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SOCIAL STATISTICS AND DEMOGRAPHY

# Quantifying the Patterns of Road Traffic Crashes in the Sultanate of Oman: Statistical Evaluation of Aggregate Data from Police Records

by

**AMIRA KHAMIS AL AAMRI**

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# Quantifying the Patterns of Road Traffic Crashes in the Sultanate of Oman: Statistical Evaluation of Aggregate Data from Police Records

## SYNOPSIS

The alarming growth of Road Traffic Crashes (RTCs) and related outcomes remain an unresolved global public health emergency in low- and middle-income countries. The risks of RTCs are considerably high in the Gulf Cooperation Council (GCC) countries, where the oil-driven economy has overtime sparked rapid economic growth accompanied by large influx of expatriates, rapid urbanisation and unprecedented growth in motor vehicles. Oman has the second highest death rate from RTCs within GCC countries. Although, there is a growing body of peer-reviewed literature on the trends and behavioural characteristics associated with RTCs in Oman, the interactive effects of associated demographic, environmental and spatial factors are not well understood. The higher representation of expatriate population and rapid urbanisation level adds further complexity in understanding and quantifying these risks.

The overarching **aim** of this research is to apply robust statistical techniques to identify and evaluate the *multi-dimensional* social, demographic, spatial and technological factors associated with the likelihood of RTCs and associated outcomes in Oman. Data for the research are drawn from the Royal Oman Police (ROP) National Road Traffic Crashes (NRTC) database which recorded 35,851 cases in aggregate format for the period 2010–2014. In addition, the researcher independently generated the geographical coordinates (latitude and longitude) for the Muscat governorate based on transcripts recorded within the NRTC database and using Google maps, which was then linked to the Muscat road network and statistically validated using the pilot data from iMAAP network based crash analysis system developed by the UK Transport Research Laboratory.

**Format and contents of the thesis**: The thesis presents the findings in a three-paper format, addressing different dimensions of road traffic crashes. The first analysis applied ordered logit models to systematically investigate the underlying interactive effects of age and sex of drivers on the severity of fatal and non- fatal RTC outcomes in Oman. The second analysis applied negative binomial regression models to investigate the statistical association between the timing of road crashes highlighting the peak hours of traffic congestion and the severity of fatal and non-fatal road injuries. The third analysis used the geocoded data from the Muscat governorate to evaluate the spatial and temporal dimensions, identifying the high risk areas or hot-zones where RTCs are more frequent. The analysis considered an adjacency network analysis integrating GIS and RTC data using robust estimation techniques including: Kernel Density Estimation (KDE) of both 1-D and 2-D space dimensions, Network-based Nearest Neighbour Distance (Net-NND), Network-based K-Function, Random Forest Algorithm (RF) and spatiotemporal Hot-zone analysis. Finally, a critical appraisal of existing data collection procedures and recording systems is undertaken, reflecting on the strengths and weaknesses of NRTC database, and suggesting coherent ways to record, monitor and analyse road crash data. The thesis concludes with a summary and discussion of key findings, policy recommendations, study limitations, and an agenda for future research.

**Key findings**: The first analysis demonstrates evidence that the high burden of severe and fatal RTCs in Oman is attributed to over speeding behaviour of particularly young male drivers. The findings suggest that the existing systems to monitor and impose penalties on risky driving attitudes and deviant behaviours of young people are inadequate and weak. The second analysis shows evidence that the severity of road injuries varied by the peak hours of congestion with fatal RTCs peak mostly around 18:00 hours, while the peak hour for nonfatal crashes occurred around 15:00 hours. The potential dominant factors for early evening fatal crashes are driver fatigue and drowsiness. The final analysis highlights evidence of spatial clustering and recurrence of RTC hot-zones on long roads

demarcated by intersections and roundabouts in Muscat. The findings confirm that road intersections elevate the risk of RTCs than other effects attributed to road geometry features.

**Overall scientific contribution:** The thesis contributes to a systematic understanding of the sociodemographic and behavioural factors and spatial patterns underlying high burden of RTCs and related injury outcomes in the Sultanate of Oman. Additionally, the thesis evaluates the quality of NRTC data and proposes recommendations for improvements in data recording and processing for research and policy use.

**Policy implications**: The findings offer new insights to understanding the demographic spatial and temporal effects of RTCs in Oman, where evidence-based interventions for road safety are critical to tackling the high burden of injuries. Interventions promoting road safety awareness should focus on enabling behavioural changes in drivers particularly in RTC hot-zones near road intersections where crashes are recurrent as well as impose control measures and penalty to restrict over speeding. The policies and programme interventions should target both natives and expatriates particularly new drivers, families, educational institutions and work places. It is also equally important to initiate policies to address and document the broader social and human consequences of road crashes and related injury outcomes in public health promotion and road safety awareness campaigns.

**Keywords:** Road traffic crashes, injuries, Oman, severity, fatal and nonfatal outcomes, causes of injury, peak hours of traffic, generalised ordered logit model, Negative Binomial Regression, spatiotemporal modelling, Kernel Density estimation, Clustering, Aggregate data from Police records

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# Academic Thesis: Declaration of Authorship

I, Amira Khamis AL-Aamri................................................................................................................

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.

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I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. 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;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. 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;
5. I have acknowledged all main sources of help;
6. 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;
7. Parts of this work have been published as:

Al-Aamri, A.K., Padmadas, S.S., Zhang, L.C. and Al-Maniri, A.A., 2017. Disentangling age–gender interactions associated with risks of fatal and non-fatal road traffic injuries in the Sultanate of Oman. *BMJ global health*, *2*(3), p.e000394.

Signed: ..........................................................................................................................................

Date: ..........................................................................................................................................

# Dedication

*I dedicate this thesis to the memory of my late father Khamis Zahir Sultan Al-Aamri for his eternal love and kindness to me and my whole family. The journey to this doctoral research began with his dream, motivation and confidence in me. He has remained as a guiding force throughout my life.*

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# Definitions and Abbreviations

| | |
|---|---|
| RTC | Road Traffic Crashes |
| RTI | Road Traffic Injuries |
| WHO | World Health organisation |
| LMICs | Low- and Middle-Income Countries |
| EMR | Eastern Mediterranean Region |
| MENA | Middle East and North African |
| UK | United Kingdom |
| USA | United States of America |
| UAE | United Arab Emirates |
| GCC | Gulf Corporation Council |
| ROP | Royal Oman Police |
| TRC | The Research Council in Oman |
| RSRP | Road Safety Research Programme |
| NCSI | National Centre of Statistics and Information |
| ONTC | Oman National Transport Company |
| GDP | Gross Domestic Product |
| NRTC | National Road Traffic Crash |
| iMAAP | integrated Microcomputer Accident Analysis Package system |
| AADT | Average Annual Daily Traffic |
| ACDA | Assured Clear Distance Ahead |
| BAC | Blood Alcohol Concentration |

Definitions and Abbreviatioins

| | |
|---|---|
| DALYs | Disability-Adjusted Life Years |
| NBM | Negative Binomial model |
| LSA | Local spatial autocorrelation |
| KDE | Kernel Density Estimation |
| PKDE | Planar Kernel Density Estimation |
| NND | Nearest Neighbour Distance |
| Net-NND | Network Nearest Neighbour Distance |
| GIS | Geographic information based systems |
| RF | Random Forest |

# Chapter 1

# Introduction

This thesis contributes to a systematic understanding of the sociodemographic and behavioural factors and spatial patterns underlying high burden of road traffic crashes and related injury outcomes in the Sultanate of Oman. It further evaluates the quality of National Road Traffic Crash data and proposes recommendations for improvements in data recording and processing for research and policy use.

## 1.1 Background and Rationale

When motor vehicles were firstly invented, they were seen as a new form of safe transportation for enhancing people's daily lives and economic development. By the end of the last century, with rapid urbanisation and modernisation, the use of motor vehicles increased almost exponentially across the world. The unprecedented increase in motor vehicles introduced significant challenges for road safety including a steady increase in road traffic accidents leading to loss of human lives and disabilities. The alarming number of the global annual deaths attributed to road traffic crashes has been seen by many commentators to indicate a major global public health crisis (Peden and Hyder, 2002; Ameratunga and Norton, 2006; Sharma, 2008; Agnihotri et al., 2016; Staton et al., 2016; Hyder et al., 2017). Globally, more than 1.2 million people die every year from road traffic crashes (RTCs) and between 20 and 50 million suffer non-fatal injuries and subsequent disability directly attributed to RTCs (WHO, 2015). In 2013, RTCs were ranked the seventh leading cause of global disability-adjusted life years (DALYs) and leading cause of death for young people aged between 15 and 29 years (Murray, et al., 2015). It is estimated that each year about 5% of gross domestic product (GDP) in low- and middle-income countries (LMICs) are lost due to road traffic injuries (RTIs) and fatalities (WHO, 2015). LMICs alone account for about 90% of both road crash deaths and of the DALYs lost (WHO, 2015; Sharma, 2008).

Although it is common that LMICs have higher death rates from RTCs, high-income countries in the Eastern Mediterranean Region (EMR) have higher rates compared to the average death rate in their region (22.4 per 100,000 population compared to 19.7) (WHO, 2015). This rate is also more than twice the average global rate of high-income countries (9.2 per 100,000 population) (WHO, 2015). The most recent Global Burden of Disease study (GDB 2015) has confirmed that road traffic injuries are currently among the top five leading causes of DALYs lost worldwide and the leading cause of DALYs in Oman, Saudi Arabia, and United Arab Emirates (Murray et al., 2015). Additionally, the average economic cost of road injuries in high-income countries in the MENA region is about 3.9% of their annual GDP with Oman representing the worst scenario where this cost is about 7.4% of its GDP (Dahdah and Bose, 2013).

Oman has the second highest death rate from RTCs within Gulf Cooperation Council (GCC) countries (WHO, 2015). In 2010, the proportions of people who died due to RTCs were higher than those who died due to cardiovascular disorders or cancer diseases in Oman (IHME, 2015). The years of life lost attributed to RTCs had also increased by two-fold from 11·8% in 1990 to 21% in 2010 in Oman (IHME, 2015), exerting significant burden on economy and healthcare resources. The increase in RTCs and associated mortality burden remain unprecedented since mid-1990s (Al-Maniri et al., 2013), and this is associated with economic growth, rapid urbanisation, road infrastructure and a steady increase in motor vehicle use (Al-Reesi et al., 2013). The coverage of paved roads increased from 3 km in 1970 to 31,622 km in 2014 whereas the number of registered motor vehicles increased from 1,016 in 1970 to 1,302,312 in 2015 (ROP, 2016). The unprecedented increase in private motor vehicles in Oman could be partly attributed to the limited availability of public transport and railway services. Similarly, the number of driving license holders has grown from 502,013 in 2000 to 1,333,077 in 2015 (ROP, 2016), meaning that there is one motor vehicle per each license holder. The population has also doubled in the last two decades in Oman particularly the expatriate population, currently representing 46% of the total population (NCSI, 2016). The majority of expatriate population are South Asian immigrants (Based on 2013 stats, 644,704 from India, 148,314 from Bangladesh and 117,208 from Pakistan), and most of them are low-skilled workers and not well educated (Mansour, 2017).

In 2015, 6,279 RTCs were registered in Oman, of which 78% resulted in nonfatal injuries and more than 11% fatal injuries with expatriate drivers represented 32% of RTCs' fatalities and 24% of RTCs' injuries (ROP, 2016). Amongst those had fatal outcomes, 32% aged 16-25 years, and 46% in the 26-50 age-range, mostly healthy, men and those driving the vehicle at the time of incident (ROP, 2016). The high burden of mortality and disability has considerable economic, social and health care implications for the left-behind families, as these victims are usually the primary breadwinners. Al-Reesi et al. (2013) concluded that risky driving behaviours and violation of traffic law are the major risk factor for road safety in Oman.

The Omani government has committed extensive resources and efforts to reduce the number of RTCs and casualties by introducing a number of safety intervention programmes and increasing awareness among people across the whole country (AL-Bulushi et al., 2015). The launch of road safety campaigns, the new Standards of Highway Design (Plankermann, 2014), the strategic programme on Road Safety Research in The Research Council (TRC), compulsory wearing of front seat belts, implementation of road speed limits (using speed cameras) and prohibiting the use of mobile phones while driving are examples of such intervention measures (AL-Bulushi et al., 2015).

However, few systematic evaluations of these interventions have been done and thus it is inconclusive whether these interventions are reducing the burden of road traffic crashes and injuries. More importantly, the type, pattern, and randomness of RTCs are not well understood in Oman. A related observation is the lack of understanding of complex human behaviour and skills associated with risks of reckless driving in the country. The high representation of expatriate population and rapid urbanisation level adds further complexity in understanding and quantifying these risks.

Although Western countries have considerable investment in road safety research, developing countries are still at the infancy stage in this field due to a range of complex factors including road infrastructure, weak legislation, economic conditions and inequality; so it is questionable whether road safety measures used in western countries can be applied in developing countries (Plankermann, 2014). Research conducted in other countries demonstrated evidence that factors attributed to human are crucial (Jafarpour and Rahimi-Movaghar, 2014; Plankermann, 2014). More than 90% of road crashes have been attributed to the human factors as a sole or as contributory factor along with road environment and vehicle related factors (Islam and Al-Hadhrami, 2012).

The application of systematic approaches, such as reliable RTC database and statistical analyses, has resulted in a significant decrease in the number of road fatalities in many high-income countries in the last three decades (Memon, 2012). The accuracy of road crash data has been considered as the key starting point for this achievement in western high-income countries (Memon, 2012), however unfortunately this is not the case in high-income developing countries. Reliable RTC data and statistical evidence are fundamental to identifying the risk factors more accurately, identifying priority areas for policies and interventions, monitoring performance and evaluating intervention programmes, and thus enabling policies and decision makers in designing suitable remedial measures and effective strategies (Peden, 2004; WHO, 2010; Memon, 2012).

## 1.2 Aims of the thesis

The overarching **aim** of this research is to apply robust statistical techniques to identify and evaluate the *multi-dimensional* social, demographic, spatial and technological factors associated with the likelihood of RTCs and associated outcomes in Oman.This aim is clearly linked to the goals and mission of one of the strategic programme of The Research Council (TRC) of the Sultanate of Oman, in particular addressing ***themes 1, and 2*** which focus on crash analysis, and socio-behavioural issues (TRC, 2010). Additionally, this research will explore the spatial dimension, especially in identifying the high risk or hot spot areas where road crashes are frequent. The results of this study will feed directly into current road safety policy and programme interventions in Oman. The study is also aimed at generating significant social and health impact in Oman by identifying and quantifying the risks and patterns of traffic crashes in the Sultanate. This research will also contribute to one of the major strategic programmes of the Research Council in Oman: Road Safety Research Programme (RSRP).

## 1.3 Research questions

The proposed study will address the following research questions in a four-paper format:

1. What are the social, demographic, economic, spatial and technological factors associated with the likelihood of traffic crashes and fatalities in Oman?

2. What are the patterns of fatal and non-fatal injury outcomes of road traffic crashes in Oman? How do these vary and interact by age and sex of the drivers?

3. What is the nature of association between the severity of motor vehicle crash and timing of the incident? More specifically, does the intensity of crash severity vary during certain hours of the day? How do demographic factors mediate the relationship between crash severity and timing of the incident?

4. Where are the high risk or hot-zone areas for road crashes in Muscat Governorate where crashes are more frequent? How can we use the spatial analysis to understand and model the patterns of road crashes integrating relevant predictors such as road geometry and traffic related features?

5. How can we improve the existing data collection systems of the National Road Traffic Crash (NRTC) database to better understand and measure road traffic crashes and related injury outcomes in Oman?

## 1.4 Objectives

In order to undertake this research study, the following objectives are proposed:

- Liaise and engage with Royal Oman Police (ROP), Ministry of Transport and Communication, Ministry of Health and The Research Council (TRC) to access the road accident database in Oman, and obtain the required research data.
- Develop a conceptual framework to identify the causal pathways and multidimensional factors associated with road traffic crashes, injuries and fatalities, situating the Omani social context;
- Systematically examine the quality and reliability of National Road Traffic Crash (NRTC) database to address the specific research questions;
- Apply a range of robust and advanced statistical modelling techniques to examine the factors associated with the likelihood of crashes and fatality rates in Oman;
- Publish and disseminate the research findings to relevant policy and decision makers and suggest appropriate solutions for designing appropriate interventions to reduce the burden of traffic crashes in Oman.

## 1.5 National Road Traffic Crash Database

The data for this research are drawn from the ROP NRTC Database for the period 2010–2014. The database is made available for research use by The Research Council of the Sultanate of Oman, who coordinates the National Road Safety Research Programme jointly with ROP, five government ministries representing health, transport, regional municipalities, housing, social development, Muscat Municipality, Sultan Qaboos University and Petroleum Development Oman.

NRTC database is maintained and published by the Directorate of Road Traffic within ROP. The details of crashes are manually recorded in an Accident Report Form. The form includes information such as time and date of the crash, sex, age and nationality of the drivers, type of injuries, number of fatalities, type and number of vehicles involved, cause of crash, type of collision, location, type of road, weather conditions, and crash description along with handwritten diagrams and photographs of the crash (Farag et al., 2014).

According to ROP (2006), serious crashes are those crashes involving an injury, public property damage or an inability of the involved vehicles' drivers to resolve between themselves who was at fault. In contrast, minor crashes are those crashes that not having the three above criteria so that insurance companies can resolve the situation without the involvement of ROP (AL-Bulushi et al., 2015).

Definitions of deaths related to road traffic crashes differ from country to country. At the international level, the World Health Organisation (WHO) identifies RTCs' death as a death occurring within 30 days of being involved in a RTC. However, in Oman, ROP identifies road traffic deaths as those deaths that take place between the time of the crash and the closure of the case file on 31$^{st}$ of January of next year. Thus, it is difficult to determine the extent of accuracy of the direct comparison with other countries using the WHO definition (AL-Bulushi et al., 2015). For fatal outcomes, the researcher assumes that the death occurred at the time or within 30 days of the incident.

NRTC database had details of 35,851 registered road traffic crashes in anonymised format, collected between 1$^{st}$ January 2010 and 2$^{nd}$ November 2014 – the most recent data that the author could access. The researcher sought permission for data analysis from TRC and the study was approved by the University of Southampton Research Ethics Committee. The data were carefully evaluated for potential inconsistencies and quality in terms of recording errors and incomplete information.

The key findings and results of this research will:

- Provide insights of relevant application of statistical methods to understand and model traffic crash and fatality data;
- Strengthen the research capacity and broader scientific understanding of road safety interventions measures in Oman;
- Contribute to reducing the problem of traffic crashes and mortality burden, and provide direction for policies and decision makers in Oman.

## 1.6 Structure of the thesis

This thesis consists of seven chapters. Tables and figures are presented in the body of the text where appropriate and full details of the fitted statistical models are provided in the appendices. Research background, overview of the study, aims, objectives, questions, contribution and description of the data used in the study are presented in this chapter.

Chapter two summarises the relevant literature concerning road traffic crashes. It highlights the patterns and trends of road traffic crashes globally, in the Middle East and North African (MENA) region and in Oman. It also reviews the broader risk factors associated with road traffic injuries followed by a conceptual framework organising the risk factors, outcomes and interventions of RTCs in a systematic manner. Finally, comparison of the policy and programme interventions used in selected high- low- and middle-income countries and those used in the GCC countries and Oman is discussed at the end of the chapter.

The statistical analysis of the first paper is presented in chapter three. This analysis is a systematic investigation of the underlying interactive effects of age and sex on the severity of fatal and non-fatal RTC outcomes in Oman. A generalised ordered logit regression has been applied to estimate the effect of driver's age and sex on the severity of RTCs, controlling for personal characteristics, risk behaviours, vehicle, road, traffic, environment conditions and geographical location. The main finding of this paper indicates that the high burden of severe and fatal road traffic injuries (RTIs) in Oman was primarily attributed to over-speed driving behaviour of young males aged 20-29 years.

Chapter four presents the statistical analysis of the second paper. It aims at investigating the statistical association between the peak hours of traffic congestion and severity of fatal and non-fatal road injuries in Oman. The outcome variable was the number of fatal and non-fatal crashes. Negative Binomial Regression models have been applied to examine the association between peak and non-peak hours of traffic congestion within the 24 hours of a day and the number of fatal and non-fatal road injuries, adjusting for day of the week, personal characteristics of the driver and spatial-related factors. This analysis confirms that the severity of road injuries varied by the peak hours of congestion.

Chapter five presents the spatial and temporal dimensions of RTCs. It aims at identifying the locations of hot-zones (groups of neighbouring hotspots) and spatial clustering of RTCs in the Muscat governorate, especially in identifying the high risk or hot spot areas where RTCs are more frequent. Geocoded RTC data from the Muscat governorate were used to evaluate the spatial and temporal dimensions of RTCs. The analysis considered an adjacency network analysis integrating GIS and RTC data using robust estimation techniques including: Kernel Density Estimation (KDE) of both 1-D and 2-D space dimensions, Network-based Nearest Neighbour Distance (Net-NND), Network-based K-Function, Random Forest Algorithm (RF) and spatiotemporal Hot-zone analysis. The results from GIS application of NRTC data are validated using the sample data generated by iMAAP database. The findings demonstrate evidence of spatial clustering of RTC hot-zones on long roads demarcated by intersection and roundabouts.

Chapter six provides a critical appraisal of existing data collection procedures and recording systems, identify the strengths and weaknesses, and suggest coherent ways to record, monitor and analyse data on road crashes. It also reflects on the usefulness of iMAAP application in understanding the trends and patterns of road crashes and related outcomes. The key recommendations in this chapter are based on the review of NRTC database and findings presented in Chapters 3-5.

Chapter seven summarises the main findings of the thesis reflecting on the evidence from statistical analysis and concludes with a set of recommendations for policy interventions aimed at risk reduction and prevention of RTCs. This is followed by a discussion of the scientific and policy implications of the study to improve the road safety interventions in Oman. The thesis concludes with a reflection of the study limitations and prospects for future research on road safety.

# Chapter 2

## Understanding Road Traffic Crashes and Related Outcomes in a Global and Omani Context: A Literature Review

ABSTRACT

This chapter presents an overview of relevant literature concerning road traffic crashes, including definition and measures, trends and patterns, and safety interventions. It highlights the global patterns and trends of road traffic crashes and compare these patterns across high-income and middle- and low-income countries, and further examines the trends of road traffic crashes in the Middle East and North African (MENA) region followed by an assessment of the trends in Oman. Following this, the chapter reviews and discusses the risk factors associated with road traffic injuries and relevant conceptual frameworks, and synthesises the findings and develop refined conceptual framework for understanding the factors and outcomes of road traffic crashes. The chapter concludes by reviewing the policy and interventional programmes related to the major risk factors by comparing policies implemented in high-income countries to those in low- and middle-income countries, with a focus on GCC countries including Oman.

**Key messages**

- Road traffic crashes remain an unresolved global public health emergency in most low- and middle-income countries.
- Fatal road traffic crashes are a routine public health emergency, and reducing the burden of RTCs is a national-level high priority policy agenda in Oman.
- There is little systematic statistical analyses of how individual risk factors such as demographic, behavioural, and spatio-temporal factors determine RTC outcomes in Oman.

**Keywords:** Road traffic crashes, injuries, global public health, Oman, MENA, GCC, developed/developing countries, low- middle- and high-income countries, causes of injury, age, sex, severity of injury, risk factors, risk behaviours, conceptual frameworks, Road safety legislation, Policy and interventional programmes

## 2.1 Introduction

This chapter presents the concepts, measures and empirical frameworks related to road traffic crashes, with an overview and synthesis of global and regional trends and associated risk factors and relevant safety policy and programme interventions. It then summarises evidence from the literature and propose a conceptual framework for understanding the behavioural, economic social, technological and environmental factors associated with road crashes and related injury outcomes.

### 2.1.1 Definition of road traffic crash

Different terms have been commonly used to describe road traffic crashes. Among these terms are the following: road traffic injury, motor vehicle accident, motor vehicle traffic collision, car accident, car crash, auto accident, car smash, motor vehicle collision, road accident, road traffic accident, road traffic incident, road traffic collision, and road traffic crash. The author used search terms: road, injury, crash, accident, motorways, fatal, non-fatal, mortality, disability, morbidity, age, sex, gender, injury severity, risk factors, risk behaviour, fatigue, sleep, drink-driving, road safety, public health, global, GCC, Gulf Cooperation Council, Oman, Middle-East, MENA, high/low/middle income countries, developed/developing countries, economy, technology, cell/mobile phones, and seatbelt on key database including Google Scholar, Web of Science and US National Library of Medicine National Institutes of Health (Pubmed). After carefully considering the terminology during the search for relevant literature, the terms “Road Traffic Crash” and “Road Traffic Injury” have been chosen to be used throughout the thesis.

A road traffic crash occurs as a result of an unanticipated interaction either between two moving objects, or a moving and a fixed object, and this movement can be seen as a function of land use system (Al-Rawas, 1993). A road traffic crash can be defined as “rare, random, multifactor event proceeded by a situation in which one or more persons have failed to cope with their environment” (Al-Rawas, 1993, P. 227). However, this definition seems to be not accurate because environmental conditions such as poor road infrastructure and traffic regulation systems exacerbate the risks of RTCs. Road traffic crash can also be defined as an event involving a collision between a vehicle with another vehicle, pedestrian, animal or any other roadside object such as a tree or other stationary obstruction (Ansari et al., 2000; Ruikar, 2013). Further definition describes road traffic crash as: “an event involving at least one vehicle, occurring on a road open to public circulation, and in which at least one person is injured or killed" (Ruikar, 2013, P. 1; The National Institute of Statistics and Economic Studies, 2016).

## 2.2 Global patterns and trends in road traffic crashes

Although motorisation has an important role in enhancing people's daily lives and economic development, there is also a cost associated with it. This cost is reflected in the substantial societal and economic costs of the road traffic crashes (RTCs) and their corresponding injuries and fatalities (Gopalakrishnan, 2012). The alarming growth of RTCs and the related injuries and deaths is acknowledged to be a global phenomenon and most countries of the world are confronted with the increase in the number fatalities and serious injuries attributed to RTCs (Jacobs and Aeron-Thomas, 2000). Of even greater interest is the fact that road traffic injuries may lead to survivors with either short-term or permanent disabilities consequently resulting in permanent restrictions on their physical functioning and quality of lives. Thus, to fully reflect the burden of disease due to RTCs both mortality and injury morbidity should be considered in evaluating the scale and impact of RTCs (Peden et al., 2004).

The first injury due to petrol-engine-car crash was recorded in New York City on the 30th of May 1896 and later after a few months Bridget Driscoll was the first victim killed[1] in a crash of petrol-engine car in London (Peden et al., 2004). Thereafter, as countries began to modernise with rapid use of motor vehicles, the number of RTCs and associated mortalities and injuries has also started to increase substantially. The approximate cumulative total of RTC related deaths was 25 million people in 1997 although the exact number of fatalities is not systematically documented due to the lack of reliable data in the late 19th and the early 20th century (Peden et al., 2004). Towards the end of 20th century, RTCs have become a major global health burden, increasingly so in middle-income countries. In response to rising road traffic crashes, the United Nations General Assembly adopted resolution 64/255 in 2010 proclaiming 2011-2020 as Decade of action for Road Safety (WHO, 2015). The WHO mission is aimed at stabilising and reducing the alarming trend in road traffic deaths, with a target of 5 million lives to be saved over this decade (WHO, 2015).

According to the WHO (2015), RTCs are currently the 9th leading cause of death across all age groups worldwide and projected to be the 7th leading cause of death by 2030. Further, the recent statistics

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[1] The first motor vehicle crash fatal outcome was recorded in 1869 when Mary Ward, an Anglo-Irish amateur scientist, was killed after falling under the wheels of an experimental steam car (Mastinu and Plöchl, 2014).

of WHO indicate that the annual approximate number of RTCs' fatalities is 1.25 million and a further 20 to 50 million people are injured globally due to RTCs (WHO, 2015). Most RTCs' victims are overwhelmingly young and healthy prior to crash (WHO, 2015). Recently RTCs have been classified globally as the second leading cause of death among people aged 5-29 years, the first leading cause of death among adolescent aged 15-29 years, and the third leading cause of death among those aged 30-44 years (Kamruzzaman et al., 2013; Al-Mazruii et al., 2015; WHO, 2015). It also has been found that 48% of road traffic deaths involve people of working ages (15-59 years).

The high burden of mortality and disability has considerable economic, social and health care implications for the left-behind families, as these victims are usually the primary breadwinners. The lives of the left-behind families could be adversely affected by these tragedies and millions of people are subject to coping with the death or disability of their primary breadwinners (Kamruzzaman et al., 2013; Majdan et al., 2013; Al-Mazruii et al., 2015; WHO, 2015). Therefore, it is clear that the economic cost of RTCs is considerably large, at the household, national and global level (Majdan et al., 2013).

Although low- and middle-income countries represent 82% of the total global population and 54% of total registered vehicles, they account for 90% of road traffic fatalities (WHO, 2015). Most of these countries are experiencing economic transition and rapid urbanisation, with increase in the number of registered motor vehicles (WHO, 2015). Road networks and transport infrastructure are poor in most of these countries, with no comprehensive road safety policies or law enforcement (Dharmaratne et al., 2015; WHO, 2015). On the other hand, many high-income countries have safer road infrastructure, traffic regulations, law enforcement and safety check measures to reduce the risk of road traffic injuries (WHO, 2015). Additionally, the good monitoring and recording of crash data in developed countries have enabled them in designing, implementing and evaluating effective safety interventions to reduce the number and severity of RTCs (Majdan et al., 2013; WHO, 2015).

Road traffic death rates are usually expressed as deaths per 100,000 populations (WHO, 2015). The global death rate attributed to RTCs is 17.4 per 100,000 population as based on RTC data of the year 2013 (WHO, 2015). However, this rate varies significantly by income level of the countries: the death rates have been found to be more than twice as high in low- and middle-income countries (24.1 and 18.4 per 100,000 respectively) compared to high-income ones (9.2 per 100,000) (WHO, 2015). Besides, according to the 2015 global status report on road safety, which covers data from 180 countries/ areas out of 195 countries of the world, 68 countries have recorded an increase in RTCs' death rates since 2010 with 84% of this increase observed in low- and middle-income countries (WHO, 2015).

The 2015 global status report on road safety has classified countries of the world into six main geographic regions: Africa, Eastern Mediterranean, Western Pacific, South-east Asia, Americas and European. Significant variations have been noticed in the risk of road traffic death from one region to the other and only little change in the regional death rates has been observed since 2010 (WHO, 2015). As it can be seen from ***Figure 2.1***, African Region has recorded the highest rates (26.6 per 100,000 population), while the lowest rate is seen in European Region (9.3). Similarly, a wide disparity in fatality rates can be seen within particular regions. For example, in the Western Pacific region, it has been found that some countries in this region such as Australia has one of the lowest death rate globally, while there are other middle-income countries in this region which have recorded high death rates of 24 per 100,000, much higher than the world average death rate. Likewise, although it is common that low- and middle-income countries appear to have higher road traffic death rates than high-income countries, high-income countries in the Eastern Mediterranean Region (EMR) have been observed to record higher rates compared to the average rate in this region (22.4 compared to 19.7) (WHO, 2015). This rate is also more than twice the average global rate of high-income countries (9.2) (WHO, 2015).

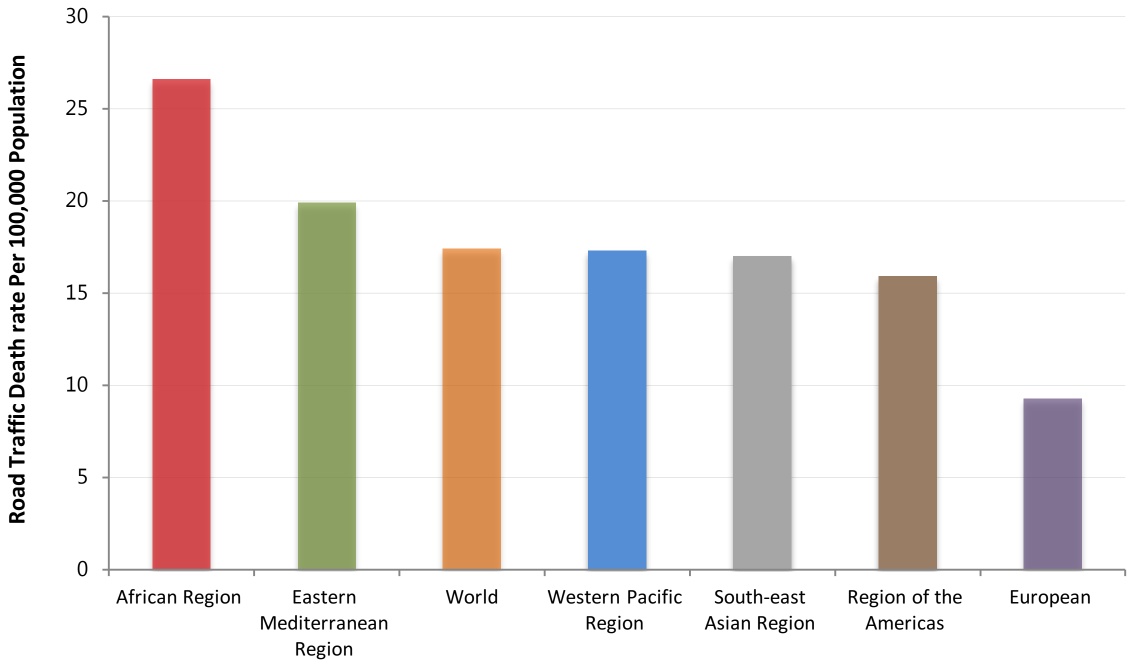



***Figure 2.1*** *Road traffic fatality rates per 100,000 population by WHO regions*
*(Source adapted from: WHO, 2015. The Global Status Report on Road Safety 2015, P.6).*

## 2.3 Overview of RTC trends in the Middle East and North African (MENA) region

Although Arab countries represent only 3.6% of global population and they own 1% of the total world vehicles, 4.8% of the annual global road traffic deaths noticed to occur in these countries (WHO, 2004). Additionally, the Eastern Mediterranean Region (EMR) recorded the highest death rate due to RTCs among people aged 15-29 years; in 2004 this rate was 34.2 deaths per 100,000 population (Al-Maniri et al., 2012).

The WHO Global Status Report on Road Safety (2013) stated that, 82,000 people were killed due to road injuries in Middle East and North African (MENA) countries in 2010 (WHO, 2013). When the road safety performance is measured in terms of mortality rates, MENA countries have been found to have rather poor performance compared to other countries of the same level of income (Dahdah and Bose, 2013; WHO, 2013). The annual mortality rate of road traffic injuries in these countries was 22 deaths per 100,000 population in 2010, and this was about 4.5 times higher than the rate recorded in the best road safety performing countries ( Dahdah and Bose, 2013). Additionally, among the top ten countries which have the worst performing in terms of road safety, four of them are from the MENA region namely: Oman, Saudi Arabia, Iran, and Libya ( Dahdah and Bose, 2013). A mixture of risk factors can play a role in the poor road safety performance in these countries including: high speeding associated with lack of police enforcement together with the ineffective penalty system, rapid motorisation growth and road networks along with the poor road design and traffic regulations ( Dahdah and Bose, 2013).

As mentioned above, MENA countries have an alarming RTC incidence rate, and RTCs are the leading cause of death among adults aged 20-29 years in this region ( Dahdah and Bose, 2013). Comparing the mortality rates of RTCs, healthy years of life lost, and the percentage of GDP lost due to RTCs, MENA countries are currently among the worst performers in road safety worldwide ( Dahdah and Bose, 2013). These findings reveal that while there is an increase in the level of wealth among MENA countries in the last decades, however this increase has not played a positive role in reducing the incidences of RTCs ( Dahdah and Bose, 2013). Consequently, it is clear that achieving a high level of economic progress alone is not enough to improve the performance of the road safety. This highlights the need to take immediate transformational changes in the management of the road system and all the relative stakeholders should collaborate together and start taking actions to effectively reverse the high trends of road traffic deaths and injuries in this region ( Dahdah and Bose, 2013).

The most recent Global Burden of Disease study (GDB 2015), which covered 188 countries around the world, has confirmed that road traffic injuries are currently among the top five leading causes of disability-adjusted life-years (DALYs) (Murray et al., 2015). According to this study, road injuries are the leading cause of DALYs lost in three Gulf Cooperation Council (GCC) countries: Saudi Arabia, Sultanate of Oman and United Arab Emirates. Further, the average economic cost of road injuries in high-income countries in the MENA region is about 3.9% of their annual GDP with Oman ranks the worst case as this cost represents about 7.4% of its annual GDP (Dahdah and Bose, 2013). The next section gives an overview of RTCs in Oman.

## 2.4 RTCs in Oman: the broader context

The Sultanate of Oman is a country located in the southern tip of the Arabian Peninsula. The total area of Oman is 309.5 thousand km$^2$ and it shares borders with three Arab countries: The United Arab Emirates to the north, The Kingdom of Saudi Arabia to the west, and The republic of Yemen to south-west (Ministry of Information, 2017). As of the Royal Decree No. 114/2011, Oman consists of 11 governorates: Muscat (the capital of Oman), Dhofar, Musandam, North Al Batinah, South Al Batinah, Adh Dhahirah, Al Buraimi, Ad Dakhliyah, North Ash Sharqiyah, South Ash Sharqiyah and Al Wusta, ***Figure 2.2*** (Ministry of Information, 2017). However, in this PhD thesis, these governorates have been reduced into eight governorates by combining: Al Buraimi and Adh Dhahirah, North and South Al Batinah, and North and South Ash Sharqiyah. These eight governorates are: Muscat, Musandam, Dhofar, Ad Dakhliyah, Ash Sharqiyah, Al Batinah, Adh Dhahirah, and Al Wusta.

The total population of Oman has almost doubled since 2010; it increased from 2,773,479 in 2010 to 4,414,051 in 2016 with expatriates representing about 46% of the total population and about 87% of them are males (NCSI, 2016). As of the mid-year 2016, 33% of the total population and about 47% of the expatriates live in Muscat Governorate (NCSI, 2016). Muscat Governorate has also the highest population density (345 per km$^2$) followed by North and South Al Batinah and South Ash Sharqiyah (90, 75 and 24 persons per km$^2$ respectively) (NCSI, 2016). Data have also shown that about 65% of the total population are males, 65% aged below 29 years and 20% of Omani people aged 15-24 year (NCSI, 2016). ***Figure 2.3*** presents the distribution of Oman population by sex, age and nationality groups (Omanis verse Expatriates).

According to WHO (2015), Oman is classified as a high-income country (per capita income is \$25,150). Besides, Oman, as other GCC countries, has seen remarkable social and economic developments following the discovery of oil (Al-Reesi et al., 2013; Farag et al., 2014; AL-Bulushi et al., 2015; Farag, 2015). The developments have been seen in different sectors in the country including educational, health and social sectors. Moreover, in parallel with other development programs, road construction has seen a remarkable development and this has been reflected on the increase in the motorisation rate and the growth in the road networks (Islam and Al-Hadhrami, 2012). Compared with only 1,016 registered vehicles and three kilometres paved in 1970, these figures have grown to 1,302,312 vehicles in 2015 and 31,622 Kilometres in 2014 respectively (ROP, 2016). The development of road infrastructure has led to a steady increase in the use of motor vehicles in Oman especially since the beginning of this century. Additionally, the lack of public transportation in the country could be a major contributing factor to the disproportionate increase of the private vehicles in 2015. The number of driving license holders has also grown from 502,013 in 2000 to 1,333,077 in 2015 (ROP, 2016). Besides, Oman, unlike Saudi Arabia, does not have gender discrimination against driving, and hence part of the increase in the number of license holders could be attributed to the increasing trend in the number of female drivers. According to ROP (2016), females represented about 19.1% of the total number of license holders and 26.6% of the new issued licenses in 2015. It is also worth noting that the number of Omani female workers has also increased from 57,815 in 2006 to 130,077 in 2015 (NCSI, 2016).

Moreover, the use of private vehicles to commute both short and long distance to workplace, shopping and leisure centres are becoming increasingly common in Oman, especially when commuting from adjoining governorates to Muscat. This has led to an increase in the concentration of daily commuting within limited major roads, which in turn has resulted in a high level of traffic congestion coupled with a high rate of traffic crashes (Al-Rawas, 1993).

The rapid urbanisation in Oman has also prompted large migration flows from rural to urban areas (Islam and Al Hadhrami, 2012). The higher representation of expatriate population and rapid urbanisation level[2] are also among of the major changes that the country has seen in the last four decades. As previously mentioned, about 46% of the population in Oman are expatriates representing diverse socioeconomic and cultural background. In 2015, expatriate drivers represented 32% of road traffic fatalities and 24% of road traffic injuries in Oman (ROP, 2016). This highlights the importance of the role and risk behaviours of expatriates in understanding road safety in Oman.

[2] 70% of Omanis live in urban areas (NCSI, 2014).


***Figure 2.2*** *Sultanate of Oman, political map*
*(Source: www.smartraveller.gov.au, accessed 24/03/2017).*

According to the National Health Survey, RTCs are the first leading cause of incidence and injury in Oman and they accounted for 61% of the total incidents in 2000 (Islam and Al Hadhrami, 2012). In the period from 1985 to 2009, RTCs had resulted in 13,722 deaths and 165,757 injuries in Oman (Al-Bulushi et al., 2015). In 2011, more than 7,700 RTCs with 1,056 related-deaths were documented by ROP in Oman, meaning that on average about one crash occur every hour and one death every 10 hours (Al-Bulushi et al., 2015; ROP, 2016). According to the 2015 global status report on road safety, Oman has the second highest death rate from road injuries within GCC in 2013 (25.4 deaths per 100,000 population) (WHO, 2015). Oman also ranks the third in terms of the country with the highest death rate due to RTCs in the EMR (WHO, 2015). In addition, road crashes have been recorded as the leading cause of death among people aged 20-29 years in Oman; accounting for 64% of the total death among this age group (Farag et al., 2014). In Oman, the years of life lost attributed to RTCs had increased by two-fold from 11·8% in 1990 to 21% in 2010 (IHME, 2015). In 2007, 73.3% of total hospital deaths, which classified as deaths due to external causes, were attributed to road traffic injuries (Al-Bulushi et al., 2015). In addition, a significant number of those who survived road traffic injuries are suffering from physical, emotional and behavioural disabilities (Al-Bulushi et al., 2015). This suggests that road traffic crashes are exerting significant burden on economy and healthcare resources.

