutionary Bayesian belief network methodology for participatory decision making under uncertainty: An application to groundwater management', *Integrated environmental assessment and management*, 8(3), pp. 456-461.

Farrugia, P. *et al.* (2010) 'Research questions, hypotheses and objectives', *Canadian journal of surgery*, 53(4), p. 278.

Favarò, F.M. *et al.* (2017) 'Examining accident reports involving autonomous vehicles in California', *PLoS one*, 12(9), p. e0184952.

Fenton, N. and Neil, M. (2012) *Risk Assessment and Decision Analysis with Bayesian Networks*. CRC Press.

References

Fenton, N.E. and Neil, M. (1999) 'A critique of software defect prediction models', *IEEE Transactions on software engineering*, 25(5), pp. 675-689.

Fenton, N.E., Neil, M. and Caballero, J.G. (2007) 'Using ranked nodes to model qualitative judgments in Bayesian networks', *IEEE Transactions on Knowledge and Data Engineering*, 19(10), pp. 1420-1432.

Fenz, S. (2012) 'An ontology-based approach for constructing Bayesian networks', *Data & Knowledge Engineering*, 73, pp. 73-88.

Flage, R. and Aven, T. (2015) 'Emerging risk–Conceptual definition and a relation to black swan type of events', *Reliability Engineering & System Safety*, 144, pp. 61-67.

Fong, T. (2018) *Autonomous systems: Nasa capability overview*. NASA.

Fortus, D. (2009) 'The importance of learning to make assumptions', *Science Education*, 93(1), pp. 86-108.

Froese, T., Virgo, N. and Izquierdo, E. (2007) *European Conference on Artificial Life*. Springer.

Frost, C.R. (2010) *Frontiers of Engineering: Reports on Leading-Edge Engineering from the 2010 Symposium*. New York. Washington, DC: The National Academies Press.

Frost, S., Goebel, K. and Celaya, J. (2012) 'A Briefing on Metrics and Risks for Autonomous Decision-making in Aerospace Applications', in *Infotech@ Aerospace 2012*. p. 2402.

García-Herrero, S. *et al.* (2020) 'Sensitivity analysis of driver's behavior and psychophysical conditions', *Safety Science*, 125, pp. N.PAG-N.PAG.

Gasparetto, A. *et al.* (2015) 'Path planning and trajectory planning algorithms: A general overview', in *Motion and operation planning of robotic systems*. Springer, pp. 3-27.

Gasson, S. (2004) 'Rigor in grounded theory research: An interpretive perspective on generating theory from qualitative field studies', in *The handbook of information systems research*. IGI Global, pp. 79-102.

Gavanas, N. (2019) 'Autonomous road vehicles: Challenges for urban planning in European Cities', *Urban Science*, 3(2), p. 61.

Gawron, J.H. *et al.* (2018) 'Life cycle assessment of connected and automated vehicles: sensing and computing subsystem and vehicle level effects', *Environmental science & technology*, 52(5), pp. 3249-3256.

Geldmacher, W. and Pleșea, D.A. (2016) *European Conference on Innovation and Entrepreneurship*. Academic Conferences International Limited.

Genders, W. and Razavi, S.N. (2016) 'Impact of connected vehicle on work zone network safety through dynamic route guidance', *Journal of Computing in Civil Engineering*, 30(2), p. 04015020.

Geuther, S. and Shih, A. (2016) 'BBN-BASED PORTFOLIO RISK ASSESSMENT FOR NASA TECHNOLOGY R&D OUTCOME', *Proceedings of the 2017 International Annual Conference of the American Society for Engineering Management*. p. 1. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=edb&AN=129318975&site=eds-live.

Ghabayen, S.M., McKee, M. and Kemblowski, M. (2006) 'Ionic and isotopic ratios for identification of salinity sources and missing data in the Gaza aquifer', *Journal of hydrology*, 318(1-4), pp. 360-373.

Gheraibia, Y., Djafri, K. and Krimou, H. (2018) 'Ant colony algorithm for automotive safety integrity level allocation', *Applied Intelligence*, 48(3), pp. 555-569.

Gilovich, T., Griffin, D. and Kahneman, D. (2002) *Heuristics and Biases: The Psychology of Intuitive Judgment*. Cambridge University Press.

Gioia, D.A., Corley, K.G. and Hamilton, A.L. (2013) 'Seeking qualitative rigor in inductive research: Notes on the Gioia methodology', *Organizational research methods*, 16(1), pp. 15-31.

Girimonte, D. and Izzo, D. (2007) 'Artificial intelligence for space applications', in *Intelligent Computing Everywhere*. Springer, pp. 235-253.

Glaser, S. *et al.* (2010) 'Maneuver-based trajectory planning for highly autonomous vehicles on real road with traffic and driver interaction', *IEEE Transactions on intelligent transportation systems*, 11(3), pp. 589-606.

Glassbrook, A. (2017) *The Law of Driverless Cars: An Introduction*. Minehead, UK: Law Brief Publishing.

Gluckman, P. (2016) *Making decisions in the face of uncertainty: Understanding risk*. Auckland, New Zealand.

Godin, B. (2002) *The rise of innovation surveys: Measuring a fuzzy concept*. (Downloaded: 19/03/2022).

Gong, C. (2009) *2009 International Conference on Intelligent Human-Machine Systems and Cybernetics*. IEEE.

Gonzalez-Redin, J. *et al.* (2016) 'Spatial Bayesian belief networks as a planning decision tool for mapping ecosystem services trade-offs on forested landscapes', *Environmental Research*, 144, pp. 15-26.

Goodall, N. (2020) 'Ethical Decision Making During Automated Vehicle Crashes' [Working Paper]. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=edsarx&AN=edsarx.2010.16309&site=eds-live.

Gopalswamy, S. and Rathinam, S. (2018) *2018 IEEE Intelligent Vehicles Symposium (IV)*. Changshu, China. IEEE.

Greene, J.D. (2016) 'Our driverless dilemma', *Science*, 352(6293), pp. 1514-1515.

Greenlee, E.T., DeLucia, P.R. and Newton, D.C. (2018) 'Driver vigilance in automated vehicles: Hazard detection failures are a matter of time', *Human factors*, 60(4), pp. 465-476.

Gregoriades, A. and Mouskos, K.C. (2013) 'Black spots identification through a Bayesian Networks quantification of accident risk index', *Transportation Research Part C: Emerging Technologies*, 28, pp. 28-43.

Groth, K.M. and Mosleh, A. (2012) 'Deriving causal Bayesian networks from human reliability analysis data: A methodology and example model', *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 226(4), pp. 361-379.

Grover, J. (2016) *The Manual of Strategic Economic Decision Making: Using Bayesian Belief Networks to Solve Complex Problems*. Springer International Publishing.

Gruel, W. and Stanford, J.M. (2016) 'Assessing the long-term effects of autonomous vehicles: a speculative approach', *Transportation research procedia*, 13, pp. 18-29.

Guanetti, J., Kim, Y. and Borrelli, F. (2018) 'Control of connected and automated vehicles: State of the art and future challenges', *Annual reviews in control*, 45, pp. 18-40.

Guerra, E. (2016) 'Planning for cars that drive themselves: Metropolitan planning organizations, regional transportation plans, and autonomous vehicles', *Journal of Planning Education and Research*, 36(2), pp. 210-224.

Guerrero-Ibanez, J.A., Zeadally, S. and Contreras-Castillo, J. (2015) 'Integration challenges of intelligent transportation systems with connected vehicle, cloud computing, and internet of things technologies', *IEEE Wireless Communications*, 22(6), pp. 122-128.

Guo, C. *et al.* (2017) 'Human-like Behavior Generation in Urban Environment based on Learning-based Potentials with a Low-cost Lane Graph', *IEEE Transactions on Intelligent Vehicles, Intelligent Vehicles, IEEE Transactions on, IEEE Trans. Intell. Veh.*, PP(99), pp. 1-1.

Guo, H. and Hsu, W. (2002) *Join Workshop on Real Time Decision Support and Diagnosis Systems*.

Guo, J., Kurup, U. and Shah, M. (2019) 'Is It Safe to Drive? An Overview of Factors, Metrics, and Datasets for Driveability Assessment in Autonomous Driving', *IEEE Transactions on Intelligent Transportation Systems*.

Haimes, Y.Y. (2018) 'Risk modeling of interdependent complex systems of systems: Theory and practice', *Risk Analysis*, 38(1), pp. 84-98.

Hajiloo, R. *et al.* (2020) 'Integrated Steering and Differential Braking for Emergency Collision Avoidance in Autonomous Vehicles', *IEEE Transactions on Intelligent Transportation Systems*.

Hall, J.K. and Martin, M.J. (2005) 'Disruptive technologies, stakeholders and the innovation value-added chain: a framework for evaluating radical technology development', *R&d Management*, 35(3), pp. 273-284.

Hamet, P. and Tremblay, J. (2017) 'Artificial intelligence in medicine', *Metabolism*, 69, pp. S36-S40.

Hancock, P.A. (2019) 'Some pitfalls in the promises of automated and autonomous vehicles', *Ergonomics*, 62(4), pp. 479-495.

Hancock, P.A. *et al.* (2020) 'Challenges to human drivers in increasingly automated vehicles', *Human factors*, 62(2), pp. 310-328.

Hanea, A., Morales-Napoles, O. and Ababei, D. (2015) 'Non-parametric Bayesian networks: Improving theory and reviewing applications', *Reliability Engineering & System Safety*, 144, pp. 265-284.

Hanna, M.J. and Kimmel, S.C. (2017) 'Current US federal policy framework for self-driving vehicles: Opportunities and challenges', *Computer*, 50(12), pp. 32-40.

Hänninen, M. (2014) 'Bayesian networks for maritime traffic accident prevention: benefits and challenges', *Accident Analysis & Prevention*, 73, pp. 305-312.

Hansson, S.O. and Aven, T. (2014) 'Is risk analysis scientific?', *Risk Analysis*, 34(7), pp. 1173-1183.

Hardy, J. and Campbell, M. (2013) 'Contingency planning over probabilistic obstacle predictions for autonomous road vehicles', *IEEE Transactions on Robotics*, 29(4), pp. 913-929.

Havaei-Ahary, B. (2019) *Road Traffic Estimates: Great Britain 2018*DfT (Annual Road Traffic Estimates). Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/808555/road-traffic-estimates-in-great-britain-2018.pdf (Accessed: 18/11/2020).

Hawking, S. *et al.* (2014) 'Stephen Hawking:'Transcendence looks at the implications of artificial intelligence-but are we taking AI seriously enough?'', *The Independent*, 2014(05-01), p. 9313474.

He, X. *et al.* (2019) 'Emergency steering control of autonomous vehicle for collision avoidance and stabilisation', *Vehicle system dynamics*, 57(8), pp. 1163-1187.

Helton, J.C. *et al.* (2010) 'Representation of analysis results involving aleatory and epistemic uncertainty', *International Journal of General Systems*, 39(6), pp. 605-646.

Hengstler, M., Enkel, E. and Duelli, S. (2016) 'Applied artificial intelligence and trust—The case of autonomous vehicles and medical assistance devices', *Technological Forecasting and Social Change*, 105, pp. 105-120.

Hertzog, M.A. (2008) 'Considerations in determining sample size for pilot studies', *Research in nursing & health*, 31(2), pp. 180-191.

Hexmoor, H., Castelfranchi, C. and Falcone, R. (2012) *Agent Autonomy*. Springer US.

Ho, N. *et al.* (2017) *2017 IEEE/AIAA 36th Digital Avionics Systems Conference (DASC)*. IEEE.

Hoffman, F.O. and Hammonds, J.S. (1994) 'Propagation of uncertainty in risk assessments: the need to distinguish between uncertainty due to lack of knowledge and uncertainty due to variability', *Risk analysis*, 14(5), pp. 707-712.

Hoffman, R.R. *et al.* (2013) 'Trust in automation', *IEEE Intelligent Systems*, 28(1), pp. 84-88.

Holstein, T. (2017) *Multidisciplinary Digital Publishing Institute Proceedings*.

Hopkins, D. and Schwanen, T. (2018) 'Experimentation with vehicle automation', in *Transitions in energy efficiency and demand*. Routledge, pp. 72-93.

Huang, H.-M. *et al.* (2005) 'A framework for autonomy levels for unmanned systems (ALFUS)', *Proceedings of the AUVSI's Unmanned Systems North America*, pp. 849-863.

Huang, M.-H. and Rust, R.T. (2018) 'Artificial intelligence in service', *Journal of Service Research*, 21(2), pp. 155-172.

Huang, Z., Yang, L. and Jiang, W. (2019) 'Uncertainty measurement with belief entropy on the interference effect in the quantum-like Bayesian networks', *Applied Mathematics and Computation*, 347, pp. 417-428.

Hugemann, W. (2002) *Proceedings of XI EVU (European Association for Accident Research and Accident Analysis) Annual Meeting. Portorož, Slovenija*.

Hulse, L.M., Xie, H. and Galea, E.R. (2018) 'Perceptions of autonomous vehicles: Relationships with road users, risk, gender and age', *Safety Science*, 102, pp. 1-13.

Hutchison, C. *et al.* (2018) *2018 IEEE/ACM 40th International Conference on Software Engineering: Software Engineering in Practice Track (ICSE-SEIP)*. IEEE.

Ieropoulos, I., Melhuish, C. and Greenman, J. (2003) *European Conference on Artificial Life*. Springer.

Ilková, V. and Ilka, A. (2017) *2017 21st international conference on process control (PC)*. IEEE.

Intan Suhana, M. *et al.* (2014) 'Identification of hazardous road sections: crash data versus composite index method', *International Journal of Engineering and Technology*, 6(6), p. 481.

Isaac, L. (2016) 'Driving towards driverless: A guide for government agencies', *WSP-Parsons Brinckerhoff, New York, NY, www. wsp-pb. com/Globaln/USA/Transportation% 20and%*

20Infrastructure/driving-towards-driverless-WBP-Fellow-monograph-lauren-isaac-feb-24-2016. pdf, accessed, 20.

Ismail, M.A. *et al.* (2011) 'Developing a road performance index using a Bayesian belief network model', *Journal of the Franklin Institute*, 348(9), pp. 2539-2555.

Ivanchev, J. *et al.* (2019) *International Conference on Computational Science*. Faro, Portugal. Springer.

Jamson, A.H. *et al.* (2013) 'Behavioural changes in drivers experiencing highly-automated vehicle control in varying traffic conditions', *Transportation research part C: emerging technologies*, 30, pp. 116-125.

Ji, J. *et al.* (2016) 'Path planning and tracking for vehicle collision avoidance based on model predictive control with multiconstraints', *IEEE Transactions on Vehicular Technology*, 66(2), pp. 952-964.

Jia, D. and Ngoduy, D. (2016) 'Enhanced cooperative car-following traffic model with the combination of V2V and V2I communication', *Transportation Research Part B: Methodological*, 90, pp. 172-191.

Johnson, C. (2017) 'Readiness of the road network for connected and autonomous vehicles', *RAC Foundation: London, UK*.

Kabir, G. *et al.* (2015) 'Evaluating risk of water mains failure using a Bayesian belief network model', *European Journal of Operational Research*, 240(1), pp. 220-234.

Kaduk, S.I., Roberts, A.P. and Stanton, N.A. (2020a) 'The circadian effect on psychophysiological driver state monitoring', *Theoretical Issues in Ergonomics Science*, pp. 1-25.

Kaduk, S.I., Roberts, A.P. and Stanton, N.A. (2020b) 'The manual shift in phase: the impact of circadian phase on semi-autonomous driving. What can we learn from current understanding in manual driving?', *Theoretical Issues in Ergonomics Science*, pp. 1-21.

Kaikkonen, L. *et al.* (2021) 'Bayesian networks in environmental risk assessment: A review', *Integrated environmental assessment and management*, 17(1), pp. 62-78.

Kalra, N. and Paddock, S.M. (2016) 'Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability?', *Transportation Research Part A: Policy and Practice*, 94, pp. 182-193.

Kashani, M. *et al.* (2013) 'Improving assessment of cardiovascular disease risk by using family history: an integrative literature review', *Journal of Cardiovascular Nursing*, 28(6), pp. E18-E27.

Kassens-Noor, E. *et al.* (2020) 'Sociomobility of the 21st century: Autonomous vehicles, planning, and the future city', *Transport Policy*, 99, pp. 329-335.

Kato, S. *et al.* (2015) 'An open approach to autonomous vehicles', *IEEE Micro*, 35(6), pp. 60-68.

Katrakazas, C., Quddus, M. and Chen, W.-H. (2019) 'A new integrated collision risk assessment methodology for autonomous vehicles', *Accident Analysis & Prevention*, 127, pp. 61-79.

Katrakazas, C. *et al.* (2020) 'Cyber security and its impact on CAV safety: overview, policy needs and challenges', in Milakis, D., Thomopoulos, N. and van Wee, B. (eds.) *Policy Implications of Autonomous Vehicles*. 1 edn. Elsevier, pp. 73-94.

Katyal, N. (2013) 'Disruptive Technologies and the Law', *THE GEORGETOWN LAW JOURNAL*, 102, p. 1685.

Kaur, K. and Rampersad, G. (2018) 'Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars', *Journal of Engineering and Technology Management*, 48, pp. 87-96.

Kazaras, K., Kontogiannis, T. and Kirytopoulos, K. (2014) 'Proactive assessment of breaches of safety constraints and causal organizational breakdowns in complex systems: A joint STAMP–VSM framework for safety assessment', *Safety science*, 62, pp. 233-247.

Keeney, R.L. and Von Winterfeldt, D. (1991) 'Eliciting probabilities from experts in complex technical problems', *IEEE Transactions on engineering management*, 38(3), pp. 191-201.

Kellerman, A. (2018) *Automated and Autonomous Spatial Mobilities*. Edward Elgar Publishing Limited.

Khan, J.A. *et al.* (2019) *Proceedings of the 2nd ACM/EIGSCC Symposium on Smart Cities and Communities*.

Khonji, M., Dias, J. and Seneviratne, L. (2019) 'Risk-Aware Reasoning for Autonomous Vehicles' [Working Paper]. Available at: http://search.ebscohost.com/login.aspx?direct=true&db=edsarx&AN=edsarx.1910.02461&site=eds-live.

Kim, B. *et al.* (2016) 'Testing autonomous vehicle software in the virtual prototyping environment', *IEEE Embedded Systems Letters*, 9(1), pp. 5-8.

Kim, H. *et al.* (2018) 'Autonomous Emergency Braking Considering Road Slope and Friction Coefficient', *International Journal of Automotive Technology*, 19(6), pp. 1013-1022.

Kim, J. and Canny, J. (2017) *Proceedings of the IEEE international conference on computer vision*.

Kim, K. *et al.* (2021) 'Cybersecurity for autonomous vehicles: Review of attacks and defense', *Computers & Security*, p. 102150.

Kocić, J., Jovičić, N. and Drndarević, V. (2018) *2018 26th Telecommunications Forum (TELFOR)*. IEEE.

Kohl, C. *et al.* (2018) 'Anticipating acceptance of emerging technologies using twitter: the case of self-driving cars', *Journal of Business Economics*, 88(5), pp. 617-642.

Koller, D. and Pfeffer, A. (1997) *Proceedings of the Thirteenth conference on Uncertainty in artificial intelligence*. Morgan Kaufmann Publishers Inc.

Koller, G. (1999) *Risk Assessment and Decision Making in Business and Industry: A Practical Guide*. Taylor & Francis.

König, M. and Neumayr, L. (2017) 'Users' resistance towards radical innovations: The case of the self-driving car', *Transportation research part F: traffic psychology and behaviour*, 44, pp. 42-52.

Koopman, P. *et al.* (2019) *International Conference on Computer Safety, Reliability, and Security*. Turku, Finland. Springer.

Koopman, P., Osyk, B. and Weast, J. (2019) *International Conference on Computer Safety, Reliability, and Security*. Turku, Finland. Springer.

Koopman, P. and Wagner, M. (2016) 'Challenges in autonomous vehicle testing and validation', *SAE International Journal of Transportation Safety*, 4(1), pp. 15-24.

Koopman, P. and Wagner, M. (2017) 'Autonomous vehicle safety: An interdisciplinary challenge', *IEEE Intelligent Transportation Systems Magazine*, 9(1), pp. 90-96.

Kopardekar, P., Prevot, T. and Jastrzebski, M. (2008) *AIAA Guidance, Navigation and Control Conference and Exhibit*.

Korb, K.B. and Nicholson, A.E. (2003) *Bayesian Artificial Intelligence*. Taylor & Francis.