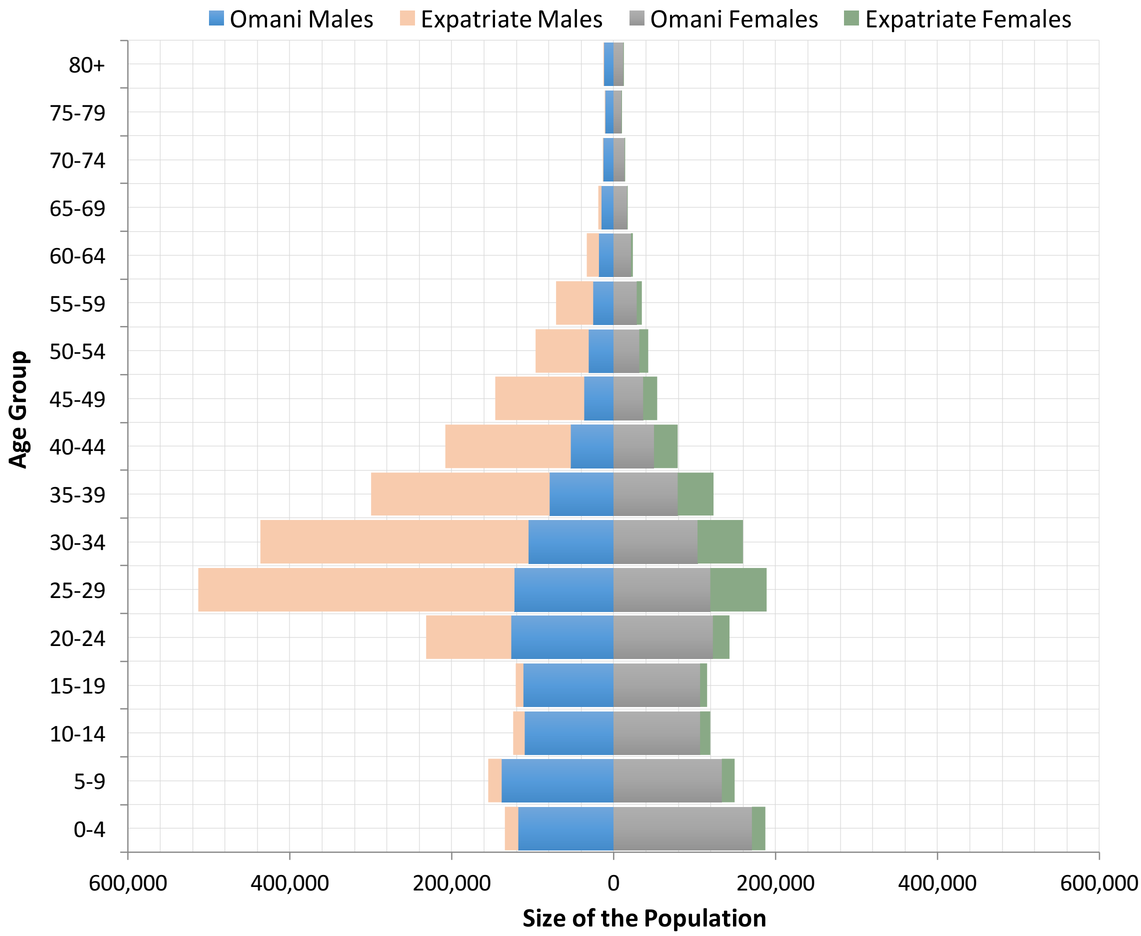



***Figure 2.3*** Size of the *population by sex, age and nationality group, Oman, 2016*
*(Source: adapted from NCSI, 2016, P.69)*

In the recent years, Oman has invested considerably to reduce the burden of traffic crashes. Reducing road traffic crashes and their associated fatality rates have been given the highest priority on the national government agenda[3]. A number of intervention measures have been introduced to reduce RTCs in Oman. The compulsory wearing of front seat belts, the implementation of speed limits (using speed cameras), the establishment of many educational programs for the prevention of motor vehicle crashes in Oman, and prohibiting the use of mobile phones while driving are examples of such intervention measures (Al-Bulushi et al., 2015). However, considerable multisectoral efforts are still needed to engage organisations, government departments and the wider population collaborating together to prevent the increasing number of traffic crashes in Oman (Al-Bulushi et al., 2015).

Furthermore, few systematic evaluations have been made to examine the efficiency of these interventions and hence it is inconclusive on whether these interventions are reducing the burden of RTCs and their related injuries. More importantly, the type, pattern, randomness, and severity of RTCs are not well understood in Oman. A related observation is the lack of understanding of complex human behaviour and skills associated with risks of reckless driving in the country.

## 2.5 Risk factors for road traffic crashes

The identification of the causes of RTCs is not an easy task. The occurrence of a RTC involves a multiplicity of factors found in complex circumstances interacting with each other and leading to the occurrence of this crash (Al-Rawas, 1993). These factors generally fall into three main categories: road user, vehicle and road environment (Al-Rawas, 1993; Thomas et al., 2013). In most circumstances two or more factors interact with each other resulting in a road crash so that no one of these factors can by itself lead to the occurrence of the crash without the presence of the other factors (Al-Rawas, 1993; Jafarpour and Rahimi-Movaghar, 2014). Factors attributed to human are considered to be the crucial determinant (Jafarpour and Rahimi-Movaghar, 2014), and in fact 90-95% of road crashes have been attributed to the human factor as sole or interacting with other factors (Lewin, 1982; Rumar, 1985; Evans, 1991; and Elander et al., 1993 cited in Islam and Al-Hadhrami, 2012).

[3] His Majesty Sultan Qaboos delivered a public speech in 2009: “What is happening on our roads should be of everybody’s concern. Misuse of vehicles of different categories by different people causing many deaths is an irritating and worrisome phenomenon” (Al-Lamki, 2010, P. 1).

### 2.5.1 Demographic factors

The traffic environment nowadays is more complex than ever before; there are more vehicles, more congestion and more complex intersections and motorways (Shope, 2006). Similarly, drivers have become more discourteous, distracted and aggressive (Shope, 2006). The predominance of young drivers, particularly males, in road traffic injuries highlights the age and gender differences in risk-taking, economic opportunities, types of employment and exposure to risk such as access to vehicle, driving experience, and daily driven distance (Ameratunga et al., 2006; Tucker et al., 2015).

**Being male** is argued to be a significant risk factor for all types of injuries including road traffic injuries (Rebecca et al., 2017). Several studies have claimed that male drivers, especially the young ones, are at higher risk of RTCs compared to their female counterparts (Massie et al., 1995; Böhning and Ayutha, 1997; Abdel-Aty and Radwan, 2000; WHO, 2002; Shope, 2006; Smith et al., 2008). The global road traffic death rate of males is approximately three times that of females; 27.6 compared to 10.4 per 100,000 population respectively (Rebecca et al., 2017). The worst situation in gender differentials has been seen in low-income countries where males account for 67% to 99.5% of road traffic deaths (Rebecca et al., 2017).

According to a study conducted in Georgia to explore risky driving behaviours among young drivers aged 16-19 years, males were found exceeding the 20 mph speed limit more than females do (WHO, 2002). This study also found that males were more likely to overtaking other cars in non-overtaking zones, even overtaking two to three cars at the same time in a two-lane road and engaging in risky driving for fun. In addition, the study demonstrated that young male drivers had the lowest motivation to comply with traffic rules compared to other sex-age groups. Young male drivers are more likely to report risky driving behaviours as less dangerous compared to females (Oltedal and Rundmo, 2006).

Al-Maniri et al. (2013) reported that males aged 16-25 years are at high risk to be involved in RTCs in Oman, with a death rate as high as between 38.7 and 59.7 per 100,000 inhabitants. Likewise, Al-Reesi et al. (2015) found that young male drivers accounted for 28.1% and 34.5% of RTCs’ fatalities and injuries respectively for the period from 2009 to 2011 in Oman. In addition, this study found that male drivers were the predominant group in those crashes with speeding and nighttime driving as the main causes of fatal crashes. The authors attributed the high prevalence of young males in such crashes to their tendency towards risk taking, over-speeding and inexperience.

Conversely, a study conducted by Williams (2003) demonstrated that the consideration of crash involvement per mile driven indicated that **female drivers** have slightly higher risk of being involved in RTC than males. Abdel-Aty and Radwan (2000) found that female drivers are at higher risk of being involved in a crash during heavy traffic volume than males. Additionally, they found that female drivers have higher crash risk on roads with narrow lane width as well as with larger number of lanes compared to their male counterparts. On the other hand, the authors found that male drivers have higher probability to be involved in RTCs while speeding.

**The high risk of involving males** in road traffic injuries and fatalities compared to females could be explained by their greater exposure to driving and their tendency towards risk taking behaviours (WHO, 2002; Ameratunga et al., 2006; Rebecca et al., 2017). The greater exposure to driving is associated with the restrictions imposed on women in some nations around the world, for example Saudi Arabia. Due to these restrictions, driving is more common among men and they are more likely to own vehicles than women (WHO, 2002). In addition, working as a driver and mechanic for cars and trucks, including long-haul vehicles, is more common among males (WHO, 2002). Although the number of females who have driving license is fewer than the number of males (Rosenbloom, 2001 cited in Di Milia et al., 2011), they are also less likely to drive at younger age compared to males (Siren and Hakamies, 2004 cited in Di Milia et al., 2011). This implies that males have greater exposure to driving than females. Therefore, the differences in the type of employment and role of males and females have resulted in males having higher exposure to the risk of road traffic injuries and fatalities ( WHO, 2002).

The overall exposure of an event depends on the **population characteristics** (Mohan, 2006). Similarly, changes in the proportions of different age groups in the population will have a significant impact on the road traffic toll (Mohan, 2006). According to the Global Burden of Disease Study, there will be an increase in the average age of the world's population by 2020 as compared to the year 1990 so that growth in older populations would be expected in developed countries while developing countries are expected to have a growth in the younger population (Murray and Lopez, 1997). Therefore, major changes in the burden of disease and injuries (including road traffic injuries) would result from these differential rates of increase in different population age groups (Murray and Lopez, 1997).

Rifaat and Chin (2007) demonstrated that **age of the driver** has a significant impact on the crash severity. Several past studies have shown that there is a negative association between age of the driver and crash rate and this association is stronger after age of 30 years when rate level starts to level off (Doherty et al., 1998; Shope, 2006; Islam and Al Hadhrami, 2012; Ngo et al., 2012). These studies have also confirmed that **young drivers** at productive ages are more likely to be disproportionately affected by RTCs. For example, Islam and Al Hadhrami (2012) found that young drivers aged 17-36 years caused 70% of RTCs in Oman in 2009. Young drivers, especially males, are more likely to suffer severe injuries in single-vehicle crashes due to lack of experience, immaturity, loss of control, late night driving, alcohol abuse, driving on rural roads and having teenage passengers (Williams, 2003; Keall et al., 2005; Clarke et al., 2006; Shope, 2006; Rifaat and Chin 2007; Clarke et al., 2010). In addition, they pose a high crash risk to themselves and to other road users when overspeeding, closely follow other vehicles, weaving through traffic and making illegal lane change (Abdel-Aty and Radwan, 2000; Shope, 2006). They are also more likely failing to yield the right lane at controlled intersections compared to mature drivers (Shope, 2006). Furthermore, they are less likely to notice the unseen traffic risks and they may not be able to react appropriately to such risks (Shope, 2006). Al-Reesi et al. (2013) found that over-speeding and aggressive violations are the most common behaviours among young drivers in Oman. Similarly, young drivers who are less educated found to be more likely to practice risky driving behaviours compared to those who have higher level of education (Shope, 2006). However, this relationship varies slightly by sex and by different stages of education (Shope, 2006).

According to Shope (2006), **age of obtaining a driving license** could be considered as a contributory factor to crash risk. Shope also reported that the physical growth and developmental issues are prominent during the time when young people, i.e. teenagers, are learning to drive. They have high level of energy with rapid changes in body hormones. Shope further pointed that during teenage the brains of young people, particularly the prefrontal cortex where judgement and decision-making are centred, are still developing, and this development may continue until age of 25 years.

On the other hand, ageing leads to a steady deterioration of physiological, circadian and sleep systems suggesting that there is a linear relationship between chronological age and driver fatigue (Di Milia et al., 2011). Besides, young people and adults have different sleep patterns and needs (Shope, 2006). Due to their biological and psychological or emotional changes, young people are socially active; they sleep less and drive during late hours, thereby increasing their risk to RTCs.

People with high tolerance of **deviance-accepting behaviours** which most people believe as immoral or wrong behaviours-, those with high tendency of aggression and hostility and those with a sensation seeking personality are more likely to cause more crashes (Shope, 2006). Several past studies have examined the impact of sensation seeking and excitement-seeking on risky driving behaviour such as over-speeding (Jonah, 1997; Oltedal and Rundmo, 2006; Clarke et al., 2010). Sensation Seeking “is a trait defined by the seeking of varied, novel, complex, and intense sensations and experiences and the willingness to take physical, social, legal, and financial risks for the sake of such experiences" and key to this trait is "the optimistic tendency to approach novel stimuli and explore the environment" (Zuckerman, 1994 p.27 and p. 384 cited in Jonah, 1997, p. 651).

Jonah (1997) reviewed 40 studies and noted that 10-15% of variance in risky driving behaviours is explained by **sensation seeking**. Besides, Jonah stated that the majority of the studies have found sensation seeking to be positively associated with crash involvement rate. Additionally, the author pointed that the correlation between high sensation seeking and risky driving behaviours could be mediated by risk perceptions, so that drivers who are high sensation seekers may not identify certain driving behaviours such over speeding, drive after drinking and follow closely, as risky behaviours – because they can claim that their perceived superior driving skills can still enable them to drive safely. Alternatively, it is possible that those drivers may initially perceive such driving behaviours as being risky, however they take the risk to experience the thrill of engaging in that risk (Jonah, 1997). Consequently, when they have the opportunity to experience a given risk without having negative consequences, they would be more likely to engage in the same risky behaviour more often in the future as they may reduce the perceived level of that risk (Jonah, 1997). Sensation seeking was also found to be more common among high crash risk group of the young drivers, and that drivers of risky driving behaviours have higher sensation-seeking scores (Oltedal and Rundmo, 2006). Additionally, compared to low sensation seekers, high sensation seekers were found to have high tendency to speed, not wear seat-belts, more likely to drink and drive (Oltedal and Rundmo, 2006).

The **perceptions** of young drivers about driving risk can be developed from their perceived wider world, i.e. the community, the culture and the media (Shope, 2006). From these sources, young drivers can learn about risky driving behaviours, the likelihood of being involved in a crash, the likelihood of someone to be injured or killed and how a driver could be fined or jailed for a specific driving violation (Shope, 2006).

Considering the crash rate per miles driven, teen drivers were found to have the highest crash rate, though similar level was seen among the very oldest drivers (Shope, 2006). Besides, several past studies have confirmed that in heavy traffic volume situations, the crash risk for young and older drivers is higher than the risk for middle-aged drivers (Abdel-Aty and Radwan, 2000; AL-Ghamdi, 2002; Eluru et al., 2012). Similarly, narrow lane width and larger number of lanes were found to increase the crash risk for both young and older drivers (Abdel-Aty and Radwan, 2000).

Rifaat and Chin (2007) confirmed that **older drivers** are more likely to suffer severe injuries in both single-vehicle crashes and multiple-vehicle crashes. The decline in the visual and physical abilities of this age group could provide explanations to why older drivers are more at risk to be involved in fatal or severe injury crash (Hao et al., 2015). In addition, Eluru et al. (2012) argued that older individuals are more likely to suffer severe RTC injury than their younger counterparts because the propensity to a severe injury increases with age.

The behaviour of the driver can be affected by **age and sex of the co-passengers** so that the crash risk may differ by the nature of relationship among the occupants of the vehicle, purpose of the trip along with other factors (Williams, 2003). In fact, the presence of passengers has a physical effect so that the higher vehicle occupancy has been proven to increase the risk for personal injury if a crash occurs (Doherty et al., 1998). The channel capacity theory suggests that co-passengers can be a source of distraction for the driver because they can play a role in diverting the attention away from the driving task (Doherty et al., 1998). However, this theory is rejected by some studies because it suggests that all passengers should have the same influence. Further, the empirical evidence refutes this assertion as the age of the driver play a major role in mediating this effect (Doherty et al., 1998).

In general, the crash risk for young drivers, especially teenage drivers, has been found to increase when carrying passengers, whereas drivers aged 30 years and over have a lower crash risk when carrying passengers (Williams, 2003; Keall et al., 2004). For young male drivers, having male friends was found to lead to higher level of risk taking, whereas having a female passenger or parents found to lead to more careful and safe driving (Rolls and Ingham, 1992 and Arnett et al., 1997 cited in Doherty et al., 1998). Young male passengers were also found to be associated with unsafe driving practices and increase the crash risk for female drivers (Williams, 2003). Young drivers with young male passengers are more likely to drive more dangerously than those who drive alone (Mckenna et al., 1998 cited in Williams, 2003). Although having one female passenger was found to decrease the crash risk for young male drivers, having two or more female passengers found to increase the crash risk for teenage male drivers (Chen et al., 2000 cited in Keall et al., 2004). Williams (2003) confirmed that the crash risk for teenage drivers increases exponentially with the presence of one, two, three or more passengers and the author found that the presence of three or more passengers increases the crash risk by four times compared with when driving alone. In addition, according to a study conducted by Chen et al. (2000 cited in Williams, 2003), the existence of one male passenger doubles the death rate for the teenage driver compared with the case when driving alone and this rate increases even more with the presence of two or more male passengers. Moreover, Doherty et al. (1998) confirmed that time of the day is an important factor in understanding the driver behaviour in the presence of passengers. The results of Doherty et al.' study indicated that the presence of passenger at nighttime increases the crash risk for young drivers. Therefore, it could be argued that young male passengers encourage young drivers to practice risky driving behaviours (Keall et al., 2004).

Beyond passengers, **parents and peers** could affect the driving behaviour of young drivers. Living with both parents has been found to positively reduce the level of risky behaviours among young drivers, and this can be attributed to the ability of parents to control their teens' behaviour (Shope, 2006). Further, Shope stated that young people tend to simulate the way of their parents in driving when their perceptions about driving have been formed from the time they were born. Shope also added that young people are more likely to have fewer crashes and offenses when their parents are not overly permissive and have higher expectation about their young drivers.

Conversely, having peers of risky driving behaviour is associated with driving problems among young drivers (Shope, 2006). Likewise, the expectations and norms of a partner, e.g. girlfriend, boyfriend and spouse could have a significant impact on young drivers' driving behaviour (Shope, 2006).

Other than age and sex of the driver, **nationality** of the driver as native or expatriate could affect the crash involvement rates. Recently, the influence of culture has gained high attention in road safety (Al-Bulushi et al., 2015). The proportion of expatriates has increased significantly in Oman since 1970. They represented 26.5% of the total Oman population in 1993 and 36% in 2009 (De Bel-Air, 2015). As mentioned earlier, the recent data published by NCSI (2016) has shown that about 46% of Oman population are expatriates from different socioeconomic backgrounds. As of mid-2014, 89% of the whole expatriates in Oman are males, have mean age of 33 years, 74% have low level of education (i.e. below secondary school level) and 87% come from the Indian subcontinent: India, Bangladesh and Pakistan (De Bel-Air, 2015). The significant proportion of expatriates could be considered as one of the potential explanations of the high road crash rate in Oman since the differences in cultures, attitudes and habits can lead to road safety-related problems (Ofosu et al., 1988 cited in Abdalla, 2002). Expatriates drivers, especially those coming from countries of very different cultures (e.g. have opposite hand side driving direction, different road infrastructure, traffic regulations, law enforcement and safety measures), are expected to face driving difficulties as they are unfamiliar with the driving system of the country that they move to. Several past studies have concluded that foreign drivers have a higher crash risk compared to domestic drivers (Leviäkangs, 1998; Thomson and Tolmie, 2001; Sivak and Schoettle, 2010). Thomson and Tolmie

(2001) argued that the migrant's country of origin has an effect on crash involvement rate. The authors stated that migrants who come from countries of similar cultures to the UK would adapt quicker to the road environment than those who come from different cultures. Conversely, a study conducted by Michalaki et al. (2015) to explore the factor affecting motorway crash severity in England found that left hand side driving vehicles has lower level of crash severity in hard shoulder roads. The authors attributed that to the caution of foreign drivers when driving in an unfamiliar environment. Besides, the authors claimed that the left hand driving position could give a better visibility of the hard shoulders.

### 2.5.2 Behavioural factors

Driving behaviour is a complex issue influenced by a wide range of factors including driver's age, sex, experience, psychological factors, sociocultural factor, and level of governance and law enforcement (Jafarpour and Rahimi-Movaghar, 2014). While some driving behaviours can be classified as discourteousness such as not complying with parking disciplines, the majority of these behaviours (i.e. the risky driving behaviours) represent potential risk to the driver and other road users (Jafarpour and Rahimi-Movaghar, 2014). Studies have shown that exceeding the sign-posted speed limit of the road is thought to be the most common type of traffic violations and the main cause of traffic crashes in terms of the number and severity of RTCs (Aljanahi et al., 1999; Wong et al., 2005; Aarts and Van Schagen, 2006; Mannering, 2009). Similar evidence was reported in Oman and United Arab Emirates (Abdalla, 2002; Islam and Al-Hadhrami, 2012).

There is no precise definition of what excessive speed means (Wong et al., 2005). The definition of **over-speeding** is correlated with the speed limits, the average speed, the design speed of the road facility (i.e. from engineering perspectives and site characteristics) and drivers' perceptions (Wong et al., 2005; Jafarpour and Rahimi-Movaghar, 2014). Several studies have pointed that drivers tend to exceed the speed limits when they believe that the assigned limits are unreasonable and that exceeding the speed would not put them and other road users at risk (Aljanahi et al., 1999; Wong et al., 2005; Mannering, 2009; Jafarpour and Rahimi-Movaghar, 2014). Mannering (2009) stated that speeding behaviour could be, in part, attributed to how people define speeding. Mannering also claimed that the lack of awareness of the purposes of the assigned speed limits could have an effect on how these speed limits are perceived. The author also pointed to the results of a survey conducted on behalf of Transport Canada (EKOS Research Associates, 2005) of how Canadians define speeding. The survey indicated that Canadians defined speeding in the following three ways:

(1) ***Technical:*** exceeding the posted speed limit by any amount (e.g. 81 km/h in an 80 km/h road). However, a small proportion of the participants articulated this definition.

(2) ***Relative:*** when a driver could safely exceed the speed limit without affecting the crash risk, and the driver has to account for his/ her driving experience, road surface, weather condition, traffic volume, and vehicle type.

(3) ***Absolute:*** when a driver exceeds the posted speed limit by a specific amount (e.g. driving at speed of 120 km/h in a 100 km/h zone). Mannering (2009) stated that drivers who believe in this definition were more likely to associate their belief with limit at which they will receive a speeding fine.

Abdalla (2002) argued that the delay in paying the speed offences in the UAE, and this is also the situation in Oman, may prevents the occurrence of the intended deterrence effect of these fines on stopping the speed violation in the country. Abdalla stated that in order to raise the level of awareness about the surrounding risk of excessive speed among drivers, speed violators should be given the ticket at the time of the offence and impose an immediate economic penalty instead of giving them the chance to pay all the fines once a year.

Several past studies have confirmed that exceeding speed limit has a positive association with the crash risk in terms of number of crashes and severity level, particularly the number of death and severe injuries, regardless of the amount of exceeding posted speed limits and regardless of road type (i.e. main or minor road) (Aarts and Van Schagen, 2006) and characteristics of the geographical areas (i.e. urban or rural areas) (Rock, 1995; Wong et al., 2005). For instance, Aarts and Van Schagen (2006) reviewed a number of empirical studies of the association between driving speed; particularly absolute speed either at individual vehicle level or at road section level, and crash rates. The authors found that the increase of speed on minor roads is associated with a faster increase in the crash rate compared with major roads. Further, Aarts and Van Schagen reviewed other type of studies, which examined the association between speed dispersion and crash rate. The authors concluded that larger differences in speed between vehicles on the same road are associated with a higher crash rate. That is driving with higher speed than other traffic around is associated with higher crash risk, however evidence is inconclusive for a vehicle moving at speed lower than the other traffic around.

Aljanahi et al. (1999) conducted a study to examine the relationship between different measures of traffic speed (i.e. average speed and speed dispersion) in the UK (Tyne and Wear County) and in Bahrain under free flow conditions. The authors found a significant association between average speed and crash rate in Bahrain. However, in the UK this association was not as strong as in Bahrain. They also found stronger association between crash rates and speed variance in Tyne and Wear County.

It has also been proved that driving at high speed implies that the driver has to stop in a shorter time to avoid a crash (Mohan, 2006). For example, it has been proven that a driver speeding at 40 km/h will require 8.5 meters to stop the vehicle, while a driver travelling at 50 km/h will need 13 meters to stop (Mohan, 2006).

The association between the driving speed, speed limits and crash rate is mediated by a number of contributory factors including: types of road facilities, road geometric design, traffic flow, weather, reason for travelling, drivers' characteristics and the volume of vulnerable road users (e.g. such as pedestrian and cyclist) (Aljanahi et al., 1999; Wong et al., 2005; Aarts and Van Schagen, 2006). As an illustrative example, USDOT (1995) cited in Wong et al. (2005) found that local roads were associated with higher fatality rates despite the fact that these roads have the lowest speed limits while these rates were much lower on the interstate highways although they have higher speed limits. This finding was attributed to the high volume of vulnerable road users on the local roads.

Further, it is not always true that higher speed limits lead to a negative impact on road safety but the speed limit in a particular road must be consistent with its traffic and geometric conditions (ECMT 1996 report cited in Wong et al., 2005). For example, the increase of the road speed limit in Greater London in 1960 to 40 mph did not result in higher number of traffic crashes (Wong et al., 2005).

**Overtaking** is a complex driving task and it is more common phenomenon on two lane highways (Chandra and Shukla, 2012). Overtaking has been considered as one of the significant criteria in the analysis of RTCs (Chandra and Shukla, 2012; Vlahogianni, 2013). Overtaking is a dangerous manoeuvre as drivers rarely get the chance to learn and practice this driving skill during their driving lessons (Clarke et al., 1998). Overtaking crashes are more common on single-carriage trunk roads and on roads where greater variability of speeds occurs so that the traffic speed is lower than the design speed and drivers have the tendency to maintain a desired speed while driving (Clarke et al., 1998; Chandra and Shukla, 2012; Vlahogianni, 2013). According to a study conducted by Hills (1980 cited in Clarke et al., 1998), failure in judgement of the oncoming traffic speed is among the possible reasons of why overtaking crashes occur. In addition, Hills (1980) found that even in conditions of reduced visibility due to road geometry, drivers show little or no reduction in speed. Hills argued that the acceptance of risk-taking behaviour in these conditions and other similar conditions is attributed to drivers' expectancy that they will not face obstructions. Therefore, this can explain the occurrence of high number of overtaking crashes in the vicinity of bends, hill-crests and dips in the road. Clarke et al. (1998) studied the differences in manoeuvre as a function of driver age in ten types of overtaking crashes in Nottinghamshire, England. They found that the most common injury-crash for overtaking-driver is collision with a right-turning vehicle, which occurs because of a faulty overtaking decision made by young drivers. In addition, Clarke et al. (1998) found that head-on collision affects all age groups while the 'return-and-lose-control' overtaking crashes are more common among young drivers.

Sugiyama and Nagatani (2013) used the extended optimal velocity model to study the multiple-vehicle collision when a vehicle decelerates suddenly in a single-lane traffic flow. They argued that drivers can cause traffic crash by **driving too close to the vehicle in front** and not taking into account the traffic conditions of the road. They also pointed to the importance of knowing the conditions leading to the occurrence of a crash when the vehicle in front slows down and decelerates suddenly. In order to avoid a collision with a vehicle in front, Sugiyama and Nagatani pointed to the importance of having a sufficient clear distance to the vehicle ahead and that the speed of the vehicle should not be high to be able stop successfully. Likewise, Leibowitz et al. (1998) highlighted the importance of the **Assured Clear Distance Ahead** (ACDA) rule in avoiding collision with any obstacle that could appear in the path of the vehicle. The ACDA rule means that it is the responsibility of the driver to keep the speed of the vehicle low enough to enable him/herself to stop within the range of vision and hence to avoid collision with any obstacle that could appear in the vehicle's path (Leibowitz et al., 1998). A significant proportion of RTCs have been attributed to the behaviour of driving too close to the vehicle in front: 33%, 28% and 13% in Australia, the USA and Europe respectively (Najm et al., 2003; Van Kampen, 2003; Baldock et al., 2005 all cited in Adell et al., 2011).

**Wearing seatbelts** while driving has been proven to be an effective way in reducing the severity of RTCs (Lipovac et al., 2015). A study conducted by Elvik et al. (2004 cited in Lipovac et al., 2015) stated that wearing seat belt by front seat occupants reduce the number of RTC fatalities by 40%. Likewise, Salzberg et al. (2002 cited in Lipovac et al., 2015) found that the proportion of road injuries is reduced by 67% when using seat belt while driving.

Abay et al. (2013) carried out a study using the joint analysis of injury severity of drivers in two-vehicle crashes in Denmark. Their empirical analysis supported the notion that aggressive driving behaviours offset the restraint benefits of seatbelt use. It could be possible that due to the severe outcome of RTCs resulted from aggressive driving behaviour, even though the occupants were using the seatbelt, could devaluate the usefulness of using seat belt while driving. Clarke et al. (2010) conducted a study about fatal RTCs in the UK. They used a sample of 1,185 fatal vehicle occupant cases from ten UK police forces for the period 1994-2005. They found that more than 65% of the crashes involved over-speeding, a driver having alcohol concentration higher than the legal limit, or non-belt wearing, or some combination of these factors. The authors found that drivers who experiencing fatal outcomes were not wearing seatbelt and this was more prevalent when the driver aged below 35 years, though this was the case throughout all age groups of driver. Clarke et al. also claimed that not wearing seatbelt was much more prevalent in the fatal crashes examined than when it observed by the UK Department of Transport for the whole driving population.

**Drink-driving** is a major problem in road safety and it increases the risk of crash involvement and the severity of resulting injuries (Mohan, 2006; Clarke et al., 2010; WHO, 2013). A greater risk of alcohol-related crashes has been found during night and early morning hours, particularly during weekend (Smith et al., 2008; Clarke et al., 2010). Other high-risk driving behaviours are also associated with drinking and driving including speeding and not wearing seatbelt (WHO, 2015). In addition, it has been found that impaired drivers have a tendency to drive towards the centre of the road, have higher variability in their driving speed and changing the road lane, and have higher probability of driving off the road (Smith et al., 2008). According to the 2015 global status report on road safety, 98% (176 countries) of the assessed countries have a national drink-driving law in place, however only 34 countries have drink-driving laws for the general population and for young and novice drivers in line with best practice (i.e. law of a general breath alcohol concentration (BAC) limit of less than or equal to 0.05 g/dl and BAC limit of less than or equal to 0.02 g/dl for young/novice drivers) (WHO, 2015). Further, in some countries (e.g. Morocco) where alcohol consumption is legally prohibited, they still need to have a drink–driving law based on BAC of less than or equal to 0.05 g/dl for non-national (WHO, 2015). Excessive alcohol consumption (i.e. above the legal limit) has been attributed to about 20% of fatalities among drivers in many high-income countries and about 33% to 69% in low-income countries (Mohan, 2006). The risk of being involved in alcohol-related crash varies by the age and experiences of the impaired drivers with teenage drivers found to be significantly having higher probability to die in such crashes compared to older drivers (Mohan, 2006). Further, inexperienced young drivers driving with BAC of 0.05g/dl found to be 2.5 times more likely to be involved in a crash than experienced drivers and this risk is even higher when they have passengers than when driving alone (Peden et al., 2004 cited in Mohan, 2006).

Yet another critical factor associated with RTCs is **sleepiness** (Smith et al., 2008; Ting et al., 2008; Michalaki et al., 2015). Fatigue is the alternative term used to describe sleepiness, although it is more precise to define fatigue as an interaction between sleepiness, duration of driving task and the demands of the road environment (Australian Road Safety research, 2008 cited in Smith et al., 2008). Chronic sleepiness, sleep deprivation, disruption of 24-hours rhythms and drug and alcohol use are also among the factors most commonly associated with driver fatigue (Mohan, 2006; Ting et al., 2008). Fatigue-related crashes found to be more common in the truck industry where some truck drivers have reported that they have fatigue related problems while driving (Häkkänen and Summala, 2001). In addition, high risk of fatigue-related crashes was observed among the following groups: young driver aged 16-29 years, particularly males; shift workers whose sleep is disturbed by night working hours; and drivers who have untreated sleep apnoea syndrome or narcolepa (Mohan, 2006). A significant proportion of fatigue-related crashes has been observed during early morning hours (02:00-06:00) (Mohan, 2006; Ting et al., 2008) and during afternoon (14:00-16:00) and this could be attributed to circadian and homeostatic influence when human activity in the early morning and mid-afternoon significantly reduces alertness (Ting et al., 2008). A number of criteria have been used to define fatigue-related crashes, for example a police observer uses scene decision that fatigue is the primary contributing factor for the crash and when a single vehicle crash happen on a rural, high speed road (Smith et al., 2008). However, it is possible that fatigue-related crashes are underestimated when the reporting system tend to document cases where fatigue is the only contributing factor to the crash after rejecting all other causes (Smith et al., 2008).

Finally, **drivers' perceptual errors** under low lighting conditions (Plainis and Murray, 2001), is a risk factor for turning- and merging-related RTCs (McGwin and Brown 1999). Stamatiadis (1996) found that failure to yield the right way, followed too closely and improper turn are the second, third and fourth types of violations in Kentucky respectively. Stamatiadis also found that failure to yield the right way accounted for almost one-half of elderly driver violations (43.3% for males and 47.5% for females), although these drivers have almost the same proportions of improper turns as middle-aged drivers. The author argued that the high proportion of elderly drivers in turning- and merging-related crashes could be attributed to the misjudgement of the speed of the oncoming head on vehicle or merging angle vehicle along with the failure to estimate the available gap of the vehicle ahead. Likewise, Cooper (1990) and McGwin and Brown (1999) have reported that older drivers have higher risk to be involved in turning- and merging-related crashes (e.g. left turns and left lane change).

### 2.5.3 Social and economic factors

The association between **income** and RTCs and fatalities has been examined in several past studies (e.g. Jacobs and Cutting, 1986; Söderlund and Zwi, 1995; Van Beeck et al., 2000; Kopits and Cropper, 2005; Anbarci et al., 2006; Bishai et al., 2006; Paulozzi et al., 2007; Grimm and Treibich, 2010). Most of these studies have stated that at the very low levels of income, a positive relationship exists between road traffic fatalities per 100,000 inhabitants and income and this could be attributed to the large economic inequalities and poor road infrastructure in low-income countries. However, this relation holds true up to a certain threshold of income level after which countries are expected to be able to invest in road safety measures, such as safer vehicles and more restrictions and enforcement in traffic regulation, so that the traffic crashes and fatalities go down (Grimm and Treibich, 2010). This implies that road traffic fatalities and income have an inverted U-shaped relation (Grimm and Treibich, 2010; Lin, 2016), which has been firstly explored by Van Beeck et al. (2000). Lin (2016) stated that countries vary significantly in their investment in health and road infrastructure and thus vary in their ability to change road cultures. A study conducted by Wintermute (1985 cited in Grimm and Treibich, 2010) demonstrated that a broader set of determinants, e.g. geography, road traffic legislations, urbanisation, cultural factors, development of infrastructure, and availability of medical service, should be taken into account when exploring the relationship between RTC outcomes and income. La Torre et al. (2007) analysed the role of alcohol consumption and employment rate in determining road traffic deaths and they found that both of these variables are statistically correlated and have positive association with RTC fatalities. Traynor (2008) considered population density, the proportion of teenage drivers and the incidence of alcohol abuse in his analysis to examine the relationship between income and traffic fatalities across a number of counties in the U.S. state of Ohio. Traynor found significant associations between the county fatality rate on one hand and its population density, the presence of severe alcohol abuse, the existence of interstate highways in rural counties, and the proportion of teenage drivers and the existence of a large population of college students on the other hand.

Moreover, the level of income has a significant impact in determining **the mode of travel** that people use. As income per capita increases, the number of vehicles increases and this consequently could result in more crashes on the road (Komba, 2007). In Oman, due to the absence of both the railway networks and waterways, roads are the primary mean of travel in the country (Islam and Al-Hadhrami, 2012). In addition, the lack of public transport and the limited presence of intercity public transport (run by a single company called Oman National Transport Company (ONTC)) have contributed to the high proportions of using private cars and private taxi as major modes of travel in Oman (Islam and Al-Hadhrami, 2012). Islam and AL-Hadhrami found that 70% of the registered vehicles in Oman in 2009 were private cars, followed by vehicles for commercial use (21%) and private taxis (4%). The authors stated that during the period 2000-2009 the number of private cars had increased annually by 7% while vehicles of commercial use increased by 2.7%. Further, the authors reported that the rate of owning private vehicle had increased from 126 vehicles per 1000 population in 2000 to 195 vehicles per 1000 population in 2009.

**The type of vehicle** is also an important factor associated with the risk of RTCs. Comparing minivan vehicles, which are more likely to be driven as family vehicles, and pickup trucks with passenger cars, Wenzel and Ross (2005) reported that both minivans and pickup trucks represent higher risk-to-other-road users than cars do. On the other hand, cars represent higher risk-to-driver and this risk is expected to increase as the mass of the car decreases, although reducing the mass of the vehicle is a major goal of new vehicle designers to improve the fuel economy (Wenzel and Ross, 2005).

In terms of **driver behaviour and level of income**, Grimm and Treibich (2010) found that taxi drivers in poor countries have high level of risky driving behaviours. This could be attributed to their tendency to earn the necessary return in short time although most of these drivers are not protected by any insurance so if they are involved in a severe crash they may easily lose their entire physical and human capitals (Grimm and Treibich, 2010).

**Level of urbanisation**[4] has been found to influence the rate of RTCs and their related mortalities (Yang et al., 1997; La Torre et al, 2007). In a study to explore the effect of urbanisation index on RTCs-related mortalities in Taiwan, Yang et al. (1997) found a significant linear relationship between urbanisation level and road traffic fatalities. The authors found that in the most urban municipalities, the standardised mortality ratios (SMRs) attributed to RTCs were significantly lower than expected, however in the two most rural municipalities SMRs were higher than expected. Further, they found that mountainous municipalities have the highest SMRs. Yang et al. attributed this finding to the very small population densities in rural areas accompanied with poorly maintained roads, older vehicles, and inadequate emergency and medical care.

[4] Several demographic and socioeconomic factors can be used to derive the urbanisation index for a certain region and these factors can reflect the degree of urbanisation rather than using the population density alone (Yang et al., 1997).

Similarly, La Torre et al. (2007) found that the higher the employment rate, the higher the road fatality rate; the higher the level of urbanisation, the lower the case-fatality index; and the higher the employment rate and the level of urbanisation, the higher the rate of RTCs.

### 2.5.4 Geospatial, physical environment, and structural factors

The **physical and social environment** on which people drive has a strong impact on their driving behaviours (Shope, 2006; Komba, 2007). This section highlights the effects of the physical environment such as road infrastructure, traffic condition, purpose and length of trip and weather condition on driving behaviours and crash risk.

The effects of **the road infrastructure characteristics**, such as road types, quality of pavement, road segments, lane and shoulder width, junction layout and traffic control devices, have been investigated in several studies (e.g. McGwin and Brown, 1999; Karlaftis and Golias, 2002; Greibe, 2003; Shope, 2006; Komba, 2007; Flores et al., 2009; Aworemi et al., 2010; Michalaki et al., 2015). There is evidence suggesting that improvements to highway design could significantly reduce the number of RTCs (Karlaftis and Golias, 2002). Mohamedshah et al. (1993 cited in Karlaftis and Golias, 2002) conducted a study to predict the annual crash involvement rate per mile for trucks in seven thousand miles of roadway log in Utah using Average Annual Daily Traffic (AADT) and truck AADT per lane, vertical gradient, horizontal curvature and shoulder width as explanatory variables. The study concluded that the truck involvement rate increases with higher degree of curvature and gradient and with higher level of ADDT and truck AADT.

Abdel-Aty and Radwan (2000) found that the likelihood of crash involvement increases with heavy traffic volume, higher speed, larger number of lanes, narrow lane width, narrow shoulder and median widths and on urban roadway sections. In a following study to explore the effects of road geometry and traffic volume on rural roadway crash rates; Karlaftis and Golias (2002) stated that for two-lane rural roads, the importance of lane width increases in heavier traffic conditions, however due to the higher speed, the quality of road pavement seems to be more important in lower traffic flow conditions. On the contrary, the authors reported that for rural multilane roads, access control and median width are the most important factors in higher and lower flows respectively. In contrast, Greibe (2003) conducted a study to predict traffic crash rates for both signalised and non-signalised junctions on urban roads. The results indicated that both signalised and non-signalised junctions have the same safety level and they differ only by type of crashes (signalised junctions have more rear-end crashes but fewer crossing crashes). Caliendo et al. (2007)

conducted a study to develop a crash-prediction model for multilane roads. The authors concluded that the annual number of both total and severe crashes occurring on curves increases with the increase in road length, degree of curvature and level of AADT. Caliendo et al. also found that the number of severe crashes increases with the presence of a junction on a road section and the authors argued that road engineers should give a considerable attention towards junctions.