KPMG (2015a) *Automobile Insurance in the Era of Autonomous Vehicles* (NDPPS 348936). Available at: https://assets.kpmg/content/dam/kpmg/pdf/2016/05/kpmg-automobile-insurance-in-era-autonomous.pdf.

KPMG (2015b) *Connected and Autonomous Vehicles – The UK Economic Opportunity*. Available at: https://assets.kpmg/content/dam/kpmg/pdf/2015/04/connected-and-autonomous-vehicles.pdf.

KPMG (2018) *Autonomous Vehicles Readiness Index: Assessment Countries' Openness and preparedness for autonomous vehicles*. Available at: https://assets.kpmg/content/dam/kpmg/nl/pdf/2018/sector/automotive/autonomous-vehicles-readiness-index.pdf.

Kuang, Y., Qu, X. and Yan, Y. (2017) 'Will higher traffic flow lead to more traffic conflicts? A crash surrogate metric based analysis', *PLoS one*, 12(8), p. e0182458.

Kuderer, M., Gulati, S. and Burgard, W. (2015) *2015 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE.

Kumar, K., Parida, M. and Katiyar, V.K. (2015) 'Short term traffic flow prediction in heterogeneous condition using artificial neural network', *Transport*, 30(4), pp. 397-405.

Kurzhanskiy, A.A. and Varaiya, P. (2015) 'Traffic management: An outlook', *Economics of Transportation*, 4(3), pp. 135-146.

Lachapelle, V. *et al.* (2021) 'Expert elicitation to estimate the feed safety impact of criteria included in the Canadian Food Inspection Agency risk assessment model for feed mills', *Journal of Food Protection*, 84(4), pp. 611-627.

Laitila, P. and Virtanen, K. (2016) 'Improving construction of conditional probability tables for ranked nodes in Bayesian networks', *IEEE Transactions on Knowledge and Data Engineering*, 28(7), pp. 1691-1705.

Lam, W. and Bacchus, F. (1994) 'Learning Bayesian belief networks: An approach based on the MDL principle', *Computational intelligence*, 10(3), pp. 269-293.

Lamkin-Kennard, K.A. and Popovic, M.B. (2019) 'Sensors:Natural and Synthetic Sensors', in Popovic, M.B. (ed.) *Biomechatronics*. Elsevier Science, pp. 81-107.

Landuyt, D. *et al.* (2014) 'An ecosystem service approach to support integrated pond management: a case study using Bayesian belief networks–highlighting opportunities and risks', *Journal of environmental management*, 145, pp. 79-87.

Langseth, H. and Nielsen, T.D. (2006) 'Classification using hierarchical naive bayes models', *Machine learning*, 63(2), pp. 135-159.

Lardinois, F. (2016) *US Government Plans To Invest $4B In Autonomous Driving Research Over The Next 10 Years*. Available at: https://techcrunch.com/2016/01/14/us-government-plans-to-invest-4b-into-autonomous-driving-research-over-the-next-10-years/2016/01/14/us-government-plans-to-invest-4b-into-autonomous-driving-research-over-the-next-10-years/ (Accessed: 15/01/2020).

Lari, A., Douma, F. and Onyiah, I. (2015) 'Self-driving vehicles and policy implications: current status of autonomous vehicle development and minnesota policy implications', *Minn. JL Sci. & Tech.*, 16, p. 735.

Law Commission of England and Wales (2022) *Automated Vehicle: joint report* (HC 1068) (Law Com No 404). The UK. Available at: https://s3-eu-west-2.amazonaws.com/lawcom-prod-storage-11jsxou24uy7q/uploads/2022/01/Automated-vehicles-joint-report-cvr-03-02-22.pdf.

Leavitt, H.J. (1965) 'Applied Organizational Change in Industry: Structural, Technological, and Humanistic Approaches', in March, J.G. (ed.) *Handbook of Organizations*. 1st edn. Chicago, US: Rand McNally & Company, pp. 1144 – 1170.

Lee, E., Park, Y. and Shin, J.G. (2009) 'Large engineering project risk management using a Bayesian belief network', *Expert Systems with Applications*, 36(3), pp. 5880-5887.

Lee, J. *et al.* (2019) *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*. IEEE.

Lee, S.-H., Yang, K.-M. and Cho, S.-B. (2015) 'Integrated modular Bayesian networks with selective inference for context-aware decision making', *Neurocomputing*, 163, pp. 38-46.

Lengyel, H. and Szalay, Z. (2018) *35th international colloquium on advanced manufacturing and repair technologies in vehicle industry*. Łagów Lubuski, Poland. University of Zielona Góra.

Leslie, E. *et al.* (2022) *AIAA SCITECH 2022 Forum*.

Leveson, N. (2004) 'A new accident model for engineering safer systems', *Safety science*, 42(4), pp. 237-270.

LEVITATE (2019) *Societal Impacts of Connected and Autonomous Vehicles*. Available at: https://levitate-project.eu/ (Accessed: 05/11/2021).

Li, B.-h. *et al.* (2017) 'Applications of artificial intelligence in intelligent manufacturing: a review', *Frontiers of Information Technology & Electronic Engineering*, 18(1), pp. 86-96.

Li, G. *et al.* (2021) 'Risk assessment based collision avoidance decision-making for autonomous vehicles in multi-scenarios', *Transportation research part C: emerging technologies*, 122, p. 102820.

Li, L. *et al.* (2016) 'Intelligence testing for autonomous vehicles: A new approach', *IEEE Transactions on Intelligent Vehicles*, 1(2), pp. 158-166.

Li, P.-c. *et al.* (2012) 'A fuzzy Bayesian network approach to improve the quantification of organizational influences in HRA frameworks', *Safety science*, 50(7), pp. 1569-1583.

Li, W., Zhang, L. and Liang, W. (2017) 'An Accident Causation Analysis and Taxonomy (ACAT) model of complex industrial system from both system safety and control theory perspectives', *Safety science*, 92, pp. 94-103.

Li, Y. and Liu, Q. (2020) 'Intersection management for autonomous vehicles with vehicle-to-infrastructure communication', *PLoS one*, 15(7), p. e0235644.

Li, Y. *et al.* (2018) 'Influence of cyber-attacks on longitudinal safety of connected and automated vehicles', *Accident; analysis and prevention*, 121, pp. 148-156.

Liberati, A. *et al.* (2009) 'The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration', *PLoS medicine*, 6(7), p. e1000100.

Lidoris, G. *et al.* (2011) 'System interdependence analysis for autonomous robots', *The International Journal of Robotics Research*, 30(5), pp. 601-614.

Lim, H.S.M. and Taeihagh, A. (2018) 'Autonomous vehicles for smart and sustainable cities: An in-depth exploration of privacy and cybersecurity implications', *Energies*, 11(5), p. 1062.

Lin, C.-F., Juang, J.-C. and Li, K.-R. (2014) 'Active collision avoidance system for steering control of autonomous vehicles', *IET Intelligent Transport Systems*, 8(6), pp. 550-557.

Lipson, H. and Kurman, M. (2016) *Driverless: Intelligent Cars and the Road Ahead*. MIT Press.

Lisinska, J. and Kleinman, M. (2021) *Autonomous vehicles: automotive, maritime and aerial: A policy landscape review*. Available at: https://doi.org/10.18742/pub01-064.

Litman, T. (2015) *Autonomous vehicle implementation predictions: Implications for transport planning*.

Litman, T. (2017) *Autonomous vehicle implementation predictions*. Victoria Transport Policy Institute Victoria, Canada.

Liu, G. and Zhai, R. (2018) *International Conference on Transportation and Development 2018: Planning, Sustainability, and Infrastructure Systems*. American Society of Civil Engineers Reston, VA.

Liu, Y. *et al.* (2019) *Journal of Physics: Conference Series*. IOP Publishing.

Liu, Z.-Q. (2001) 'Causation, bayesian networks, and cognitive maps', *Acta automática sinica*, 27(4), pp. 552-566.

Loutchkina, I. *et al.* (2013) 'The systems integration technical risk assessment fusing of Bayesian Belief Networks and parametric models', *Journal of Intelligent & Fuzzy Systems*, 24(2), pp. 281-296.

Lu, K.-L. and Chen, Y.-Y. (2019) *2019 IEEE International Conference on Connected Vehicles and Expo (ICCVE)*. IEEE.

Lu, Q. and Tettamanti, T. (2021) 'Impacts of connected and automated vehicles on freeway with increased speed limit', *International Journal of Simulation Modelling*, 20(3), pp. 453-464.

Lu, Z., Coster, X. and De Winter, J. (2017) 'How much time do drivers need to obtain situation awareness? A laboratory-based study of automated driving', *Applied ergonomics*, 60, pp. 293-304.

Luigi, P. and Daniele, C.R. (2015) *Modeling And Analysis Of Dependable Systems: A Probabilistic Graphical Model Perspective*. World Scientific Publishing Company.

Lundgren, B. (2020) 'Safety requirements vs. crashing ethically: what matters most for policies on autonomous vehicles', *AI & SOCIETY*, (36), pp. 1-11.

Lundgren, B. (2021) 'Safety requirements vs. crashing ethically: what matters most for policies on autonomous vehicles', *AI & SOCIETY*, 36(2), pp. 405-415.

Luo, C. *et al.* (2020) *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE.

Lutin, J.M., Kornhauser, A.L. and Lerner-Lam, E. (2013) 'The revolutionary development of self-driving vehicles and implications for the transportation engineering profession', *Cell*, 215, pp. 630-4125.

Luxhøj, J.T. (2015) 'A socio-technical model for analyzing safety risk of unmanned aircraft systems (UAS): An application to precision agriculture', *Procedia Manufacturing*, 3, pp. 928-935.

Luxhøj, J.T. and Topuz, K. (2012) *Industrial and Systems Engineering Research Conference*.

Lv, C. *et al.* (2017) 'Analysis of autopilot disengagements occurring during autonomous vehicle testing', *IEEE/CAA Journal of Automatica Sinica*, 5(1), pp. 58-68.

Lyons, J.B. *et al.* (2017) *International Conference on Applied Human Factors and Ergonomics*. Springer.

Ma, K. and Wang, H. (2019) 'Influence of exclusive lanes for connected and autonomous vehicles on freeway traffic flow', *IEEE Access*, 7, pp. 50168-50178.

Maathuis, M. *et al.* (2018) *Handbook of Graphical Models*. CRC Press.