The risk of nighttime crash has been found to be associated with **visibility and road lighting conditions** (Clarke et al., 2006; Smith et al., 2008). Improvements to road lighting could lead to a reduction in the number of nighttime RTCs, although no difference was observed in the number of nighttime crashes on lit and unlit roads (Smith et al., 2008). Clarke et al. argued that nighttime is not only the time of artificial lighting and poor visibility, but it also differs from morning and afternoon times in that during nighttime different groups of road users are travelling for different purposes. For example, driving for social purposes and for pleasure during nighttime is more common among younger drivers than in other age groups (Stradling and Meadows, 2000 cited in Clarke et al., 2006). In terms of nighttime crashes what is matter is not the visibility, but who uses the roads at night, and why and how they drive (Clarke et al., 2006).

Several studies have investigated the impacts of **weather conditions** on crash risk (Shope, 2006; Komba, 2007; Flores et al., 2009; Aworemi et al., 2010; Michalaki et al., 2015). Most of these studies have stated that prevailing extreme weather conditions, such as heat, rain, high winds, fog, flooding and avalanches, have significant effects on road crashes in various aspects. For example, heavy tropic rainfalls can threaten roadway safety by increasing the crash risk, affecting roadway mobility by causing slippery surfaces and decreasing roadway capacity (Komba, 2007). Rainfall was found to affect drivers in various ways and this effect could be mediated by the characteristics of geographic areas and times of the day (Michalaki et al., 2015). Flores et al. (2009) stated that drivers are more likely to slow down during heavy rainfalls to avoid the occurrence of traffic crashes. However, greater rate of crashes was observed during fair weather as drivers have higher tendency to speed up during such conditions. Further, strong winds can cause a variety of problems for road vehicles depending on the dynamics of the wind, and vehicle type and shape (Edwards, 1994 cited in Michalaki et al., 2015). Strong winds can affect the stability of the vehicles on the road, especially the lightweight vehicles and large trucks (Aworemi et al., 2010).

### 2.5.5 Technology factors

There is no denying that nowadays, **technology** plays a major role in all aspects of our life. Since the last century, technology has made significant changes on transportation system including vehicles, road infrastructure and communication system among different road users.

Technology factors have a significant impact on vehicle's features. The design and mass of the vehicle along with its braking system, lighting system, safety technology such as frontal height, stiffness, air bags, Antilock Braking System (ABS), electronic stability system and back-up sensing system have been found to affect the crash involvement rate and crash severity either positively or negatively (Wenzel and Ross, 2005; Komba, 2007; Aworemi et al., 2010; Lee and Li, 2014). The characteristics of the vehicle can represent risk to its driver and it also imposes risk for the driver of other vehicles and other non-motorised road users (Wenzel and Ross, 2005).

In addition to the technology in the mode of travel, other forms of technology, such as use of **mobile phones**, can be a source of distraction to the driver's attention. According to Ontario Agency for Health Protection and Promotion (2014), **distracted driving** occurs when a diversion in the attention of the driver takes him/her away from the driving task. There are three forms of distracted driving: manual distraction (when the driver takes his/her hands off the wheel); visual distraction (when taking his/her eyes off the road); and cognitive (when taking his/her mind off the road. Further, Ontario Agency added that there are two main sources of distraction: internal which comes from within the vehicle or the mind of the driver, and external which comes from outside the vehicle. For example, using mobile phone for texting while driving can be classified as a manual, visual and cognitive distraction as the driver takes off his/her hands, eyes and mind away from the driving task. It can be also considered as an internal distraction as it comes from within the vehicle. Talking on a phone, typing and reading emails and text messages while driving can have adverse effects on road safety level (Tucker et al., 2015). These behaviours have been reported to be more common among young drivers (Ontario Agency for Health Protection and Promotion, 2014; Tucker et al., 2015) and they increase the likelihood of crash or near crash by 23 times when compared with driving without distraction (Ontario Agency for Health Protection and Promotion, 2014). In addition, eating food, smoking, chatting with other occupants in the vehicle and using CD players while driving can be also considered as internal sources of distraction (Shope, 2006).

**The installation of speed cameras** on the road to prevent road traffic crashes and injuries is another example of technology applications in road safety. Since police cannot be existent on all roads at all times, many countries have used speed cameras as a detection device on their roads (Wilson et al., 2010). Speed cameras take an image of the vehicles passing them at a speed higher than the predetermined trigger speed (Blincoe et al., 2006). From this photographic evidence, the details of the vehicle are read, allowing the owner of the vehicle to be contacted (Blincoe et al., 2006). The aim of using speed cameras is to reduce the driving speeds and enforce the drivers to comply with the posted speed limits. To achieve this goal, drivers who exceed the speed limit are enforced to pay fine or other forms of punishment such as the withdrawal of a driving license or imprisonment (Blincoe et al., 2006). To ensure that drivers must believe that if they exceed the speed limit then they will be caught, the enforcement of complying with speed limits must be sufficient (Wilson et al., 2010).

Past studies have found evidences that using speed cameras can enforce drivers to comply with the road speed limits, which in turn can contribute significantly in reducing the number and severity of RTCs (e.g. Blincoe et al., 2006; Wilson et al., 2010). For example, Wilson et al. (2010) reviewed 35 studies to examine the effects of using speed cameras in preventing road traffic injuries and deaths. The results of this systematic review demonstrated that speed cameras reduce the number of all levels of crash severity. Likewise, Keall et al. (2001 cited in Blincoe et al., 2006) found that when speed camera enforcements integrated with road safety campaigns in Australia and New Zealand, 32% and 14% reduction in personal injury crashes have been reported in urban areas and rural areas respectively. Similarly, an earlier study conducted by Elvik (1997 cited in Blincoe et al., 2006) used a meta-analysis of 10 studies to examine the effect of speed cameras in seven European countries. The results of this study showed a decrease of 19% in road traffic injuries in the studied countries after deploying speed cameras.

Whilst evidences from past studies have suggested that speed cameras may significantly lead to a reduction in RTCs and casualties by enforcing drivers to reduce the speed, it has been found that speed cameras are not affecting all drivers in the same way (Blincoe et al., 2006). To gain better understanding of speed cameras effects, the traffic system must be considered as a social environment, which implies that drivers interact with each other and thus they can influence the behaviour of each other (Haglund and Aberg, 2000 cited in Blincoe et al., 2006). Blincoe et al. argued that the driver beliefs and judgements about other road users is a key factor that needs to be taken into account. They found evidence that most drivers have the tendency to believe that they are more skilful than other drivers on the road and they believe that traffic rules should be only apply to less skilful drivers.

Moreover, an earlier study conducted by Corbett (1995 cited in Corbett and Simon, 1999) concluded that the initial reactions of the drivers towards the installation of speed cameras can be classified into four main categories. The first category is ***conformer*** drivers who reported that cameras make no difference to them since they are normally complied with road speed limits. The second category is the ***deterred*** drivers who reduce their speed when speed cameras are installed on the road. The third category is the ***manipulator*** drivers who only slow down on approach to speed cameras and accelerated after passing them. The last category is the ***deifier*** drivers who do not change their driving speed when passing the speed cameras although they are exceeding the speed limit. Corbett and Simon (1999) further argued that the ideal aim of speed cameras should be to maintain the proportion of conformer drivers, enlarge the proportion of deterred drivers, encourage the manipulators to comply with the speed limit all over the road and to reduce the proportion of deifier drivers. In addition, Corbett and Simon pointed that the knowledge of the fixed-camera sites could lead to more RTCs when deifier drivers join those who slow down before passing the speed camera site and those who accelerate after passing it.

## 2.6 Frameworks for understanding road traffic crash risks, outcomes and interventions

Number of analytical frameworks has been used to identify the risk factors associated with road traffic injuries (Mohan, 2006). This section presents three frameworks that are mostly used in the literature: the public health approach; the Haddon matrix; the C3R3 systems approach, and the safe system approach. Following these, a conceptual framework is developed reflecting on the broader literature review.

### 2.6.1 Public health approach

The public health approach can be considered as a generic analytical framework in the field of public health to respond to many diseases and health-related problems such as road traffic injuries (Mohan, 2006). This approach consists of four interrelated steps (Figure 2.4):

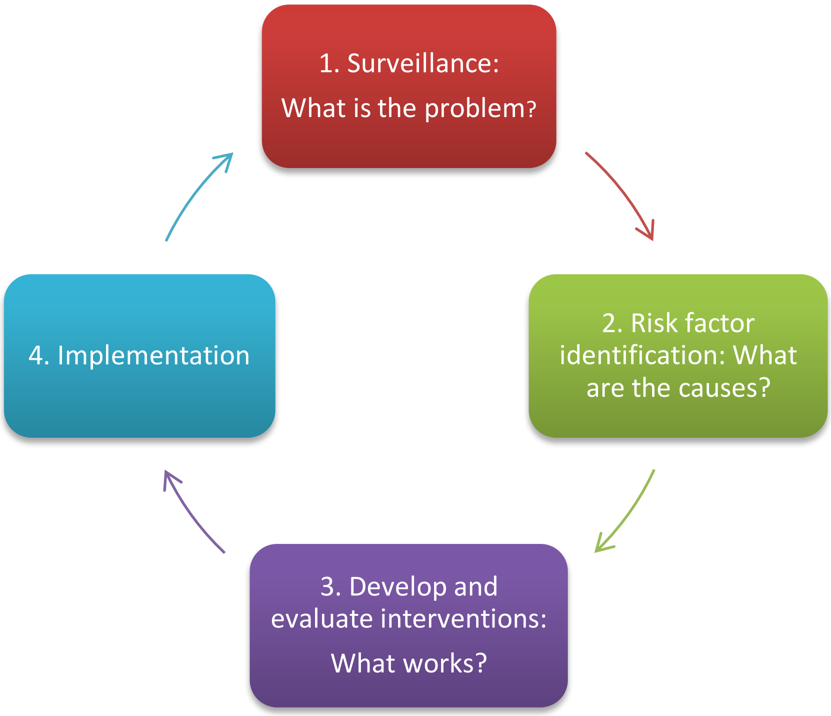



***Figure 2.4*** *The Public Health Approach (Source: Mohan, 2006, P. 23)*

1. The first step involves determining the magnitude, scope and characteristic of the problem. According to this approach, defining the problem does not mean counting the cases only, but it goes beyond that by specifying mortality, morbidity, and risk taking behaviour (Mohan, 2006). In road traffic injuries, this step implies gathering information about the demographic characteristics of the people involved, the geographical and temporal features of the crash, the circumstances under which the crash occurred and the severity and the cost of the outcomes (Mohan, 2006). In general, this step looks at who, where, when, what and how the incidence occurred.

2. The second step looks at why the incident occurred. It identifies the factors which increase the risk of the incidence so that the potential modifiable factors can be determined (Mohan, 2006). This step could also be useful in defining population at high risk for road injuries and hence to suggest some interventions (Mohan, 2006).

3. The third step aims at developing countermeasures and interventions to prevent the problem based upon the information obtained from the first two steps. For example, to reduce RTCs involving children going to schools, the following interventions could be useful:

    a. Specify safer routs to schools;

b. Reduce the road speed limits next to schools;

c. Reducing the traffic volume next to schools and reducing the speed limits at schools' opening and closing times;

After developing the possible interventions, then these and other extant interventions are tested and evaluated to examining their impact on health outcomes (Mohan, 2006).

4. The fourth and final step is to implement the most effective interventions. These interventions should be effective on the broad scale when they target the broader population. Besides, the cost-effectiveness of such interventions should be determined as this could be helpful to policy-makers in determining the optimal intervention (Mohan, 2006).

### 2.6.2 Haddon matrix

This matrix has been developed by Dr. William Haddon to identify the risk factors for each of the three phases of traffic crash: the pre-crash; the crash; and the post-crash stage (Zein and Navin, 2003; Mohan, 2006). These three phases represent the temporal sequences of the crash (Zein and Navin, 2003). Each phase can be analysed through the three components of the traffic system: human; vehicle; and road and other environmental factors (Zein and Navin, 2003; Mohan, 2006). The combinations of these factors together produce what is called "Haddon matrix" (Table 2.1). The three elements of the temporal sequences represent the rows of the matrix and the three elements of the traffic system represent the columns so that the matrix will end-up with nine cells (Zein and Navin, 2003). Once the interrelated factors associated with a crash are specified, a range of potential risk factors can be identified, and interventions and countermeasures can be developed and implemented over both short- and long-time periods (Runyan, 2003; Mohan, 2006). In the pre-crash phase, countermeasures should aim at preventing the crash from occurring. Countermeasures for the crash phase should aim at preventing injury from occurring and reducing the level of severity if an injury does occur. Countermeasures for the last phase (i.e. post-crash phase) should aim at reducing the adverse outcome of the crash once it occurred (Mohan, 2006). Although this matrix has had widespread applications and used as a brainstorming tool in identifying road safety problems and led to many successful safety interventions, however, there are limitations associated to this model (Runyan and Yonas, 2008; Thomas et al., 2013). It does not facilitate the interaction between the three elements of traffic system, nor it incorporates the effect of exposure to crash risk such as distance travelled and level of traffic volume (Thomas et al., 2013).

***Table 2.1*** *The Haddon matrix*
*(Source: Mohan, 2006, P. 24)*

| **Phase** | | **Factors** | | |
|---|---|---|---|---|
| | | **Human** | **Vehicle and equipment** | **Road environment** |
| **Pre-crash** | Crash prevention | Information<br>Attitudes<br>Impairment<br>Police enforcement | Roadworthiness<br>Lighting<br>Braking Handling<br>Speed management | Road design and road layout<br>Speed limits<br>Pedestrian facilities |
| **Crash** | Injury prevention during the crash | Use of restraints<br>Impairment | Occupant restraints<br>Other safety devices<br>Crash protective design | Crash-protective roadside objects |
| **Post-crash** | Life sustaining | First-aid skill<br>Access to medics | Ease of access<br>Fire risk | Rescue facilities<br>Congestion |

### 2.6.3 The C3-R3 Systems Approach

The C3-R3 systems approach has been developed by Zein and Navin in 2003 and it has been considered as an elaboration of the Haddon matrix (Hermans, 2009). The C3-R3 approach could be best defined as "***the study of the temporal and spatial inter-relationship between a diverse set of elements that influence road user, vehicle, and road environment performance***" (Zein and Navin, 2003, P.7).

The fundamental blocks of this approach (Figure 2.5) are:

- The Entities: (the road users, the vehicle and the road environment).
- The Timeline Phases: (the pre-crash timeline phases and the post-crash timeline phases).

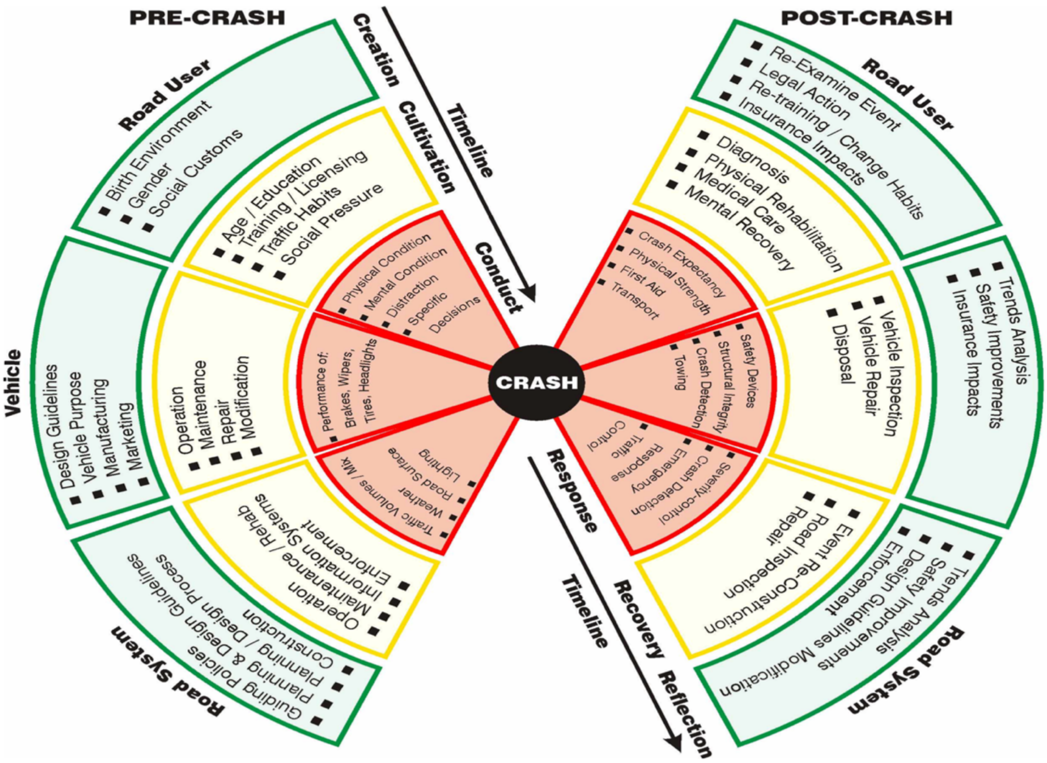



***Figure 2.5*** *The C3-R3 Systems Approach.*
*(Source: Zein and Navin, 2003, P. 22)*

According to Zein and Navin (2003), the pre-crash timeline consists of three phases (the three “Cs”): creation, cultivation and conduct phases. The creation phase starts when an entity is born so that its initial characteristics are formed. The cultivation phase represents the development and the maturity stage of the entity so that its operational characteristics are set. The conduct phase represents the actions and the condition of the entity immediately before the occurrence of the crash.

The post-crash timeline consists of three “Rs” phases: response, recovery and reflection. The response phase represents the immediate response action of the entity to the crash once it occurred. The recovery phase represents the action taken by the entity to recover the pre-crash form. The reflection phase represents the reflection of the entity on the events of the crash in order to prevent the reoccurrence of the crash in the future.

Each cell in the C3-R3 systems approach is a combination of entity and timeline phase and it represents the individual elements need to be understood by the traffic safety professionals in an attempt to reduce the crash risk (see Figure 2.5). This approach focuses mainly on the interrelationship between the components of the transport system and the timeline of crash stages, so that effective road safety countermeasures can be identified by linking all these elements of transport system (Hermans, Brijs, and Wets, 2008). For example, the elements in the pre-crash C3 phases aim at reducing the number of RTCs, while the elements in the post-crash R3 phases aim at reducing the severity of the crash.

### 2.6.4 The Safe system approach

The introduction of a safe system project in any country is the first step towards achieving sustainable long-term progress in road safety (Bliss and Breen, 2009). The Safe system approach is considered as a "paradigm shift" in road safety approach (Mooren et al., 2011). The concept of safe system approach has derived from the vision zero (i.e. zero fatality and zero severe injuries) and sustainable safety concepts which were introduced in the mid 1990s (Bliss and Breen, 2009; Mooren et al., 2011). The aim of this approach is to ensure that the road safety efforts of the country are systematic, measurable and accountable to achieve rapid progress in safety performance for all road users (Bliss and Breen, 2009). It aims at eliminating road deaths and severe injuries so that these injuries and fatalities should not be considered as inevitable price of mobility and economic development (Bliss and Breen, 2009; Mooren et al., 2011). It also aims at making the road traffic transport system to be inherently safe for all road users (Mooren et al., 2011).

The key principle of the safe system approach is giving a greater responsibility for road system managers and designers to build safe transport system that tolerates human errors and prevents injury-causing crashes instead of only considering road users being responsible for their behaviour on the road (Mooren et al., 2011). The safe system approach is derived from the vision zero principles, so that the managers and designers of roads and vehicles have the responsibility to design, produce and manage the road infrastructure and vehicles and put in place the rules and guidance for safe system use while tolerating and correcting human errors to reduce harm consequences of these errors (Mooren et al., 2011). The priority of the safe system approach is affording protection to all road users, particularly pedestrians, young and old people, cyclists and motorcyclists who are considered as the most vulnerable at-risk groups (Bliss and Breen, 2009). At the same time, the community should be educated about the actual injury risks standing in the current road infrastructure and should be consulted in what is needed to be done in short and long terms make the transport system safe for all users (Mooren et al., 2011).

Reducing the road travel speeds has been considered as the practical start to adopt with a Vision Zero in road safety. The philosophy of Vision Zero aims at preventing serious harm to the health of all road users, and reducing the speed limit is one of the alternatives to reduce the serious harm if no fund is available for engineering interventions (Mooren et al., 2011). However, one of the biggest challenges in reducing the speed limit is receiving the public support to convince them that this is a demand for safer travel so that all stakeholders, agencies and road users should share the responsibility of road safety (Mooren et al., 2011).

There has also been a growing debate that the investment in long-term safe system goal of preventing deaths and serious injuries will be cheaper than making gradual safety improvements or just investing in crash prevention approaches (Bliss and Breen, 2012). Investments in governance and institutions, infrastructure, vehicle fleets and other health related investments are required to achieve the optimal results of the safe system approach in low- and middle-income countries (Bliss and Breen, 2012). There is a growing concern that integrating road safety investments with a range of sectors and other sustainable development goals is one of the most effective ways to improve the road safety performance of any country (Bliss and Breen, 2012). Aligning road safety priorities with other high priority sustainable development projects from different sectors especially those related to planning for urban areas and environmental policies aimed is important to capture the interrelated co-benefits of integrated initiatives (Bliss and Breen, 2012). For example, there is a growing recognition that managing unsafe speed is associated with creating livable cities as this will result in less local air pollution and this explains the co-benefits of road safety and environmental policies aimed (Bliss and Breen, 2012).

The road safety management system consists of the following three interrelated elements: institutional management functions, designing interventions, and results (Figure) (Bliss and Breen, 2012). Therefore, to improve the country road safety performance, close attention must be given to all these three elements (Bliss and Breen, 2012). At the base of the pyramid are the institutional management functions which are delivered by the government road safety agencies and also by integrating with other other sectors including the private sector and civil society (Bliss and Breen, 2012). The pivotal and primary function of all institutional functions is to achieve the desired focus on results so that all other functions should contribute towards achieving this goal (Bliss and Breen, 2012).

Since the issues involved in road safety represent the core of government decision-making, the presence of governmental lead agency is vital to manage the efforts of road safety in the country (Bliss and Breen, 2012). This governmental agency should have the power to make road safety related decisions, control human and financial resources, and coordinate the efforts of all participating agencies (e.g. governmental and private sector agencies, and civil society) to achieve the ambitious goals of road safety in the country (Bliss and Breen, 2012). Reviews of road safety management capacity indicated that with the absence of governmental lead agency, all the action plans remain as 'paper' plans leading to no sustainable improvement in road safety performance in the country (Bliss and Breen, 2012). For example, the successful achievement of Sweden in road safety indicated that the strong presence of governmental agency is crucial for the successful engagement of private agencies and civil society in road safety actions (Bliss and Breen, 2012). Therefore, any initiatives designed to improve the road safety performance in the country should be managed by the lead agency and consulted by road safety specialists to strengthen the national leadership (Bliss and Breen, 2012). Using crash data to evaluate and gain a good understanding of the key factors causing the most harmful of all types of road crashes is one of the key inputs of the safe system approach (Mooren et al., 2011), and this emphasises the need for building solid and accurate database to record road traffic crashes.

The safe system initiatives and interventions are multisectoral targeting high-risk areas and the outcomes of these initiatives are reliably measurable (Bliss and Breen, 2009). Road safety interventions should account for the limitations in human capacities in setting the rules and standards of planning, designing, and operating and using the road network; the entry and exit of road users and vehicles to the road network; and the recovery and rehabilitation of RTC victims from the road network (Bliss and Breen, 2012). The measurement and evaluation of the desired results and expressing them as final outcomes, intermediate outcomes, and output is the final step of the road safety management system. The quality of the institutional management functions determines the quality of the delivered interventions which in turn determines the level of road safety in the country.

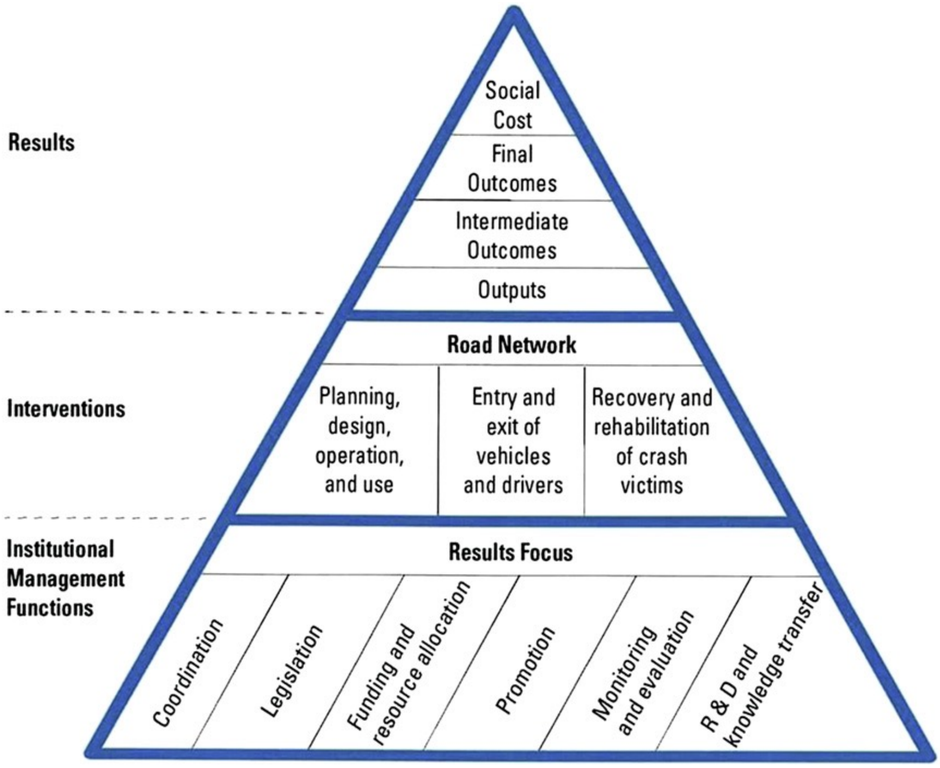



***Figure 2.6*** *The* road safety management system
(Source: Bliss and Breen, 2012, P. 51)

### 2.6.5 Summarising the literature review: A conceptual framework

This part presents the conceptual framework that the author of this thesis has come out with after reviewing the literature and the previous frameworks used in road traffic studies. As it is clear from Figure 2.6, road traffic crash is a global term that covers a multiplicity of factors found in a given circumstance, and these factors interact with each other leading to the occurrence of an individual road crash (Al-Rawas, 1993). The primary factors contributing to the occurrence of road traffic crash generally fall into three main categories: the behaviour of road user, vehicle and road environment. In most circumstances, two or more of these factors interact with each other leading to the occurrence of a RTC. For example, the behaviour of the driver could be influenced by some of the road characteristics (e.g. road speed limits, road design) or vehicle features (e.g. sport cars), and similarly, the quality of the road and driver behaviours have an impact on the vehicle performance. However, the occurrence of a RTC cannot be only attributed to these three factors without considering the effects of other factors such as traffic policy, socio-cultural factors, technological factors and economic and life style factors.

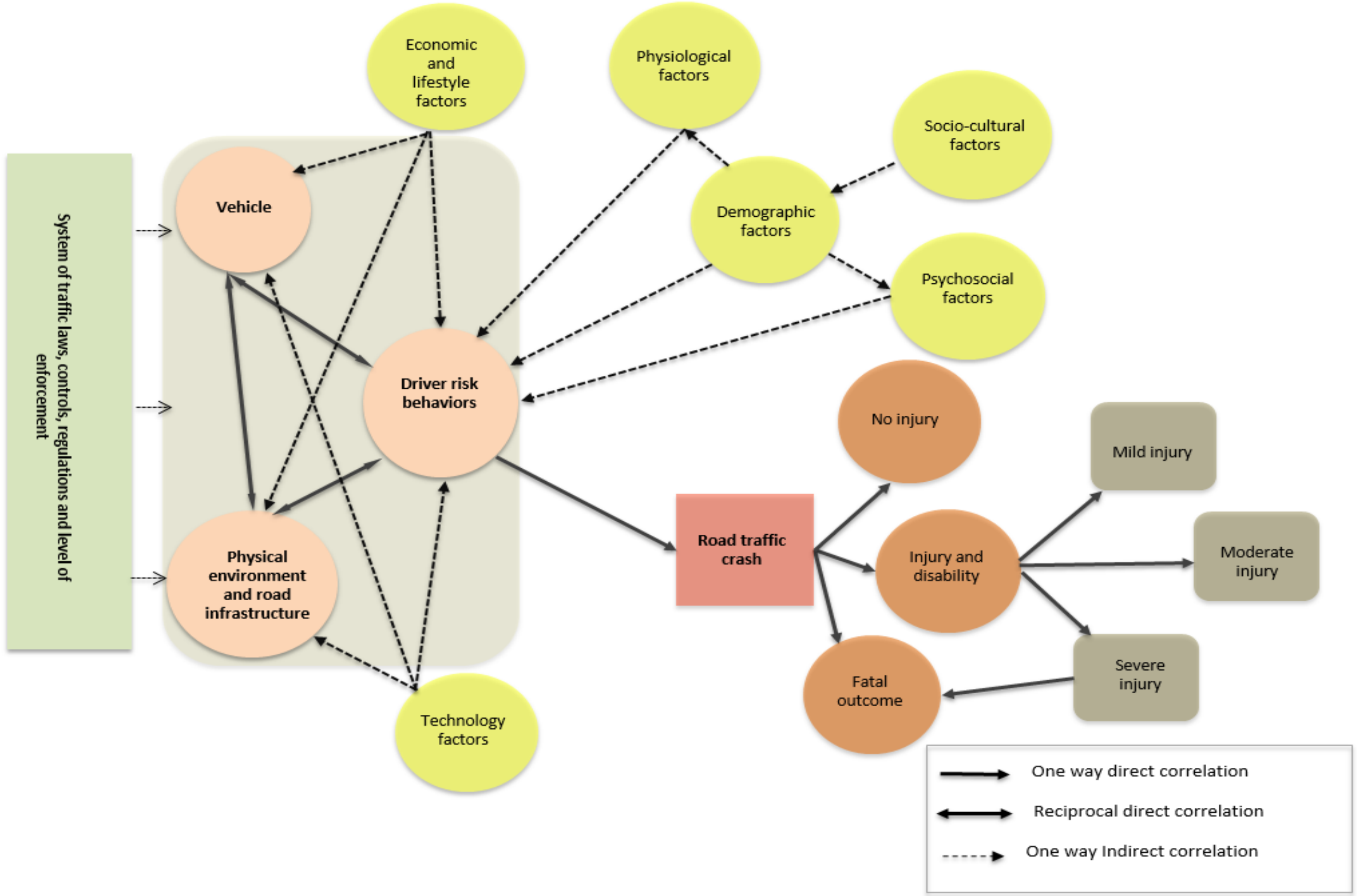
From the left hand-side, the first box indicates that road safety policies, regulations, interventions and level of enforcement have an influence on the road infrastructure, vehicle characteristics and driver behaviours. For example, the inclusion of road safety education within curriculum at schools could improve the road crossing and driving behaviours among children and young drivers.

Similarly, economic and life style factors such as level of income, employment rate and urbanisation have an impact on determining the mode of travel people use and the characteristics of road infrastructure. For instance, in Oman, the economic growth has resulted in rapid urbanisation, improvement in road infrastructure and a steady increase in number of registered motor vehicles in the country. Besides, economic and lifestyle factors have a significant impact on driver behaviours. Likewise, technology factors such mobile phones and music system inside the vehicle could be considered as a source of distraction for the drivers and other road users. These factors could take the attention of the driver away from the driving task and this consequently could lead to risky behaviours such as over-speeding and reckless driving.

The psychosocial factors such as thoughts, feelings, and other cognitive characteristics affect the attitudes towards the driving behaviours, particularly among young drivers. Likewise, the physiological factors influence the driving behaviour especially for those aged below 25 years as the prefrontal cortex of their brains is still at its development stage (Shope, 2006), so this could affect the decisions that young drivers make when they face unexpected circumstances while driving. Besides, the physiological, circadian and sleep systems change at different stages of age suggesting that there is a linear relationship between chronological age and fatigue related crashes (Di Milia et al., 2011).

The perceptions of young drivers about driving risk could be also influenced by the culture of the community in which they live (Shope, 2006). From their community, young drivers can learn the risk of driving, the likelihood of being involved in a crash, the likelihood of someone to be injured or killed, and how a driver could be fined or jailed for a specific driving violation (Shope, 2006). The driving culture in Oman put men at higher risk of road traffic crash; men are more likely to be the breadwinner for their families. Therefore, they are more likely to spend longer hours at work and on the road causing drivers exhaustion.

In general, it is clear that road traffic crash is an outcome of the interaction of a multiplicity of factors although some factors may not appear directly associated with the occurrence of road traffic crashes (Mohan, 2006).




| Demographic factors: | Socio-cultural factors: | Psychosocial factors: | Physiological factors: | Economic and lifestyle factors: | Technology factors: | Physical environment and road infrastructure: |
|---|---|---|---|---|---|---|
| Age, sex, nationality | Religious beliefs, customs, values, traditions | Thoughts, feelings and other cognitive characteristics that affect the attitudes | Body growth and sex hormones, sleep and wakefulness | Income, employment, urbanisation | Mobile phones, Speed cameras, Music system, GPS systems | Weather condition, road design, speed limit, traffic lights |

***Figure 2.7*** *The conceptual framework of road traffic crashes*

## 2.7 Road safety legislation: Policy and interventional programmes

Road safety legislation is a critical factor in road safety. It is a dynamic field that needs to be reviewed and updated over time even in high performing countries (WHO, 2015). Road traffic laws are set to improve the behaviour of road users in order to reduce the number of RTCs and their related deaths and injuries (WHO, 2015). According to the 2015 global status report on road safety, the reduction in road traffic injuries has been seen in countries where effective road safety programmes with legislative change have been used. The report also pointed that the highest percentage of the positive changes in the behaviour of road users occurs when road safety legislation is accompanied with high level of enforcement and when the traffic law is known and accepted by the public. However, Buttler (2016) stated that the public knowledge of the traffic laws is not sufficient for law compliance. The author argued that in order to get road users obeying the traffic rules, sanction mechanism should be defined and implemented. Buttler added that the greater effect of sanction mechanism is achieved when that sanction is well matched with the norms, values and the sense of justice held by the public.

According to the 2015 global status report on road safety, introducing legislation to meet the five key behavioural risk factors for road injuries: speed, drink-driving, using motorcycle helmets, seat-belts and child restraints has a strong impact on reducing road traffic crashes, injuries and deaths. The following paragraphs and ***Table 2.2*** highlight the main findings from the 2015 global status report on road safety with regard to the progress made in traffic legislation that meet the key behavioural risk factors in the countries covered in the global status report

- **Reducing Speed:**

Most countries set national speed limits, however, only few countries set laws of speed limits for motorways, and urban and rural roads. Only 97 countries out of the 180 countries have set maximum urban speed limits of less than or equal to 50 km/h. In terms of the enforcement level, the report stated that only 27 countries have a good enforcement level (80% or above) of speed laws, interestingly Oman, Qatar, Saudi Arabia and United Arab Emirates (UAE) are among the counties which meet this level of enforcement (Table 2.2). Additionally, only 47 countries set speed law that meet both the maximum urban speed limits of 50 km/h and have a local authority power to reduce this limit for safety reasons. Out of these 47 countries, 24 are high-income countries, and in the GCC countries, Kuwait is the only one where this law is met (Table 2.2).

- **Drink-driving:**

Drink-driving is found to be associated with other high-risk driving behaviours such as over-speeding and not wearing seatbelt (WHO, 2015). Drink-driving legislation plays a major role in reducing alcohol-related crashes when accompanied with visible and strong enforcement (WHO, 2015). According to the 2015 global status report on road safety, 98% (176 countries) of the participating countries have a national drink-driving law and only 74% (134 countries) have set the law based on BAC limits. Additionally, in terms of the maximum BAC limit, only 47% (84 countries) set this limit to be less than or equal to 0.05 g/dl (i.e. best practice) for the general population. Such laws are more prevalent in high-income countries (73%) than in low- and middle- income countries (13% and 43% respectively). The report has also argued that even in countries where alcohol is prohibited, it is recommended to set a drink-driving law based on BAC with limits of less than or equal 0.05 g/dl.

Additionally, due to the increased risk of RTCs among young and novice drivers when they drive under the influence of alcohol, many countries have implemented lower BAC limits (≤0.02 g/dl) for this high-risk group of drivers. Such law is enforced in 19% (35 countries) out of all the countries covered in the global road safety report. Taken together drink-driving laws for the general population and for young and novice drivers, only 34 countries have implemented both laws of which 21 countries are European countries. Referring to Table 2.2, it is clear that among the GCC countries, UAE is the only one where the national drink-driving law is applied for the general population and for young and novice drivers (both of BAC limits ≤0.05 g/dl) although alcohol consumption is prohibited in all of the GCC countries.

- **Motorcycle helmets:**

According to the 2015 road safety report, 94% (169 countries) set a national law of using helmets among motorcyclist, and only 84% (151 countries) have set this law for all occupants of the motorcycles and for all road and engine types. Besides, only 41% (74 countries) of the countries require the helmet to be correctly fastened in order to comply with the law. Taken all these laws together, only 39% (70 countries) set a national helmet law applied for all drivers and passengers, all types of roads and engines, and stated that helmets need to be correctly fastened. It is clear from Table 2.2 that all GCC countries have a national helmet law applied for all drivers and passengers, however it is not clear whether this law is applied for all road types and all engine types. The proper wear of the helmet is only applied in Saudi Arabia.

Furthermore, the United Nation (UN) has set a high quality international helmet standard (UN ECE regulation 22 cited in WHO, 2015) because the effectiveness of helmet laws in reducing injuries highly correlated with the quality of the helmet (WHO, 2015). The 2015 road safety report stated that only 24% (44 countries) have helmet laws applied to occupants of the vehicle, all types of road and engines, stated that helmets need to be properly fastened, and have particular helmet standards. Most of these countries are high-income European countries. It is clear from Table 2.2 that none of the GCC countries have a particular helmet standard.

- **Seat-belt and child restraint laws:**

With regard to seat-belt laws, although all GCC countries have a national seat belt law, however, only Oman and Saudi Arabia set the law for both front and rear seats occupants. However, the enforcement of using the seat belt for the rear seat passengers in Oman is questionable. Furthermore, Bahrain, Oman and Saudi Arabia have national child restraint laws in the GCC region, although the enforcement of this law in such countries is debatable. Additionally, all the GCC countries except Oman have restrictions on children sitting in front seats.

Listed below are the articles of selected traffic rules in Oman, which are relevant to the current study. These articles are issued by the Royal Decree 28/93 and published by the legal Affairs Department at the ROP.

**Article 35: "**It shall be prohibited to drive a vehicle on the road without care or drive it at a high speed or under the influence of alcohol or drugs or in a manner which form a risk or expose the life of others or their properties to the hazards. The driving license shall be withdrawn in case of the violation of the rule of the previous paragraph without prejudice to the imposed penalty" (ROP, 2005, P.20).

**Article 38: "**If the driver of the vehicle commits an accident, which results in injuries or damages to the public or private properties he shall stop and report the accident to the nearest police station or ambulance immediately. It shall be prohibited for any person or workshop to repair any vehicle exposed to a traffic accident without obtaining a permit from the Directorate or the police station or the authorities determined by a decision from the Inspector General according to the control measures indicated by the Executive Regulations" (ROP, 2005, P.21).

**Article 39: "**The owner of the vehicle or the person under whose name the vehicle is licensed or the holder or the person who is in charge of it shall be fully responsible of any violations to the rules of this law or its Executive Regulations and decisions unless it is proved that the driver of the vehicle at the time of the accident is somebody else, and he shall be obliged to provide the necessary information which lead to his identification" (ROP, 2005, P. 21).

**Article 41:** "The owner of the motor vehicle shall not assign the driving of the vehicle to somebody else who does not hold the necessary license, which entitles him to drive such type of vehicles" (ROP, 2005, P. 22).

**Article 42:** "The police may request the name and address of the person who is driving the vehicle during the commitment of the violation from the owner of the vehicle and if he refused or deliberately intended to give incorrect information he shall be subject to the same penalty stipulated in this law to the driver of the vehicle who commits the violation without prejudice to any other penalties stipulated by other laws" (ROP, 2005, P. 22).

**Article 96: "**The vehicles driver shall keep enough distance between himself and the vehicle in front of him and shall pay attention to its traffic signals given by its driver and he shall not use the brakes suddenly and without reason" (ROP, 2005, P. 64).

**Article 130:**

1. "The driver of a vehicle may be apprehended in anyone of following cases:

(a) Driving the vehicle under the influence of alcohol or drugs or any other mentally affecting substances.

(b) Causing a traffic accident which result in fatality or serious injuries or considerable damages to the properties of the others.

(c) Failure to report to the police any accident he commits or fleeing from the site of the accident or the police station.

(d) Driving the vehicle with high speed and rashness, which constitute a hazard to the road users.

(e) Driving the vehicle without obtaining a driving license or refusal to present it to the policemen on request.

(f) Passing the red light signal.

(g) Exceeding the maximum speed limit by more than 75 km per hour.

(h) Arrangement of races on the road without obtaining a permit in advance." (ROP, 2005, P. 87-88).

**Table 2.2** *Traffic legislation to meet the key behavioural risk factors for road injuries in GCC countries and other selected high-, middle- and low-income countries according to the 2015 global status report on road safety*

| Country | Speed Laws | | | | | | Drink Law | | | | National drug-driving law | Law on mobile phone use while driving | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | National Speed limit law | Max urban speed limit | Max rural speed limit | Max motorway speed limit | Local authorities can modify limits | Enforcement | National Drink Law | BAC limit (general population) | BAC limit – young or novice drivers | Random breath testing carried out | | National Law on mobile phone | Law prohibits hand-held | Law also applies to hands-free phones |
| **GCC Countries** | | | | | | | | | | | | | | |
| Bahrain | Yes | 60 km/h | 100 km/h | No | No | 70% | Yes | - | - | No | Yes | Yes | Yes | No |
| Kuwait | Yes | 45 km/h | 80 km/h | 80 km/h | No | 50% | Yes | - | - | No | Yes | Yes | Yes | No |
| Oman | Yes | - | - | No | No | 90% | Yes | - | - | Yes | Yes | Yes | Yes | No |
| Qatar | Yes | 100 km/h | 120 km/h | 120 km/h | No | 80% | Yes | - | - | No | Yes | Yes | Yes | No |
| Saudi Arabia | Yes | 80 km/h | 120 km/h | No | Yes | 80% | Yes | - | - | No | Yes | Yes | Yes | No |
| United Arab Emirates | Yes | 90 km/h | 120 km/h | 120 km/h | Yes | 100% | Yes | ≤ 0.01 g/dl | ≤ 0.01 g/dl | Yes | Yes | Yes | Yes | No |
| **High-Income Countries** | | | | | | | | | | | | | | |
| Australia | Yes | 50 km/h | 100–130 km/h | 100–130 km/h | Yes | 80% | Yes | 0.049 g/dl | 0.00 g/dl | Yes | Yes | Yes | Yes | No |
| Canada | Yes | 50 km/h | 50-110 km/h | 80-110 km/h | Yes | 60% | Yes | 0.04–0.08 g/dl | 0.00– 0.08 g/dl | Yes | Yes | Yes | Yes | No |
| France | Yes | 50 km/h | 90 km/h | 130 km/h | Yes | 90% | Yes | < 0.05 g/dl | < 0.05 g/dl | Yes | Yes | Yes | Yes | No |
| Japan | Yes | 60 km/h | 60 km/h | 100 km/h | Yes | 70% | Yes | ≤ 0.03 g/dl | ≤ 0.03 g/dl | Yes | Yes | Yes | Yes | No |
| New Zealand | Yes | 50 km/h | 100 km/h | 100 km/h | Yes | 80% | Yes | ≤ 0.05 g/dl | 0.00 g/dl | Yes | Yes | Yes | Yes | No |
| Norway | Yes | 50 km/h | 80 km/h | 100 km/h | Yes | 80% | Yes | < 0.02 g/dl | < 0.02 g/dl | Yes | Yes | Yes | Yes | No |
| Singapore | Yes | 70 km/h | No | 90 km/h | No | 80% | Yes | ≤ 0.08 g/dl | ≤ 0.08 g/dl | Yes | Yes | Yes | Yes | No |
| UK | Yes | 48 km/h | 96 km/h | 112 km/h | Yes | - | Yes | ≤ 0.08 g/dl | ≤ 0.08 g/dl | Yes | Yes | Yes | Yes | No |
| **Middle-Income Countries** | | | | | | | | | | | | | | |
| Brazil | Yes | 80 km/h | 60 km/h | 110 km/h | Yes | 70% | Yes | 0.00 g/dl | 0.00 g/dl | Yes | Yes | Yes | Yes | No |
| India | Yes | No | No | No | Yes | 30% | Yes | ≤ 0.03 g/dl | ≤ 0.03 g/dl | Yes | Yes | Yes | Yes | Yes |
| Lebanon | Yes | 50 km/h | 70 km/h | 100 km/h | Yes | 50% | Yes | ≤ 0.05 g/dl | 0.00 g/dl | Yes | Yes | Yes | Yes | Yes |
| South Africa | Yes | 60 km/h | 100 km/h | 120 km/h | Yes | 30% | Yes | < 0.05 g/dl | < 0.05 g/dl | Yes | Yes | Yes | Yes | No |
| Turkey | Yes | 50 km/h | 110 km/h | 120 km/h | No | 40% | Yes | ≤ 0.05 g/dl | ≤ 0.05 g/dl | Yes | Yes | Yes | Yes | Yes |
| **Low-Income Countries** | | | | | | | | | | | | | | |
| Bangladesh | Yes | No | 112 km/h | No | No | 30% | Yes | - | - | No | Yes | No | - | - |
| Cambodia | Yes | 40 km/h | 90km/h | 100 km/h | No | 40% | Yes | ≤ 0.05 g/dl | ≤ 0.05 g/dl | Yes | Yes | Yes | Yes | No |
| Kenya | Yes | 50 km/h | 100 km/h | 110 km/h | Yes | 60% | Yes | ≤ 0.08 g/dl | ≤ 0.08 g/dl | Yes | Yes | No | - | - |
| Uganda | Yes | 50 km/h | 100 km/h | No | No | 50% | Yes | ≤ 0.08 g/dl | ≤ 0.08 g/dl | Yes | Yes | Yes | Yes | No |

***Table 2.2*** *Traffic legislation to meet the key behavioural risk factors for road injuries in GCC countries and other selected high-, middle- and low-income countries according to the 2015 global status report on road safety. Contd.*

| *Country* | *Seat-belt Law* | | | | *Child restraint Law* | | | | | *Motorcycle helmet law* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *National seat-belt law* | *Applies to front and rear seat occupants* | *Enforce-ment* | *Seat-belt wearing rate* | *National Child restraint Law* | *Restrictions on children sitting in front seat* | *Child restraint law based on* | *Enforce-ment* | *% children using child restraints* | *Applies to drivers and passengers* | *Law requires helmet to be fastened* | *Law refers to helmet standard* | *Enforce-ment* |
| ***GCC Countries*** | | | | | | | | | | | | | |
| *Bahrain* | Yes | No | 70% | 20% Drivers | Yes | Yes | - | 0% | - | Yes | No | No | 90% |
| *Kuwait* | Yes | No | 30% | - | No | Yes | - | - | - | Yes | No | No | 70% |
| *Oman* | Yes | Yes | 90% | 97% Drivers | Yes | No | Age | 50% | - | Yes | No | No | 100% |
| *Qatar* | Yes | No | 70% | - | No | Yes | - | - | - | Yes | No | No | 80% |
| *Saudi Arabia* | Yes | Yes | 50% | - | Yes | Yes | - | 20% | - | Yes | Yes | No | 30% |
| *United Arab Emirates* | Yes | No | 100% | - | No | Yes | - | - | - | No | No | No | 100% |
| ***High-Income Countries*** | | | | | | | | | | | | | |
| *Australia* | Yes | Yes | 70% | 97% front seats, 96% Rear seats | Yes | Yes | Age | 60% | - | Yes | Yes | Yes | 80% |
| *Canada* | Yes | Yes | 80% | 96% front seat, 89% rear seat | Yes | No | Age/weight | 80% | 77% | Yes | Yes | Yes | 100% |
| *France* | Yes | Yes | 90% | 99% front seats, 87% rear seats | Yes | Yes | Weight/ height | 80% | - | Yes | Yes | Yes | 90% |
| *Japan* | Yes | Yes | 80% | 98% Front seats, 68% rear seats | Yes | Yes | No | Age | 80% | Yes | Yes | Yes | 90% |
| *New Zealand* | Yes | Yes | 90% | 96% Front seats, 90% Rear seats | Yes | Yes | Age | 90% | 92-96% | Yes | Yes | Yes | 90% |
| *Norway* | Yes | Yes | 80% | 96-97% Drivers, 94-96% Front seats | Yes | Yes | Age/Height | 60% | - | Yes | No | No | 100% |
| *Singapore* | Yes | Yes | 80% | - | Yes | No | Weight/ Height | 80% | - | Yes | Yes | Yes | 90% |
| *UK* | Yes | Yes | - | 95-98% Front seats, 88-95% Rear seats | Yes | Yes | Age/Height | - | - | Yes | Yes | Yes | - |
| ***Middle-Income Countries*** | | | | | | | | | | | | | |
| *Brazil* | Yes | Yes | 70% | 73% front seats, 37% Rear seats | Yes | Yes | Age | 60% | 57% | Yes | Yes | Yes | 60% |
| *India* | Yes | Yes | 40% | 26% Driver, 26% front seats | No | No | - | - | - | Yes | No | Yes | 40% |
| *Lebanon* | Yes | Yes | 30% | 14% Drivers | Yes | Yes | Age | 0% | - | Yes | Yes | Yes | 20% |
| *South Africa* | Yes | Yes | 20% | 33% Drivers, 31% Front Seats | No | No | - | - | - | Yes | Yes | No | 50% |
| *Turkey* | Yes | Yes | 20% | 44% Drivers, 36% Front seats | Yes | Yes | Age/weight/height | 30% | - | Yes | No | Yes | 30% |
| ***Low-Income Countries*** | | | | | | | | | | | | | |
| *Bangladesh* | No | - | - | - | No | No | - | - | - | Yes | No | Yes | 40% |
| *Cambodia* | Yes | No | 50% | - | Yes | No | Age | 0% | - | No | No | No | 50% |
| *Kenya* | Yes | Yes | 60% | - | No | No | - | - | - | Yes | No | Yes | 40% |
| *Uganda* | Yes | Yes | 30% | - | No | No | - | - | - | Yes | No | No | 30% |

## 2.8 Conclusions

Road traffic crashes remain an unresolved global public health emergency in most low- and middle-income countries. The risks of RTCs are considerably high in GCC countries including in Oman where the oil-driven economy has overtime sparked rapid economic growth accompanied by large influx of expatriates, rapid urbanisation and unprecedented growth in motor vehicles. Most RTC research have been conducted in western societies. After reviewing the literature, one can conclude that, RTCs are complex events, and they occur as a result of a combination and interaction of many factors including drivers' behaviours and characteristics, vehicles' characteristics, environmental conditions, and road geometry. Therefore, to understand the whole picture of RTCs, exploring the interrelationships among these factors is a key to reduce the number, severity and consequences of RTCs.

Although, there is a growing body of peer-reviewed literature on the trends and behavioural characteristics associated with RTCs in Oman, however, the human factors, type, pattern, randomness, and severity of RTCs are not well understood. Besides, there is a lack of understanding of complex human behaviour and skills associated with risks of reckless driving in the country. Additionally, although a number of intervention measures have been introduced to reduce RTCs in Oman; however, few systematic evaluations have been made for these interventions. Therefore, it is inconclusive on whether these interventions are reducing the burden of RTCs and their related injuries.

# Chapter 3

## Fatal and non-fatal road traffic injuries in the Sultanate of Oman: Quantifying the age-sex interactions using national registration database[5]

ABSTRACT

### Objective

Road traffic injuries (RTIs) are the leading cause of disability-adjusted life years lost in Oman, Saudi Arabia and United Arab Emirates. Injury prevention strategies often overlook the interaction of individual and behavioural risk factors in assessing the severity of RTI outcomes. The aim of this analysis is to undertake a systematic investigation of the underlying interactive effects of age and gender on the severity of fatal and non-fatal RTI outcomes in the Sultanate of Oman.

### Methods

This study was based on 35,785 registered incidents: of these, 10.2% fatal injuries, 6.2% serious, 27.3% moderate, 37.3% mild injuries and 19% only vehicle damage but no human injuries. We applied a generalised ordered logit regression to estimate the effect of age and gender on RTI severity, controlling for risk behaviours, personal characteristics, vehicle, road, traffic, environment conditions and geographical location.

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[5] A shorter version of this chapter was presented in the 2016 BSPS conference in Winchester and in a Joint forum on Evidence-base for strengthening road safety policies and interventions in the Sultanate of Oman, GCC Road Safety Week, Royal Oman Police, 14th March 2017. The aims of the joint forum were to engage researchers, decision makers, policy specialists and relevant stakeholders to: (i) review the scientific evidence and existing road safety interventions; (ii) identify the gaps in evidence-base for further research and (iii) translate research evidence for designing appropriate policies and interventions to improve road safety and related outcomes.
A shorter version was also published in BMJ:
Al-Aamri, A.K., Padmadas, S.S., Zhang, L.C. and Al-Maniri, A.A., 2017. Disentangling age–gender interactions associated with risks of fatal and non-fatal road traffic injuries in the Sultanate of Oman. *BMJ global health*, *2*(3), p.e000394.
A shorter version of this chapter has been accepted for poster presentation as part of the scientific program for the World SAFETY 2018, which will be held in November 2018 in Bangkok, Thailand.

### Findings

The most dominant group at risk of all types of RTIs was young male drivers. The probability of severe incapacitating injuries was the highest for drivers aged 25–29 (26.6%) years, whereas the probability of fatal injuries was the highest for those aged 20–24 (26.9%) years. Analysis of three-way interactions of age, gender and causes of crash show that overspeeding was the primary cause of different types of RTIs. In particular, the probability of fatal injuries among male drivers attributed to overspeeding ranged from 3%–6% for those aged 35 years and above to 13.4% and 17.7% for those aged 25–29 years and 20–24 years, respectively.

### Conclusions

The high burden of severe and fatal RTIs in Oman was primarily attributed to overspeed driving behaviour of young male drivers in the 20–29 year age range. Our findings highlight the critical need for designing early gender-sensitive road safety interventions targeting young male and female drivers.

### Key messages

- In Oman, one in three of the road crash victims had a mild or moderate injury, and one in ten had a fatal injury.
- The odds of severe incapacitating and fatal injuries are significantly higher for young male drivers than their older and female counterparts.
- Overspeed driving behaviour of young males in the 20–29 years age range was the primary factor associated with severe and fatal road injuries in Oman.

**Keywords:** Road Traffic Crash, Injury, Severity, Fatigue, Oman, generalised ordered logit model

## 3.1 Background and Rationale

Road traffic crashes represent a significant burden to the resources of health care and to the national economic in Oman (Islam and Al Hadhrami, 2012; Dahdah and Bose, 2013; Farag et al., 2014; Al-Bulushi et al., 2015). The severity of the crash injuries can be measured in terms of the type and size of injury of the involved victims, and the damage to the public properties on the roadside and to the involved vehicles. ROP classifies the severity of RTCs into five categories: fatal, serious, medium, slight and damage only (i.e. damage to property). For consistency purpose, the present study redefine these terms as follow: fatal, severe, moderate, mild, and no-injury respectively. RTC is classified as fatal when at least one victim died as a result of the injuries sustained in the crash, whereas severe crashes are those crashes involving one or more type of severe injury, including bone fractures, permanent impairment of vision or hearing or serious disfigurement, damage to internal organs, or severe burn (Dharmaratne et al., 2015). Severe/ serious RTI is also defined as any crash injury due to which the casualty is admitted to a hospital (Weijermars et al., 2018). Recently, severe RTIs have been added as a new road safety performance indicator due to their high proportion as they exerting significant burden on the economy and healthcare resources (Weijermars et al., 2018). Moderate and mild injury crashes are recorded when the victim complains of injury, or there is evidence that the victim is injured but not incapacitating, and the severity is unknown (Dharmaratne et al., 2015).

RTCs occur as a result of a complex combination of risk factors such as drivers' behavioural and personal characteristics, time of the day, road geometry, vehicle, traffic and environmental conditions (Petridou and Moustaki, 2000; Elvik, 2013). Personal behavioural risk factors, such as lack of driving experience, violation of traffic rules, carelessness, low visibility, fatigue, sleepiness, psychological stress, alcohol, harmful and sedative drugs consumption, and using mobile phones while driving, exacerbate the risks and the extent of road crash injuries (Petridou and Moustaki, 2000; Rifaat and Chin, 2007; Robb et al., 2008; Elvik, 2013; Abegaz et al., 2014; Michalaki et al., 2015). Therefore, quantifying the effects of these factors is important to explore the main characteristics of RTCs of a specific network system and to improve the road safety performance (Farag et al., 2014).

Several past studies have considered age and sex of the driver as critical risk factors for RTCs (Petridou and Moustaki, 2000; Rifaat and Chin, 2005; Russo, Biancardo and Dell'Acqua, 2014). Past studies have found male drivers are at higher risk to be involved in RTCs compared to their female counterparts (Massie et al., 1995; Abdel-Aty and Radwan, 2000; WHO, 2002). Young males found to be more vulnerable to RTCs and fatal outcomes than their female counterparts, and this is mainly attributed to their risky behaviours such as over-speeding, overtaking, aggressive attitudes, risky driving for fun and poor compliance of traffic regulations (Oltedal and Rundmo, 2006; Russo et al., 2014; WHO, 2015). However, in terms of the propensity of road crashes per mile driven, female drivers have been found to have a slightly higher crash risk than males (Williams, 2003).

Ageing is also found leading to a steady deterioration of physiological, circadian and sleep systems, suggesting that there is a linear relationship between chronological age and fatigue (Di Milia et al., 2011). Falling asleep could be considered as one of the factors related to fatigue-related crashes (Pack et al., 1995). People, who are excessively sleepy, may suffer from performance lapses and have slow reaction times (Pack et al., 1995). They may temporarily be unaware of their surroundings (Pack et al., 1995). Crashes resulting from falling asleep were found to be more severe and leading to fatalities (Pack et al., 1995). Past studies have found that the occurrence of sleep-related crashes could be considered as a function of age, and the highest rate of these crashes has been observed to be more common among young and inexperienced drivers (Pack et al., 1995; Sagberg, 1999). Lack of sleep and the small number of total night sleeping hours could be among the potential factors for the high rate of fallen-asleep crashes among adolescents (Pack et al., 1995). Sagberg (1999) argued that sleep-related crashes are more likely to occur when driving at speed higher than average road speed which consequently increases the severity of this type of RTCs. Sagberg also stated that the risk of being involved in sleep-related crashes has a positive association with the trip length.

The role of sleepiness in road crash involvements is difficult to be assessed because it can be affected by other factors (Pack et al., 1995). Traffic congestion is one of these factors, it was considered as one of the potential contributory factors to sleep-related crashes (Pack et al., 1995). Although high traffic flow was found to positively increase the risk of RTCs, it was found to result in less severe crashes (Quddus et al., 2009). The average traffic speed in high congested condition is relatively low compared to uncongested conditions, and this could be one reason for the low level of crash severity during the high traffic flows (Quddus et al., 2009). However, the association between crash severity and level of traffic congestion may not be straightforward as it is affected by other factors including drivers' characteristics, vehicle characteristics and features of road infrastructure (Quddus et al., 2009).

The mass of the vehicles involved in RTCs found to have significant impact on the type of injuries resulting from road crashes (Thomas and Frampton, 2002). RTCs have been found to be worse and resulting in more severe injuries when a heavy vehicle is involved in a two-vehicle crash (Rifaat and Chin, 2007). The absolute mass of the heavy vehicle could be one reason for this high risk which implies that this type of vehicles will require longer braking distance to stop at the moment of collision and this consequently increases the probability of colliding either with another vehicle or with any object on the roadside (Rifaat and Chin, 2007). Al-Bulushi et al. (2015) found that single vehicle crashes, i.e. overturn and collision with fixed object crashes, are less likely to end with fatal outcomes compared with multiple vehicle crashes in Oman. The authors claimed that this finding is not surprising, especially in the case when the multiple-vehicle crash involve light weight vehicles and a heavy vehicle so that the big mass of the heavy vehicle increases the risk of fatalities of the drivers of the light weight vehicles.

The exposure to RTCs also depends on the number of driving licenses (Di Milia et al., 2011). The minimum legal age for holding a driving license is 18 years in Oman, although the traffic authorities can issue a license at age 17 in certain circumstances (Al-Reesi et al., 2016). The share of male license holders is disproportionately high (ROP, 2016). Overall, males are over-represented at all ages especially in the working ages in Oman population (NCSI, 2016). This is attributed to high volume of male migration particularly from South Asia, and recent data show that non-Omani male expatriates in the working ages have outnumbered Omani nationals (NCSI, 2016). Unlike Saudi Arabia, there is no gender discrimination for driving in Oman; females represent about 20% of total driving license holders and about 26% of the new licenses issued in 2015 (ROP, 2016) and female work force in Oman has also increased significantly from 57,815 to 130,077 between 2006 and 2015 (NCSI, 2016).

The variation of crash risk by day of the week has gained a great concern, and evidences pointed to the over-representation of young drivers in RTCs during weekends (Doherty et al., 1998; Anowar et al., 2013). Risky driving behaviours are more likely to appear during holidays and weekends, and this could be one reason for the severe outcomes of RTCs during weekend compared to weekday (Anowar et al., 2013). Gray et al. (2008) conducted a study to explore the difference between weekday and weekend RTCs and they found that young male drivers in the UK are more likely to be involved in more severe crashes on Thursdays (excluding crashes in London) to Sundays compared to other days of the week. The authors attributed the high number of RTCs on these days to the high density of commuters on the roads towards the end of the week. They also attributed the high of RTCs on Sunday early mornings to the big number of young males on the road driving to home after a Saturday evening.

Rifaat and Chin (2007) found evidences about the significant association between road type and crash location on one hand and the severity of the crash on the other hand, they demonstrated that crashes on expressways and crashes along curves are more likely to result in more severe injuries. Al-Reesi et al. (2016) found that two-way roads (i.e. single-carriageway roads) increase the likelihood of road crash involvement among young drivers in Oman. The authors attributed this to the high likelihood of overtaking behaviours so that the drivers are at higher risk of being involved in a crash on these roads either by colliding with fixed object on the roadside or overturn on the outer edge of the road, or entering the oncoming traffic and colliding with another vehicle.

A total of 6,279 road traffic crashes were registered in Oman in 2015, of which 72% resulted in injuries and 11% were fatal (ROP, 2016). Among those had fatal outcomes, 32% were aged 16-25 years, 46% in the 26-50 age range, mostly healthy, men and those driving the vehicle at the time of incident (ROP, 2016). The high burden of mortality and disability has considerable economic, social and health care implications for the left-behind families, as these victims are usually the primary breadwinners (Al-Maniri et al., 2013; Al-Reesi et al., 2016). Over speeding, overtaking, driver fatigue and collision between vehicles in non-signalled intersections and roundabouts were reported as the main causes of crashes in Oman (AL-Maniri et al., 2013; Al-Reesi et al., 2016; ROP, 2016).

There is a growing body of peer-reviewed literature on trends and behavioural characteristics associated with RTIs in Oman (Al-Reesi et al., 2013; AL-Maniri et al., 2013; Al-Bulushi et al., 2015; Al-Azri et al., 2016; Al-Reesi et al., 2016). However, there is little systematic demographic analysis of the age-sex differentials associated with RTC outcomes. This analysis addresses this pertinent research gap by examining the underlying interactive effects of age and sex of road crash victims on the extent of severity of RTCs in Oman.

This analysis addresses two inter-related policy relevant questions:

1. What are the underlying effects of age and sex on the extent of severity of RTCs outcomes in Oman? More specifically, does the intensity of crash severity vary by age and sex of the driver?

2. How do these effects mediate when controlled for other attributes including the nationality of the driver, vehicle conditions, environmental factors and time-related factors?

We **hypothesise** that the risks of serious and fatal RTCs are the highest among young males than their older and female counterparts. Disentangling the age-sex interactions associated with RTCs will enable policy makers to identify and design appropriate behavioural interventions specific to certain high-risk groups. Fatal road traffic Crashes have become a routine public health emergency and reducing the burden of RTCs is a national high priority policy agenda in Oman. As previously stated in the literature review chapter, in Oman most of the hospital deaths due to external causes are attributed to road crashes (Al-Bulushi et al., 2015), and increasingly a significant proportion of public and private funds is spent on managing, treating injuries and associated chronic physical and mental disorders (Abdel-Aty and Radwan, 2000). The need for evidence-based policy interventions was recommended in the 2015 WHO Global Status Report on Road Safety (WHO, 2015) and reiterated in the 2030 UN agenda for sustainable development goals, particularly target 3.6 aimed at reducing global road traffic deaths and injuries by 50% in 2020.

The **aim** of this analysis is to identify the underlying effects of age and sex of the driver on the extent of severity of RTC outcomes in Oman. The study considers a set of risk factors including the drivers' personal characteristics (e.g. nationality), vehicle conditions (e.g. type of vehicle) and road infrastructure and time-related factors (e.g. day of the week) on mediating the association between crash severity and drivers' sex and age.

In order to participate in developing related RTCs countermeasures, one should distinguish between two types of risk factors:

1. Road infrastructure and other contextual factors (e.g. road type, time, vehicle type)
2. Driver-related factors such as age, sex, and cause of RTCs.

Therefore, to develop countermeasures targeting the driver-related factors, we need to identify the high driver-related- risk factors while controlling for other risk factors.

## 3.2 Methods

### 3.2.1 Data

A total of 35,785 crashes were eligible for inclusion in this study. Out of these crashes, there were 3,665 (10.2%) fatal injury crashes, 2,226 (6.2%) severe injury crashes, 9,758 (27.3%) moderate injury, 13,346 (37.3%) mild injury and 6,790 (19%) no-injury crashes.

### 3.2.2 Modelling approach

As mentioned above, the extent of crash severity can be measured in terms of the degree of victims' injuries and the damage to their vehicles and other properties on the road. The severity level of RTC outcome was used as the dependent variable in the current study and it represents the level of severity in an ordinal scale, i.e. no-injury, mild, moderate, severe and fatal injury. As this variable has more than two categories, a set of modelling alternatives were explored to examine the association between crash severity on one side and factors related to road users, road characteristics, vehicle characteristics, traffic and environment conditions on the other side. Considering the order of values measuring crash severity, the ordered logistic regression is appropriate for modelling the effect of age and sex on severity of RTC injuries. The parallel line or proportional odds is one of the underlying assumptions of the ordered logit model, and it implies that the relationship between each pair of the outcome categories is the same with different categories of the covariate variables. If this assumption is violated by at least one of the independent variables, then the results of the ordered logit model can lead to bias and errors in estimation. Therefore, to allow the relaxation of the proportional odds assumption, a generalised ordered logit model is considered to conduct this analysis.

The generalised ordered logit model consists of two parts: the proportional odds model and the partial proportional odds model. The partial proportional odds model allows the coefficients of the variable to vary among the thresholds of the response variable. Assuming that only a subset of variables may violate the proportional odds assumption, the generalised ordered logit model can be written as:

$$P(y_i > j) = \frac{\exp\,(X_{1i}\beta_1 + X_{2j}\beta_{2j} - \phi_j)}{1 + \exp\,(X_{1i}\beta_1 + X_{2j}\beta_{2j} - \phi_j)} \quad j=1,\,2,\,\ldots\ldots,\,m-1 \tag{3.1}$$

where $\beta_1$ is a vector of parameters that meet the proportional odds assumption and it is associated with a subset $X_{1i}$ of the explanatory variables, while $\beta_{2j}$ is a vector of parameters that represents the partial proportional odds part of the generalised ordered logit model and associated with a subset $X_{2j}$ of the explanatory variables and m is the number of categories of the dependent variable. In this study, the dependent variable has five categories and hence four panels of coefficients are presented so that the coefficient of a given variables is recoded as 1 vs. 2, 3, 4 and 5; 1 and 2 vs. 3, 4 and 5 and so on. The positive coefficients suggest that higher values on the independent variables make the higher values/ order of the response variable more likely to occur. In other words, the higher positive value of a coefficient, the higher is the severity of RTC injures.

After fitting the generalised ordered model, two types of risks can be obtained:

1) ***Type-I*** of risks: P (Y|X), X = a group of given explanatory variable such as a specific age group, and Y = crash type. For example, P(Fatal|20-24) represents the risk that the fatal crash presents for a driver of age 20-24 years. This type of risks is useful for insurance premier calculations, but it fails to take into account the different prevalence of RTCs among the different age groups of drivers.

2) Therefore, to account for the different prevalence, ***Type-II*** of risks P (X|Y), i.e. ***risk*** of an age group for a given type of road crashes should be calculated by applying the Bayesian Theorem as follow:

$$\mathrm{P(X|Y)} = \frac{\mathrm{P(Y|X)P(X)}}{\mathrm{P(Y)}} \tag{3.2}$$

For example, P(20-24|fatal) represents the risk of drivers aged 20-24 years involved in fatal crashes. Defining this type of risks is useful for developing RTCs related countermeasures so that the estimated probabilities will allow identifying the most important contributors to various RTC outcomes for targeted policy interventions.

Sex and age of driver along with cause of the crash were used as the primary predictors in this study and they were treated as categorical variables. Sex has two categories; male and female, age of the driver has eight categories; (1=<20 years, 2= 20-24years, 3=25-29 years, 4=30-34 years, 5=35-39 years, 6=40-44 years, 7=45-49 years, and 8=50+ years), and cause of the crash has five categories (1= Over-speeding, 2= Negligence, 3= Fatigue/ wrong manoeuvre, 4= Alcohol drunk, and 5= Non-human factors).

However, nationality of the driver, time-related factors (i.e. day of the week, month and year), regional Headquarter, environmental factors (i.e. road type), and vehicle conditions (i.e. number of vehicles and type of vehicle) were used as secondary predictors. All these variables were treated as categorical variables and the categories of each of them are as follow:

- Nationality :(1=Omani, 2=Indian, 3=Bangladesh, 4=Pakistan, 5=Arab, and 6=others).
- Day of the week (1= weekday and 2=weekend).
- Month of the crash (1=January-March, 2=April-June, 3=July-September, and 4=October-December).
- Year of the crash (1=2010, 2=2011, 3=2012, 4=2013, and 5=2014).
- Regional Headquarter (1=Muscat, 2= Musandam, 3=Dhofar, 4= Ad Dakhliyah, 5=Ash Sharqiyah, 6=Al Batinah, 7=Adh Dhahirah, and 8= Al Wusta).
- Road type (1=one way, and 2=two ways).
- Number of vehicles (1=single vehicle, and 2=multiple vehicle).
- Type of vehicle (1=saloon, 2= four-wheel, 3=pickup, 4=bus, 5= heavy-vehicle).

The descriptive analyses of this study were conducted using SPSS V22.0 (IBM SPSS Statistics for Windows, Version 22.0 Armonk, NY: IBM Corp) and Stata V13.0 (Stata Corporation, College Station, TX, USA) was used for the multivariate analysis.

## 3.3 Results

As mentioned above, a total of 35,785 crashes were eligible for inclusion in the present study, of which 10.2% were fatal injury crashes, 6.2% severe injury crashes, 27.3%moderate injury crashes, 37.3% mild injury crashes and 19% no-injury crashes. A total of 4,585 people were killed and a further 78,922 were injured due to these crashes. The percentage distribution of severity of RTC outcomes by each group of the selected variables is presented in ***Table 3.1***. One in three of road crash victims had mild or moderate injury respectively, and one in ten had fatal injury. Male drivers were twice as likely to experience fatal and severe injuries as females. The propensity for fatal injuries was the highest among males below 20 and those aged 45-49. The propensity for severe injury was pronounced particularly among those below 20 years. The age-sex patterns associated with the severity of RTIs are illustrated graphically in ***Figure 3.1,*** so that each colour of represents the proportion of a given level of crash severity for a given age and sex group out of all reported RTCs during the study period and the grey colour represents the proportion of a given age/sex group out of the total population. Most crash victims are in the age range between 20 and 30 years, predominantly male drivers whereas their female counterparts were mostly represented between ages 25 and 30. Interestingly, a small minority of males involved in road injuries appear to be driving illegally below age 18. There were only a few male drivers after age 60. Females were less likely to drive after age 40. The density of severe and fatal injuries increased considerably among males after age 19 and remained high until age 30.

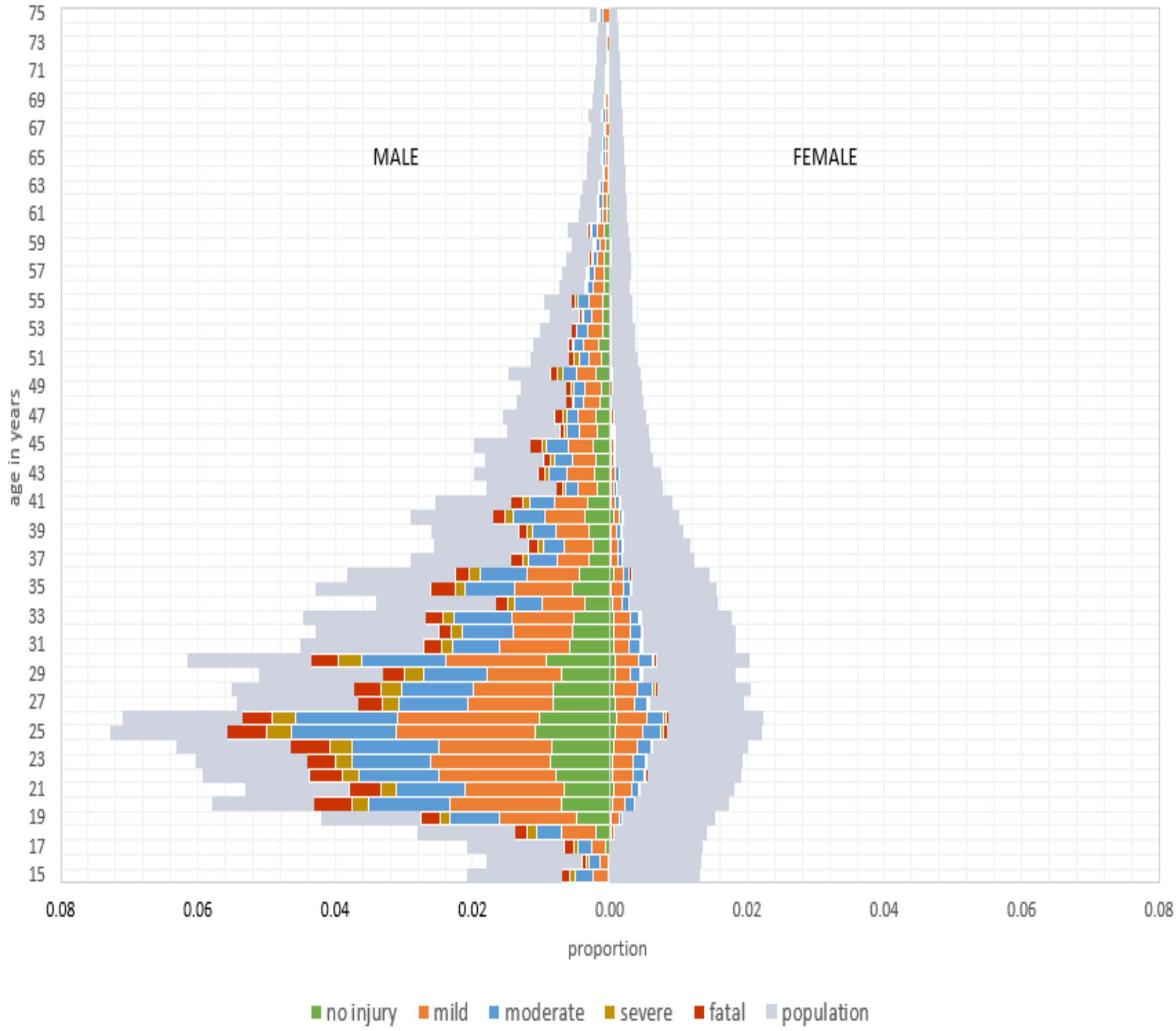
Over-speeding, fatigue and negligence were the three dominant causes of RTCs. However, the most common cause of fatal injuries were non-human factors and over-speeding. Fatal injuries were high for crashes in both one- and two-way roads, where a single vehicle was involved, mostly four wheelers, bus and heavy vehicles such as lorry and trucks, during weekend and during festive and holiday season (July-September). There was no uniform pattern of injuries across time. Expatriate drivers from Bangladesh, other Arab countries and Pakistan involved in a road crash had higher risk of fatal injuries. The variations in severe and fatal injuries were noticeable across governorates or regional headquarters. Al Wusta and the southern and largest governorate Dhofar recorded the worst in terms of fatal injuries (44.2%and 32.4% respectively). However, both severe and fatal injuries were the lowest in the most populous Muscat governorate.

| ***Table 3.1*** *Percentages of the severity of RTI outcomes for each group of the selected variables, Oman, 2010-14* | | | | | | |
|---|---|---|---|---|---|---|
| | **% Severity of road traffic crash injuries** | | | | | |
| **Characteristics** | **No injury (n=6790)** | **Mild (n=13346)** | **Moderate (n=9758)** | **Severe (n=2226)** | **Fatal (n=3665)** | **Number of crashes** |
| **Driver's sex** | | | | | | |
| Male | 19.9 | 35.8 | 27.0 | 6.5 | 10.9 | 31763 |
| Female | 11.9 | 49.3 | 29.6 | 4.0 | 5.1 | 4022 |
| **Driver's age (years)** | | | | | | |
| <20 | 13.9 | 37.4 | 28.1 | 8.2 | 12.3 | 2217 |
| 20-24 | 17.2 | 39.3 | 27.1 | 5.5 | 10.8 | 8631 |
| 25-29 | 19.5 | 36.8 | 28.0 | 6.8 | 9.0 | 8983 |
| 30-34 | 19.8 | 37.3 | 28.1 | 6.4 | 8.5 | 5848 |
| 35-39 | 19.5 | 35.5 | 27.7 | 6.4 | 10.9 | 3605 |
| 40-44 | 21.1 | 35.7 | 26.6 | 5.8 | 10.7 | 2379 |
| 45-49 | 21.9 | 35.5 | 23.9 | 5.1 | 13.6 | 1535 |
| 50+ | 21.0 | 37.3 | 24.7 | 5.7 | 11.3 | 2587 |
| **Cause of crash** | | | | | | |
| Over-speeding | 19.9 | 34.0 | 26.6 | 6.9 | 12.7 | 19757 |
| Negligence | 16.3 | 41.8 | 28.9 | 5.7 | 7.3 | 5567 |
| Fatigue, wrong manoeuvre | 14.7 | 44.3 | 29.6 | 5.5 | 5.9 | 8050 |
| Alcohol | 55.8 | 21.4 | 15.8 | 2.8 | 4.2 | 720 |
| Non-human factor | 21.9 | 34.8 | 24.0 | 4.5 | 14.8 | 1691 |
| **Driver's nationality** | | | | | | |
| Oman | 18.2 | 38.1 | 27.7 | 6.2 | 9.9 | 29292 |
| India | 25.7 | 35.1 | 24.1 | 5.6 | 9.5 | 2357 |
| Bangladesh | 12.4 | 31.3 | 31.8 | 9.5 | 15 | 814 |
| Pakistan | 23.2 | 31.6 | 25.0 | 6.8 | 13.4 | 1735 |
| Arab | 21.5 | 34.0 | 22.9 | 6.2 | 15.4 | 1021 |
| Others | 24.2 | 38.7 | 26.0 | 4.2 | 6.9 | 566 |
| **Day of the crash** | | | | | | |
| Weekday | 19.2 | 37.7 | 27.3 | 6.2 | 9.7 | 25517 |
| Weekend | 18.5 | 36.3 | 27.2 | 6.3 | 11.7 | 10268 |
| **Month of the crash** | | | | | | |
| Jan-March | 18.6 | 38.1 | 27.6 | 6.2 | 9.4 | 9400 |
| Apr-June | 20.5 | 36.8 | 27.2 | 6.1 | 9.5 | 9744 |
| July-Sept | 18.0 | 36.9 | 27.3 | 6.5 | 11.3 | 8958 |
| Oct-Dec | 18.6 | 37.4 | 26.9 | 6.2 | 10.9 | 7683 |

Contd.

***Table 3.1*** *Percentages of the severity of RTI outcomes for each group of the selected variables, Oman, 2010-14 (contd.)*

| | % Severity of road traffic crash injuries | | | | | |
|---|---|---|---|---|---|---|
| **Characteristics** | **No injury (n=6790)** | **Mild (n=13346)** | **Moderate (n=9758)** | **Severe (n=2226)** | **Fatal (n=3665)** | **Number of crashes** |
| **Year of the crash** | | | | | | |
| 2010 | 26.0 | 33.3 | 25.4 | 6.1 | 9.3 | 7366 |
| 2011 | 17.7 | 37.1 | 27.4 | 7.1 | 10.8 | 7561 |
| 2012 | 18.3 | 39.4 | 26.0 | 5.4 | 10.8 | 8054 |
| 2013 | 18.6 | 38.7 | 27.3 | 5.8 | 9.7 | 7657 |
| 2014 | 12.3 | 37.9 | 31.8 | 7.2 | 10.8 | 5147 |
| **Regional headquarter** | | | | | | |
| Muscat | 23.0 | 42.1 | 26.3 | 3.8 | 4.7 | 12491 |
| Musandam | 26.7 | 35.5 | 25.1 | 8.6 | 4.0 | 546 |
| Dhofar | 3.5 | 14.3 | 36.4 | 13.4 | 32.4 | 945 |
| Ad Dakhliyah | 17.4 | 39.9 | 26.1 | 6.4 | 10.1 | 5275 |
| Ash Sharqiyah | 19.9 | 38.5 | 28.3 | 5.7 | 7.7 | 6739 |
| Al Batinah | 12.9 | 28.0 | 30.1 | 10.0 | 19.0 | 5578 |
| Adh Dhahirah | 19.8 | 37.9 | 24.1 | 6.9 | 11.3 | 3729 |
| Al Wusta | 5.8 | 16.8 | 25.9 | 7.3 | 44.2 | 482 |
| **Type of road** | | | | | | |
| One-way | 20.6 | 37.7 | 26.0 | 5.7 | 10.0 | 11270 |
| Two-way | 18.2 | 37.1 | 27.9 | 6.5 | 10.3 | 24515 |
| **No. of vehicles involved** | | | | | | |
| Single | 24.3 | 30.7 | 26.8 | 6.6 | 11.7 | 19531 |
| Multiple | 12.6 | 45.3 | 27.9 | 5.8 | 8.5 | 16254 |
| **Type of vehicle** | | | | | | |
| Saloon | 19.3 | 39.7 | 26.4 | 5.7 | 8.9 | 22761 |
| Four-wheel | 19.1 | 34.5 | 26.6 | 6.4 | 13.4 | 4239 |
| Pickup | 18.8 | 34.0 | 29.1 | 6.8 | 11.3 | 3813 |
| Bus | 13.5 | 35.6 | 32.2 | 6.3 | 12.4 | 872 |
| Heavy vehicle | 18.1 | 30.5 | 30.2 | 8.3 | 12.8 | 4100 |




Based on data from the Royal Oman Police national database on road traffic crashes. The shaded grey area represents the proportion of population at each age (source US Census Bureau International Database; https://www.census.gov/population/international/data/idb/ informationGateway.php; accessed Dec 15, 2016).[6]

***Figure 3.1*** *Proportions of different level of* crash severity among all reported road traffic crashes *by age and sex, Oman, 2010-14*

However, the percentages mentioned above, i.e. ***Type-I*** risk, fail to take into account the prevalence of crashes among the different groups. For example, Table 3.1 indicates that given a driver of the age 25-29 years is involved in a road crash, 36.8% incurs mild injury compared to 9% fatal injury, whereas the corresponding probabilities are 35.5% and 13.6% for someone aged 45-49 years. However, this does not mean that 45-49 year-olds pose a higher risk to fatal crash than 25-29 year-olds, despite it is clear that the proportion of fatal crashes for drivers aged 45-49 years is greater than that of those aged 25- 29 years. This is because the comparison above fails to take into account

[6] The proportions of crash severity levels are conditional estimates for reported road crashes and were not adjusted for the whole population.

the different prevalence of crashes between the two groups (as reflected by the counts 8,983 and 1,535).