Mack, C.A. (2011) 'Fifty years of Moore's law', *IEEE Transactions on semiconductor manufacturing*, 24(2), pp. 202-207.

Mackenzie, A.K. and Harris, J.M. (2015) 'Eye movements and hazard perception in active and passive driving', *Visual cognition*, 23(6), pp. 736-757.

Mackieson, P., Shlonsky, A. and Connolly, M. (2019) 'Increasing rigor and reducing bias in qualitative research: A document analysis of parliamentary debates using applied thematic analysis', *Qualitative Social Work*, 18(6), pp. 965-980.

Madan, B.B., Banik, M. and Bein, D. (2019) 'Securing unmanned autonomous systems from cyber threats', *The Journal of Defense Modeling and Simulation*, 16(2), pp. 119-136.

Mader, R. *et al.* (2012) *2012 Proceedings Annual Reliability and Maintainability Symposium*. IEEE.

Madni, A.M. *et al.* (2018) 'Model-based approach for engineering resilient system-of-systems: Application to autonomous vehicle networks', in *Disciplinary Convergence in Systems Engineering Research*. Springer, pp. 365-380.

Madsen, A.L. *et al.* (2003) *European conference on symbolic and quantitative approaches to reasoning and uncertainty*. Springer.

Maierhofer, S. *et al.* (2020) *2020 IEEE Intelligent Vehicles Symposium (IV)*. IEEE. Available at: https://ieeexplore.ieee.org/abstract/document/9304549.

Malin, F., Norros, I. and Innamaa, S. (2019) 'Accident risk of road and weather conditions on different road types', *Accident Analysis & Prevention*, 122, pp. 181-188.

Manfreda, A., Ljubi, K. and Groznik, A. (2021) 'Autonomous vehicles in the smart city era: An empirical study of adoption factors important for millennials', *International Journal of Information Management*, 58, p. 102050.

Manivasakan, H. *et al.* (2021) 'Infrastructure requirement for autonomous vehicle integration for future urban and suburban roads–Current practice and a case study of Melbourne, Australia', *Transportation Research Part A: Policy and Practice*, 152, pp. 36-53.

Manzur Tirado, A.M., Brown, R. and Valdez Banda, O.A. (2019) *Risk and safety management of autonomous systems: a literature review and initial proposals for the maritime industry* (9526084993). Helsinki, Finland.

Marcot, B.G. and Penman, T.D. (2019) 'Advances in Bayesian network modelling: Integration of modelling technologies', *Environmental modelling & software*, 111, pp. 386-393.

Marcot, B.G. *et al.* (2006) 'Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation', *Canadian Journal of Forest Research*, 36(12), pp. 3063-3074.

Mariani, R. (2018) *2018 IEEE International Reliability Physics Symposium (IRPS)*. IEEE.

Marletto, G. (2019) 'Who will drive the transition to self-driving? A socio-technical analysis of the future impact of automated vehicles', *Technological Forecasting and Social Change*, 139, pp. 221-234.

Martin, J. *et al.* (2015) 'Certification for autonomous vehicles', *Automative Cyber-physical Systems course paper, University of North Carolina, Chapel Hill, NC, USA*.

Marzbani, H. *et al.* (2019) 'Autonomous vehicles: Autodriver algorithm and vehicle dynamics', *IEEE Transactions on Vehicular Technology*, 68(4), pp. 3201-3211.

Massar, M. *et al.* (2021) 'Impacts of Autonomous Vehicles on Greenhouse Gas Emissions—Positive or Negative?', *International Journal of Environmental Research and Public Health*, 18(11), p. 5567.

Matellini, D. *et al.* (2018) 'A Three-Part Bayesian Network for Modeling Dwelling Fires and Their Impact upon People and Property', *Risk analysis*, 38(10), pp. 2087-2104.

Maurer, M. *et al.* (2016) 'Autonomous driving', *Berlin, Germany: Springer Berlin Heidelberg*, 10, pp. 978-3.

McAslan, D., Gabriele, M. and Miller, T.R. (2021) 'Planning and Policy Directions for Autonomous Vehicles in Metropolitan Planning Organizations (MPOs) in the United States', *Journal of Urban Technology*, pp. 1-27.

McBride, N. (2016) 'The ethics of driverless cars', *ACM SIGCAS Computers and Society*, 45(3), pp. 179-184.

McDaniels, T. and Small, M. (2004) *Risk Analysis and Society: An Interdisciplinary Characterization of the Field*. Cambridge University Press.

McDonald, K., Ryder, D. and Tighe, M. (2015) 'Developing best-practice Bayesian Belief Networks in ecological risk assessments for freshwater and estuarine ecosystems: A quantitative review', *Journal of environmental management*, 154, pp. 190-200.

Meng, Q. and Weng, J. (2013) 'Uncertainty analysis of accident notification time and emergency medical service response time in work zone traffic accidents', *Traffic injury prevention*, 14(2), pp. 150-158.

Metz, B., Schömig, N. and Krüger, H.-P. (2011) 'Attention during visual secondary tasks in driving: Adaptation to the demands of the driving task', *Transportation research part F: traffic psychology and behaviour*, 14(5), pp. 369-380.

Meyer, G. and Shaheen, S. (2017) 'Disrupting Mobility', *Lecture Notes in Mobility. Cham: Springer International Publishing*.

Milakis, D., Thomopoulos, N. and Van Wee, B. (2020) *Policy Implications of Autonomous Vehicles*. Academic Press.

Milakis, D., Van Arem, B. and Van Wee, B. (2017) 'Policy and society related implications of automated driving: A review of literature and directions for future research', *Journal of Intelligent Transportation Systems*, 21(4), pp. 324-348.

Miller, D. *et al.* (2016) *Proceedings of the human factors and ergonomics society annual meeting*. SAGE Publications Sage CA: Los Angeles, CA.

Minhas, S. *et al.* (2020) 'Effects of Non-Driving Related Tasks During Self-Driving Mode', *IEEE Transactions on Intelligent Transportation Systems*.

Mirzaeian, N., Cho, S.-H. and Scheller-Wolf, A. (2021) 'A queueing model and analysis for autonomous vehicles on highways', *Management Science*, 67(5), pp. 2904-2923.

Mkrtchyan, L. *et al.* (2022) 'Insurability risk assessment of oil refineries using Bayesian Belief Networks', *Journal of Loss Prevention in the Process Industries*, 74, p. 104673.

Mohaghegh, Z., Kazemi, R. and Mosleh, A. (2009) 'Incorporating organizational factors into Probabilistic Risk Assessment (PRA) of complex socio-technical systems: A hybrid technique formalization', *Reliability Engineering & System Safety*, 94(5), pp. 1000-1018.

Mohaghegh, Z. and Mosleh, A. (2009) 'Incorporating organizational factors into probabilistic risk assessment of complex socio-technical systems: Principles and theoretical foundations', *Safety science*, 47(8), pp. 1139-1158.

Mohammed, M., Khan, M.B. and Bashier, E.B.M. (2016) *Machine learning: algorithms and applications*. Crc Press.

Mohan, D. *et al.* (2006) *Road traffic injury prevention: training manual*. World Health Organization.

Mohsen, I. *et al.* (2020) 'Lateral Position Measurement Based on Vehicles' Longitudinal Displacement', *Sensors*, 20(24), p. 7183.

Mok, B. *et al.* (2017) *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*.

Moody, J., Bailey, N. and Zhao, J. (2020) 'Public perceptions of autonomous vehicle safety: An international comparison', *Safety science*, 121, pp. 634-650.

Moola, S. *et al.* (2015) 'Conducting systematic reviews of association (etiology): the Joanna Briggs Institute's approach', *International journal of evidence-based healthcare*, 13(3), pp. 163-169.

Moral, S., Rumí, R. and Salmerón, A. (2001) *European Conference on Symbolic and Quantitative Approaches to Reasoning and Uncertainty*. Springer.

Morando, M.M. *et al.* (2018) 'Studying the safety impact of autonomous vehicles using simulation-based surrogate safety measures', *Journal of advanced transportation*, 2018.

Moreira, C. and Wichert, A. (2016) 'Quantum-like bayesian networks for modeling decision making', *Frontiers in psychology*, 7, p. 11.

Morgan, S.L. and Winship, C. (2015) *Counterfactuals and causal inference*. Cambridge University Press.

Mostafa, S.A., Ahmad, M.S. and Mustapha, A. (2019) 'Adjustable autonomy: a systematic literature review', *Artificial Intelligence Review*, 51(2), pp. 149-186.

Mullins, G.E., Stankiewicz, P.G. and Gupta, S.K. (2017) *2017 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE.

Munn, Z. *et al.* (2018a) 'Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach', *BMC medical research methodology*, 18(1), pp. 1-7.

Munn, Z. *et al.* (2018b) 'What kind of systematic review should I conduct? A proposed typology and guidance for systematic reviewers in the medical and health sciences', *BMC medical research methodology*, 18(1), pp. 1-9.

Nahavandi, S. (2019) 'Trust in Autonomous Systems-iTrust Lab: Future Directions for Analysis of Trust With Autonomous Systems', *IEEE Systems, Man, and Cybernetics Magazine*, 5(3), pp. 52-59.

Narla, S.R. (2013) 'The evolution of connected vehicle technology: From smart drivers to smart cars to… self-driving cars', *Ite Journal*, 83(7), pp. 22-26.

Natale, S. and Ballatore, A. (2017) 'Imagining the thinking machine: Technological myths and the rise of artificial intelligence', *Convergence*, p. 1354856517715164.

Nitsche, P., Mocanu, I. and Reinthaler, M. (2014) *2014 International Conference on Connected Vehicles and Expo (ICCVE)*. IEEE.

Noh, S. (2018) 'Decision-making framework for autonomous driving at road intersections: Safeguarding against collision, overly conservative behavior, and violation vehicles', *IEEE Transactions on Industrial Electronics*, 66(4), pp. 3275-3286.

Novickis, R. *et al.* (2020) *2020 17th Biennial Baltic Electronics Conference (BEC)*. IEEE.

NTSB (2018) *Preliminary Report Released for Crash Involving Pedestrian, Uber Technologies, Inc., Test Vehicle* (HWY18MH010). Washington. Available at: https://www.ntsb.gov/news/press-releases/Pages/NR20180524.aspx (Accessed: 19/11/2020).

Nur, K. and Gammons, T. (2019) 'The benefits of accessing transport data to support intelligent mobility', in Coppola, P. and Esztergár-Kiss, D. (eds.) *Autonomous Vehicles and Future Mobility*. Elsevier Science.