***Table 3.2*** presents the coefficients and 95% confidence intervals (CI) from the generalised ordered logit regression, controlling for primary and secondary predictors and control variables. It is clear that the influence of drivers' characteristics and risky behaviours shows significant effects when accounting for demographics, over-speeding, careless behaviour, alcohol drunk and fatigue. The probability of RTCs increased significantly towards severe and fatal outcomes for males whereas female drivers had higher probability of being involved in the lowest threshold between mild and no injury road traffic crashes.

***Table 3.2*** *Generalised ordered logit regression coefficients and 95% confidence intervals of different severity levels of road traffic injuries*

| | Threshold between | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No injury and mild injury | | | Mild and moderate injuries | | | Moderate and severe injury | | | Severe and fatal injury | | |
| **Characteristics** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** |
| **Driver's sex** | | | | | | | | | | | | |
| Male (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| Female | 0.609 | [0.506, 0.712] | 0.000 | -0.057 | [-0.128,0.014] | 0.115 | -0.431 | [-0.546, -0.316] | 0.000 | -0.458 | [-0.606, -0.312] | 0.000 |
| **Driver's age** | | | | | | | | | | | | |
| <20 | 0.459 | [0.308, 0.611] | 0.000 | 0.192 | [0.075, 0.309] | 0.001 | 0.124 | [-0.021, 0.268] | 0.093 | -0.027 | [-0.198, 0.144] | 0.755 |
| 20-24 | 0.197 | [0.091, 0.304] | 0.000 | 0.042 | [-0.048,0.132] | 0.362 | -0.076 | [-0.188, 0.036] | 0.185 | -0.111 | [-0.240, 0.017] | 0.089 |
| 25-29 | 0.055 | [-0.049, 0.158] | 0.302 | 0.030 | [-0.059, 0.119] | 0.508 | -0.203 | [-0.314, -0.091] | 0.000 | -0.406 | [-0.537, -0.276] | 0.000 |
| 30-34 | 0.021 | [-0.089, 0.131] | 0.706 | 0.017 | [-0.077, 0.111] | 0.727 | -0.236 | [-0.356, -0.116] | 0.000 | -0.407 | [-0.549, -0.266] | 0.000 |
| 35-39 | 0.062 | [-0.060, 0.183] | 0.319 | 0.060 | [-0.043, 0.163] | 0.255 | -0.152 | [-0.282, -0.023] | 0.021 | -0.238 | [-0.389, -0.087] | 0.002 |
| 40-44 | -0.009 | [-0.142, 0.124] | 0.892 | 0.035 | [-0.079, 0.148] | 0.549 | -0.113 | [-0.258, 0.032] | 0.127 | -0.162 | [-0.331, 0.007] | 0.060 |
| 45-49 | 0.013 | [-0.104, 0.129] | 0.830 | 0.013 | [-0.104, 0.129] | 0.830 | 0.013 | [-0.104, 0.129] | 0.830 | 0.013 | [-0.104, 0.129] | 0.830 |
| 50+ (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| **Cause of crash** | | | | | | | | | | | | |
| Over-speeding (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| Negligence | -0.068 | [-0.152,0 .016] | 0.112 | -0.147 | [-0.211, -0.083] | 0.000 | -0.432 | [-0.522, -0.342] | 0.000 | -0.551 | [-0.664, -0.437] | 0.000 |
| Fatigue, wrong manoeuvre | -0.085 | [-0.166, -.005] | 0.038 | -0.163 | [-0.224, -0.103] | 0.000 | -0.568 | [-0.655, -0.482] | 0.000 | -0.759 | [-0.871, -0.648] | 0.000 |
| Alcohol | -1.597 | [-1.756, -1.438] | 0.000 | -1.088 | [-1.266, -0.910] | 0.000 | -1.095 | [-1.385, -0.805] | 0.000 | -1.114 | [-1.482, -0.746] | 0.000 |
| Non-human factor | -0.095 | [-0.218,0 .028] | 0.131 | -0.297 | [-0.402, -0.193] | 0.000 | -0.288 | [-0.420, -0.156] | 0.000 | -0.138 | [-0.286, 0.009] | 0.066 |

Contd.

***Table 3.2*** *Generalised ordered logit regression coefficients and 95% confidence intervals of different severity levels of road traffic injuries (contd.)*

| | Threshold between | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No injury and mild injury | | | Mild and moderate injuries | | | Moderate and severe injury | | | Severe and fatal injury | | |
| **Characteristics** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** |
| **Driver's nationality** | | | | | | | | | | | | |
| Oman (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| India | -0.280 | [-0.385, -0.176] | 0.000 | -0.209 | [-0.302, -0.116] | 0.000 | -0.088 | [-0.214, 0.037] | 0.168 | -0.078 | [-0.230, 0.074] | 0.313 |
| Bangladesh | 0.314 | [0.184, 0.444] | 0.000 | 0.314 | [0.184, 0.444] | 0.000 | 0.314 | [0.184, 0.444] | 0.000 | 0.314 | [0.184, 0.444] | 0.000 |
| Pakistan | -0.309 | [-0.434, -0.184] | 0.000 | -0.154 | [-0.260, -0.047] | 0.005 | 0.083 | [-0.051, 0.216] | 0.224 | 0.190 | [0.031, 0.348] | 0.019 |
| Arab | -0.096 | [-0.253, 0.061] | 0.229 | -0.005 | [-0.137, 0.126] | 0.937 | 0.205 | [0.044, 0.366] | 0.013 | 0.313 | [0.132, 0.494] | 0.001 |
| Others | -0.221 | [-0.377, -0.065] | 0.006 | -0.221 | [-0.377, -0.065] | 0.006 | -0.221 | [-0.377, -0.065] | 0.006 | -0.221 | [-0.377, -0.065] | 0.006 |
| **Regional headquarter** | | | | | | | | | | | | |
| Muscat (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| Musandam | -0.148 | [-0.347, .051] | 0.146 | 0.024 | [-0.156, 0.204] | 0.795 | 0.366 | [0.104, 0.628] | 0.006 | -0.220 | [-0.655, 0.215] | 0.321 |
| Dhofar | 2.141 | [2.011, 2.272] | 0.000 | 2.141 | [2.011, 2.272] | 0.000 | 2.141 | [2.011, 2.272] | 0.000 | 2.141 | [2.011, 2.272] | 0.000 |
| Ad Dakhliyah | 0.413 | [0.327, 0.499] | 0.000 | 0.295 | [0.227, 0.364] | 0.000 | 0.750 | [0.653, 0.847] | 0.000 | 0.819 | [0.700, 0.938] | 0.000 |
| Ash Sharqiyah | 0.249 | [0.167, 0.332] | 0.000 | 0.210 | [0.142, 0.278] | 0.000 | 0.455 | [0.355, 0.556] | 0.000 | 0.489 | [0.364, 0.614] | 0.000 |
| Al Batinah | 0.645 | [0.554, 0.737] | 0.000 | 0.944 | [0.877, 1.011] | 0.000 | 1.431 | [1.346, 1.517] | 0.000 | 1.514 | [1.412, 1.616] | 0.000 |
| Adh Dhahirah | 0.201 | [0.106, 0.296] | 0.000 | 0.230 | [0.153, 0.308] | 0.000 | 0.780 | [0.674, 0.886] | 0.000 | 0.838 | [0.709, 0.967] | 0.000 |
| Al Wusta | 1.889 | [1.505, 2.272] | 0.000 | 1.787 | [1.567, 2.008] | 0.000 | 2.349 | [2.152, 2.545] | 0.000 | 2.593 | [2.388, 2.798] | 0.000 |
| **Day of crash** | | | | | | | | | | | | |
| Weekday (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| Weekend | 0.108 | [0.048, 0.168] | 0.000 | 0.053 | [0.005, 0.100] | 0.030 | 0.087 | [0.024, 0.149] | 0.006 | 0.153 | [0.079, 0.227] | 0.000 |

Contd.

*Table 3.2* *Generalised ordered logit regression coefficients and 95% confidence intervals of different severity levels of road traffic injuries (contd.)*

| | Threshold between | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No injury and mild injury | | | Mild and moderate injuries | | | Moderate and severe injury | | | Severe and fatal injury | | |
| **Characteristics** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** |
| **Type of road** | | | | | | | | | | | | |
| One-way (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| Two-way | 0.058 | [-0.005, 0.121] | 0.069 | -0.022 | [-0.073, 0.029] | 0.393 | -0.170 | [-0.237, -0.102] | 0.000 | -0.230 | [-0.312, -0.149] | 0.000 |
| **Year of crash** | | | | | | | | | | | | |
| 2010 (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| 2011 | 0.486 | [0.406, 0.566] | 0.000 | 0.208 | [0.141, 0.275] | 0.000 | 0.214 | [0.126, 0.303] | 0.000 | 0.185 | [0.076, 0.295] | 0.001 |
| 2012 | 0.411 | [0.332, 0.491] | 0.000 | 0.034 | [-0.032, 0.101] | 0.309 | 0.067 | [-0.023, 0.156] | 0.143 | 0.144 | [0.036, 0.252] | 0.009 |
| 2013 | 0.417 | [0.337, 0.498] | 0.000 | 0.059 | [-0.008, 0.126] | 0.086 | 17.000 | [-0.074, 0.108] | 0.717 | 0.058 | [-0.053, 0.170] | 0.303 |
| 2014 | 0.900 | [0.799, 1.001] | 0.000 | 0.348 | [0.274, 0 .423] | 0.000 | 0.226 | [0.127, 0.324] | 0.000 | 0.209 | [0.089, 0.330] | 0.001 |
| **Month of crash** | | | | | | | | | | | | |
| Jan-March | 0.048 | [-0.004, 0.100] | 0.072 | 0.048 | [-0.004, 0.100] | 0.072 | 0.048 | [-0.004, 0.100] | 0.072 | 0.048 | [-0.004, 0.100] | 0.072 |
| Apr-June (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| July-Sept | 0.121 | [0.068, 0.174] | 0.000 | 0.121 | [0.068, 0.174] | 0.000 | 0.121 | [0.068, 0.174] | 0.000 | 0.121 | [0.068, 0.174] | 0.000 |
| Oct-Dec | 0.147 | [0.092, 0.203] | 0.000 | 0.147 | [0.092, 0.203] | 0.000 | 0.147 | [0.092, 0.203] | 0.000 | 0.147 | [0.092, 0.203] | 0.000 |
| **No. of vehicles involved** | | | | | | | | | | | | |
| Single (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| Multiple | 0.899 | [0.833, 0.966] | 0.000 | -0.028 | [-0.077, 0.022] | 0.272 | -0.053 | [-0.119, 0.012] | 0.112 | -0.027 | [-0.106, 0.053] | 0.510 |

Contd.

***Table 3.2*** *Generalised ordered logit regression coefficients and 95% confidence intervals of different severity levels of road traffic injuries (contd.)*

| | Threshold between | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No injury and mild injury | | | Mild and moderate injuries | | | Moderate and severe injury | | | Severe and fatal injury | | |
| **Characteristics** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** | **β** | **95% CI.** | **P-value** |
| **Type of vehicle** | | | | | | | | | | | | |
| Saloon (ref) | 0.000 | | | 0.000 | | | 0.000 | | | 0.000 | | |
| Four-wheel | 0.014 | [-0.071,0.100] | 0.742 | 0.178 | [0.109, 0.246] | 0.000 | 0.290 | [0.203, 0.378] | 0.000 | 0.350 | [0.248, 0. .452] | 0.000 |
| Pickup | 0.025 | [-0.066, 0.117] | 0.590 | 0.186 | [0.113, 0.259] | 0.000 | 0.110 | [0.015, 0.205] | 0.023 | 0.094 | [-0.020, 0.209] | 0.107 |
| Bus | 0.400 | [0.276, 0.525] | 0.000 | 0.400 | [0.276, 0.525] | 0.000 | 0.400 | [0.276, 0.525] | 0.000 | 0.400 | [0.276, 0.525] | 0.000 |
| Heavy vehicle | 0.114 | [0.021, 0.207] | 0.016 | 0.392 | [0.318, 0.465] | 0.000 | 0.319 | [0.225, 0.412] | 0.000 | 0.265 | [0.151, 0.379] | 0.000 |
| **Constant** | 0.232 | [0.108, 0.356] | 0.000 | -0.785 | [-0.895, -0.675] | 0.000 | -2.148 | [-2.289, -2.007] | 0.000 | -2.661 | [-2.826, -2.496] | 0.000 |

Number of observations: 35785; Log-likelihood: -48569; Pseudo R2: 0.060

The age effects were marginally significant in most categories except for the below 20 and 20-24 age group. When the probability increased from severe to fatal injuries, the risks to fatal injuries were significantly higher among those aged 50 and above when compared to those aged between 25 and 44.

The results in ***Table 3.2*** are interpreted in conjunction with model-based conditional probabilities presented in ***Table 3.3*** (Type-II relative risk P (X|Y), i.e. the scenarios of single risk factor). The results show that the probabilities of severe and fatal injuries were relatively much higher for male drivers. Although results from generalised ordered logit model indicate that drivers aged below 20 years is the riskiest group in terms of crash severity, however, Table 3.3 indicates that the probability of fatal injuries was the highest among drivers aged 20-24 (26·6%) and severe injuries were more accentuated among those aged 25-29 (26·9%). Over-speeding was the dominant cause of injuries resulting in 60% of severe injuries and 67% of fatal injuries. ***The relative risk*** of over-speeding versus fatigue and wrong manoeuvre for fatal and no injuries, calculated as (67·1/14·3)/(52·0/22·6), was twice as high and this means that the ***relative*** risk of over-speeding vs. fatigue and wrong manoeuvre is heightened for fatal crashes than for no-injury crashes.

The coefficients of control variables further confirmed that crashes in one-way road, four wheel, bus and heavy vehicles, those occurring during weekend and festive (post) season, those involving expatriates especially Bangladeshi and other Arab drivers were significant and at heightened risk of severe and fatal injuries (***Table 3.2***). However, Omani nationals were the dominant group among those who had fatal injuries. The severity of RTCs increased significantly in other governorates when compared to Muscat, particularly Al Wusta and Dhofar.

The scenarios of multiple risk factors, which were produced from the three-way interactions including age, sex and cause of the crash, are shown in ***Figures 3.2 and 3.3*** and ***Table 3.4***. Figure 3.2 and Figure 3.3 show the relative risk of injury severity among young drivers aged below 30 years presented by the three major causes of crashes in Oman, namely: over-speeding, fatigue and wrong manoeuvre and negligence.

**Table 3.3** *Scenarios of Single risk factor related to predicting the likelihood of road traffic injury severity by different groups of the selected variables, Oman 2010-14*

| | Severity of road traffic injury | | | | |
|---|---|---|---|---|---|
| **Characteristics** | **No injury** | **Mild** | **Moderate** | **Severe** | **Fatal** |
| **Driver's sex** | | | | | |
| Male | 0.928 | 0.864 | 0.875 | 0.912 | 0.918 |
| Female | 0.072 | 0.136 | 0.126 | 0.088 | 0.078 |
| **Driver's age** | | | | | |
| <20 | 0.047 | 0.064 | 0.062 | 0.077 | 0.073 |
| 20-24 | 0.223 | 0.250 | 0.236 | 0.224 | 0.266 |
| 25-29 | 0.259 | 0.249 | 0.257 | 0.269 | 0.216 |
| 30-34 | 0.172 | 0.161 | 0.168 | 0.165 | 0.140 |
| 35-39 | 0.103 | 0.099 | 0.104 | 0.096 | 0.100 |
| 40-44 | 0.071 | 0.064 | 0.065 | 0.061 | 0.070 |
| 45-49 | 0.046 | 0.042 | 0.039 | 0.040 | 0.052 |
| 50+ | 0.077 | 0.071 | 0.065 | 0.066 | 0.087 |
| **Cause of crash** | | | | | |
| Over-speeding | 0.520 | 0.537 | 0.539 | 0.602 | 0.671 |
| Negligence | 0.155 | 0.162 | 0.164 | 0.149 | 0.119 |
| Fatigue, wrong manoeuvre | 0.226 | 0.234 | 0.245 | 0.210 | 0.143 |
| Alcohol | 0.051 | 0.015 | 0.011 | 0.010 | 0.009 |
| Non-human factor | 0.048 | 0.053 | 0.041 | 0.033 | 0.051 |
| **Driver's nationality** | | | | | |
| Oman | 0.795 | 0.823 | 0.833 | 0.827 | 0.808 |
| India | 0.079 | 0.067 | 0.058 | 0.062 | 0.061 |
| Bangladesh | 0.017 | 0.021 | 0.026 | 0.028 | 0.029 |
| Pakistan | 0.058 | 0.047 | 0.041 | 0.044 | 0.055 |
| Arab | 0.030 | 0.028 | 0.026 | 0.028 | 0.037 |
| Others | 0.018 | 0.017 | 0.015 | 0.014 | 0.013 |
| **Day of crash** | | | | | |
| Weekday | 0.729 | 0.712 | 0.710 | 0.722 | 0.689 |
| Weekend | 0.270 | 0.289 | 0.287 | 0.280 | 0.315 |
| **Year of crash** | | | | | |
| 2010 | 0.274 | 0.186 | 0.195 | 0.198 | 0.188 |
| 2011 | 0.196 | 0.206 | 0.215 | 0.243 | 0.224 |
| 2012 | 0.222 | 0.238 | 0.212 | 0.203 | 0.231 |
| 2013 | 0.210 | 0.224 | 0.211 | 0.196 | 0.205 |
| 2014 | 0.096 | 0.147 | 0.164 | 0.164 | 0.156 |
| **Month of crash** | | | | | |
| Jan-March | 0.268 | 0.265 | 0.260 | 0.259 | 0.258 |
| Apr-June | 0.287 | 0.277 | 0.264 | 0.259 | 0.257 |
| July-Sept | 0.241 | 0.247 | 0.254 | 0.258 | 0.261 |
| Oct-Dec | 0.203 | 0.211 | 0.220 | 0.226 | 0.229 |
| **Regional headquarter** | | | | | |
| Muscat | 0.426 | 0.383 | 0.345 | 0.221 | 0.169 |
| Musandam | 0.020 | 0.015 | 0.013 | 0.020 | 0.006 |
| Dhofar | 0.005 | 0.010 | 0.036 | 0.061 | 0.075 |
| Ad Dakhliyah | 0.131 | 0.159 | 0.139 | 0.154 | 0.150 |
| Ash Sharqiyah | 0.191 | 0.201 | 0.190 | 0.166 | 0.143 |
| Al Batinah | 0.116 | 0.114 | 0.173 | 0.244 | 0.285 |
| Adh Dhahirah | 0.109 | 0.108 | 0.091 | 0.113 | 0.108 |
| Al Wusta | 0.003 | 0.007 | 0.013 | 0.020 | 0.050 |

Contd.

***Table 3.3*** *Scenarios of Single risk factor related to predicting the likelihood of road traffic injury severity by different groups of the selected variables, Oman 2010-14, (Contd.)*

| | **Severity of road traffic injury** | | | | |
|---|---|---|---|---|---|
| **Characteristics** | **No injury** | **Mild** | **Moderate** | **Severe** | **Fatal** |
| **Type of vehicle** | | | | | |
| Saloon | 0.648 | 0.668 | 0.612 | 0.597 | 0.587 |
| Four-wheel | 0.119 | 0.112 | 0.115 | 0.123 | 0.145 |
| Pickup | 0.107 | 0.101 | 0.114 | 0.110 | 0.107 |
| Bus | 0.018 | 0.023 | 0.027 | 0.029 | 0.031 |
| Heavy vehicle | 0.107 | 0.097 | 0.132 | 0.142 | 0.132 |
| **No. of vehicles involved** | | | | | |
| Single | 0.711 | 0.458 | 0.545 | 0.564 | 0.553 |
| Multiple | 0.294 | 0.540 | 0.454 | 0.436 | 0.450 |
| **Type of road** | | | | | |
| One-way | 0.324 | 0.308 | 0.300 | 0.321 | 0.361 |
| Two-way | 0.675 | 0.693 | 0.695 | 0.681 | 0.650 |

Over-speeding appears to be the main cause of all types of crash injury severities among those three age groups, (i.e. <20, 20-24, 25-29 years). It is also clear from Figure 3.2 that the likelihood of experiencing fatal and severe injury outcomes increases significantly with over-speeding behaviours compared fatigue and wrong manoeuvre and negligence behaviours among the males aged below 30 years. Similarly, it is also noticeable that males aged below 20 appear to be at higher risk of suffering fatal and severe injuries in all the three causes of crashes.

Alternatively, Figure 3.3 indicates that although males and females are more likely to be involved in over-speeding crashes compared to other causes of crashes, females are more likely to experience less severe injuries (i.e. mild and moderate injuries). In addition, males aged 20-24 and those aged 25-29 appeared to have almost the same probability of crash involvement, however this is not the case among female drivers as females aged 25-29 years have higher likelihood of crash involvement compared to females aged 20-24.

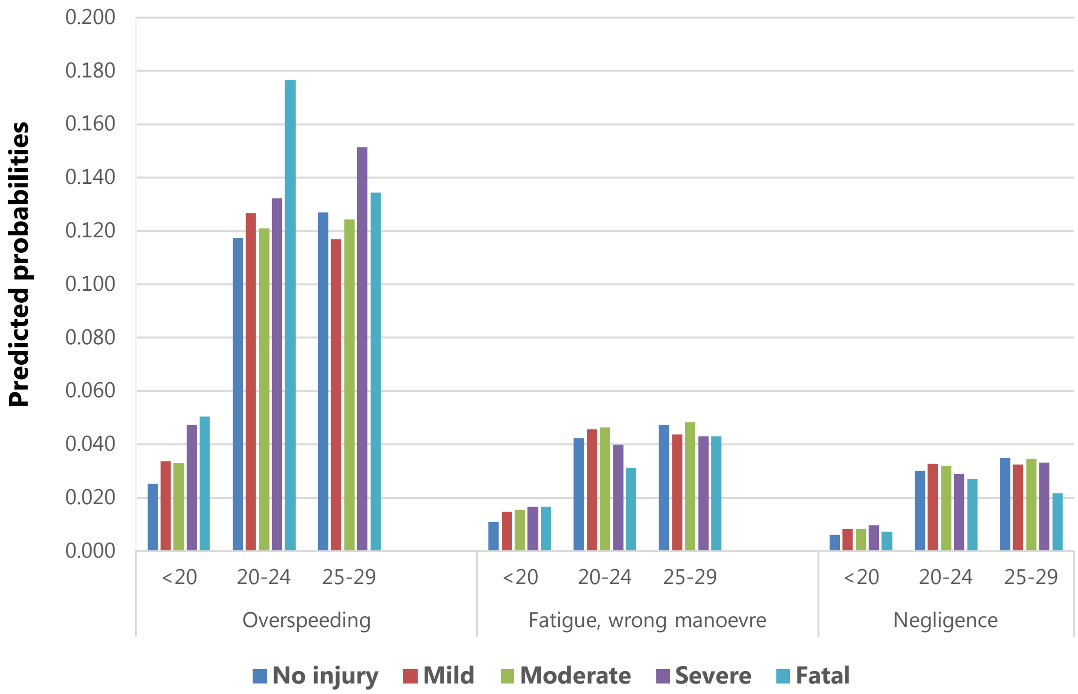



***Figure 3.2*** *Scenarios of multiple risk factors among males aged below thirty years by three major causes of RTCs, predicting the likelihood of each level of road traffic injury severity out of the total reported crashes, Oman, 2010-14*

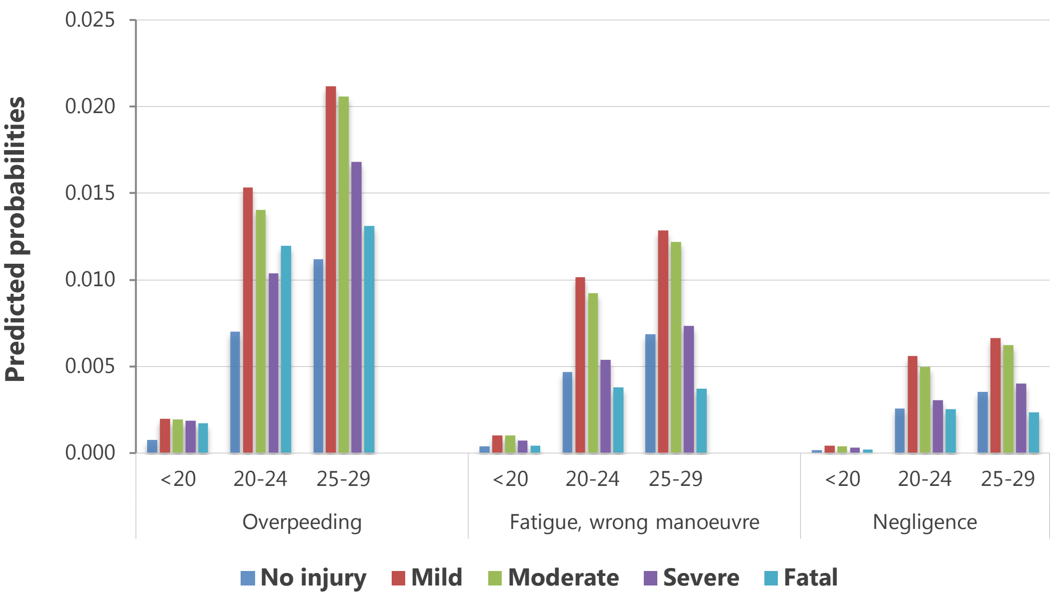



***Figure 3.3*** *Scenarios of multiple risk factors among females aged below thirty years by three major causes of RTCs, predicting the likelihood of each level of road traffic injury severity out of the total reported crashes, Oman, 2010-14*

Results from the three-way interaction indicate that over-speeding featured as the leading cause of RTCs for most risk groups, predominantly young males, followed by fatigue, wrong manoeuvre and negligence (Table 3.4). Males aged below 30 years represent 42% and 44.6% of fatal and severe injury crashes respectively. The probabilities of fatal injuries among males attributed to over-speeding ranged from 4-6% for those aged 40 and above, 5·1% for males aged below 20 to 13·4% among 25-29 and 17·7% for those aged 20-24. It is also noticeable that the relative risk of over-speeding crashes involving males of 20-24 years old compared to those involving 25-29 years old is heightened for fatal crashes than for mild-injury crashes.[7] In addition, Table 3.4 indicates that fatigue and wrong manoeuver and negligence behaviours were more common among males aged 20-29 years and these factors cause 11.6% and 5.8% of the total severe and fatal crashes respectively among this group of drivers.

***Table 3.4*** *Ranking of top ten conditional probabilities of three-way risk factor combination for a given RTC outcome out of the total reported RTCs, Oman 2010-14*

| | **Male** | | | | | **Female** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **No injury** | **Mild** | **Moderate** | **Severe** | **Fatal** | **No injury** | **Mild** | **Moderate** | **Severe** | **Fatal** |
| <20 | | 0·034 | 0·033 | 0.047 | 0·051 | | | 0.009 | | |
| 20-24 | 0·042 | 0·046 | 0·046 | 0·040 | 0·031 | 0·003 | 0·010 | 0·009 | 0·005 | 0·004 |
| | 0·117 | 0·127 | 0·121 | 0·132 | 0·177 | 0.007 | 0.015 | 0.014 | 0.010 | 0.012 |
| | | 0·033 | 0·032 | | 0·027 | 0·005 | 0·006 | 0·005 | 0·003 | 0·002 |
| 25-29 | 0·127 | 0·117 | 0·124 | 0·151 | 0·134 | 0·011 | 0·021 | 0·021 | 0·017 | 0·013 |
| | 0·047 | 0·044 | 0·048 | 0·043 | | 0·005 | 0·010 | 0·008 | 0·006 | 0·003 |
| | 0·035 | 0·033 | 0·035 | 0·033 | | 0·004 | 0·007 | 0·006 | 0·004 | 0·002 |
| 30-34 | 0·079 | 0·071 | 0·076 | 0·087 | 0·082 | 0·008 | 0·015 | 0·015 | 0·011 | 0·009 |
| | 0·033 | | 0·033 | | | 0·005 | 0·009 | | 0·005 | 0·002 |
| | | | | | | 0·002 | 0·004 | | | |
| 35-39 | 0·047 | 0·043 | 0·047 | 0·050 | 0·058 | 0·004 | 0·007 | 0·007 | 0·005 | 0·005 |
| | | | | | | | | 0·004 | | |
| 40-44 | 0·032 | | | 0·031 | 0·039 | | | | 0·003 | 0·003 |
| 45-49 | | | | | 0·030 | | | | | |
| 50+ | 0·036 | 0·031 | | 0·034 | 0·050 | | | | | |

**Over-speeding** **Fatigue, wrong manoeuvre** **Negligence**

[7] This was calculated as (0.177/0.134) / (0.127/0.117) > 1.

## 3.4 Discussion and Conclusions

Addressing the underlying effects of age and sex on the extent of severity of RTCs outcomes is crucial to improve road safety measures. The purpose of this analysis was to investigate the differences in driver injury severity across sex/age groups in Oman. The study aimed to explore the effects of other factors such as drivers' nationality, environmental factors, time-related factors (day of the week, year and month of the crash), and vehicle conditions on mediating the association between crash injury severity and sex and age of the driver as this is essential to gain a better understanding of RTCs phenomenon in Oman.

A generalised ordered logit model was applied to account for the ordered nature of crash injury severity, while allowing the violation of the proportional odds assumption across severity levels. The findings from this analysis offer new insights to understanding the demographic influence of RTCs in Oman, where evidence-based interventions for road safety are critical to tackling the high burden of RTCs.

Overall, the presented evidences confirm our research hypothesis that the odds of severe incapacitating and fatal injuries are significantly higher for young males than their older and female counterparts. In the event of a road crash with severe and fatal injuries, males aged 20-29 represent the highest risk group. In comparison, females aged 25-29 are more likely to be involved in mild and moderate injuries. Analysis of multiple risk factors demonstrates compelling evidence of over-speeding as the primary cause of fatal and severe injuries especially among young males, significantly more than the other causes.

In terms of gender effects, the results demonstrate that male drivers have high level of crash severity and they relate to an increase probability of severe (incapacitating) injuries and fatalities along with an increase in the probability of no injury crashes compared to their female counterparts. However, females appear to have higher probability of being involved in mild and moderate injury crashes. The results also confirm that males are also more likely to drive at younger age than females do and they even have a tendency to drive without holding a driving license. These findings are in line with findings of past studies, which have provided evidence that male drivers are at higher risk to be involved in RTCs compared to their female counterparts and they are more likely to cause fatal and severe injury crashes than females (Massie et al., 1995; Abdel-Aty and Radwan, 2000; WHO, 2002; Williams, 2003; Clarke et al., 2006; Clarke et al., 2010). The possible explanation to this finding is that male drivers in Oman have greater exposure to driving (according to ROP (2016), males represent 80.9% of the total license holders in Oman in 2015). Moreover, males are more likely to be the breadwinners of their families along with their greater tendency to be engaged in risky driving behaviours. In addition, working as a driver and mechanics in cars and trucks, including long-haul vehicles, is more common among males, and hence this implies that males are more likely to spend longer time on the road. Therefore, it is clear that because of the differences in the role of males and females, male drivers have a higher exposure to the risk of RTCs injuries and fatalities.

In regards to the effect of driver's age, the results indicate that the highest risk for fatal crashes is seen to be among drivers aged 20-24 years, followed by those aged 25-29 years. In addition, the scenarios of the multiple risk factors of the fitted model indicated that 42% to 44.6% of fatal and severe injury crashes were caused by males aged below 30 years, with over-speeding appears to be the main cause of these crashes. Sensation seeking and excitement-seeking on risky driving behaviour such as speeding and overtaking could explain the high proportion of young males in more severe injury crashes (Oltedal and Rundmo, 2006). Furthermore, the results confirm that the relative risk of over-speeding behaviour among males aged 20-24 years compared to those aged 25-29 years is heightened for fatal crashes than for mild-injury crashes. Inexperience could be one of the factors that explain the higher proportion of involving younger male drivers in over-speeding fatal crashes. The results also indicate that age and sex of the drivers play a major role on determining the primary cause of RTCs and influencing the severity of crash injuries in Oman. Fatigue and wrong manoeuvre and negligence are more likely to contribute to more severe and fatal crashes among male drivers aged 20-29 compared to other age groups. However, males aged below 20 years appear to be always at higher risk of suffering fatal and severe injuries regardless the type of driving behaviour (i.e. over-speeding, fatigue and wrong manoeuvre of negligence behaviour).

The high risk of fatal and severe injuries among young males exert a huge long-term impact on the left-behind families in terms of emotional, economic and social wellbeing. In addition, healthcare expenditure for managing disability and chronic conditions can be catastrophic for families and health systems in Oman. There is also an increase in the number of female drivers in Oman and this highlights the need to initiate early gender-sensitive interventions targeting potential young male and female drivers.

The challenges to designing and implementing road safety interventions are complex and context-specific, particularly in terms of achieving target 3.6 of the UN Sustainable Development Goals (WHO, 2015). About two-third of male population in Oman are below age 25, which highlights the dire need for comprehensive targeted policy interventions and legislation to improve road safety measures. Institution-based (school, college, workplace) and family-based interventions could focus on promoting awareness about road safety and the implications of road traffic crashes; countermeasures such as routine traffic surveillance especially for heavy vehicles, harsh penalty and license restrictions for young drivers could reduce the number and severity of RTCs (Oltedal and Rundmo, 2006; Rifaat and Chin, 2007).

The relative risk of Oman natives compared to the foreigners is heightened for fatal crashes than no-/mild-injury crashes. The difficulty of driving or inexperience of foreign drivers in Oman driving system could provide a possible explanation for this result, as those drivers are more likely to be more cautious while driving in a non-familiar environment (Michalaki et al., 2015). Therefore, this finding highlights the need for safety interventions targeting the expatriate population, particularly new drivers from other low and middle income countries (LMICs) who might not have adequate skills, knowledge about rules and regulations or driving experience in GCC countries. In addition, since the representation of expatriates adds further complexity in understanding and quantifying crash risk in Oman, future research should be conducted to study the impact of culture on road safety in the country (AL-Bulushi et al., 2015).

Considering the effect of the day of week on crash severity, the results indicate that while the highest percentages of all types of crashes occur during weekdays, the relative risk of weekday vs. weekend is heightened for no-injury crashes than for fatal crashes. This result could be explained by the assumption that risky driving behaviours are more likely to appear during weekend days. This finding has been confirmed in some of the past studies (Symmons et al., 2004; Michalaki et al., 2015). Further, the study confirms that fatal and severe injury crashes are more likely to occur during July-September compared with other months of the year. This can be related to the fact that these months have the highest temperature in the year and consequently this could increase the probability of the occurrence of vehicle defects (e.g. tyres' defects and mechanical faults), which in turns increases the probability of the occurrence of severe crashes. In addition, since schools are closed in July and August most people prefer to take their annual leave during this period to spend their holiday with their families. Additionally, Salalah[8] Tourism Festival starts in July and it continues until the end of August and many Omanis as well as many tourists, particularly tourists from the neighboring Arabian Gulf countries, go there to spend their summer holiday. Consequently, these drivers are more likely to experience driving on non-familiar environment for long hours[9] and this in turn increases the likelihood of being involved in RTCs as the risk of falling asleep-related crashes (fatigue-related crashes) increases considerably even after driving for short trips (Sagberg, 1999). Therefore, awareness campaigns about the risk of driving for long distances and risky driving

[8] Salalah is a city in South Oman. It locates in Dhofar Governorate, which is famous for its seasonal weather, locally known as monsoon or "Khareef" during July-August. During this period Dhofar is clothed in lush greenery and its hills surrounded by white fog along with Light rains drizzle to cool the air (Ministry of Tourism, 2016).

[9] Salalah is 1,040 kilometers far from Muscat (Ministry of Tourism, 2016).

behaviours and providing more information about the characteristics of the road infrastructure through television channels, radio station, and other social media are recommended. Besides, development of road infrastructure with safety features such as roadway design and road hazards, especially in places where more people are expected to go spending their holidays, is recommended to reduce the RTCs during this period of the year.

The majority of RTCs in this study occurred on two-way roads and these crashes tend to be more severe compared to those occurred on one-way roads. This result is not surprising as the presence of multiple users along with the limited maneuvering ability of the drivers on the two-ways roads can play a major role on the high level of severity of such crashes. Consequently, this increases the probability of being involved in a crash either by colliding with fixed object on the roadside or overturn on the outer edge of the road, or entering the oncoming traffic and colliding with another vehicle (Al-Reesi et al., 2016). Therefore, the investment in converting two-way roads into one-way is recommended, whereas advanced driving courses, focusing on increasing the awareness of drivers to drive on the multilane two-ways roads, are also needed (Kaplan et al., 2012).

Although these data should only include serious crashes, with the possibility of occurrence of confusion between the involved drivers to determine who was at fault, it is still possible that minor crashes have been mistakenly recorded as serious crashes. Data on RTCs based on police judgement might be subject to bias and misclassification, although these records are verified for legal and insurance reasons. It is likely that some of the severe injuries could lead to fatal outcomes during or after hospitalisation. Additionally, this analysis did not explore the fatal and non-fatal injury outcomes of passengers including children due to lack of data. Since literature have verified that the behaviour of the driver can be affected by age and sex of the passengers, it is recommended that ROP should record details about the personal characteristics of passengers in the NRTC database. The availability of such data would help to develop a better understanding of the differential effects of various types of passengers on drivers, particularly young male drivers. Furthermore, the definition of deaths related to road traffic crashes in Oman differs from definition used in the international level according to the WHO; thus, the comparison to other countries would be inaccurate (AL-Bulushi et al., 2015).

Other information such as distance travelled, driving experience, personal factors (e.g. license status, mobile phone use, stress, health conditions, previous incidents) could help validate and improve our understanding of the risk behaviours. Behavioural factors other than risky driving were not disentangled due to data limitations. Despite these limitations, this study demonstrates systematic quantitative evidence of complex age-sex interactions in determining the severity of RTCs.

# Chapter 4

## Severity of road crash injuries during peak hours of traffic congestion in the Sultanate of Oman: Evidence from the National Road Traffic Crash database[10]

ABSTRACT:

**Objective:**

The ***aim*** of this chapter is to investigate the statistical association between the peak hours of traffic congestion and number of fatal and non-fatal road crashes in Oman. We hypothesise that the peak hours of traffic congestion have no effect on the number and severity of injury outcomes.

**Methods:**

The analysis considered 35,785 individual case records comprising 5,891 fatal and 29,894 non-fatal injuries. The outcome variable is the number of fatal and non-fatal road traffic crashes. Negative Binomial regression models were applied to examine the association between peak and non-peak hours of traffic congestion within the 24 hours of a day and the number of fatal and non-fatal road injuries, adjusting for day of the week and driver's personal characteristics.

**Findings:**

The severity of road injuries varied by the peak hours of congestion. Regression analyses demonstrate evidence that the peak hour for fatal crashes occurred mostly around 18:00 hours, while the peak hour for nonfatal crashes occurred around 15:00 hours. The off-peak hours for both types of traffic crashes occurred during early morning hours (05:12 for fatal crashes and 04:24 for nonfatal crashes). Sex and age of the drivers, day of the week and crash location appear to be critical factors in mediating the association between the number of fatal and nonfatal crashes and time of

[10] Findings of this analysis were presented at the departmental seminar on 04/03/2016.

the day. Overall, compared to other sex-age groups, young males aged 21-30 years are more likely to cause higher number of fatal and non-fatal crashes during weekday and weekend.

**Conclusion:**

The findings reject our hypothesis and confirm that peak hours of traffic congestion have significant effect on the outcomes of traffic crashes in Oman. Road safety interventions should consider measures to monitor driver behaviours during the peak hours of traffic during both the weekdays and weekends.

**Key messages**

- The severity of road injuries varied by the peak hours of congestion with fatal RTCs peaking around 18:00 hours, while the peak hour for nonfatal crashes occurred around 15:00 hours.
- The potential dominant factors for early evening fatal crashes are driver fatigue and drowsiness. The high density of traffic volume during the rush hours could be the potential factor for the high density of nonfatal RTCs at 15:00 hours.
- Age and sex of the driver, day of the week and crash location are critical factors in mediating the association between the density and severity of RTCs and time of day.

**Keywords:** Road crash injuries, Oman, fatal and nonfatal crash, crash severity, peak and off-peak hour, Negative Binomial Regression

## 4.1 Background and Rationale

This chapter aims at investigating the statistical association between the peak hours of traffic congestion and number of fatal and non-fatal road injuries in Oman. The analysis considered a Negative Binomial regression models and adjusting for day of the week, driver's personal characteristics and spatial factors.

Road traffic crashes are complicated events, and they occur as a result of a combination and interaction of several factors including drivers' behaviours and characteristics, vehicles' characteristics, environmental conditions, and road geometry (Farag et al., 2014). Gaining a better understanding of the relationship between the severity of the injuries resulting from RTCs and associated risk factors is necessary to reduce incidence of RTCs.

The density of RTCs are not the same during different times of the day. The traffic flow on the road could be on of the main contributory factor of the occurrence RTCs. According to Al-Rawas (1993), the traffic flow starts after 0500 hours in the early morning and decline after 1800 hours in Oman. The author added that there are two traffic peaks towards Muscat, the morning peak occur between 0600 and 0700 hours and the second peak occur between 1600 and 1800 hours.

Lenné et al. (1997) argued that driving performance is affected by time of day. They found that impaired driving performance and sleep propensity are more common during nighttime, early morning (0200 and 0600 hours), and early afternoon. They also argued that the increase in the number of RTCs during afternoon is associated with the predominance of performance dips which occurs at 1400 hours, (the post-lunch dip). The authors added that this dip in performance following the post-lunch time is more predominant in tasks involving longer periods of sustained attention.

In contrast, Moller et al. (2003) conducted a study on 16 subjects to investigate the effect of circadian variation on driving performance by classifying the micro-sleep episodes and the attention lapses into four points of time: 1000, 1200, 1400 and 1600 hours. They found no significant variation in attention lapses, off-road events, lane variations, and average and standard deviation of speed during these four points of time. However, they found that mid-afternoon (1600) hours is the time at which micro-sleep episodes commonly occur. Conversely, Reimer et al. (2007) suggested that time of day has an impact on driver speed and speed variability but they claimed that this relation depends on the road environment since characteristics of road design could positively influence the alertness of the drivers.

Although the number of nighttime crashes is less than daytime crashes, due to the heavy traffic volume during daytime, it has been found that driving at night represents a higher risk when considering the level of traffic volume during day and nighttime (Smith et al., 2008). Although the overall risk of nighttime driving is less certain for all levels of crash severity, it has been found that this risk is more likely to be associated with fatal injury crashes (Smith et al., 2008). The risk of being involved in fatal injury crash found to be three to four times higher among young drivers compared with other drivers (Smith et al., 2008).

The risk of nighttime crash found to be associated with the level of visibility and road lighting conditions (Clarke et al., 2006; Smith et al., 2008). Although improving road lighting condition could be argued to result in reductions in the number of nighttime collisions, however, Smith et al. (2008) found no difference in the number of nighttime crashes on lit and unlit roads. Clarke et al. (2006) argued that nighttime is not only the time of artificial lighting and poor visibility, but it also differs from morning and afternoon times in that different groups of road users are travelling for different purposes. For example, driving for social purposes and for pleasure during nighttime have been seen to be more common among younger drivers than in other age groups (Stradling and Meadows, 2000 cited in Clarke et al., 2006). Clarke et al. argued that in terms of nighttime crashes what matter is not the visibility, but who uses the roads at night, and why and how.

Fatigue/sleepiness is a significant contributory factor associated with fatal and serious injury crashes (Armstrong et al., 2013). Sleep related crashes defined as those crashes affected by the time of the day (Philip et al., 2005). RTCs from work to home have been classified as one of the major causes of death and injury among workers due to the conflict between physiological needs, and social and professional requirements, sleep deprivation is high among workers especially those engaged in shifts or on call workers (Philip et al., 2005). For example, professional drivers tend to compensate sleep to gain economic rewards. Similarly, nurses and physicians face the same challenge, as they often have to work overnight for very long hours. Consequently, those workers have high probability of fatigue and risk of causing road crash (Gaba and Howard, 2002 cited in Philip et al., 2005). Armstrong et al. (2013) found that many drivers had experienced a sleep related incident when commuting to and from work, especially on low speed roads which are commonly located in high-populated urban areas. Filtness et al. (2017) stated that driving in high populated urban areas requires quick responses and quick decision making, as roads on these areas are complex and shared by different parties. The authors also argued that flexibility of decision-making in cognitive tasks is impaired by sleepiness and thus sleepy drivers could produce impaired responses when they face critical situations. Therefore, integrating sleep schedules before and during the work period within the work schedules is important for preventing the occurrence of road traffic crashes (Philip et al., 2005).

Sleep related crashes found to result in high severity outcomes regardless the speed limit of the road zone (Filtness et al., 2017). The high severity outcomes of such crashes can be attributed to the failure of the driver of taking reactions (e.g. reducing speed) to avoid the crash (Filtness et al., 2017). No sign of braking was observed in sleep related crashes due to the non-reactive response of sleepy drivers (Horne and Reyner (2001) cited in Filtness et al., 2017). Compared to sleep related crashes, other impairment related RTCs, e.g. those associated with alcohol or drugs, found to end with lower severe outcomes and this is because drunk drivers could produce slow reaction when they become alert during the crash (Filtness et al., 2017).

Sleep loss found to be more prevalent among young people due to developmental and social factors (Filtness et al., 2017). Young adult drivers are more likely to have impaired driving performance following sleep loss compares to older drivers (Filtness et al., 2017). Reimer et al. (2007) stated that younger drivers are more likely to have poorer judgement of risk assessment of their own speed and other road users. However, what affords some relief for their poor judgement and inexperience are their faster reaction times, lower proportions of off road movements, and better lane discipline. Filtness et al. (2017) found that young male drivers aged 16-24 year are overrepresented in sleep related crashes which highlights the importance of targeting driver sleepiness intervention towards young novice drivers. Likewise, Otmani et al. (2005) demonstrated evidence that sleep related crashes are more prevalent among young drivers aged 20-30 year.

The density of RTCs are not the same during different days of the week. The outcomes of RTCs during weekend found to be more severe compared to those occurring during weekday, and this could be attributed to the higher likelihood of risky driving behaviours during holidays and weekends compared to weekday (Anowar et al., 2013). Symmons et al. (2004) found that the highest percentage of RTCs on rural Victorian roads took place on Fridays, Saturdays and Sundays, i.e. weekends, while the lowest number of crashes occurred on Mondays, Tuesdays and Wednesdays, i.e. weekdays. In general, they found that 32% of these crashes occurred during weekends, and this percentage was higher than expected (29%), which would be obtained by assuming that all days of the week has the same number of road traffic crashes.

Sex of the driver is a critical factor in determining the crash risk. Previous studies have claimed that male drivers are at higher risk to be involved in RTCs compared to their female counterparts (Massie et al., 1995; Böhning and Ayutha, 1997;Abdel-Aty and Radwan, 2000; WHO, 2002; Oltedal and Rundmo, 2006 ). The higher risk for males to be involved in RTCs can be explained by their greater exposure to driving aside from their risky driving behaviours; males are more likely to own vehicle, working as a driver and mechanics in cars and trucks, including long-haul vehicles compared to females( WHO, 2002). This implies that males are more likely to spend more days and nights on the road, so they have a higher exposure to the risk of being involve in RTCs ( WHO, 2002). Böhning and Ayutha (1997) found that driving for long hours per day increase the odds to the crash risk. Male drivers were found more likely to be involved in fatal RTCs, whereas female drivers aged over 25 years have a higher risk to be involved in non-fatal crashes compared to their male counterparts

(Massie et al., 1995). According to a study conducted by Abdel-Aty and Radwan (2000), female drivers are more likely to have a higher risk to be involved in a crash during heavy traffic volume than male drivers.

Lower motivation to comply with traffic rules found among young males (WHO, 2002). Young male drivers found to report risky driving behaviours as less dangerous compared to their female counterparts (Oltedal and Rundmo, 2006). Although, it is argued that young male drivers have quicker reaction times to avoid impending crashes, but their reaction could be negatively affected if there is low visibility due to darkness or other environmental related factors such as weather or road conditions (Massie et al., 1995). Accordingly, they have a greater probability to die or suffer severe injuries as most of these crashes often involve high speed driving (Massie et al., 1995).

There is little systematic analysis of the association between time of the day and RTC outcomes in Oman. The ***aim*** of this chapter is to investigate the statistical association between the peak hours of traffic congestion and number of fatal and non-fatal road crashes in Oman. The chapter addresses the following questions:

1. What is the nature of relationship between the number and severity of crash outcomes and timing of the incident? More specifically, do crash number and severity increase during certain hours of the day or night, or during any particular day(s) in the week or weekend?

2. How do demographic and spatial factors mediate the relationship between crash severity and timing of the incident?

We hypothesised that peak hours of traffic congestion have no effect on the number and severity of RTC outcomes. Exploring the association between time of the day and RTCs will enable policy makers to identify and design appropriate interventions specific to certain high risk times and high risk groups.

## 4.2 Methods

### 4.2.1 Data

Data from national road traffic crashes database for the period 2010–2014 was used as a data source for this analysis. As mentioned in chapter three, RTCs are classified into five levels of severity based on the degree of outcome injuries and the damage to their vehicles and other properties on or next to the road namely: fatal, serious, medium, slight and damage only (i.e. damage to property) crashes. In this analysis, we reduced these five levels into two main categories: fatal crashes (this is a combination of the fatal and serious injury crashes) and non-fatal crashes (this includes the three remaining levels of crash severity) due to similar patterns of crash types in each of these two groups with respect to time of day. The data include 35,785 individual case records comprising 5,891 fatal and 29,894 non-fatal injuries.

### 4.2.2 Modelling approach

Poisson and negative Binomial models, Zero-inflated negative Binomial models, negative Binomial with random effects models, and Conway-Maxwell-Poisson generalised linear models have been frequently used to predict the frequency of road crashes (Anastasopoulos and Mannering, 2008). Lord (2006) argued that the traditional Poisson and Poisson-Gamma (or Negative Binomial) are the most common probabilistic structures used for modelling traffic crashes, however, Poisson-Gamma model is preferred when data show signs of over-dispersion. The over-dispersion observed in crash data can be described in terms of the "represented traits" and "unrepresented traits". In other words, the root cause of the over-dispersion is that entities with the same represented traits have different means because of the unrepresented traits (measured or unmeasured) not included in the model.

The over-dispersion occurs as a result of the actual nature of the crash process, and it can be described as result of Bernoulli trials with unequal probability of independent events (Park and Lord, 2009). Since crash data often exhibit over-dispersion, the analysis of modelling crash data becomes more complex, and the level of this complexity becomes more significant with small sample size and low sample mean values (Park and Lord, 2009). Consequently, this can significantly undermine the estimation of confidence intervals for the gamma mean and the predicted response, which can significantly affect the quality of fit of the statistical models.

The outcome variable ($y_i$) was the number of fatal and non-fatal RTCs. We considered various statistical modelling options to examine the association between time of the day (in 24 hours) on the number of fatal and non-fatal RTCs, controlling for relevant individual variables (age and sex of the driver) and day of the week. The same modelling approach was undertaken, however, instead of considering both male and female drivers, only data related to male drivers was used to explore this association with the previous factors and adding the spatial effect of crash location (i.e. Governorate) on the severity of crash outcome.

Time of day, in 24 hours, was defined as a continuous variable, and used as the primary predictor in this study. Sex of driver and day of the week variables were treated as categorical variables with two categories for each; male and female, and weekday and weekend respectively. Age of the driver was defined as a categorical variable with five categories; (15-20, 21-30, 31-40, 41-50, and 50+ years). The spatial factor, Governorate, was also defined as categorical factor consisting of the following 8 governorates: Muscat, Musandam, Dhofar, Ad Dakhliyah, Ash Sharqiyah, Al Batinah, Adh Dhahirah, and Al Wusta.

Poisson regression methodology was initially considered. However, since the variance of the dependent variable exceeds its mean, indicating extensive over-dispersion in data, Negative Binomial regression models were applied to examine the association between peak and non-peak hours of traffic congestion within the 24 hours of the day and the number of fatal and non-fatal road injuries, adjusting for day of the week and driver's personal characteristics. The Negative Binomial model (NBM) is an extension of the Poisson modelling approach which allows the variance of the data to be different from its mean.

NBM can be expressed from the Poisson regression by specifying:

$$\ln(y_i) = \beta x_i + \varepsilon \tag{4.1}$$

Where, $y_i$ is the expected number of fatal/ non-fatal RTCs; β is the vector representing parameters to be estimated; $x_i$ is the vector representing the explanatory variables (time of day, driver's sex and age and day of the week); ε is the error term, where exp (ε) has a gamma distribution with mean 1 and variance $\alpha^2$.

The resulting probability distribution becomes as follows:

$$Prob(n_i|\varepsilon) = \frac{\exp\left[-y_i \exp(\varepsilon)\right] y_i^{n_i}}{n_i!} \tag{4.2}$$

Where, $n_i$ is the number of fatal/non-fatal crashes for a specific weekday/weekend sex-age group occurred at a given hour i. The unconditional distribution of $n_i$ is obtained by integrating ε out of expression (2). The formulation of this distribution is obtained as follow:

$$Prob(n_i) = \frac{\Gamma(\theta+n_i)}{(\Gamma(\theta)n_i!)} u_i^{\theta}(1-u_i)^{n_i} \tag{4.3}$$

Where $u_i = {}^{\theta}/_{(\theta + y_i)}$ and $\theta = {}^{1}/_{\alpha}$.

The following maximum likelihood function can be used to estimate the Negative Binomial model:

$$L(y_i) = \prod_{i=1}^{N} \frac{\Gamma(\theta+n_i)}{\Gamma(\theta)n_i!} u_i^{\theta}(1-u_i)^{n_i} \tag{4.4}$$

Where $N$ is the number of sex-age groups. To obtain coefficient estimates for β and α this function should be maximized. α is an additional parameter for NBM compared to Poisson regression, so that:

$$Var[n_i] = E[n_i]\{1 + \alpha E[n_i]\} \tag{4.5}$$

The value of α affects the choice between Poisson regression and NBM. That is, if the value of α is different from 0 then NBM is preferred, however, if its value is 0 then NBM reduces to a Poisson regression with $Var[n_i] = E[n_i]$.

SPSS V22·0 was used for data management and descriptive analysis and Stata V13·0 for regression analysis.

## 4.3 Results

The proportions of each level of crash severity[11] at each hour of the of day are shown in ***Figures 4.1 and 4.2*** *and they* indicate the both fatal and serious injury crash outcomes have similar patterns, and the other three types of crash injuries have almost the same patterns. Therefore, it was reasonable to combine fatal and serious injury crashes in one data subgroup and the three remaining types were joined in the second subgroup.

The proportion distribution of severity of RTC outcomes by time of the day (in 24 hours) is presented in ***Figure 4.3***. The propensity for fatal injuries was the highest during the nighttime, particularly between 1800 and 2100 hours. The propensity for non-fatal injury was pronounced at times between 1000 and 1700 hours. The off-peak hours of both fatal and nonfatal RTCs were between 0300 and 0500 in the early morning.

The total number of both fatal and non-fatal RTCs aggregated by weekday and weekend for each sex-age group of drivers is presented in ***Table 4.1***. Males aged 21-30 years appeared to cause the highest number of both fatal and non-fatal RTCs compared to other groups. Similarly, females aged 21-30 years caused higher number of fatal and non-fatal RTCs compared to other female groups. Although the total number of both fatal and non-fatal RTCs during weekday was higher than those that occurred during weekend, the average total number of both fatal and nonfatal crashes per day during weekend was greater than that of weekday, 3.65 vs. 3.21 and 16.67 vs. 14.78 respectively. This implies that more than 31% (calculated as 1845/5891*100 and 8420/27068*100) of both fatal and nonfatal RTCs occurred during weekends and this percentage is higher than the expected percentage (28.6%). Comparing the total number of fatal RTCs occurred on weekday and weekend, young females aged 15-20 years were the only group for which the total number of RTCs during weekends exceeds those occurred during weekdays. Old drivers aged above 50 years appeared to cause lower rate of both fatal and non-fatal RTCs compared to other age groups.

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[11] The proportions of fatal crashes are calculated so that the denominator represents the total number of fatal crashes occurred during the 5-year monitoring period and the same method is used to calculate the proportions of the other levels of crash severity.

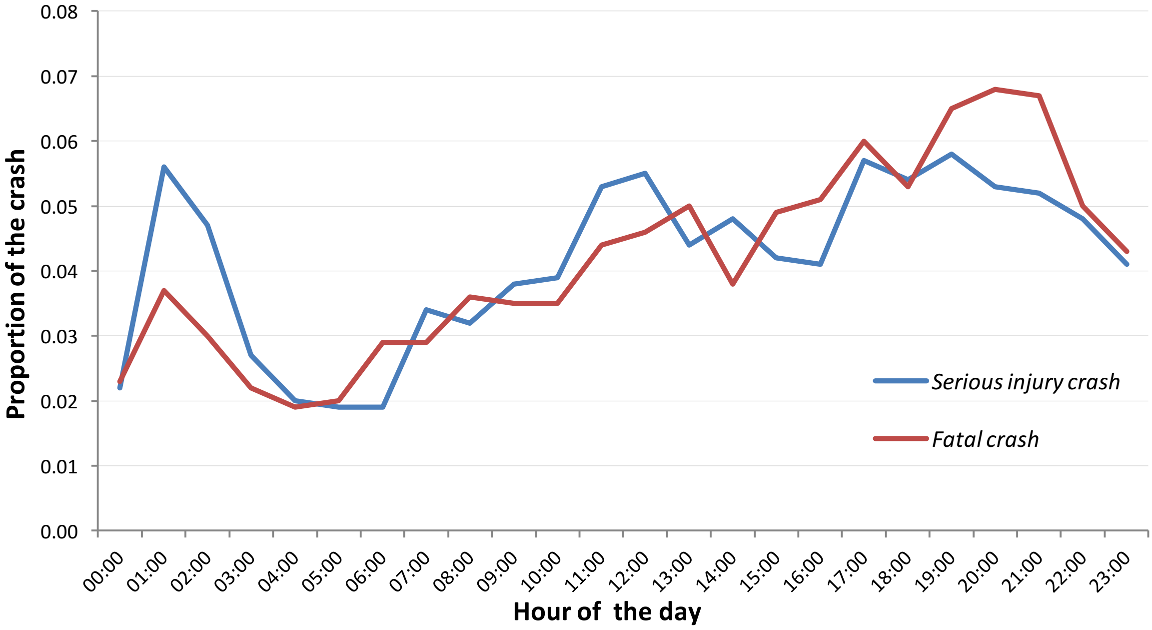


***Figure 4.1*** *Proportion of fatal and serious injury crashes at each hour of the day calculated as out of the total number of crashes of each level of severity during the 5-year monitoring period*

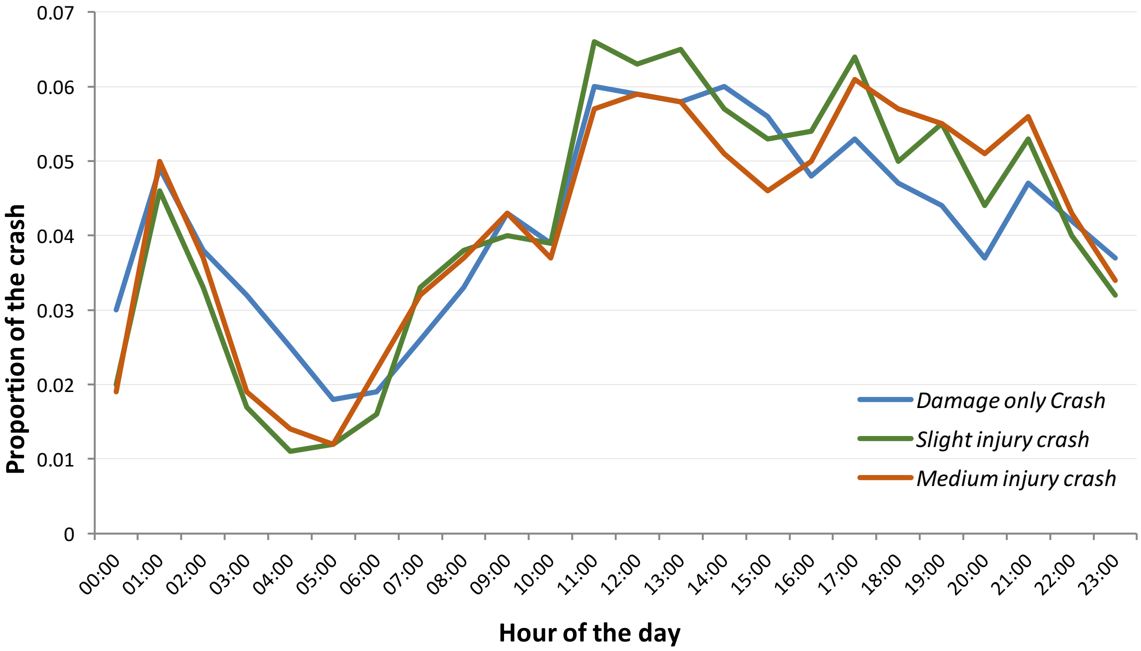


***Figure 4.2*** *Proportion of medium, slight and no injury crashes at each hour of the day calculated as out of the total number of crashes of each level of severity during the 5-year monitoring period*

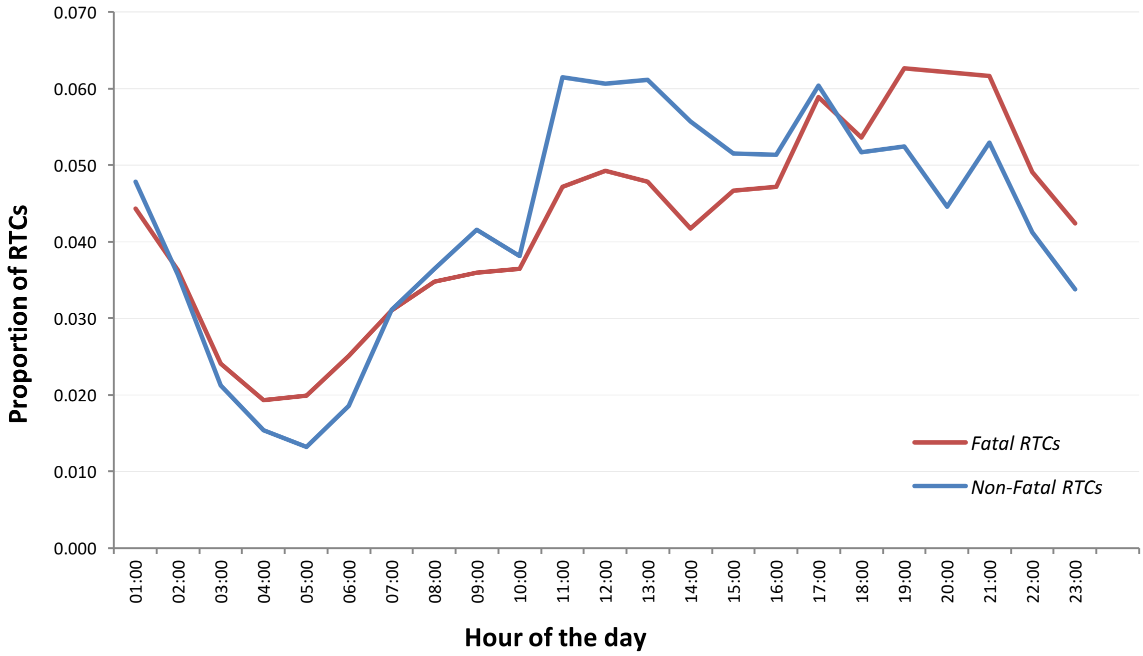


***Figure 4.3*** *Proportion of fatal and non-fatal RTCs at each hour of the day calculated as out of the total number of crashes of fatal and non-fatal RTCs respectively*

***Table 4.1*** *Total number of fatal and non-fatal RTCs by day of the week for each age-sex group, Oman, 2010-14*

| ***Drivers' age-sex group*** | ***Total fatal RTCs*** | | ***Total non-fatal RTCs*** | |
|---|---|---|---|---|
| | ***Weekday*** | ***Weekend*** | ***Weekday*** | ***Weekend*** |
| ***Female:*** | | | | |
| *15-20 year* | 5 | 9 | 176 | 45 |
| *21-30 year* | 156 | 41 | 1591 | 474 |
| *31-40 year* | 85 | 32 | 791 | 228 |
| *41-50 year* | 24 | 15 | 203 | 62 |
| *50+ year* | 2 | 0 | 62 | 18 |
| ***Male:*** | | | | |
| *15-20 year* | 497 | 233 | 2030 | 896 |
| *21-30 year* | 1757 | 870 | 9070 | 3781 |
| *31-40 year* | 831 | 370 | 4269 | 1730 |
| *41-50 year* | 412 | 183 | 1944 | 712 |
| *50+ year* | 277 | 92 | 1335 | 474 |
| ***Total crashes*** | 4046 | 1845 | 18648 | 8420 |
| ***Total RTC/day***[12] | 3.206 | 3.653 | 14.777 | 16.673 |

[12] The data included crashes of a total of 1767 days from 01/10/2010 to 02/11/2014. For weekday, this is calculated as (total RTCs occurring during weekday/1262) since we approximately have a total of 1262 weekdays in the 5-year monitoring period. For weekend, this calculated as (total RTCs occurring during weekend/505) since we have a total of about 505 weekend days in the 5-year monitoring period.

The conditional mean and variance of fatal and nonfatal RTCs for each level of the categorical predictors are shown in Table 4.2. The results clearly indicate that the variances within each group of these factors are exceeding the means suggesting that the data have right skewed distribution. These results also indicate that over-dispersion is present and NBM is more appropriate to model these data.

In order to explore the association between the number of fatal and non-fatal RTCs and time of the day, number of Negative Binomial models (NBM) were constructed (See Appendices A and B). For each model, the estimates, standard error, the 95% confidence interval, and the significant level for each of the predictor variables along with Negative Binomial predictor α were calculated. In addition, the Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) were calculated for each model to select the best model. As it was clear from Figure 4.3, polynomial terms of time of day are more appropriate to represent the association between time of day and number of fatal and non-fatal RTCs. Number of nested models were built using forward selection approach, so that the first model included constant term and first degree of the polynomial terms of time of day. Then, the other factors and terms were added one by one to construct the following models. The final selected models are presented in Table 4.3.

Alpha ($\alpha$) is the estimate of the dispersion parameter; this is an additional parameter for NBM compared to Poisson regression. If this parameter equals zero, then NBM is simply reduced to a Poisson model. As it is clear from Table 4.3, ($\alpha$) is significantly greater than zero, and this indicates that the data are over-dispersed, meaning that these data are better to be estimated using NBM than a Poisson model.

Results from the final fitted model suggest that the incident rate of fatal and non-fatal RTCs for female drivers is 0.005 and 0.043 times the incident rate of fatal and non-fatal RTCs for males holding other variables constant.

***Table 4.2*** *Mean and variance of fatal and non-fatal RTCs[13] by driver's sex and age and day of the week, Oman, 2010-14*

| ***Factor*** | ***Fatal RTCs*** | | ***Non-fatal RTCs*** | |
|---|---|---|---|---|
| | ***mean*** | ***variance*** | ***mean*** | ***variance*** |
| ***Sex of driver*** | | | | |
| *males* | 2.008 | 494.385 | 109.338 | 13512.500 |
| *females* | 1.536 | 6.560 | 15.208 | 591.086 |
| **Age of driver** | | | | |
| *15-20 year* | 7.750 | 97.726 | 32.781 | 1444.025 |
| *21-30 year* | 29.417 | 1008.435 | 155.375 | 25062.620 |
| *31-40 year* | 13.729 | 221.294 | 73.104 | 5569.252 |
| *41-50 year* | 6.604 | 59.547 | 30.427 | 1276.731 |
| *50+ year* | 3.865 | 31.844 | 19.677 | 705.947 |
| ***Day of week*** | | | | |
| *weekday* | 16.858 | 541.813 | 89.463 | 14575.440 |
| *weekend* | 7.688 | 365.439 | 35.083 | 2492.102 |

All age groups of male drivers appear to have higher incident rate to be involved in both fatal and non-fatal RTCs compared to the older age group (drivers aged over 50 year), with drivers aged 21-30 years expected to have the highest incident rate ratio (more than 7 times the rate of the old drivers). Similarly, the comparison of older females' age group with other females indicates that females aged 21-30 year have the highest rate of being involved in fatal and non-fatal RTCs. The incident rate ratio of both fatal and non-fatal RTCs during weekday is more than two times higher than the incident rate ratio during weekend, holding other variables in the models constant. ***Table 4.4*** shows the predicted total number of fatal and non-fatal RTCs for each group of the factors used to construct the NBM. The results in Table 4.4 confirm the results presented in Table 4.3.

[13] *mean and variance of total number of crashes occurring at each hour of the day during all the 5 years of the study period*

***Table 4.3*** *Final fitted Negative Binomial Model for fatal and non-fatal RTCs, Oman, 2010-14*

| ***Parameters*** | ***Fatal RTCs (Fatal and serious injury crashes)*** | | | | ***Non-fatal RTCs (medium, slight and no injury crashes)*** | | | |
|---|---|---|---|---|---|---|---|---|
| | ***Model estimates*** | | | | ***Model estimates*** | | | |
| | ***IRR*** | ***Std. Error*** | ***95% CI*** | ***P-value*** | ***IRR*** | ***Std. Error*** | ***95% CI*** | ***P-value*** |
| *Intercept* | 11.572 | 1.278 | [9.321, 14.368] | <0.000 | 95.660 | 12.788 | [73.610,124.315] | <0.000 |
| *Time* | 0.789 | 0.030 | [0.742, 0.839] | <0.000 | 0.497 | 0.033 | [0.436, 0.566] | 0.010 |
| *Time$^2$* | 1.030 | 0.003 | [1.024, 1.036] | <0.000 | 1.125 | 0.012 | [1.101, 1.148] | <0.000 |
| *Time$^3$* | 0.999 | 0.000 | [0.999, 0.999] | <0.000 | 0.994 | 0.001 | [0.992, 0.995] | <0.000 |
| *Time$^4$* | - | - | - | - | 1.000 | 0.000 | [1.000, 1.000] | <0.000 |
| ***Driver's sex:*** | | | | | | | | |
| *Female* | 0.005 | 0.004 | [0.001,0.022] | <0.000 | 0.043 | 0.006 | [0.033, 0.057] | <0.000 |
| *Male (reference group)* | - | - | - | - | - | - | - | - |
| ***Driver's age group:*** | | | | | | | | |
| *15-20 year* | 2.012 | 0.158 | [1.726,2.346] | <0.000 | 1.703 | 0.130 | [1.467, 1.979] | <0.000 |
| *21-30 year* | 7.368 | 0.527 | [6.404,8.477] | <0.000 | 7.571 | 0.562 | [6.546, 8.757] | <0.000 |
| *31-40 year* | 3.317 | 0.248 | [2.865,3.840] | <0.000 | 3.495 | 0.262 | [3.017, 4.048] | <0.000 |
| *41-50 year* | 1.640 | 0.132 | [1.401,1.920] | <0.000 | 1.490 | 0.114 | [1.382, 1.733] | <0.000 |
| *50+ year (reference group)* | - | - | - | - | - | - | - | - |
| ***Age *Sex group:*** | | | | | | | | |
| *15-20 year female* | 3.484 | 2.653 | [0.783,15.495] | 0.101 | 1.571 | 0.267 | [1.125, 2.192] | 0.008 |
| *21-30 year female* | 13.237 | 9.475 | [3.255,53.835] | <0.000 | 3.286 | 0.510 | [2.424, 4.453] | <0.000 |
| *31-40 year female* | 17.532 | 12.598 | [4.288,71.690] | <0.000 | 3.495 | 0.548 | [2.556, 4.739] | <0.000 |
| *41-50 year female* | 11.940 | 8.728 | [2.850,50.027] | 0.001 | 1.491 | 0.373 | [1.602, 3.092] | <0.000 |
| *50+ year females (reference group)* | - | - | - | - | - | - | - | - |
| ***Day of the week:*** | | | | | | | | |
| *Weekend* | 0.437 | 0.017 | [-0.907, -0.750] | <0.000 | 0.366 | 0.014 | [0.339, 0.395] | <0.000 |
| *Weekday (reference group)* | | - | - | - | - | - | - | - |
| ***Negative Binomial Parameter $\alpha$*** | 0.042 | 0.009 | [-3.611, -2.744] | | 0.111 | 0.0109 | [0.092, 0.134] | |
| ***Likelihood Ratio test of $\alpha$ = 0*** | 65.150 | | Prob. >=chibar$^2$ = 0.000 | | 1240.500 | | Prob. >=chibar$^2$ = 0.000 | |

***Table 4.4*** *Predicted probabilities of total number of fatal and non-fatal RTCs[14] , Oman, 2010-14*

| Parameters | | Fatal RTCs (Fatal and serious injury crashes) | | | | Non-fatal RTCs (medium, slight and no injury crashes) | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Num. of crashes | Std. Error | 95% CI | P-value | Num. of crashes | Std. Error | 95% CI | P-value |
| **Driver's sex:** | | | | | | | | | |
| Males | | 18.013 | 0.559 | [16.918, 19.109] | 0.000 | 112.748 | 4.365 | [104.193, 121.304] | 0.000 |
| Females | | 0.618 | 0.0980 | [0.426, 0.810] | 0.000 | 10.235 | 0.479 | [9.296, 11.174] | 0.000 |
| **Driver's age group:** | | | | | | | | | |
| 15-20 year | | 2.081 | 0.289 | [1.515, 2.647] | 0.000 | 21.617 | 1.258 | [19.154, 24.084] | 0.000 |
| 21-30 year | | 14.854 | 0.719 | [13.446, 16.263] | 0.000 | 138.973 | 6.610 | [126.018, 151.929] | 0.000 |
| 31-40 year | | 7.695 | 0.444 | [6.825, 8.565] | 0.000 | 66.026 | 3.218 | [59.719, 72.332] | 0.000 |
| 41-50 year | | 3.140 | 0.277 | [2.596, 3.685] | 0.000 | 22.519 | 1.271 | [20.028, 25.011] | 0.000 |
| 50+ year | | 0.554 | 0.197 | [0.168, 0.941] | 0.005 | 10.127 | 0.747 | [8.663, 11.590] | 0.000 |
| **Age *Sex group:** | | | | | | | | | |
| males | 15-20 year | 15.063 | 0.814 | [13.467, 16.659] | 0.000 | 82.792 | 5.092 | [72.812, 92.773] | 0.000 |
| | 21-30 year | 55.162 | 2.369 | [50.518, 59.805] | 0.000 | 367.958 | 21.736 | [325.356, 410.559] | 0.000 |
| | 31-40 year | 24.830 | 1.189 | [22.500, 27.160] | 0.000 | 169.854 | 10.121 | [150.018, 189.691] | 0.000 |
| | 41-50 year | 12.279 | 0.690 | [10.926, 13.632] | 0.000 | 72.448 | 4.426 | [63.773, 81.123] | 0.000 |
| | 50+ year | 7.487 | 0.484 | [6.537, 8.436] | 0.000 | 48.602 | 3.029 | [42.665, 54.539] | 0.000 |
| Females | 15-20 year | 0.287 | 0.078 | [0.135, 0.440] | 0.000 | 5.645 | 0.510 | [4.645, 6.645] | 0.000 |
| | 21-30 year | 4.000 | 0.324 | [3.363, 4.637] | 0.000 | 52.489 | 3.218 | [46.182, 58.795] | 0.000 |
| | 31-40 year | 2.385 | 0.240 | [1.915, 2.854] | 0.000 | 25.666 | 1.683 | [22.367, 28.964] | 0.000 |
| | 41-50 year | 0.803 | 0.133 | [0.543, 1.063] | 0.000 | 7.000 | 0.602 | [5.820, 8.180] | 0.000 |
| | 50+ year | 0.041 | 0.030 | [-0.016, 0.098] | 0.158 | 2.110 | 0.270 | [1.581, 2.639] | 0.000 |
| **Day of the week:** | | | | | | | | | |
| Weekend | | 2.206 | 0.190 | [1.834, 2.578] | 0.000 | 20.551 | 0.888 | [18.811, 22.292] | 0.000 |
| Weekday | | 5.050 | 0.420 | [4.226, 5.873] | 0.000 | 56.152 | 2.199 | [51.842, 60.461] | 0.000 |

[14] *mean of total number of crashes occurring at each hour of the day during all the 5 years of the study period*

The effects of time of the day on the number of RTCs are obtained from the determination of the points at which the maximum and minimum number of RTCs occurred. This is achieved by finding the first derivative of the final selected models with respect to time (t). The formula of the final selected models can be written as, instead of the incident rate ratio (IRR) the $\beta$ estimates, $\beta = \log(IRR)$, are presented:

$$\mathbf{lo\,g}(\boldsymbol{y_1}) = 2.2448624 - 0.237296\boldsymbol{t} + 0.0294807\boldsymbol{t^2} - 0.000851\boldsymbol{t^3} - 5.206955\boldsymbol{Female} + 0.6991103\boldsymbol{Age}_{(\mathbf{15-20})} + 1.997142\boldsymbol{Age}_{(\mathbf{21-30})} + 1.198925\boldsymbol{Age}_{(\mathbf{31-40})} + 0.4947388\boldsymbol{Age}_{(\mathbf{41-50})} + 1.248144\boldsymbol{Female}_{(\mathbf{15-20})} + 2.582982\boldsymbol{Female}_{(\mathbf{21-30})} + 2.864038\boldsymbol{Female}_{(\mathbf{31-40})} + 2.479954\boldsymbol{Female}_{(\mathbf{41-50})} - 0.828302\boldsymbol{Weekend}, \tag{4.6}$$

$$\mathbf{log}(\boldsymbol{y_2}) = 4.560796 - 0.7001594\boldsymbol{t} + 0.1174337\boldsymbol{t^2} - 0.0063708\boldsymbol{t^3} + 0.0001094\boldsymbol{t^4} - 3.136995\boldsymbol{Female} + 0.5326657\boldsymbol{Age}_{(\mathbf{15-20})} + 2.024296\boldsymbol{Age}_{(\mathbf{21-30})} + 1.251268\boldsymbol{Age}_{(\mathbf{31-40})} + 0.3991938\boldsymbol{Age}_{(\mathbf{41-50})} + 0.4514322\boldsymbol{Female}_{(\mathbf{15-20})} + 1.189623\boldsymbol{Female}_{(\mathbf{21-30})} + 1.247203\boldsymbol{Female}_{(\mathbf{31-40})} + 0.8000186\boldsymbol{Female}_{(\mathbf{41-50})} - 1.00514\boldsymbol{Weekend}, \tag{4.7}$$

Where $\boldsymbol{y_1}$ and $\boldsymbol{y_2}$ are the expected number of fatal and non-fatal RTCs respectively and $\boldsymbol{t}$ is hour of the day.

So to obtain the times at which maximum and minimum number of fatal crashes occur, we take the derivative of the first equation:

$$\frac{\boldsymbol{\partial f(t)}}{\boldsymbol{\partial t}} = -0.237296 + 0.0589614\boldsymbol{t} - 0.0002553\boldsymbol{t^2}$$

To find the values of (t) at which maximum and minimum number of crashes occurred then $\frac{\partial \mathrm{f(t)}}{\partial \mathrm{t}}$ should be equated to zero.

$$\frac{\boldsymbol{\partial f(t)}}{\boldsymbol{\partial t}} = -0.237296 + 0.0589614\boldsymbol{t} - 0.0002553\boldsymbol{t^2} = \mathbf{0}$$

This is a quadratic equation and its roots are obtained by the following formula:

$\mathrm{t} = \frac{-\mathrm{b}\pm\sqrt{\mathrm{b}^2-4\mathrm{ac}}}{2\mathrm{a}}$, Where $\mathrm{a} = -0.002553, \mathrm{b} = 0.0589614, \text{and } \mathrm{c} = -0.237296.$

$t_{max} = 17.912, \text{and } t_{min} = 5.191$

Results of these calculations indicate that $\boldsymbol{t_{max}} = 17.912$, and $\boldsymbol{t_{min}} = 5.191$ are the times at which the maximum and the minimum number of fatal RTCs occurred respectively (i.e. maximum number of fatal RTCs occurred at 17:55 and minimum number occurred at about 05:12).

For **non-fatal crashes**, the derivative of the second equation should be found:

$$\frac{\partial \boldsymbol{f(t)}}{\partial \boldsymbol{t}} = -0.7001594 + 0.2348674\boldsymbol{t} - 0.0191124\boldsymbol{t^2} + 0.0004376\,\boldsymbol{t^3}$$

To find the values of $(t)$ at which maximum and minimum number of non-fatal crashes occurred then $\frac{\partial f(t)}{\partial t}$ should be equated to zero.

$$\frac{\partial \boldsymbol{f(t)}}{\partial \boldsymbol{t}} = -0.7001594 + 0.2348674\boldsymbol{t} - 0.0191124\boldsymbol{t^2} + 0.0004376\,\boldsymbol{t^3} = \boldsymbol{0}$$

This is a cubic equation and its roots are obtained by the following formula:

$$t = \sqrt[3]{\left(\frac{-b^3}{27a^3} + \frac{bc}{6a^2} - \frac{d}{2a}\right) + \sqrt{\left(\frac{-b^3}{27a^3} + \frac{bc}{6a^2} - \frac{d}{2a}\right)^2 + \left(\frac{c}{3a} - \frac{b^2}{9a^2}\right)^3}} +$$

$$\sqrt[3]{\left(\frac{-b^3}{27a^3} + \frac{bc}{6a^2} - \frac{d}{2a}\right) - \sqrt{\left(\frac{-b^3}{27a^3} + \frac{bc}{6a^2} - \frac{d}{2a}\right)^2 + \left(\frac{c}{3a} - \frac{b^2}{9a^2}\right)^3}} - \frac{b}{3a},$$

Where $a = 0.0004376, b = -0.0191124, c = 0.2348674, \text{and } d = -0.7001594.$

Applying the previous formula of cubic equation gives the following values:

$t_{min_1} = 4.3944$, $t_{max} = 14.9875, \text{and } t_{min_2} = 24.293$. The results reveal that the maximum and the minimum number of non-fatal RTCs occurred at $\boldsymbol{t_{max}} \approx 15{:}00$, $t_{min_1} = 04{:}24$ and $t_{min_2} = 00{:}18$ respectively.