Nyholm, S. and Smids, J. (2016) 'The ethics of accident-algorithms for self-driving cars: An applied trolley problem?', *Ethical theory and moral practice*, 19(5), pp. 1275-1289.

O'Hagan, A. *et al.* (2006) *Uncertain Judgements: Eliciting Experts' Probabilities*. Wiley.

O'Hagan, A. (2019) 'Expert knowledge elicitation: subjective but scientific', *The American Statistician*, 73(sup1), pp. 69-81.

Office for Artificial Intelligence (2021) *National AI Strategy*Office for Artificial Intelligence. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1020402/National_AI_Strategy_-_PDF_version.pdf.

Olofsson, B. and Nielsen, L. (2020) 'Using Crash Databases to Predict Effectiveness of New Autonomous Vehicle Maneuvers for Lane-Departure Injury Reduction', *IEEE Transactions on Intelligent Transportation Systems*.

Osam, E.K., Bergman, M. and Cumberland, D.M. (2017) 'An integrative literature review on the barriers impacting adult learners' return to college', *Adult Learning*, 28(2), pp. 54-60.

Oviedo-Trespalacios, O. *et al.* (2018) 'Driving behaviour while self-regulating mobile phone interactions: A human-machine system approach', *Accident Analysis & Prevention*, 118, pp. 253-262.

Özkan, T. and Lajunen, T. (2011) 'Person and environment: Traffic culture', in *Handbook of traffic psychology*. Elsevier, pp. 179-192.

Papadopoulos, Y. *et al.* (2010) *Proceedings of the 1st workshop on critical automotive applications: robustness & safety*.

Papadoulis, A., Quddus, M. and Imprialou, M. (2019) 'Evaluating the safety impact of connected and autonomous vehicles on motorways', *Accident Analysis & Prevention*, 124, pp. 12-22.

Papakosta, P., Xanthopoulos, G. and Straub, D. (2017) 'Probabilistic prediction of wildfire economic losses to housing in Cyprus using Bayesian network analysis', *International journal of wildland fire*, 26(1), pp. 10-23.

Park, K. and Trudell, C. (2019) *Hyundai to Set Up $4 Billion Joint Venture to Develop Driverless Cars*. Available at: https://www.bloomberg.com/news/articles/2019-09-23/hyundai-motor-group-to-form-autonomous-car-venture-with-aptiv (Accessed: 25/10/2019).

Parkhurst, J. (2017) *The politics of evidence: from evidence-based policy to the good governance of evidence*. Taylor & Francis.

Parkinson, S. *et al.* (2017) 'Cyber threats facing autonomous and connected vehicles: Future challenges', *IEEE transactions on intelligent transportation systems*, 18(11), pp. 2898-2915.

Paté-Cornell, E. (2012) 'On "Black Swans" and "Perfect Storms": risk analysis and management when statistics are not enough', *Risk Analysis: An International Journal*, 32(11), pp. 1823-1833.

Patel, N. *et al.* (2019) 'A deep learning gated architecture for UGV navigation robust to sensor failures', *Robotics and Autonomous Systems*, 116, pp. 80-97.

Paul, N. and Chung, C. (2018) 'Application of HDR algorithms to solve direct sunlight problems when autonomous vehicles using machine vision systems are driving into sun', *Computers in Industry*, 98, pp. 192-196.

Pearl, J. (1982) *Reverend Bayes on inference engines: A distributed hierarchical approach*. Cognitive Systems Laboratory, School of Engineering and Applied Science ….

Pearl, J. (1988) *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. Elsevier Science.

Pearl, J. (2000) *Causality: Models, Reasoning, and Inference*. Cambridge University Press.

Pearl, J. (2009) *Causality: Models, Reasoning, and Inference*. 2nd edn. Padstow Cornwall: Cambridge University Press.

Pearl, J. and Mackenzie, D. (2018) *The Book of Why: The New Science of Cause and Effect*. Penguin Books, Limited.

Pearl, J. and Russell, S. (2003) 'Bayesian networks', in Arbib, M.A. (ed.) *The Handbook of Brain Theory and Neural Networks*. 2nd edn. THE MIT PRESS, pp. 157-160.

Pence, J. *et al.* (2019) 'Data-theoretic methodology and computational platform to quantify organizational factors in socio-technical risk analysis', *Reliability Engineering & System Safety*, 185, pp. 240-260.

Pendleton, S.D. *et al.* (2017) 'Perception, planning, control, and coordination for autonomous vehicles', *Machines*, 5(1), p. 6.

Pérez, J., Milanés, V. and Onieva, E. (2011) 'Cascade architecture for lateral control in autonomous vehicles', *IEEE Transactions on Intelligent Transportation Systems*, 12(1), pp. 73-82.

Perhinschi, M., Napolitano, M. and Tamayo, S. (2010) 'Integrated simulation environment for unmanned autonomous systems: Towards a conceptual framework', *Modelling and Simulation in Engineering*, 2010, p. 2.

Perkusich, M., Perkusich, A. and de Almeida, H.O. (2013) *2013 BRICS Congress on Computational Intelligence and 11th Brazilian Congress on Computational Intelligence*. IEEE.

Pernestål Brenden, A., Kristoffersson, I. and Mattsson, L.-G. (2019) 'Where will self-driving vehicles take us? Scenarios for the development of automated vehicles with Sweden as a case study', in Coppola, P. and Esztergár-Kiss, D. (eds.) *Autonomous Vehicles and Future Mobility*. Joe Hayton.

Petermeijer, S. *et al.* (2017) 'Take-over again: Investigating multimodal and directional TORs to get the driver back into the loop', *Applied ergonomics*, 62, pp. 204-215.

Petersen, L. *et al.* (2019) 'Situational awareness, driver's trust in automated driving systems and secondary task performance', *SAE International Journal of Connected and Autonomous Vehicles, Forthcoming*.

Petit, J. and Shladover, S.E. (2014) 'Potential cyberattacks on automated vehicles', *IEEE Transactions on Intelligent Transportation Systems*, 16(2), pp. 546-556.

Piao, J. *et al.* (2004) *Proceedings. The 7th International IEEE Conference on Intelligent Transportation Systems (IEEE Cat. No. 04TH8749)*. IEEE.

Pibouleau, L. and Chevret, S. (2014) 'An Internet-based Method to Elicit Experts' Bbliefs for Bayesian Priors: A Case Study in Intracranial Stent Evaluation', *International Journal of Technology Assessment in Health Care*, 30(4), p. 446.

Poczter, S.L. and Jankovic, L.M. (2014) 'The Google Car: driving toward a better future?', *Journal of Business Case Studies (JBCS)*, 10(1), pp. 7-14.

Pollard, E., Morignot, P. and Nashashibi, F. (2013) *Proceedings of the 16th International Conference on Information Fusion*. Istanbul, Turkey. IEEE.

Postma, T.J. and Liebl, F. (2005) 'How to improve scenario analysis as a strategic management tool?', *Technological Forecasting and Social Change*, 72(2), pp. 161-173.

Pradhan, A.K. *et al.* (2019) 'Training and education: human factors considerations for automated driving systems', in *Road Vehicle Automation 5*. Springer, pp. 77-84.

Provan, G. (1995) *Proceedings of the Eleventh conference on Uncertainty in artificial intelligence*. Morgan Kaufmann Publishers Inc.

Puch, R.O., Smith, J.Q. and Bielza, C. (2004) 'Hierarchical junction trees: conditional independence preservation and forecasting in dynamic Bayesian networks with heterogeneous evolution', in Gamez, J.A., Moral, S. and Salmeron, A. (eds.) *Advances in Bayesian Networks*. Springer, pp. 57-75.

Pütz, F., Murphy, F. and Mullins, M. (2019) 'Driving to a future without accidents? Connected automated vehicles' impact on accident frequency and motor insurance risk', *Environment systems and decisions*, 39(4), pp. 383-395.

Qu, Z. (2009) *Cooperative Control of Dynamical Systems: Applications to Autonomous Vehicles*. Springer London.

Qureshi, Z.H. (2008) *A review of accident modelling approaches for complex critical sociotechnical systems*.

Raj, A., Kumar, J.A. and Bansal, P. (2020) 'A multicriteria decision making approach to study barriers to the adoption of autonomous vehicles', *Transportation research part A: policy and practice*, 133, pp. 122-137.

Ramchurn, S. *et al.* (2021) 'The future of connected and automated mobility in the UK: call for evidence'.

Rashed, H. *et al.* (2019) *Proceedings of the IEEE International Conference on Computer Vision Workshops*.

Rashidi, T.H. *et al.* (2020) 'What we know and do not know about connected and autonomous vehicles', *Transportmetrica A: Transport Science*, 16(3), pp. 987-1029.

Rasmussen, J. (1997) 'Risk management in a dynamic society: a modelling problem', *Safety science*, 27(2-3), pp. 183-213.

Rasouli, A., Kotseruba, I. and Tsotsos, J.K. (2017) 'Understanding pedestrian behavior in complex traffic scenes', *IEEE Transactions on Intelligent Vehicles*, 3(1), pp. 61-70.

Rasouli, A. and Tsotsos, J.K. (2019) 'Autonomous vehicles that interact with pedestrians: A survey of theory and practice', *IEEE transactions on intelligent transportation systems*, 21(3), pp. 900-918.

Ravanbakhsh, M. *et al.* (2018) *2018 21st International Conference on Information Fusion (FUSION)*. Cambridge, UK. IEEE.

Rebalski, E. *et al.* (2021) 'Too much pressure? Driving and restraining forces and pressures relating to the state of connected and autonomous vehicles in cities', *Transportation Research Interdisciplinary Perspectives*, 13, p. 100507.

Renn, O. (2008) *Risk Governance: Coping with Uncertainty in a Complex World*. Earthscan.

Renooij, S. (2001) 'Probability elicitation for belief networks: issues to consider', *The Knowledge Engineering Review*, 16(3), pp. 255-269.

Rey, D. and Levin, M.W. (2019) 'Blue phase: Optimal network traffic control for legacy and autonomous vehicles', *Transportation research part B: methodological*, 130, pp. 105-129.

Rietbergen, C. *et al.* (2016) 'Expert elicitation of study weights for bayesian analysis and meta-analysis', *Journal of Mixed Methods Research*, 10(2), pp. 168-181.

Riggs, W. (2018) *Disruptive Transport: Driverless Cars, Transport Innovation and the Sustainable City of Tomorrow*. Taylor & Francis.