Substituting these values of $\boldsymbol{t}$ for a specific weekday/weekend sex- age group and calculating the rate of change in the number of crashes at $\boldsymbol{t_{max}}$ and $\boldsymbol{t_{min}}$, the slope, provides indication about how quickly can a certain sex-age group move from the minimum point to the maximum point of RTCs. The value of the slope would give an indication about the behavioural differences of a given group of divers between the times at which the minimum and maximum number of crashes occur. This result is useful for policy intervention as it helps to identify the group of drivers of the greatest risk behaviour so the safety interventions will target this group.

Results from ***Table 4.5*** indicate that compared to other sex-age groups, males aged 21-30 years caused the highest number of fatal and nonfatal RTCs and had the greatest behavioural difference as moving from the minimum to the maximum point of fatal crashes during both weekday and weekend.

The graphical comparison between fatal RTCs occurring during weekday and weekend by sex-age groups is given in ***Figures 4.4, 4.5, 4.6 and 4.7.*** Compared to other age groups, drivers aged 21-30 years appeared to be more likely to be involved in fatal and non-fatal RTCs.

***Table 4.5*** *The effect of time of day on* the number and severity of RTC outcomes

| ***Sex-Age group*** | | ***Fatal RTCs (Fatal and serious injury crashes)*** | | ***Non-fatal RTCs (medium, slight and no injury crashes)*** | |
|---|---|---|---|---|---|
| | | ***Weekday*** | ***Weekend*** | ***Weekday*** | ***Weekend*** |
| | | $\frac{e^{f(t_{max})} - e^{f(t_{min})}}{t_{max} - t_{min}}$ | $\frac{e^{f(t_{max})} - e^{f(t_{min})}}{t_{max} - t_{min}}$ | $\frac{e^{f(t_{max})} - e^{f(t_{min})}}{t_{max} - t_{min}}$ | $\frac{e^{f(t_{max})} - e^{f(t_{min})}}{t_{max} - t_{min}}$ |
| ***Males*** | *15-20 years* | 1.195 | 0.522 | 10.569 | 3.868 |
| | *21-30 years* | 4.376 | 1.912 | 51.104 | 17.192 |
| | *31-40 years* | 1.970 | 0.795 | 21.684 | 7.936 |
| | *41-50 years* | 0.974 | 0.426 | 9.249 | 3.385 |
| | *50+ years* | 0.594 | 0.259 | 6.205 | 2.271 |
| ***Females*** | *15-20 years* | 0.023 | 0.010 | 0.721 | 0.264 |
| | *21-30 years* | 0.507 | 0.139 | 6.701 | 2.452 |
| | *31-40 years* | 0.189 | 0.083 | 3.277 | 1.199 |
| | *41-50 years* | 0.064 | 0.028 | 0.894 | 0.327 |
| | *50+ years* | 0.003 | 0.000 | 0.269 | 0.099 |

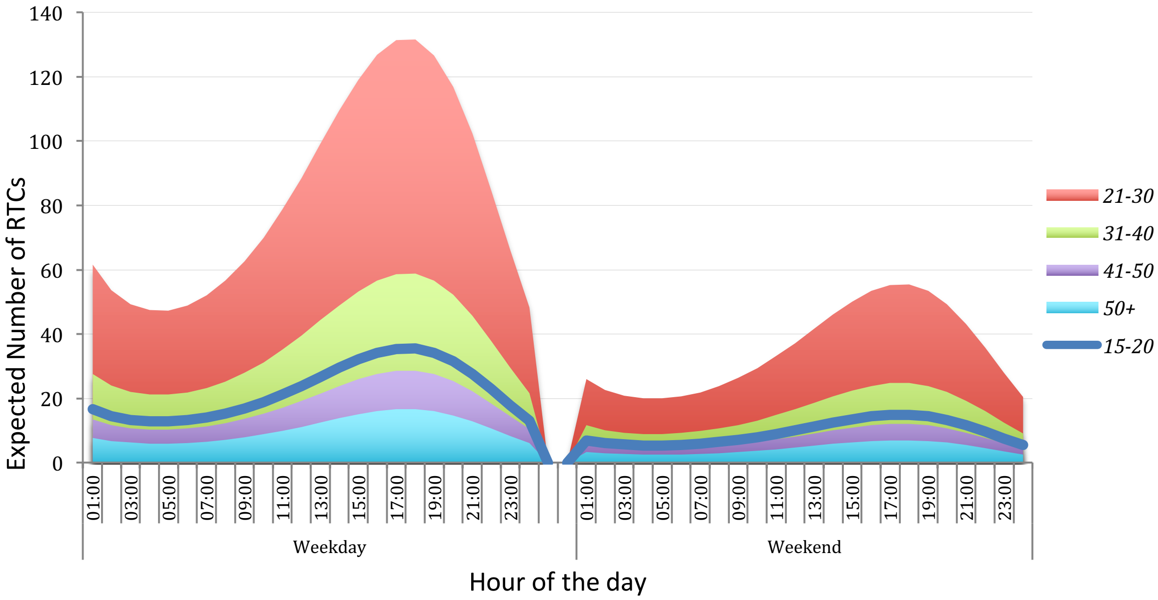


***Figure 4.4*** *Comparison of fatal RTCs caused by male drivers during weekday and weekend by age group*

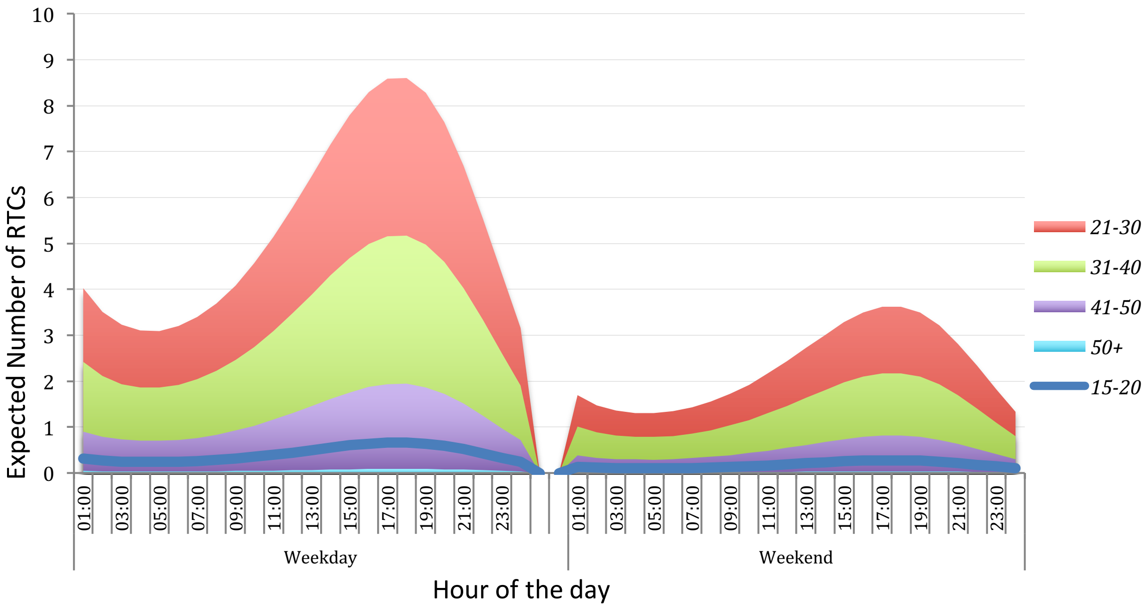


***Figure 4.5*** *Comparison of fatal RTCs caused by female drivers during weekday and weekend by age group*

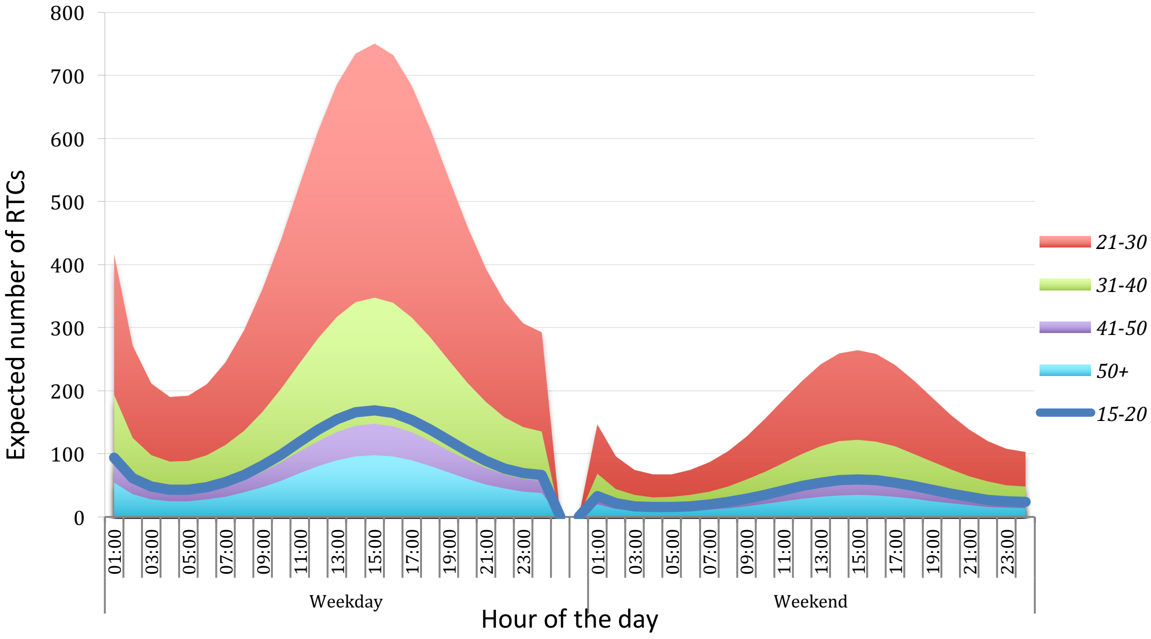


***Figure 4.6*** *Comparison of non-fatal RTCs caused by male drivers during weekday and weekend by age group*

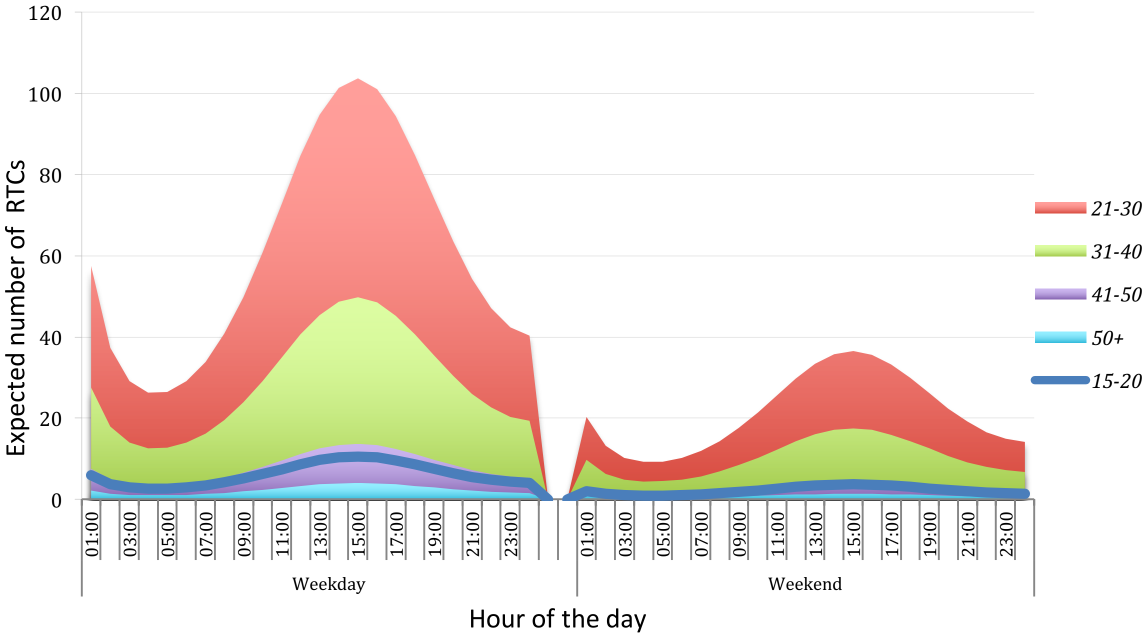


***Figure 4.7*** *Comparison of non-fatal RTCs caused by female drivers during weekday and weekend by age group*

### Spatial effect of crash location on number and severity of male drivers-related crashes[15]

Due to the small proportion of RTCs caused by female drivers, male drivers related data used to explore the spatial effect on crash outcome. ***Table 4.6*** compares the mean and and variance in the total number of fatal and nonfatal crashes for each group of the predictors used to model male-related data. The results validate the NBM is more appropriate as over-dispersion is clearly present in this data.

***Table 4.7*** summarised the results of the NBM. The effects of driver's age, day of week and time of day are very similar to those results produced NBM when modelling male and female drivers. Looking at the effect of the spatial factor, the results indicate that only Al-Batinah Governorate had higher number of fatal RTCs when compared to Muscat Governorate. However, the highest proportion of non-fatal RTCs occurred in Muscat. The predicted probabilities for driver's age, day of week and Governorates in ***Table 4.8*** validate the results produced by the NBM. Interestingly, Al-Wusta is the only Governorate where the number of fatal RTCs predicted to exceed the number of non-fatal RTCs.

***Table 4.6*** *Mean and variance of fatal and non-fatal RTCs[16]( data related to male drivers only) by age groups, governorate and day of the week, Oman, 2010-14*

| ***Factor*** | ***Fatal RTCs (Fatal and serious injury crashes)*** | | ***Non-fatal RTCs (medium, slight and no injury crashes)*** | |
|---|---|---|---|---|
| | ***mean*** | ***variance*** | ***mean*** | ***variance*** |
| ***Age of driver*** | | | | |
| *15-20 year* | 1.901 | 5.228 | 7.620 | 91.850 |
| *21-30 year* | 6.841 | 41.706 | 33.466 | 1584.62 |
| *31-40 year* | 3.128 | 10.200 | 15.622 | 346.110 |
| *41-50 year* | 1.549 | 3.125 | 6.917 | 88.359 |
| *50+ year* | 0.961 | 1.766 | 4.711 | 46.133 |
| **Governorate** | | | | |
| *Muscat* | 4.040 | 4.071 | 39.283 | 1714.179 |
| *Musandam* | 0.279 | 0.436 | 1.883 | 5.568 |
| *Dhofar* | 1.788 | 3.641 | 2.104 | 7.014 |
| *Ad Dakhliyah* | 3.358 | 13.804 | 16.142 | 352.499 |
| *Ash Sharqiyah* | 3.575 | 14.061 | 22.750 | 655.0251 |
| *Al Batinah* | 6.250 | 47.268 | 14.663 | 263.706 |
| *Adh Dhahirah* | 2.679 | 9.240 | 11.563 | 163.896 |
| *Al Wusta* | 1.008 | 2.167 | 0.950 | 2.190 |
| ***Day of week*** | | | | |
| *weekday* | 3.876 | 23.705 | 19.425 | 880.082 |
| *weekend* | 1.821 | 7.711 | 7.909 | 138.527 |

[15] This is only preliminary result and future research will include an extension of spatial effect with relative to time of day for each group of male drivers.

[16] *mean and variance of total number of crashes occurring at each hour of the day during all the 5 years of the study period*

***Table 4.7*** *Final fitted Negative Binomial Model for fatal and non-fatal RTCs (data related to male drivers only), Oman, 2010-14*

| ***Parameters*** | ***Fatal RTCs (Fatal and serious injury crashes)*** | | | | ***Non-fatal RTCs (medium, slight and no injury crashes)*** | | | |
|---|---|---|---|---|---|---|---|---|
| | ***Model estimates*** | | | | ***Model estimates*** | | | |
| | ***IRR*** | ***Std. Error*** | ***95% CI*** | ***P-value*** | ***IRR*** | ***Std. Error*** | ***95% CI*** | ***P-value*** |
| *Intercept* | 0.791 | 0.073 | [0.024, 0.646] | 0.024 | 7.330 | 0.528 | [2.294, 2.528] | 0.000 |
| *Time* | 0.860 | 0.023 | [0.816, 0.906] | 0.000 | 0.829 | 0.017 | [0.796, 0.862] | 0.000 |
| *Time$^2$* | 1.019 | 0.002 | [1.014, 1.024] | 0.000 | 1.025 | 0.002 | [1.021, 1.029] | 0.000 |
| *Time$^3$* | 0.999 | 0.000 | [0.999, 1.000] | 0.000 | 0.999 | 0.000 | [0.999, 0.999] | 0.000 |
| ***Driver's age group:*** | | | | | | | | |
| *15-20 year* | 1.959 | 0.132 | [1.716, 2.237] | 0.000 | 1.654 | 0.073 | [1.517, 1.803] | 0.000 |
| *21-30 year* | 7.117 | 0.425 | [6.331, 8.001] | 0.000 | 7.409 | 0.298 | [6.848, 8.017] | 0.000 |
| *31-40 year* | 3.261 | 0.207 | [2.880, 3.693] | 0.000 | 3.529 | 0.148 | [3.251, 3.830] | 0.000 |
| *41-50 year* | 1.612 | 0.113 | [1.406, 1.849] | 0.000 | 1.485 | 0.066 | [1.360, 1.620] | 0.000 |
| *50+ year (reference group)* | - | - | - | - | - | - | - | - |
| ***Governorate*** | | | | | | | | |
| *Muscat (reference group)* | - | - | - | - | - | - | - | - |
| *Musandam* | 0.068 | 0.009 | [0.053, 0.088] | 0.000 | 0.047 | 0.003 | [0.042, 0.053] | 0.000 |
| *Dhofar* | 0.445 | 0.029 | [0.392, 0.505] | 0.000 | 0.053 | 0.003 | [0.047, 0.059] | 0.000 |
| *Ad Dakhliyah* | 0.829 | 0.046 | [0.741, 0.920] | 0.001 | 0.393 | 0.016 | [0.364, 0.425] | 0.000 |
| *Ash Sharqiyah* | 0.884 | 0.048 | [0.794, 0.948] | 0.024 | 0.574 | 0.022 | [0.532, 0.618] | 0.000 |
| *Al Batinah* | 1.531 | 0.076 | [1.390, 1.687] | 0.000 | 0.365 | 0.015 | [0.337, 0.3495] | 0.000 |
| *Adh Dhahirah* | 0.657 | 0.038 | [0.586, 0.736] | 0.000 | 0.289 | 0.012 | [0.267, 0.314] | 0.000 |
| *Al Wusta* | 0.247 | 0.019 | [0.212, 0.287] | 0.000 | 0.024 | 0.002 | [0.020, 0.027] | 0.000 |
| ***Day of the week:*** | | | | | | | | |
| *Weekend (reference group)* | - | - | - | - | - | - | - | - |
| *Weekday* | 2.191 | 0.072 | [2.054, 2.337] | 0.000 | 2.408 | 0.060 | [2.294, 2.528] | 0.000 |
| ***Negative Binomial Parameter $\alpha$*** | 0.058 | 0.012 | [0.039, 0.85] | | 0.116 | 0.008 | [0.101, 0.133] | |
| ***Likelihood Ratio test of $\alpha$ = 0*** | 43.840 | | 0.000 | | 1173.120 | | 0.000 | |

***Table 4.8*** *Predicted probabilities of fatal and non-fatal RTCs[17] (data related to male drivers only) ,Oman, 2010-14*

| Parameters | Fatal RTCs (Fatal and serious injury crashes) | | | | Non-fatal RTCs (medium, slight and no injury crashes) | | | |
|---|---|---|---|---|---|---|---|---|
| | Num. of crashes | Std. Error | 95% CI | P-value | Num. of crashes | Std. Error | 95% CI | P-value |
| ***Driver's age:*** | | | | | | | | |
| *15-20 year* | 1.254 | 0.059 | [1.138, 1.370] | 0.000 | 3.941 | 0.135 | [3.677, 4.205] | 0.000 |
| *21-30 year* | 4.556 | 0.155 | [4.251, 4.860] | 0.000 | 17.654 | 0.482 | [16.709, 18.599] | 0.000 |
| *31-40 year* | 2.087 | 0.085 | [1.921, 2.253] | 0.000 | 8.408 | 0.252 | [7.914, 8.903] | 0.000 |
| *41-50 year* | 1.032 | 0.052 | [0.930, 1.134] | 0.000 | 3.537 | 0.122 | [3.297, 3.777] | 0.000 |
| *50+ year* | 0.640 | 0.038 | [0.565, 0.715] | 0.000 | 2.383 | 0.089 | [2.208, 2.558] | 0.000 |
| ***Governorate:*** | | | | | | | | |
| *Muscat* | 2.894 | 0.124 | [2.651, 3.137] | 0.000 | 29.554 | 0.872 | [27.845, 31.262] | 0.000 |
| *Musandam* | 0.198 | 0.025 | [0.149, 0.247] | 0.000 | 1.388 | 0.080 | [1.232, 1.545] | 0.000 |
| *Dhofar* | 1.288 | 0.073 | [1.145, 1.431] | 0.000 | 1.559 | 0.086 | [1.390, 1.728] | 0.000 |
| *Ad Dakhliyah* | 2.390 | 0.109 | [2.177, 2.603] | 0.000 | 11.619 | 0.379 | [10.877, 12.361] | 0.000 |
| *Ash Sharqiyah* | 2.558 | 0.114 | [2.335,2.782] | 0.000 | 16.955 | 0.524 | [15.929, 17.981] | 0.000 |
| *Al Batinah* | 4.432 | 0.171 | [4.097, 4.767] | 0.000 | 10.784 | 0.364 | [10.071, 11.497] | 0.000 |
| *Adh Dhahirah* | 1.902 | 0.093 | [1.719, 2.085] | 0.000 | 8.549 | 0.298 | [7.965, 9.133] | 0.000 |
| *Al Wusta* | 0.714 | 0.051 | [0.615, 0.814] | 0.000 | 0.697 | 0.052 | [0.595, 0.799] | 0.000 |
| ***Day of the week:*** | | | | | | | | |
| *Weekend* | 1.021 | 0.038 | [0.946, 1.095] | 0.000 | 3.530 | 0.093 | [3.348, 3.712] | 0.000 |
| *Weekday* | 2.236 | 0.071 | [2.098, 2.375] | 0.000 | 8.499 | 0.191 | [8.124, 8.874] | 0.000 |

[17] *mean of total number of crashes occurring at each hour of the day during all the 5 years of the study period*

## 4.4 Discussion and conclusions

This analysis conducted to investigate the association between the time of the day and the number of both fatal and nonfatal RTCs in Oman registered between 2010 and 2014. It also examined the effects of drivers’ sex and age along with day of the week on mediating the relationship between RTCs severity and timing of the incident.

Overall, the findings reject our hypothesis and confirm that peak hours of traffic congestion have significant effect on the outcomes of traffic crashes in Oman. The unadjusted conditional probability indicated that the highest percentages of fatal crashes occurred at nighttime, particularly between 1800 and 2100 hours. Conversely, the peak time of the nonfatal crashes is between 1000 and 1700. The off-peak time of both fatal and nonfatal accidents is between 0300 and 0500 hours in the early morning. The results from NBM suggest that the peak time for fatal crashes is at about 1800 hours in the early evening, while the peak time of nonfatal RTCs occurs at 1500 hours in the mid afternoon. The off-peak time of both types of crash appears to occur in the early morning hours (05:12 for fatal RTCs and 04:24 for nonfatal RTCs).

The time at which fatal crashes peak (i.e. 1800 hours) could be attributed to the low level of traffic volume on the road during this time which could increase likelihood of over-speeding behaviour among drivers. According to Al-Rawas (1993), the traffic flow in Oman start to build up between 0500 and 1700 hours and decline after 1800 hours. Therefore, due to their high driving speed, the drivers may need longer time to react for the impending collision with another vehicle or with pedestrians, or with other objects on the roadside. The low visibility and drowsiness at this time of the day (because of sunset which is mostly occurring between 17:00 to 19:00 in Oman) could be another factor contributing to the high number of fatal crashes. Consequently, because of the high speed driving, the collision impact is expected to be high, and victims are more likely to suffer fatal or severe injuries. In addition, the time from 1700 to 1800 is the time at which employees who work in private sector get off from their work implying that those people are at higher risk to be involved in fatigue or sleep related crashes.

With regard to the peak time of nonfatal crashes, the high density of traffic volume could play a major role in reducing the likelihood of crash severity. That is when traffic volume is high then people are less likely to drive at high speed, and hence this makes the outcomes of the crash less severe. This could be explained by the high rate of people who are working in Muscat who are daily commuting to and from Muscat, according to 2010 censes 43.1% of total employees in Oman work in Muscat, and more than 60% of these workers are living in Ad Dakhliyah and Al Batinah Governorates which are adjacent to Muscat (NCSI, 2013)) and they are daily commuting to and from work. Therefore, they are more likely to spend long time on the road which increase their risk to be involved in a road crash (Böhning and Ayutha, 1997). This result could also reflect the effect of the post-lunch dip in driving performance which is more common in tasks demanding longer periods of sustained alertness and attention (Lenné, 1997).

The times at which the lowest density of fatal and non-fatal RTCs appears could be attributed to the fact that at these times of the day (04:24 and 05:12) people are more likely to be sleep so very few people are expected to drive at these times.

The findings mentioned above are consistent with past studies and confirmed that although the number of night traffic crashes is less than day crashes, nighttime RTCs are more likely to end with more severe outcomes compared to day-time crashes. These studies have stated that the possible contributory factors of relative high risk of fatal crashes at night are the impact of low or poor visibility, lack of experience of night driving especially among young drivers, and fatigue and alcohol drunk (Rifaat and Chin, 2007; Smith et al., 2008; Eluru et al., 2012).

The results of the NBM indicate that sex-age of drivers and day of the week are critical factors in mediating the association between the number of both fatal and nonfatal crashes and time of the day. Overall, male drivers and drivers aged 21-30 year appear to cause the highest proportions of both fatal and nonfatal RTCs. Old male drivers (i.e. drivers aged above 50 years) appear to have lower incidence rate of being involved in fatal and non-fatal RTCs compared to drivers in other age groups, with drivers aged 21-30 year have the highest incidence rate ratio (more than 7.5 times the incidence ratio of the old age group). Similarly, the comparison of old female drivers with other female drivers indicates that females aged 21-30 year have the highest incidence rate ratio of being involved in both types of RTCs.

The high proportion of male drivers in both types of RTCs could be a reflection of exposure rather than an explicit difference between characteristics of male and female drivers. According to ROP (2014), males represent more than 82% of total the driving license holders in Oman in 2014, 949,169 male drivers compared to 207,942 female drivers. Moreover, since males are commonly the breadwinners of their families, driving task is more common among men in Oman. In addition, working as a driver and mechanics in cars and trucks, including long-haul vehicles, is more common among males, and consequently this implies that males are more likely to spend longer time and nights on the road. Therefore, it is clear that because of differences in male and female role, male drivers have higher exposure to the risk of RTCs than females.

Additionally, the risk taking behaviours are more common among male drivers in Oman, particularly among young male drivers. Sensation seeking and excitement-seeking on risky driving behaviour such as speeding and overtaking could explain the high proportion of young males in both fatal and nonfatal crashes. All these findings support the findings of past studies (Keall et al., 2005; Otmani et al., 2005; Oltedal and Rundmo, 2006; Rifaat and Chin, 2007).

The results also demonstrate that the total number of both crash types during weekday is higher than that of weekend. However, the calculation of crash per day indicated that more crashes occur during weekend compared to weekday. This result could be explained by the assumption that risky driving behaviours are more likely to take place during weekend. This finding support the findings of a study conducted by Symmons et al. (2004).

The same effects of driver's age and day of week were observed when Only male drivers- related data used to construct NBM. The spatial features of the location where the crash occur are important to predict the severity of the crash outcome.

There are few limitations in this study. The lack of information of the traffic volume, daily travelled distance as well as the number of driving license holders for each sex-age group has prevented exploration of the accurate risk associated with a particular sex-age group. The availability of these data could be used as an exposure, which could give an explanation of why males aged 21-30 year have the highest rate of being involved in both fatal and nonfatal crashes.

Generally, this analysis firms statistical evidence of peak hours of crash confirming that peak hours of traffic congestion have significant effect on the outcomes of traffic crashes in Oman. Fatigue and drowsiness are possible dominant factors for both mid afternoon non-fatal and early evening fatal crashes respectively. It has also confirmed that age and sex of the driver, day of the week and spatial factors are critical factors in mediating the association between the number and severity of RTCs and time of day. Therefore, road crash risk reduction interventions should monitor the behavioural attributes of drivers. For example, education campaigns should target countermeasures that are most appropriate for a particular situation such as reducing driver sleepiness and risky behaviour towards young drivers (Filtness et al., 2017). Drivers should be aware that sleepiness occurs as a result of lack of sleep and consequently this will impair their driving performance and representing a high risk for their safety and the safety of other road users. Road safety campaigns should focus at encouraging drivers to stop driving when feel sleepy (Philip et al., 2005) and to use alternate between drivers as a countermeasure when the driver feel sleepy and have a passenger who is able to take over driving (Department of Transport and Main Roads, 2010 cited in Filtness et al., 2017). However, the recommendation of using alternate driving should be taken with caution when it is used as a countermeasure for young sleepy and fatigued drivers because having a peer passenger can adversely affect the driving behaviour (Filtness et al., 2017).

Moreover, characteristics of road infrastructure should be designed to enhance driver alertness (Reimer et al., 2007). Given that public transport has started recently in Oman and limited to certain places, seeking for alternative transport for shift workers should be given a big concern. Similarly, sleep schedules before and during the work period should be integrated with work schedules and professional regulations in workplaces (e.g. hospitals, companies, factories) (Philip et al., 2005) particularly for shift workers and professional drivers. Besides, to identify sleep and fatigue related crashes, police database should collect information on how long drivers have been awake, how many hours did their last sleep last and the length of the duration of being driving prior to the crash (Filtness et al., 2017). Further investigation needed to examine the underlying causes of RTCs (e.g. substance abuse, mobile phone use, hours/miles (long) driven, driving experience, activities prior to driving).

# Chapter 5

## Mapping road traffic crash hotspots using GIS-based methods: A case study of Muscat Governorate in the Sultanate of Oman[18]


### ABSTRACT

#### Objective:

Road traffic crashes (RTCs) are a major global public health problem and cause substantial burden on national economy and healthcare. There is little systematic understanding of the geography of RTCs and the spatial correlations of RTCs in the Middle-East region, particularly in Oman where RTCs are the leading cause of disability-adjusted life years lost. The ***overarching aim*** of this chapter is to evaluate the spatial and temporal dimensions, identifying the high risk areas or hot-zones where RTCs are more frequent using the geocoded data from the Muscat governorate.

#### Methods:

The analysis considered an adjacency network analysis integrating GIS and RTC data using robust estimation techniques including: Kernel Density Estimation (KDE) of both 1-D and 2-D space dimensions, Network-based Nearest Neighbour Distance (Net-NND), Network-based K-Function, Random Forest Algorithm (RF) and spatiotemporal Hot-zone analysis.

#### Findings:

The analysis highlight evidence of spatial clustering and recurrence of RTC hot-zones on long roads demarcated by intersections and roundabouts in Muscat. The findings confirm that road intersections elevate the risk of RTCs than other effects attributed to road geometry features. The results from GIS application of NRTC data are validated using the sample data generated by iMAAP database.


[18] A shorter version of this chapter has been accepted for oral presentation in the innovative methods & models strand at the 2018 BSPS Conference which will be held in Winchester on 10th -12th September 2018.

**Conclusion:**

The findings of this analysis provide statistical evidence and confirm the research hypothesis that that road intersections (roundabouts, crosses and bridges) represent higher risk of causing RTCs than other road geometric features. The results also demonstrate systematic quantitative evidence of spatio-temporal patterns associated with the crash risk over different locations on road network in Muscat. More importantly, the findings clearly pinpoint the importance and influence of the road and traffic related feature in road crash spatial analysis.

**Key messages**

- RTCs tend to cluster more on long roads demarcated by high number of intersections, complex bridges and roundabouts in Muscat. Road intersections elevate the risk of RTCs than other effects attributed to road geometry features.
- Road and traffic related features play a key role in determining locations of high crash risk. There is a positive association between RTC hot-zones and higher levels of road traffic.
- Speed limits signs seem to have no significant effect in increasing crash risk on road zones in Muscat. This could be due attributed to the high proportions of cyclists and pedestrians on road with low speed limits which in turn increase the likelihood of crash occurrence.

**Keywords:** Road traffic crashes, injuries, Oman, Muscat, severity, causes of injury, Road geometry features, Road intersections, spatiotemporal modelling, Kernel Density estimation, Network-based Nearest Neighbour Distance (Net-NND), Network-based K-Function, Random Forest Algorithm (RF), Clustering, RTC hot-zones

## 5.1 Background and Rationale

Identifying where and when RTCs occur is crucial for the enforcement authorities to take effective measures to reduce the risk of RTCs (Yu et al., 2014; Benedek et al., 2016). The heterogeneity in RTC frequencies and rates is attributed to complex roadside features, traffic and weather conditions and driving population (Cheng and Washington, 2005). Different terminologies have been used to describe high-risk RTC locations; hazardous road locations, high-risk locations, accident-prone locations, black spots, hot spots, hot zones, black zones, sites with promise and priority investigation locations (Montella, 2010; Choudhary et al., 2015). Past studies have no universally standard definition for hazardous road locations, which suggests that there is no clear definition or understanding of crash locations (Anderson, 2006; Elvik, 2008; Anderson, 2009; Choudhary et al., 2015). The major challenge, therefore, is to make judgements on the definitions and criteria for determining RTC hotspots (Miranda-Moreno et al., 2007; Elvik, 2008; Anderson, 2009). Overgaard Madsen (2005) stated that the following set of criteria should be used to define crash hotspots:

a. Accounting for random fluctuations in the number of crashes.

b. Accounting for all possible factors expected to influence road safety.

c. Identify sites where fatal and serious injury crashes are disproportionately high.

d. Identify sites where the substantial contribution to RTCs are due to local risk factors (i.e. factors related to road design and traffic control).

The aim of hotspot identification is to identify site on road network with overrepresented rates of RTCs compared with other sites (Ayuthya et al., 1995; Cheng and Washington, 2005; Washington et al., 2014; Yu et al., 2014). The identification of hazardous road locations has become one of the most effective approaches for the appropriate allocation of resources, planning and introducing effective strategies to improve road safety (Elvik, 1997; Miranda-Moreno et al., 2007; Anderson, 2009; Montella, 2010; Yu et al., 2014; Choudhary et al., 2015; Kaygisiz et al.,2015; Benedek et al., 2016; Hashimoto et al., 2016). Once these sites are correctly identified, further safety inspections and analyses are carried out to investigate crash patterns, contributing factors, and identify the potential countermeasures such as engineering improvements to reduce the crash risk at these sites (Miranda-Moreno et al., 2007; Montella, 2010; Mohaymany et al., 2013; Kaygisiz et al.,2015). The presence of hotspots provides evidence of spatial dependence between RTCs occurring in neighbouring road-sites, and this dependence could be attributed to one or more common causes between crashes on these sites such as tunnels, bridges, roundabouts, and vertical and horizontal curves (Anderson, 2009; Mohaymany et al., 2013; Yu et al., 2014; Kaygisiz et al., 2015).

To carry out a crash hotspot analysis, a comprehensive understanding of the severity of crash outcomes and the spatial characteristics of crash locations are important (Anderson, 2009). The effects of land use planning and road infrastructure characteristics, such as road design, road types, quality of pavement, road segments, lane and hard shoulder width, junction layout and traffic control devices, have been investigated (e.g. McGwin and Brown, 1999; Karlaftis and Golias, 2002; Greibe, 2003; Shope, 2006; Komba, 2007; Flores et al., 2009; Aworemi et al., 2010; Kaygisiz et al., 2015; Michalaki et al., 2015). There is also evidence suggesting that improvements to highway design could significantly reduce the number of RTCs (Karlaftis and Golias, 2002). Moreover, the changes in the physical environment could lead to changes in the locations of hotspots over time (Kaygisiz et al., 2015). Therefore, spatio-temporal analysis of RTC hotspots is crucial to prioritise problematic sites of road network (Mohaymany et al., 2013; Kaygisiz et al., 2015).

Abdel-Aty and Radwan (2000) found that the likelihood of crash involvement increases with heavy traffic volume, higher speed, larger number of lanes, narrow lane width, narrow hard shoulder and median widths and urban roadway sections. Karlaftis and Golias (2002) conducted a study to explore the effects of road geometry and traffic volume on rural roadway crash rates, and concluded that for two-lane rural roads, the importance of lane width increases in heavier traffic conditions, however due to the higher speed, the quality of road pavement seems to be more important in lower traffic flow conditions. On the other hand, the authors reported that for rural multilane roads, access control and median width are the most important factors in higher and lower flows respectively. In contrast, Greibe (2003) conducted a study to predict traffic crash rates for both signalised and non-signalised junctions on urban roads. The results of the study indicated that both signalised and non-signalised junctions have the same safety level, and they differ only by type of crashes (signalised junctions have more rear-end crashes but fewer crossing crashes). Caliendo et al. (2007) developed a crash-prediction model for multilane roads. The authors concluded that the annual number of both total and severe crashes occurring on curves increase with the increase in road length, degree of curvature and level of Average Annual Daily Traffic (AADT). Caliendo et al. also found that the number of severe crashes increases with the presence of a junction on a road section. The authors recommended that road engineers should give attention towards junctions as potential marker for RTCs. Node models are commonly used to describe the flows across road networks and they are useful in understanding the traffic dynamics throughout the road network (Jabari, 2016).

Different methodologies have been used for the delineation of RTC hotspots (Benedek et al., 2016). The traditional statistical methods and spatial analysis using Geographic information GIS-based systems technique are examples of the methods used for such analysis (Deshpande et al., 2011). Estimations using crash frequency, crash rate, crash density, and crash severity index are examples of simple methods that can be applied to identify RTC hotspots (Yu et al., 2014; Choudharya et al., 2015). Comparison of crash counts at different locations and ranking of these locations based on the severity of crashes has been used in the traditional methods of crash hotspots detection (Anderson, 2006). Empirical Bayes (EB) statistical method has been proven as one of the most accepted statistical methods for crash hotspot identification (Deshpande et al., 2011). EB method was found to be more superior when compared to other hotspot identification methods (Choudharya et al., 2015). However, since EB requires special statistical skills, many transportation departments still use simple methods (Choudharya et al., 2015). Although different statistical methods have been widely used for delineation of hotspots, however, combining them with spatial analysis tools will produce more efficient results RTC hotspots analysis (Deshpande et al., 2011).

Using GIS-based systems is key in estimating the crash risk at different locations and times and it helps to provide information about various risk factors and explaining variations in crash involvement rate and injury severity (Anderson, 2009; Deshpande et al., 2011). Such systems provide a platform to display a number of visualized geographical outputs to deeply understand the dynamics of RTCs (Mahmud et al., 1998; Deshpande et al., 2011). GIS has enabled road professionals to use sophisticated spatial-statistical methods to detect hotspots (Anderson, 2006). It enables the efficient manipulation, analysis and visualization of spatial data so that a more robust understanding can be gained by providing indications of the casual effects of RTCs (Anderson, 2009). Past studies used GIS for different purposes: producing maps combining different parameters of RTCs such as number of crashes, number of injuries and death, road traffic related data and demographic factors and presenting the results in a user friendly way (e.g. Pulugurtha et al., 2007; Gundogdu, 2010; Truong and Somenahalli, 2011; Qin et al., 2013); conducting spatial analysis to identify high risk sites (e.g. Aguero-Valverde and Jovanis, 2006; Erdogan, 2009; Vandenbulcke et al., 2014; Deshpande et al., 2011; Ivan et al., 2015; Rahman et al., 2017; Vandenbulcke et al., 2017); and using it to apply spatio-temporal analysis (Plug et al., 2011; Prasannakumara et al., 2011; Ivan and Haidu, 2012).

Kernel density estimation (KDE) has been widely used to analyse crime data and only recently it has been adopted to detect the spatial pattern of crash data (e.g. Flahaut et al., 2003; Anderson, 2006; Anderson, 2009; Bíl et al., 2013; Mohaymany et al., 2013; Kaygisiz et al., 2015; Thakali et al., 2015; Hashimoto et al., 2016; Rahman et al., 2017). However, since crimes can occur anywhere (e.g. street, house, park, shopping places) while RTCs are constrained to the road network (Anderson, 2006), crime hotspots detection methods should be modified to account for this difference. There are two forms of kernel density estimation: Planar Kernel Density Estimation (PKDE) and Network Kernel Density Estimation (Net-KDE) (Loo and Anderson, 2015). PKDE is used to identify hotspots of point-events and it calculates the density within 2D-space using the Euclidean distance (Loo and Anderson, 2015). PKDE is rarely used in the study of RTCs because two points which are close in terms of Euclidian can be far away when considering the distance between them on road network, so PKDE can be misleading in this case (Mohaymany et al., 2013; Kaygisiz et al.,2015; Loo and Anderson, 2015; Benedek et al., 2016). In 2003, Flauhaut et al. proposed a method estimate density along single road segment. However, because this method was not appropriate for calculating density along road network as a whole, Xie and Yan (2008) developed Net-KDE method and when they compared the results of Net-KDE with PKDE, they found that PKDE overestimates the crash density. Therefore, because of the difference of where crimes and RTCs occur, PKDE is more appropriate for crime hotspots detection, while Net-KDE is recommended to be used to calculate density of events such as RTCs occurring along network (Xie and Yan, 2008). Okabe et al. (2006) developed a toolkit called SANET (Spatial Analysis along Network) which integrates with ArcGIS software, and used specifically for network spatial analysis. For the technical details of SANET, the reader is referred Okabe and Sugihara (2012).