Righi, A.W., Saurin, T.A. and Wachs, P. (2015) 'A systematic literature review of resilience engineering: Research areas and a research agenda proposal', *Reliability Engineering & System Safety*, 141, pp. 142-152.

Roberts, K.A. *et al.* (2002) 'Factors affecting uptake of childhood immunisation: a Bayesian synthesis of qualitative and quantitative evidence', *The Lancet*, 360(9345), pp. 1596-1599.

Robinson, S. (2008) 'Conceptual modelling for simulation Part I: definition and requirements', *Journal of the operational research society*, 59(3), pp. 278-290.

Roche, F., Thüring, M. and Trukenbrod, A.K. (2020) 'What happens when drivers of automated vehicles take over control in critical brake situations?', *Accident Analysis & Prevention*, 144, p. 105588.

Rödel, C. *et al.* (2014) *Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. ACM.

Rogers, W.P. *et al.* (2019) 'Automation in the Mining Industry: Review of Technology, Systems, Human Factors, and Political Risk', *Mining, Metallurgy & Exploration*, pp. 1-25.

Rohmer, J. (2020) 'Uncertainties in conditional probability tables of discrete Bayesian Belief Networks: A comprehensive review', *Engineering Applications of Artificial Intelligence*, 88.

Rojas-Rueda, D. *et al.* (2020) 'Autonomous vehicles and public health', *Annual review of public health*, 41, pp. 329-345.

Ropohl, G. (1999) 'Philosophy of socio-technical systems', *Society for Philosophy and Technology Quarterly Electronic Journal*, 4(3), pp. 186-194.

Russell, S. and Norvig, P. (2016) *Artificial Intelligence: A Modern Approach*. Pearson.

Russo, J.-N. *et al.* (2016) 'Risks Level Assessments for Automotive Application', *IFAC-PapersOnLine*, 49(15), pp. 163-168.

References

Ryan, M. (2019) 'The future of transportation: ethical, legal, social and economic impacts of self-driving vehicles in the year 2025', *Science and engineering ethics*, pp. 1-24.

Sabaliauskaite, G., Liew, L.S. and Cui, J. (2018) 'Integrating autonomous vehicle safety and security analysis using stpa method and the six-step model', *International Journal on Advances in Security*, 11(1&2), pp. 160-169.

Sadiq, R., Kleiner, Y. and Rajani, B. (2010) 'Modelling the potential for water quality failures in distribution networks: framework (I)', *Journal of Water Supply: Research and Technology—AQUA*, 59(4), pp. 255-276.

SAE International (2016) *Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles* (J3016_201806).

Saeed, T.U. (2019) *Road Infrastructure Readiness for Autonomous Vehicles*. Doctor of Philosophy. Purdue University Graduate School.

Sagberg, F. and Bjørnskau, T. (2006) 'Hazard perception and driving experience among novice drivers', *Accident Analysis & Prevention*, 38(2), pp. 407-414.

Salehi, K. and Golafshani, N. (2010) 'Commentary: Using Mixed Methods in Research Studies-an Opportunity with Its Challenges', *International Journal of Multiple Research Approaches*, 4(3), p. 186.

Saltelli, A. (2002) 'Sensitivity analysis for importance assessment', *Risk analysis*, 22(3), pp. 579-590.

Saltelli, A. *et al.* (2008) *Global Sensitivity Analysis: The Primer*. Chichester, England: John Wiley & Sons Ltd.

Salter, A. (2021) *7 Universities that are pushing the boundaries of autonomous driving*. Available at: https://www.2025ad.com/7-universities-that-are-pushing-the-boundaries-of-autonomous-driving-2021 (Accessed: 11/03/2022).

Sanguino, T.d.J.M., Domínguez, J.M.L. and de Carvalho Baptista, P. (2020) 'Cybersecurity certification and auditing of automotive industry', in Milakis, D., Thomopoulos, N. and van Wee, B. (eds.) *Advances in Transport Policy and Planning*. Elsevier, pp. 95-124.

Sarkar, A. *et al.* (2017) *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE.

Saunders, M.N.K., Lewis, P. and Thornhill, A. (2015) *Research Methods for Business Students*. Pearson Education Limited.

Scerri, P., Pynadath, D.V. and Tambe, M. (2002) 'Towards adjustable autonomy for the real world', *Journal of Artificial Intelligence Research*, 17, pp. 171-228.

Scharre, P.D. (2015) 'The opportunity and challenge of autonomous systems', in Williams, A.P. and Scharre, P.D. (eds.) *Issues for Defence Policymakers*. Norfolk, Virginia: Headquarters Supreme Allied Commander Transformation.

Scherer, M.U. (2015) 'Regulating artificial intelligence systems: Risks, challenges, competencies, and strategies', *Harv. JL & Tech.*, 29, p. 353.

Schlatow, J. *et al.* (2017) *Design, Automation & Test in Europe Conference & Exhibition (DATE), 2017*. IEEE.

Schlossberg, M. *et al.* (2018) *Rethinking the street in an era of driverless cars*. Available at: https://scholarsbank.uoregon.edu/xmlui/bitstream/handle/1794/23331/UrbanismNext_ResearchBrief_003.pdf?sequence=1.

Schoettle, B. and Sivak, M. (2015) *A preliminary analysis of real-world crashes involving self-driving vehicles* (UMTRI-2015-34). Michigan, US: (Accessed: 28/12/2019).

Schömig, N. and Metz, B. (2013) 'Three levels of situation awareness in driving with secondary tasks', *Safety Science*, 56, pp. 44-51.

Schreurs, M.A. and Steuwer, S.D. (2015) 'Autonomous driving-political, legal, social, and sustainability dimensions', in *Autonomes Fahren*. Springer, pp. 151-173.

Schwarting, W., Alonso-Mora, J. and Rus, D. (2018) 'Planning and decision-making for autonomous vehicles', *Annual Review of Control, Robotics, and Autonomous Systems*.

Sedki, K., Polet, P. and Vanderhaegen, F. (2013) 'Using the BCD model for risk analysis: An influence diagram based approach', *Engineering Applications of Artificial Intelligence*, 26(9), pp. 2172-2183.

Serban, A.C., Poll, E. and Visser, J. (2018) *2018 IEEE International Conference on Software Architecture Companion (ICSA-C)*. IEEE.

Shangguan, A. *et al.* (2020) *2020 IEEE 9th Data Driven Control and Learning Systems Conference (DDCLS)*. IEEE.

Shannon, D. *et al.* (2021) 'Connected and autonomous vehicle injury loss events: Potential risk and actuarial considerations for primary insurers', *Risk Management and Insurance Review*, 24(1), pp. 5-35.

Sheehan, B. *et al.* (2019) 'Connected and autonomous vehicles: A cyber-risk classification framework', *Transportation Research Part A: Policy and Practice*, 124, pp. 523-536.

Sheehan, B. *et al.* (2017) 'Semi-autonomous vehicle motor insurance: A Bayesian Network risk transfer approach', *Transportation Research Part C: Emerging Technologies*, 82, pp. 124-137.

Shinar, D. (2017) *Traffic safety and human behavior*. Emerald Group Publishing.

Silva, F.S. *et al.* (2021) 'A Conformance Testing Methodology and System for Cognitive Radios', *Wireless Communications and Mobile Computing*, 2021.

Simoncic, M. (2004) 'A Bayesian network model of two-car accidents', *Journal of transportation and Statistics*, 7(2/3), pp. 13-25.

Singh, S. (2015) *Critical reasons for crashes investigated in the national motor vehicle crash causation survey*.

Snyder, H. (2019) 'Literature review as a research methodology: An overview and guidelines', *Journal of Business Research*, 104, pp. 333-339.

Sohrabi, S., Khreis, H. and Lord, D. (2020) 'Impacts of autonomous vehicles on public health: a conceptual model and policy recommendations', *Sustainable Cities and Society*, 63, p. 102457.

Song, M. and Montoya-Weiss, M.M. (2001) 'The effect of perceived technological uncertainty on Japanese new product development', *Academy of Management journal*, 44(1), pp. 61-80.

Sony, M. and Naik, S. (2020) 'Industry 4.0 integration with socio-technical systems theory: A systematic review and proposed theoretical model', *Technology in society*, 61, p. 101248.

Soole, D.W., Watson, B.C. and Fleiter, J.J. (2013) 'Effects of average speed enforcement on speed compliance and crashes: A review of the literature', *Accident Analysis & Prevention*, 54, pp. 46-56.

Soteropoulos, A. *et al.* (2020) 'Automated drivability: Toward an assessment of the spatial deployment of level 4 automated vehicles', *Transportation Research Part A: Policy and Practice*, 136, pp. 64-84.

Spenko, M., Buerger, S. and Iagnemma, K. (2018) *The DARPA Robotics Challenge Finals: Humanoid Robots To The Rescue*. Springer International Publishing.

Stampa, M. *et al.* (2021) 'Maturity levels of public safety applications using unmanned aerial systems: a review', *Journal of Intelligent & Robotic Systems*, 103(1), pp. 1-15.

Stanojević, P., Jovanović, D. and Lajunen, T. (2013) 'Influence of traffic enforcement on the attitudes and behavior of drivers', *Accident Analysis & Prevention*, 52, pp. 29-38.

Stanton, N.A. *et al.* (2017) 'State-of-science: situation awareness in individuals, teams and systems', *Ergonomics*, 60(4), pp. 449-466.

Straub, E.R. and Schaefer, K.E. (2019) 'It takes two to Tango: Automated vehicles and human beings do the dance of driving–Four social considerations for policy', *Transportation research part A: policy and practice*, 122, pp. 173-183.

Stroeve, S.H., Blom, H.A. and Bakker, G.B. (2009) 'Systemic accident risk assessment in air traffic by Monte Carlo simulation', *Safety science*, 47(2), pp. 238-249.

Sun, L. and Hua, L. (2019) 'Effects of hazard types on drivers' risk rating and hazard response in a video-based hazard perception task', *PLoS one*, 14(3), p. e0214226.

Szalay, Z. *et al.* (2018) 'Development of a test track for driverless cars: vehicle design, track configuration, and liability considerations', *Periodica Polytechnica Transportation Engineering*, 46(1), pp. 29-35.

Taeihagh, A. and Lim, H.S.M. (2019) 'Governing autonomous vehicles: emerging responses for safety, liability, privacy, cybersecurity, and industry risks', *Transport reviews*, 39(1), pp. 103-128.

Taiebat, M. *et al.* (2018) 'A review on energy, environmental, and sustainability implications of connected and automated vehicles', *Environmental science & technology*, 52(20), pp. 11449-11465.

Tan, S.Y. and Taeihagh, A. (2021) 'Governing the adoption of robotics and autonomous systems in long-term care in Singapore', *Policy and society*, 40(2), pp. 211-231.

Tang, Q. *et al.* (2021) 'Evaluation Methodology of Leader-Follower Autonomous Vehicle System for Work Zone Maintenance', *Transportation Research Record*, p. 0361198120985233.

Tao, J. *et al.* (2019) *2019 IEEE International Conference on Software Testing, Verification and Validation Workshops (ICSTW)*. IEEE.

TAS Hub (2020) *The UKRI Trustworthy Autonomous Systems (TAS)*. Available at: https://www.tas.ac.uk/ (Accessed: 05/11/2021).

Taylor-Gooby, P. and Zinn, J.O. (2006) *Risk in social science*. Oxford University Press.

Teddlie, C. and Tashakkori, A. (2009) *Foundations of Mixed Methods Research: Integrating Quantitative and Qualitative Approaches in the Social and Behavioral Sciences*. SAGE.

Teece, D., Peteraf, M. and Leih, S. (2016) 'Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy', *California Management Review*, 58(4), pp. 13-35.

Tellis, G.J. (2006) 'Disruptive technology or visionary leadership?', *Journal of Product Innovation Management*, 23(1), pp. 34-38.

the Guardian (2018) *Video released of Uber self-driving crash that killed woman in Arizona* (Accessed: 30/04/2019).

the Guardian (2021) *Paris taxi firm suspends use of Tesla Model 3 cars after fatal crash*. Available at: https://www.theguardian.com/technology/2021/dec/15/paris-taxi-firm-suspends-use-of-tesla-model-3-cars-after-fatal-accident (Accessed: 18/12/2021).

Thieme, C.A. and Utne, I.B. (2017) 'A risk model for autonomous marine systems and operation focusing on human–autonomy collaboration', *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 231(4), pp. 446-464.

Thierer, A. and Hagemann, R. (2015) 'Removing roadblocks to intelligent vehicles and driverless cars', *Wake Forest JL & Pol'y*, 5, p. 339.

Thompson, J. *et al.* (2020) 'A global analysis of urban design types and road transport injury: an image processing study', *The Lancet Planetary Health*, 4(1), pp. e32-e42.

Tidd, J. and Bessant, J. (2014) *Managing Innovation: Integrating Technological, Market and Organizational Change*. Wiley.

Tidd, J., Bessant, J. and Pavitt, K. (2005) *Managing innovation integrating technological, market and organizational change*. John Wiley and Sons Ltd.

Tobin, A. (2019) *Why Have Rival German Auto Giants Just Inked This Deal?* Available at: https://www.forbes.com/sites/annatobin/2019/07/06/why-have-rival-german-auto-giants-just-inked-this-deal/#6f265b438bf9 (Accessed: 25/10/2019).

Török, Á., Szalay, Z. and Sághi, B. (2020) 'New Aspects of Integrity Levels in Automotive Industry-Cybersecurity of Automated Vehicles', *IEEE Transactions on Intelligent Transportation Systems*.

Torraco, R.J. (2005) 'Writing integrative literature reviews: Guidelines and examples', *Human resource development review*, 4(3), pp. 356-367.

Torraco, R.J. (2016) 'Writing integrative literature reviews: Using the past and present to explore the future', *Human resource development review*, 15(4), pp. 404-428.

Tredger, E. *et al.* (2016) 'Bias, guess and expert judgement in actuarial work', *British Actuarial Journal*, 21(3), pp. 545-578.

Trucco, P. *et al.* (2008) 'A Bayesian Belief Network modelling of organisational factors in risk analysis: A case study in maritime transportation', *Reliability Engineering & System Safety*, 93(6), pp. 845-856.

Turchin, A. and Denkenberger, D. (2018) 'Global catastrophic and existential risks communication scale', *Futures*.

Twagirimana, J. (2013) *Establishing and applying speed-flow relationships for traffic on rural two-lane two-way highways in the Western Cape*. PhD. Stellenbosch: Stellenbosch University. Available at: http://scholar.sun.ac.za/handle/10019.1/85825.

UK Government (2020) *Humandrive: vehicle completes 230 mile, self-navigated drive across the UK*. Available at: https://www.gov.uk/government/case-studies/humandrive-vehicle-completes-230-mile-self-navigated-drive-across-the-uk (Accessed: 05/11/2021).

UK Government (2021) *Rules on safe use of automated vehicles on GB roads*. Available at: https://www.gov.uk/government/consultations/safe-use-rules-for-automated-vehicles-av/rules-on-safe-use-of-automated-vehicles-on-gb-roads (Accessed: 12/11/2021).

Uusitalo, L. (2007) 'Advantages and challenges of Bayesian networks in environmental modelling', *Ecological modelling*, 203(3-4), pp. 312-318.

Valenti, M. *et al.* (2007) *2007 American Control Conference*. New York City. IEEE.

Van Dam, J., Kass, S.J. and VanWormer, L. (2020) 'The effects of passive mobile phone interaction on situation awareness and driving performance', *Journal of Transportation Safety & Security*, 12(8), pp. 1007-1024.

Van Geenhuizen, M. and Nijkamp, P. (2003) 'Coping with uncertainty: an expedition into the field of new transport technology', *Transportation planning and technology*, 26(6), pp. 449-467.

van Wyk, F., Khojandi, A. and Masoud, N. (2020) 'Optimal switching policy between driving entities in semi-autonomous vehicles', *Transportation Research Part C: Emerging Technologies*, 114, pp. 517-531.

Vanderbilt, T. (2018) *Why Waymo's Fleet of Self-Driving Cars Is Finally Ready for Prime Time*. Available at: https://www.smithsonianmag.com/innovation/waymo-fleet-self-driving-cars-ready-prime-time-180970713/ (Accessed: 24/10/2019).

Vargas, J. *et al.* (2021) 'An overview of autonomous vehicles sensors and their vulnerability to weather conditions', *Sensors*, 21(16), p. 5397.

Varshney, K.R. and Alemzadeh, H. (2017) 'On the safety of machine learning: Cyber-physical systems, decision sciences, and data products', *Big data*, 5(3), pp. 246-255.

Vellinga, N.E. (2017) 'From the testing to the deployment of self-driving cars: Legal challenges to policymakers on the road ahead', *Computer Law & Security Review*, 33(6), pp. 847-863.

Verdolini, E. *et al.* (2020) 'Future prospects for energy technologies: Insights from expert elicitations', *Review of Environmental Economics and Policy*, 12(1).

Verendel, V. and Yeh, S. (2019) 'Measuring traffic in cities through a large-scale online platform', *Journal of Big Data Analytics in Transportation*, 1(2), pp. 161-173.

Verzobio, A. *et al.* (2021) 'An elicitation process to quantify Bayesian networks for dam failure analysis', *Canadian Journal of Civil Engineering*, 48(10), pp. 1235-1244.

Villagra, J. *et al.* (2020) *2020 IEEE 3rd Connected and Automated Vehicles Symposium (CAVS)*. Victoria, BC, Canada. IEEE.

Vinkhuyzen, E. and Cefkin, M. (2016) *Ethnographic Praxis in Industry Conference Proceedings*. Wiley Online Library.

Vishnevsky, V. and Kozyrev, D. (2016) *Distributed Computer and Communication Networks: 18th International Conference, DCCN 2015, Moscow, Russia, October 19-22, 2015, Revised Selected Papers*. Springer.

Vithanage, R.K., Harrison, C.S. and DeSilva, A.K. (2019) 'Importance and applications of robotic and autonomous systems (RAS) in railway maintenance sector: a review', *Computers*, 8(3), p. 56.

Vlakveld, W. *et al.* (2018) 'Situation awareness increases when drivers have more time to take over the wheel in a Level 3 automated car: A simulator study', *Transportation research part F: traffic psychology and behaviour*, 58, pp. 917-929.

Vogelpohl, T. *et al.* (2019) 'Asleep at the automated wheel—Sleepiness and fatigue during highly automated driving', *Accident Analysis & Prevention*, 126, pp. 70-84.

Vorko-Jović, A., Kern, J. and Biloglav, Z. (2006) 'Risk factors in urban road traffic accidents', *Journal of safety research*, 37(1), pp. 93-98.

Wadhwa, V. and Salkever, A. (2017) *The Driver in the Driverless Car: How Our Technology Choices Will Create the Future*. Berrett-Koehler Publishers.

Wagner, P. (2016) 'Traffic control and traffic management in a transportation system with autonomous vehicles', in Maurer, M. *et al.* (eds.) *Autonomous Driving*. Springer, pp. 301-316.

Wali, B. *et al.* (2017) 'Effectiveness of enforcement levels of speed limit and drink driving laws and associated factors–Exploratory empirical analysis using a bivariate ordered probit model', *Journal of traffic and transportation engineering (English edition)*, 4(3), pp. 272-279.

Walley, P. (1996) 'Measures of uncertainty in expert systems', *Artificial intelligence*, 83(1), pp. 1-58.

Walsh, S.T. (2004) 'Roadmapping a disruptive technology: A case study: The emerging microsystems and top-down nanosystems industry', *Technological Forecasting and Social Change*, 71(1-2), pp. 161-185.

Walz, E. (2017) *Volvo and Autoliv Form Autonomous Driving Venture Zenuity*. Available at: https://www.futurecar.com/969/Volvo-and-Autoliv-Form-Autonomous-Driving-Venture-Zenuity.

Wang, C. and Mosleh, A. (2010) *2010 Proceedings-Annual Reliability and Maintainability Symposium (RAMS)*. IEEE.

Wang, J. *et al.* (2018a) *2018 IEEE Intelligent Vehicles Symposium (IV)*. IEEE.

Wang, K. *et al.* (2020a) 'The adaptability and challenges of autonomous vehicles to pedestrians in urban China', *Accident Analysis & Prevention*, 145, p. 105692.

Wang, L. *et al.* (2019) 'Quasi-vehicle-trajectory-based real-time safety analysis for expressways', *Transportation research part C: emerging technologies*, 103, pp. 30-38.

Wang, S. *et al.* (2018b) 'Analyzing urban traffic demand distribution and the correlation between traffic flow and the built environment based on detector data and POIs', *European Transport Research Review*, 10(2), pp. 1-17.

Wang, X., Yang, M. and Hurwitz, D. (2019) 'Analysis of cut-in behavior based on naturalistic driving data', *Accident Analysis & Prevention*, 124, pp. 127-137.

Wang, Y. *et al.* (2020b) 'Longitudinal and lateral control of autonomous vehicles in multi-vehicle driving environments', *IET Intelligent Transport Systems*, 14(8), pp. 924-935.

Ward, S. and Chapman, C. (2003) 'Transforming project risk management into project uncertainty management', *International journal of project management*, 21(2), pp. 97-105.

Warwick, K. (2013) *Artificial Intelligence: The Basics*. Taylor & Francis.

Watzenig, D. and Horn, M. (2016) *Automated Driving: Safer and More Efficient Future Driving*. Springer International Publishing.

Weber, P. *et al.* (2012) 'Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas', *Engineering Applications of Artificial Intelligence*, 25(4), pp. 671-682.

Weng, J. (2011) 'Collision avoidance analysis for transition taper length', *Transportation planning and technology*, 34(8), pp. 811-822.

Wenger, E. (2014) *Artificial intelligence and tutoring systems: computational and cognitive approaches to the communication of knowledge*. Morgan Kaufmann.

Werner, C. *et al.* (2017) 'Expert judgement for dependence in probabilistic modelling: A systematic literature review and future research directions', *European Journal of Operational Research*, 258(3), pp. 801-819.

West, D.M. and Allen, J.R. (2018) *How artificial intelligence is transforming the world*. Available at: https://www.brookings.edu/research/how-artificial-intelligence-is-transforming-the-world/ (Accessed: August 25).

Whitehead, D. (2020) *Driverless, autonomous transport pods begin UK public trials*. Available at: https://news.sky.com/story/driverless-autonomous-transport-pods-begin-uk-public-trials-11913856 (Accessed: 26/01/2020).

WHO (2009) *Global status report on road safety: time for reaction*. Geneva. Available at: https://apps.who.int/iris/bitstream/handle/10665/44122/9789241563840_eng.pdf;jsessionid=EAE18A6812D47C0231B3A8C1972DB203?sequence=1 (Accessed: 03/12/2020).

Wiegmann, D.A., von Thaden, T.L. and Gibbons, A.M. (2007) 'A review of safety culture theory and its potential application to traffic safety', *Improving Traffic Safety Culture in the United States*, 113.

Wilken, R. and Thomas, J. (2019) 'Cars and Contemporary Communication| Maps and the Autonomous Vehicle as a Communication Platform', *International Journal of Communication*, 13, p. 25.

Winfield, A.F. *et al.* (2019) 'Machine ethics: the design and governance of ethical AI and autonomous systems', *Proceedings of the IEEE*, 107(3), pp. 509-517.

Winkle, T., Erbsmehl, C. and Bengler, K. (2018) 'Area-wide real-world test scenarios of poor visibility for safe development of automated vehicles', *European Transport Research Review*, 10(2), pp. 1-15.

Winner, H. *et al.* (2016) *Handbook of driver assistance systems: Basic information, components and systems for active safety and comfort*. Springer.

Wintersberger, P. and Riener, A. (2016) 'Trust in technology as a safety aspect in highly automated driving', *i-com*, 15(3), pp. 297-310.

Wolf, P. *et al.* (2018) *2018 IEEE Intelligent Vehicles Symposium (IV)*. Changshu, China. IEEE.

Wolhuter, K. (2015) *Geometric Design of Roads Handbook*. CRC Press.

Wolmar, C. (2018) *Driverless Cars: On a Road to Nowhere*. London Publishing Partnership.

Wong, C. *et al.* (2018) 'Autonomous robots for harsh environments: A holistic overview of current solutions and ongoing challenges', *Systems Science & Control Engineering*, 6(1), pp. 213-219.

Wu, W. *et al.* (2020) 'Simulation and evaluation of speed and lane-changing advisory of CAVS at work zones in heterogeneous traffic flow', *International Journal of Modern Physics B*, 34(21), p. 2050201.

Xie, Z. and Zhong, Z.W. (2016) *Applied Mechanics and Materials*. Trans Tech Publ.

Yagar, S. and Van Aerde, M. (1983) 'Geometric and environmental effects on speeds of 2-lane highways', *Transportation Research Part A: General*, 17(4), pp. 315-325.

Yan, F. *et al.* (2019) 'Driving style recognition based on electroencephalography data from a simulated driving experiment', *Frontiers in psychology*, 10, p. 1254.

Yang, G., Ahmed, M.M. and Gaweesh, S. (2019) 'Impact of variable speed limit in a connected vehicle environment on truck driver behavior under adverse weather conditions: driving simulator study', *Transportation research record*, 2673(7), pp. 132-142.

Yang, Y. *et al.* (2015) 'Towards real-time traffic sign detection and classification', *IEEE Transactions on Intelligent transportation systems*, 17(7), pp. 2022-2031.

Yao, S., Shet, R.A. and Friedrich, B. (2020) 'Managing Connected Automated Vehicles in Mixed Traffic Considering Communication Reliability: a Platooning Strategy', *Transportation Research Procedia*, 47, pp. 43-50.

Yassine, A.A. (2019) 'Managing the development of complex product systems: an integrative literature review', *IEEE Transactions on Engineering Management*, 68(6), pp. 1619-1636.

Ye, L. and Yamamoto, T. (2018) 'Impact of dedicated lanes for connected and autonomous vehicle on traffic flow throughput', *Physica A: Statistical Mechanics and its Applications*, 512, pp. 588-597.

Ye, L. and Yamamoto, T. (2019) 'Evaluating the impact of connected and autonomous vehicles on traffic safety', *Physica A: Statistical Mechanics and its Applications*, 526, p. 121009.

Ye, Y.Y., Hao, X.L. and Chen, H.J. (2018) 'Lane detection method based on lane structural analysis and CNNs', *IET Intelligent Transport Systems*, 12(6), pp. 513-520.

Yigitcanlar, T. *et al.* (2020) 'Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature', *Energies*, 13(6), p. 1473.

Yin, Z. *et al.* (2015) 'A hybrid intelligent diagnosis approach for quick screening of Alzheimer's disease based on multiple neuropsychological rating scales', *Computational and mathematical methods in medicine*, 2015.

Yoneda, K. *et al.* (2019) 'Automated driving recognition technologies for adverse weather conditions', *IATSS research*, 43(4), pp. 253-262.

Yoo, J.M., Jeong, Y. and Yi, K. (2021) 'Virtual Target-Based Longitudinal Motion Planning of Autonomous Vehicles at Urban Intersections: Determining Control Inputs of Acceleration With Human Driving Characteristic-Based Constraints', *IEEE Vehicular Technology Magazine*, 16(3), pp. 38-46.

Young, S.H., Mazzuchi, T.A. and Sarkani, S. (2017) 'A framework for predicting future system performance in autonomous unmanned ground vehicles', *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 47(7), pp. 1192-1206.

Yu, M.-Y., Vasudevan, R. and Johnson-Roberson, M. (2019) 'Occlusion-aware risk assessment for autonomous driving in urban environments', *IEEE Robotics and Automation Letters*, 4(2), pp. 2235-2241.

Yudkowsky, E. (2008) 'Artificial intelligence as a positive and negative factor in global risk', in Bostrom, N. and Ćirković, M.M. (eds.) *Global catastrophic risks*. New York: Oxford University Press, pp. 308-345.

Zagorecki, A. and Druzdzel, M.J. (2012) 'Knowledge engineering for Bayesian networks: How common are noisy-MAX distributions in practice?', *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 43(1), pp. 186-195.

Zang, S. *et al.* (2019) 'The impact of adverse weather conditions on autonomous vehicles: how rain, snow, fog, and hail affect the performance of a self-driving car', *IEEE vehicular technology magazine*, 14(2), pp. 103-111.

Zhang, G., Yau, K.K. and Chen, G. (2013) 'Risk factors associated with traffic violations and accident severity in China', *Accident Analysis & Prevention*, 59, pp. 18-25.

Zhang, J., Shu, Y. and Yu, H. (2021) *International Conference on Human-Computer Interaction*. Springer. Available at: https://doi.org/10.1007/978-3-030-77626-8_13.

Zhang, L. *et al.* (2020) 'Fuel economy in truck platooning: A literature overview and directions for future research', *Journal of Advanced Transportation*, 2020.

Zhang, T. *et al.* (2017) 'Current trends in the development of intelligent unmanned autonomous systems', *Frontiers of information technology & electronic engineering*, 18(1), pp. 68-85.

Zhang, X. *et al.* (2018) 'Safety Assessment and Risk Estimation for Unmanned Aerial Vehicles Operating in National Airspace System', *Journal of Advanced Transportation*, 2018.

Zhang, Y., Angell, L. and Bao, S. (2021) 'A fallback mechanism or a commander? A discussion about the role and skill needs of future drivers within partially automated vehicles', *Transportation research interdisciplinary perspectives*, 9, p. 100337.

Zhao, D. *et al.* (2016) 'Accelerated evaluation of automated vehicles safety in lane-change scenarios based on importance sampling techniques', *IEEE transactions on intelligent transportation systems*, 18(3), pp. 595-607.

Zhao, J., Liang, B. and Chen, Q. (2018) 'The key technology toward the self-driving car', *International Journal of Intelligent Unmanned Systems*.

Zhao, Y., Xiao, F. and Wang, S. (2013) 'An intelligent chiller fault detection and diagnosis methodology using Bayesian belief network', *Energy and Buildings*, 57, pp. 278-288.

Zheng, X. *et al.* (2018) 'A novel intelligent vehicle risk assessment method combined with multi-sensor fusion in dense traffic environment', *Journal of Intelligent and Connected Vehicles*.

Zhou, F., Yang, X.J. and Zhang, X. (2020) 'Takeover transition in autonomous vehicles: a YouTube study', *International Journal of Human–Computer Interaction*, 36(3), pp. 295-306.

Zou, B., Choobchian, P. and Rozenberg, J. (2021) 'Cyber resilience of autonomous mobility systems: cyber-attacks and resilience-enhancing strategies', *Journal of Transportation Security*, pp. 1-19.

Zurlinden, H., Baruah, A. and Gaffney, J. (2020) 'Towards linking driving complexity to crash risk', *Journal of road safety*, 31(1), p. 66.