KDE is one of the methods used to measure first-order effects of point events (Xie and Yan, 2008). Methods of first-order effects are usually used to explore the underlying properties of point events and to identify the variation in the mean value of these events (Xie and Yan, 2008). One of the advantages of using KDE as opposed to other statistical clustering techniques is the identification of the spread of crash risk in an area surrounding a defined cluster based on spatial dependency, and producing a smooth density surface of point events over space (Xie and Yan, 2008; Anderson, 2009). The calculation of the spread crash risk is done because the exact position of a given crash is affected by the accuracy of GPS device used to collect the crash data, and this means that the accurate position is difficult to found (Moridpour and Toran, 2015). Conversely, the major disadvantage of KDE method is the lack of diagnostics to determine statistical significance (Choudharya et al., 2015).

Local spatial autocorrelation (LSA) methods (also referred to as second-order effects methods) are another common technique used RTC spatial analysis (Xie and Yan, 2008; Yu et al., 2014). LSA methods are used to calculate the spatial autocorrelation of point events by evaluating the level spatial interdependence between observed RTCs occurring on adjacent spatial units, so they combine attribute similarity and location proximity in one single index (Yu et al., 2014; Choudharya et al., 2015). A high index indicates high spatial concentration of RTCs (Yu et al., 2014). Moran's I index and Getis-Ord Gi* statistics are examples of these methods, and unlike KDE, the statistical significance is available in these methods (Yu et al., 2014; Choudharya et al., 2015). Nearest Neighbour Distance and K-function are other examples describing the interactive effects of events which assume that the occurrence of one crash on a given road-site increases the likelihood of crash occurrence on other nearby sites (Mohaymany et al., 2013).

Generally, methods of crash hotspot classifications are limited to factors available in crash data itself, and rarely accounting for other factors affecting the occurrence of RTCs and available from other sources other than crash data (Anderson, 2009). Therefore, since crash hotspots can be attributed to other factors such as social, economic and environmental and land use, these effects should be taken into account to gain a comprehensive understanding of the complexity of hotspots (Anderson, 2009).

There is little systematic understanding of the spatial patterns and correlations of RTCs in the Middle-East region, particularly in Oman, where RTCs are the leading cause of disability-adjusted life years lost. The ***goal*** of this study is to identify the locations of hot-zones (groups of neighbouring hotspots) and spatial clustering of RTCs in the Muscat governorate. Muscat is the capital of Oman and the most populous governorate in the country (i.e. it has the highest population density of 345 people per $km^2$) with more than 32% of total population (NCSI, 2016; NCSI, 2018). Muscat is located in the north-eastern part of of Oman, it represents a mix of ancient cultural heritage and modern style and it is considered as the heart of the Sultanate (Ministry of tourism, 2017). Spurred by rapid economic growth and urbanisation, the use of private vehicles to commute to both short and long distance to workplace, shopping and leisure centres are becoming increasingly common in Oman, especially commuting from adjoining governorates to Muscat. This has led to an increase in the concentration of daily commuting within limited major roads, which in turn has resulted in a high level of traffic congestion coupled with a high rate of traffic crashes (annually, more than 33% of RTCs in Oman occurred in Muscat) (Al-Rawas, 1993; Royal Oman Police, 2017).

Network Kernel Density (Net-KDE) is applied to develop an adjacency network analysis by focusing on the spatial and temporal dimensions, especially in identifying the high risk or hot-zone areas where RTCs are more frequent. It also identifies the significant factors affecting these spatial patterns. The identification of these hot-zones would help transportation safety professional to identify high-crash corridors more efficiently. Consequently, these hot-zones would have a priority to benefit from a systemic safety improvement program (Young and Park, 2014).

This study addresses the following questions:

1. Where are the high risk or hot-zone areas for road crashes in Muscat Governorate where crashes are more frequent?

2. How can we use the spatial analysis to understand and model the patterns of road crashes integrating relevant predictors such as road geometry and traffic related features?

The sub-questions are:

a. What factors characterise hot-zones from normal- and cold-zones?

b. Over time, which road zones represent high risk areas for road traffic crashes in Muscat?

We **hypothesise** that road intersections (roundabouts, crosses and bridges) elevate the risks to RTCs than other road geometric features.

## 5.2 Data and Methods

### 5.2.1 Data

From a statistical aspect, data of a minimum of three years are needed for any spatial analysis to obtain credible results (Benedeka et al., 2016). This study is based on data drawn from the ROP sample iMAAP database and the National Road Traffic Crash (NRTC) database which is managed by the Royal Oman Police and made available for research use by The Research Council of the Sultanate of Oman. The data covered the period from 1st January 2010 to 2nd November 2014. Only RTCs occurred in Muscat Governorate were included in the study. The study is based on 12,438 registered incidents, however, due to disconnections found on road network, RTCs occurred on disconnected parts were removed and the final analysis considered only 9,357 incidents.

It is worth noting that not all RTCs are recorded in the ROP database. The police go to the crash site only when there is a human injury or a public property damage or if the drivers of of the vehicles involved are unable to resolve between themselves who was at fault (Al-Bulushi et al., 2015). Otherwise, all other crashes (i.e. minor traffic crashes - no casualty crashes) are managed by the insurance companies (Al-Bulushi et al., 2015). The inclusion of minor traffic crash data could improve the impact of road safety research (Benedeka et al., 2016), but unfortunately, these data are not available to the public. The database includes information about crash date, time, sex, age and nationality of drivers, type of injuries, fatalities, type and number of vehicles involved, cause of crash, type of collision, location, type of road, weather conditions, and crash description. So the coordinates of the crashes are not available, and hence the researcher herself generated these geographical coordinates. In order to generate these data, the researcher used the information given in the crash description field and Google-Maps to specify the location of the crash. The geographical coordinates were identified for each case and the researcher spent four months to generate these for the Muscat governorate. However, it is important to mention that in most cases the crash description field did not specify the direction of the road on which the crash occurred, so RTCs were geocoded to the nearest point on the road network where the road mark was located. Further refinement of the road marks was based on researcher's familiarity with the region.

Data on Muscat road network (ArcGIS shapefile format) was downloaded from the Open Street Map using ArcGIS 10.2, which included details about type of the road, road name, speed limit and the length of the road. It is also worth mentioning that the researcher used Google-Maps to specify the level of traffic for different segments along Muscat road network. The results from GIS application of data generated from NRTC database were validated using the pilot data generated by iMAAP network based crash analysis system developed by the UK Transport Research Laboratory. ROP in collaboration with The Research Council undertook a pilot project to establish the feasibility of iMAAP in the Sultanate.

### 5.2.2 Methods

This section summarises the statistical methods used for the delineation of RTC hot-zones in this study.

### a. Kernel Density Estimation

### 1. Planar Kernel Density Estimation

Both PKDE and Net-KDE were used to identify events hotspots. The formula of calculating PKDE, which requires events within a 2-D homogeneous space, is expressed as follows (Xie and Yan, 2008):

$$\lambda(s) = \sum_{i=1}^{n} \frac{1}{\pi r^2} k(\frac{d_{is}}{r}) \tag{5.1}$$

where λ(s): the density in location s,

$r$: the radius (i.e. bandwidth) of KDE and only points locating within a distance of $r$ used to calculate λ(s) ,

$k$: the weight of point $i$ at a distance $d_{is}$ from location s. $k$ is usually called the kernel function representing the relationship between $d_{is}$ and $s$.

The idea of using kernel function is that the data points $i$ in close spatial proximity of location s have influence on estimating the crash risk than those points in further distances. In other words, this kernel function gives higher weight for the points locating closer to s and down-weights the $i$ points that are further from s (Benedeka et al., 2016). Different formulae are used to calculate the kernel function such as: Triangular or Bartlett function, Epanechnikov kernel or Quadratic function, Tricubic function, Quartic function, and Gaussian function (Loo and Anderson, 2015; Benedeka et al., 2016).

## 2. One-Dimension Kernel Density Estimation

Since road traffic crashes occur in 1-Dimension space and PKDE considers road traffic crashes in 2-Dimensions leading to biased results, one-dimension kernel density (1D-KDE) has been develop to deal with events occurring on 1-D space.

1D-KDE calculates the density of point events on a network using a linear unit, while PKDE calculates it using an area unit (Young and Park, 2014; Hashimoto et al., 2016). The formula of calculating 1D-KDE is expressed as follows (Xie and Yan, 2014):

$$\lambda(s) = \sum_{i=1}^{n} \frac{1}{r} k(\frac{d_{is}}{r}) \tag{5.2}$$

where $\lambda(s)$: the density in location s,

$r$: the radius (i.e. bandwidth) of KDE and only points locating within a distance of $r$ are used to calculate $\lambda(s)$ ,

$k$: the weight of point $i$ at a distance $d_{is}$ from location $s$ (the kernel function).

## 3. Spatial analysis along network (SANET)

In this study, SANET toolkit installed within ArcGIS 10.2/ArcMap was used to implement network spatial analysis of RTCs. The formula of calculating network kernel density (Net-KDE) using SANET is the same as the formula given by Xie and Yan (2008), but instead of using Gaussian or Quartic equations to calculate the kernel function ($k$), SANET used following equation (Okabe at al., 2009):

$$K_y(x) = \begin{cases} k(x), & for -h \le x \le 2d - h \\ k(x) - \frac{n-2}{n} k(2d - x), & for\ 2d - h \le x \le d \\ \frac{2}{n} k(x), & for\ d \le x \le h \end{cases} \tag{5.3}$$

where $k(x)$: the basic kernel function,

$y$: the centre of the kernel,

$x$: a point on the network (in this study it is a road traffic crash),

$h$: the bandwidth (in meters),

$n$: the degree of a given node (*v*) (see Figure 5.1),

$d$: the shortest network distance from $y$ to $x$.

The density of RTCs on a given road segment is calculated as follows (Okabe at al., 2009):

$$D(o) = \int_{-h}^{2d-h} k(-y)dy + \int_{2d-h}^{d} \left[k(-y) - \frac{n-2}{n} k(2d+y)\right] dy + \int_{d}^{h} \frac{2}{n} k(-y)dy \qquad (5.4)$$

where $D(o)$: the density at the origin.

The graphical expression of the three ranks of kernel function is shown in ***Figure 5.2***, while the simplified graphical expression of network kernel function is given in ***Figure 5.1***.

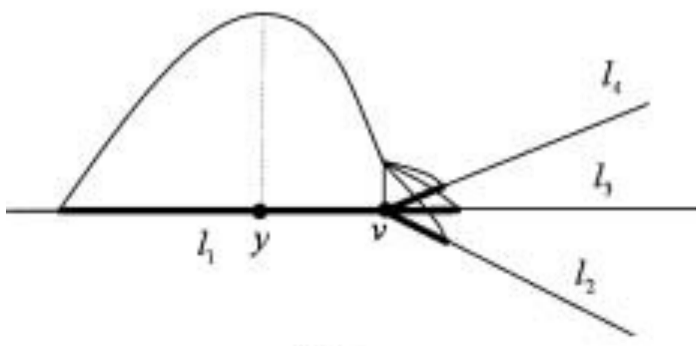


***Figure 5.1*** *The simplified example of network kernel function (Source : Okabe et al., 2009, P.19).*

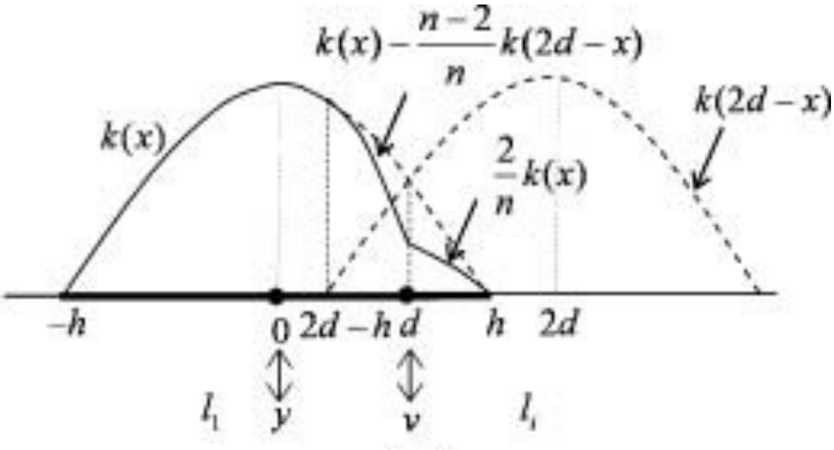


***Figure 5.2*** *The three ranges of the network kernel function (Source : Okabe et al., 2009, P.19).*

Previous research indicates that the choice of kernel bandwidth and cell size have higher impact on the results than the choice of kernel function (Loo and Anderson, 2015; Moridpour and Toran, 2015). In Net-KDE method, the cell size and bandwidth are specified based on the characteristics of the case study area (Loo and Anderson, 2015). Previous literature suggested using bandwidth ranging from 50 meters for urban areas to 1000 meters for rural areas so there is no optimal kernel bandwidth recommended in past studies and different studies used different bandwidth (Moridpour and Toran, 2015).

**b. Network-based Nearest Neighbour Distance (Net-NND)**

After applying Net-KDE, the significance of the results is validated using Network-based Nearest Neighbour Distance (Net-NND) and the K-function methods. These two methods are used to analyse the spatial patterns of incident point data (in our case is road traffic crash data). They summarise the spatial dependence (clustering or dispersion) over a range of distances.

The Net-NND test is used to examine the complete spatial randomness (CSR) hypothesis which means that RTCs crashes are independently and identically distributed over the road network (Okabe and Sugihara, 2012). Using this test, the measured distances of RTCs to their nearest neighbour are tested against the CSR hypothesis and the detected hotspots are significant if the CSR hypothesis is rejected which implies that the average nearest neighbour distance for the observed data is significantly smaller than the expected distance if they are randomly distributed (Kaygisiz et al., 2015). In this study, the Net-NND test was applied using the Monte Carlo simulation, using a cell size of 200 meters and a confidence interval of 95% to determine the statistical significance.

The Clark-Evans index, which is expressed as the ratio of the average observed Net-NND to the average expected NND, indicates whether the RTCs exhibits clustering (if the index <1.0) or dispersion (index>1.0) (Okabe and Sugihara, 2012).

### c. Network-based K-Function (Net-K-Function)

Ripley's K-Function is a method to analyse the spatial patterns of RTCs data and it has an advantage of not depending only on nearest neighbour distances but on using all point-to-point distances to analyse the spatial clustering at different scales of patterns and to determine the distances where clustering or over-dispersal is significant (Bailey and Gatrell 1995 cited in Spooner et al., 2004). However, since the K-Function calculated the Euclidean distance between incident points, it cannot be used to analyse the spatial patterns of incident points along road network such as road traffic crashes as it can lead to over-detection of spatial clustering (Spooner et al., 2004). Okabe and Yamada (2001) have developed a method to conduct K-Function analysis of point patterns along network.

The univariate network K-function (Net-K-function) was used in this study to test the CSR hypothesis in terms of number of points (RTCs) in a given point set so that the shortest distance from each point is less than a parametric shortest distance. The Net-K-function calculates the shortest path distance *(t)* from each point to the other points $P = \{p_1, \dots, p_n\}$ on the road network, where $n$ is the total number of points in network.

Let $P = \{p_1, \dots, p_n\}$ be a set of $n$ RTCs on road network, $L_T$ be a set of road network links (road segments) and $|L_T|$ be the total length of road network. Okabe and Yamada (2001) defined the Net-K-function $K(t)$ as follows:

$$K(t) = \frac{1}{\rho} E \begin{pmatrix} the\ number\ of\ points\ P \\ within\ network\ distance\ t\ to\ a\ point\ p_i\ of\ P \end{pmatrix}, \qquad (5.5)$$

Where E(.) is the expected value with respect to $p_1, \dots, p_n$ $(p_i \in P)$, $\rho$ is the density of points $P$, so that

$$\rho = \frac{n}{|L_T|} \qquad (5.6)$$

with an assumption that the points $P$ (i.e. RTCs in this study) are uniformly and independently distributed over a finite road network and follow homogeneous Binomial distribution (Spooner et al., 2004; Okabe and Sugihara, 2012). The rejection of this assumption means that RTCs are spatially interacting and not forming uniform patterns (Spooner et al., 2004; Okabe and Sugihara, 2012). Thus, the observed network K-function $\widehat{K(t)}$ is given as (Okabe and Yamada, 2001):

$$\widehat{K(t)} = \frac{|L_T|}{\mathrm{n(n-1)}} \sum_{i=1}^{n} \left(number\ of\ points\ P\ on\ L_P(t)\right) \tag{5.7}$$

Monte Carlo simulation is used to find the upper and lower critical values of a significance level α (in this study *α=5%*). From the graphical presentation of the observed Net-K-function and the expected Net-K-function together with the upper and lower confidence envelops, we can conclude at a confidence level of *1-α* (i.e. 95%) either if the RTCs tend to cluster (the graph of the observed Net-K-functions is above the upper confidence envelop) or be dispersed (the graph of the observed Net-K-functions is under the lower confidence envelop (Okabe and Yamada, 2001; Okabe and Sugihara, 2012).

Both Net-NND and Net-K-Function are employed in this study using SANET toolkit in ArcGIS10.2/ArcMap.

**d. Random Forest Algorithm (RF)**

The next step is to explore the differences between the cold-, normal- and hot-zones. What are the factors contributing to this differentiation between cold-, normal- and hot-zones? There are several machine learning techniques which can help us in classifying road network into cold-, normal- or hot-zones. Unlike regression models, machine learning techniques do not have pre-defined relationship between the response and independent variables, so they can identify the associations between the response variable and the predictors without any assumptions about the distribution of the data or pre-defined association (Jiang et al., 2016). The main advantage of the machine learning techniques compared to traditional regression models is that they can detect the complex interactions among the predictors and they are robust to outliers (Jiang et al., 2016).

**Random Forest (RF)** is one of the machine learning techniques and it is a non-parametric and ensemble statistical learning algorithm developed by Breiman (2001) to improve the Classification and Regressing Trees (CART) method by combining the results of many decision tree models (Mutanga et al., 2012; Jiang et al., 2016). It has the advantage of its capability of dealing with complex relationships and synthesizing regression and classification functions for both discrete and continuous data (Mutanga et al., 2012). RF "is a classifier consisting of a collection of tree-structured classifiers $\{h(\mathbf{x},\Theta_k),\ k=1,\ldots\}$ where the $\{\Theta_k\}$ are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input **x**." (Breiman, 2001, P.6).

Due to its simplicity to apply and its superior performance, RF algorithm has been widely used for classification and prediction purposes in many research areas including road safety (Harb et al., 2009; Jiang et al., 2016). Abdel-Aty et al. (2008) used the RF technique to identify variables significantly associated with crash occurrence on Dutch freeways. The authors concluded that the RF algorithm as a tool is more superior for variable selection compared to single decision tree method. Harb et al. (2009) employed the RF algorithm to identify the significant determinants associated with crash avoidance maneuvers, and they concluded that the RF has the capability to identify the important factors of crash avoidance maneuvers. Siddiqui et al. (2012) applied both decision tree and RF methods to recognise the important factors (focusing on factors related to trip production and attraction related factors) associated with total traffic crashes and severe crashes per Traffic Accident Zone (TAZ) in Florida. Recently, Jiang et al. (2016) investigated the feasibility of using RF models on big data for hot-zone identification and to recognise the important factors that could determine the level of crash risks on TAZ in three counties in Florida. Jiang et al. (2016) defined hot-zones as TAZs with top 25% of crash risk measures (crashes per square mile, crashes per mile, and crashes per million vehicle-mile-travelled), and the remaining TAZs as normal-zones. Results of the study found that RF method was capable to identify hot-zones with accurate classification rates ranging between 75% and 85%. The current study used the results of Net-KDE to define hot-zones and normal-zones, and then apply the RF algorithm to identify the important factors characterising hot-zones from normal-zones focusing mainly on traffic related factors and road geometry related factors.

RF algorithm works by using bootstrapping iteration and randomly selecting a number of features say $m$ from all features say $T$ in the dataset so that $m<T$. Then for each node it calculates the best split point among the $m$ features and splitting the node into two daughter nodes and it repeats this step until the proposed number of nodes has been reached. Finally, all these steps are repeated for a number of times say $D$ to build $D$ number of trees and then by applying the majority voting technique it produces the model of highest voting rate from all the constructed trees. ***Figure 5.3*** presents the architecture of RF algorithm used by Jiang et al. (2016) to classify road traffic accident zone $\mathrm{TAZ}_i$.

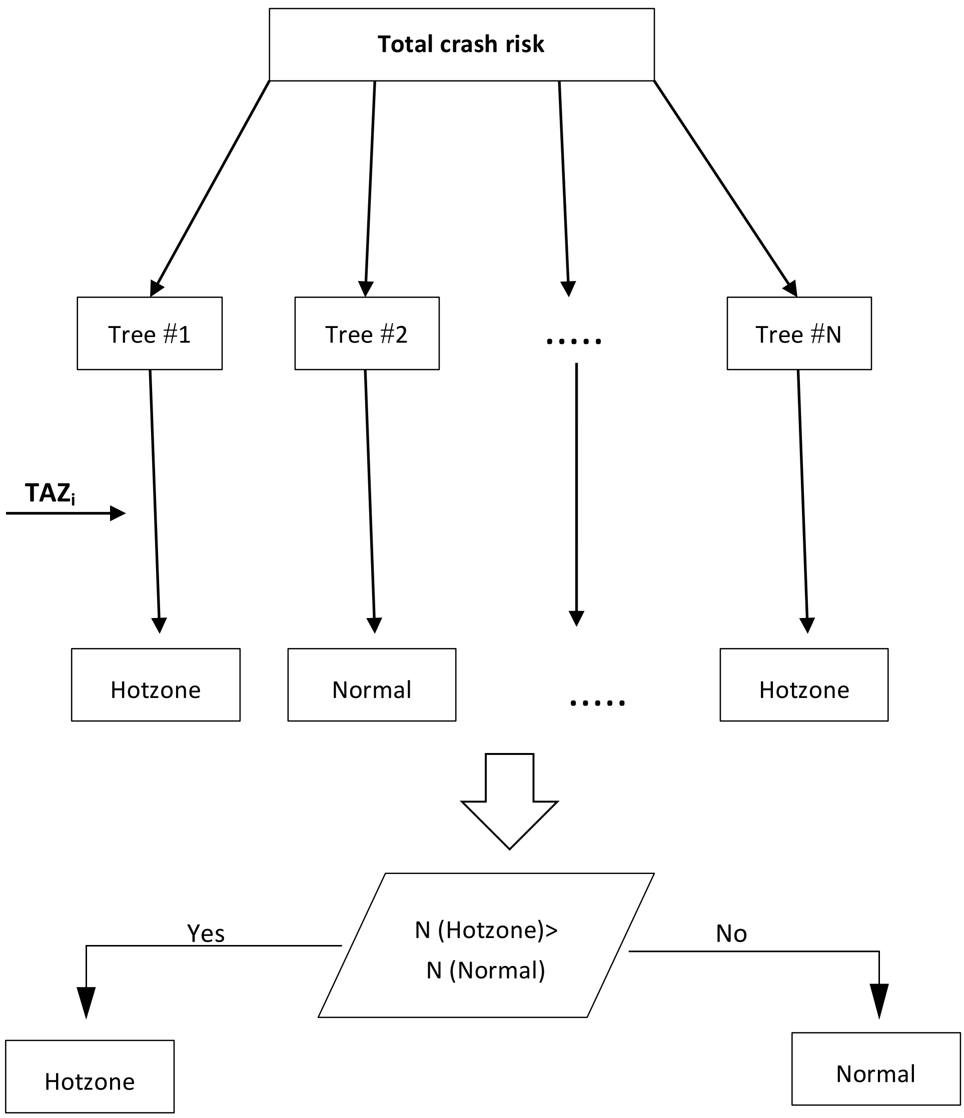


***Figure 5.3*** *The Architecture of Random Forest model to predict crash risk (Source : Jiang et al., 2016, P.56).*

In the process of constructing RF model, the dataset is divided into two sets: the training dataset (drawn from two-third of the full dataset) and the test dataset (one-third of the observations) (Jiang et al., 2016). For each bootstrap iteration and related tree, the observations not included in that sample are denoted as out-of-bag (OOB) data to estimate prediction error (called OOB error). The OOB error "is the error rate of the out-of-bag classifier on the training set" (Breiman, 2001, P.11).

To improve the performance of a RF model, the bias of each tree and the correlation among trees should be minimized (Jiang et al., 2016). Minimizing the bias is achieved by allowing each tree to grow to its maximum depth (Jiang et al., 2016). Decreasing the correlations among trees is achieved by the following two sources of randomization (Jiang et al., 2016):

a. A bootstrap sample of the training dataset should be drawn randomly, with replacement, to build each tree in the RF model.

b. A certain number of features (mtry) should be randomly selected from all the features at each node of a tree to compete for the best split and the minimum error rate is obtained.

One of the important features of the RF algorithm is its ability to provide variable importance measure and this makes the RF one of the most popular analysis techniques used in different scientific areas (Louppe, 2014). This would help not only in making the most accurate prediction but also in identifying the most important predictors in building the model (Louppe, 2014). The importance of each predictor is obtained by calculating the percentage of the increase in the mean squared error when OOB data for each predictor permuted, while keeping other predictors unchanged (Mutanga et al., 2012). Having the values of variable importance will help in ranking the strength of the relationship between the predictors and the response variable (Mutanga et al., 2012).

To calculate the variable importance measure $\overline{D}_i$ for a variable $x_i$ , the following procedures as presented in (Jiang et al., 2016) are shown. Let $L_b$ be the bootstrap sample for the tree $T_b$, and $L_b^{oob}$ be the corresponding OOB dataset, where $b = 1,2, \dots, B$:

i. Set $b = 1$, build the tree $T_1$ with bootstrap sample $L_1$

ii. Identify the corresponding OOB sample $L_1^{oob}$

iii. Use $L_1^{oob}$ to test the tree $T_1$ and record the number of correct classifications $R_1^{oob}$ in the test sample $L_1^{oob}$

iv. For $i = 1,2,3 \dots, N$

   a. Permute the values of the variable $x_i$ in $L_1^{oob}$ and save the result into $L_{1i}^{oob}$

   b. Use $L_{1i}^{oob}$ to test the tree $T_1$ and record the number of correct classifications, $R_{1i}^{oob}$

v. Redo the steps i-iv for $b = 2,3,4 \dots, B$

vi. The variable importance measure $\overline{D}_i$ for the variable $x_i$ is calculated as:

$$\overline{D}_i = \frac{1}{B}\sum_{b=1}^{B}( R_b^{oob} - R_{bi}^{oob}) \tag{5.8}$$

vii. $\overline{D}_i$ is normally distributed according to the central limit theory. By computing the standard error ($SE$) of the decrease in the correct classification, the $\overline{D}_i$ is standardised as:

$$\widehat{\overline{D}}_i = \frac{\overline{D}_i}{SE} \tag{5.9}$$

the higher the value of $\widehat{\overline{D}}_i$, the greater the importance of the variable $x_i$ (Jiang et al., 2016).

The optimum performance of RF algorithm is achieved by tuning the number of trees and the number of features (mtry) which are randomly selected at each node (Breiman, 2001; Jiang et al., 2016). Then the final decision will be based on the value of the OOB error rate, so that the lower the OOB error rate the better the performance of the model (Breiman, 2001; Jiang et al., 2016).

Before building RF algorithm in the current study, the road network in AS'Seeb[19] and Bowshar[20] (where most of road commuting occur in Muscat Governorate) were split into 82 zones. These zones represent sections of the road network where there are bridges, roundabouts, crosses, or set of T-junctions. The reason behind splitting the road network based on the location of main junctions is because results of Net-KDE indicated that the higher values of Net-KDE found on these junctions. The process of splitting the road network are as follows:

I. The centre of main junction where the zone is selected used as a centre for that given zone, and this centre is then used to determine the areas of road network covered on each zone.

II. The distance from the centre of the zone is calculated from all directions so that all road segments locating within distance not exceeding 1,000 metres are included in area covered by that given zone. However, if there are two main junctions located next to each other and the distance between the centres of the junctions is less than 2,000 metres then this shared area is divided equally between the two zones.

III. The Net-KDE for each zone is calculated by using the results of Net-KDE and adding the Net-KDE of all road segments on that given zone.

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[19] AS'Seeb is a Wilayat locating in the northern part of Muscat where Muscat Airport, Sultan Qaboos University, many public organisations and commercial activities are located.

[20] Bowshar is a Wilayat in northeastern part of Oman, where Sultan Qaboos Grand Mosque, main buildings of most Ministries, Embassies shopping malls and big companies located. The biggest hospital (the Royal Hospital) and Sultan Qaboos Sports complex are also located in this Wilayat.

RF algorithm was applied in this study using R software version 3.3.3. The algorithm was constructed using features of 82 road zones generated by combining four different datasets: the road traffic crash data of Muscat obtained from NRTC database of Royal Oman Police, results of Net-KDE, Muscat road network and the road traffic volume data generated by the researcher using Google-Maps application for each intersection in AS' Seeb and Bowshar regions in Muscat.

The features used in this algorithm include the following (most of these features are road geometry related features):

1. Net-KDE of RTCs for each zone which then classified as cold-, normal- or hot-zone (target variable),
2. Level of road traffic volume (4 different level (1-4), with 1 representing the lowest level and 4 the highest level of traffic volume)
3. Type of road (one-way direction or two-way direction)
4. Number of entrances and exits on each intersection
5. Distance (in meters) from each zone to its next nearest junction.
6. Complexity of the zone (2 levels, 0= not complex, 1=complex) and the meaning of complexity here is representing the shape of the zone, especially the shape of the bridges and roundabouts.
7. Maximum level of speed of the road on which the zone is located (five different levels 1-5, with 1 representing the lowest speed level 50km/h, and 5 the highest level 120km/h).
8. Junction Type (roundabout, bridge, cross, or set of T-junctions).

In addition, summary of the number of crashes on each zone is classified by:

a. cause of the crash: (speed, carelessness, fatigue, alcohol consumption, and non-human factor),
b. Type of the crash (Hit other vehicle, run over human, run over animal, hit fixed object on the road or overturn), and
c. Severity level of the crash (no injury, mild injury, moderate injury, severe injury and fatal crash). But these factors were not included in the construction of the RF model.

**e. Wilcoxon Test (Mann-Whitney U Test)**

Wilcoxon tests are employed to understand the different effect of each variable on hot-zones and normal-zones using SPSS software version 24.0.0.0. Wilcoxon Test (Mann-Whitney U Test) is a non-parametric method appropriate for testing the equality of means of of ranking of two populations (Jiang et al., 2016). The following annotation were drawn from (Jiang et al., 2016) explaining how Wilcoxon Sum Rank Test is applied.

Assume there are the two populations of size $n_1$ and $n_2$, the Wilcoxon test is conducted as follows:

I. list the observations of both samples from smallest to largest

II. Give a rank from 1 to $N$ (where $N = n_1 + n_2$) to all observations in ascending order. If any observation is repeated more than one times, then take the average of their rank position.

III. For each sample, sum the ranks of all observations in that sample. Let $R_1$ and $R_2$be the sum of the ranks in the first and second sample respectively. The null hypothesis of Wilcoxon test is $H_0$ : There is no difference in the mean of ranks of the two samples, while $H_1$: there is a difference in the mean of ranks of the two samples.

IV. For each sample calculate $U_{stat}$ , so that for the first sample the $U_{stat}$ is computed as:

$$U_{stat1} = R_1 - \frac{n_1(n_1+1)}{2} \tag{5.10}$$

$$U_{stat2} = R_2 - \frac{n_2(n_2+1)}{2} \tag{5.11}$$

V. Compare the values of $U_{stat}$ of both samples and specify the one with the lowest value.

VI. Specify the significance level $\alpha$ (for example, let $\alpha = 0.01$)and assume $U_{stat1}$ has the lowest value. Identify the critical value of $U_{stat}$ from the critical value of the Mann-Whitney U Test by taking the value where column number $n_1$ and row number $n_2$ cross each other, and call the value $U_{critical}$ at $\alpha = 0.01$.

VII. Compare the values of $U_{stat1}$and $U_{critical}$, if $U_{stat1}$<$U_{critical}$ at $\alpha = 0.01$, then we reject the null hypothesis and conclude that there is a difference in the mean of ranks of the two samples.

#### f. Spatio-Temporal Hot-zone Analysis

The spatio-temporal analysis is an investigation of correlation of a given factor over space and time (Mohaymany et al., 2013). The spatio-temporal analysis used to explore whether RTCs are more likely to cluster in same locations over a particular period of time or not (Mohaymany et al., 2013). In this study, the spatio-temporal analysis was conducted by applying Net-KDE for each year in the study period (2010-2014) using SANET toolkit in ArcGIS 10.2. Then, the road network in both AS'Seeb and Bowshar was split into same zones as those used in the in RF algorithm and the same procedures are used to find the Net-KDE of each zone in each year. After that, the following measure is conducted:

I. For each zone, the value of Net-KDE from year to year is calculated.

II. For each year of the study period, the values of the Net-KDE of the zones listed in descending order and each zone assigned a rank based on its position in the list.

III. For each zone, the sum of the annual ranking and variance in annual ranking are calculated.

This measure will help to identify the road zones which represent persistent problem areas for road traffic crashes in the selected cities.

## 5.3 Results

### 5.3.1 Net-KDE

The results of the Net-KDE are presented in ***Figure 5.4*** **to Figure 5.7.** They are coded into different colours, so the maps provide a clear visualisations of high risk areas where there is increase in the degree of redness of road section. Findings from the Net-KDE analysis demonstrate evidence of spatial clustering of RTC hot-zones on long roads, especially on Sultan Qaboos Highway, demarcated by intersections, and complex bridges and roundabouts. The crash-risk increases with higher density of intersections on the road network. This result is intuitive as this part of road network in Muscat has the highest level of traffic interactions which generate more safety problems among road users. It is also clear that since Muscat Expressway is extending outward from the core market and workplace areas, the crash risk tends to decrease in this area .


***Figure 5.4*** Results of Net-KDE on road network in Al-Khuwair (Area in Bowshar) where the main buildings of most Ministries, Embassies, shopping malls and big companies located

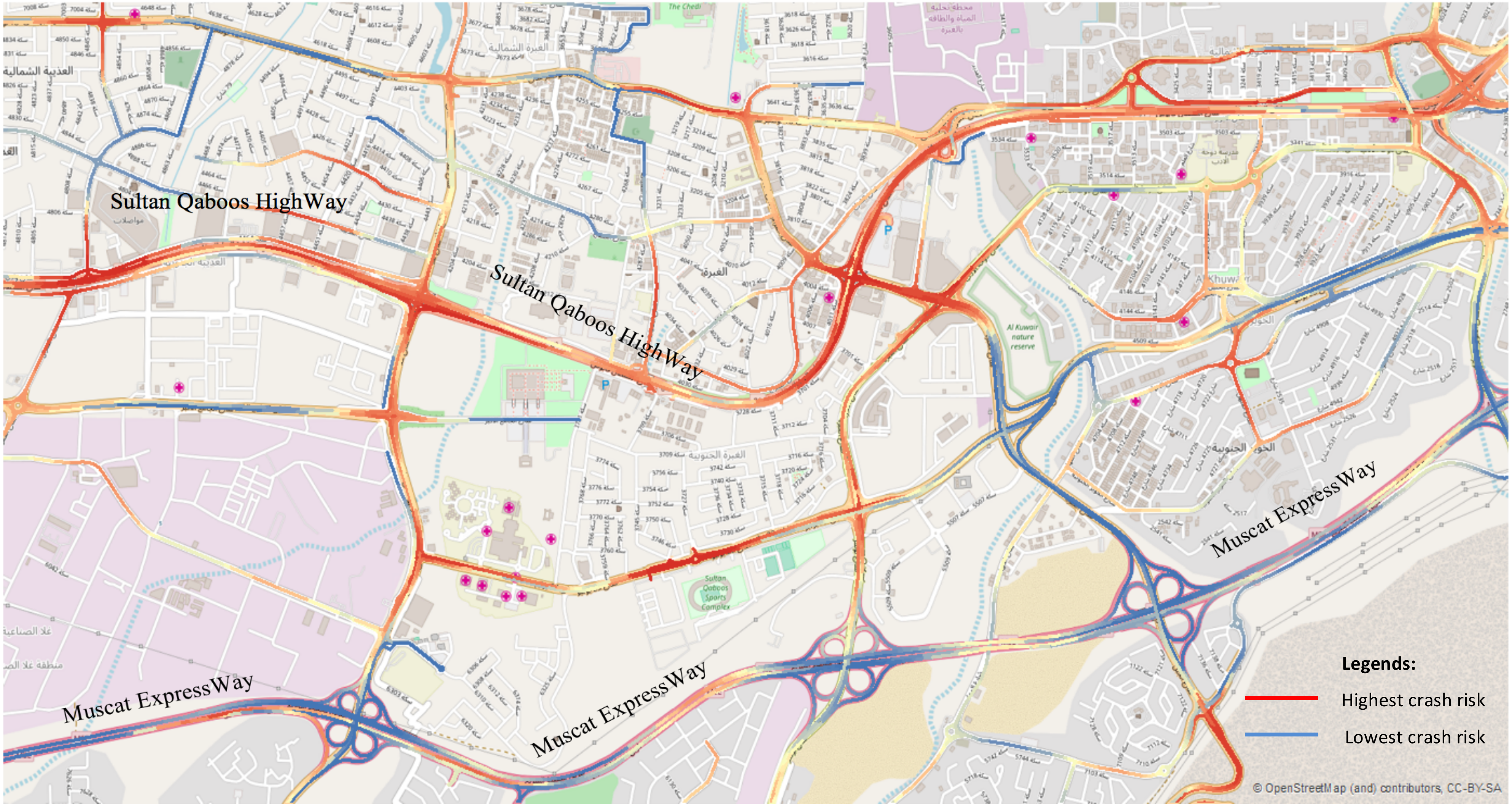


***Figure 5.5*** *Results of Net-KDE on road network from Othaibah to Al-Khuwair and Al-Ghubrah where the main buildings of most Ministries, embassies and big companies located*

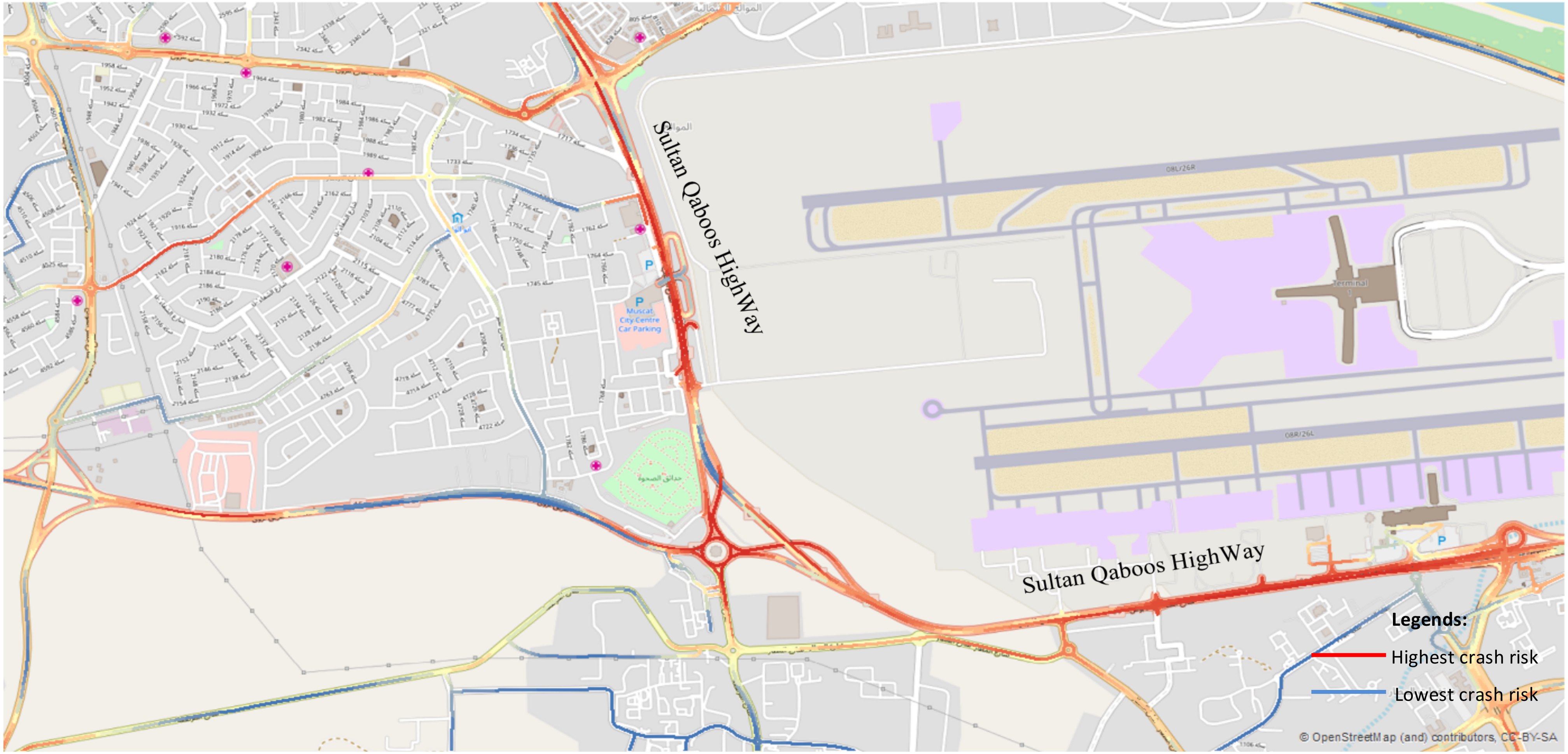


***Figure 5.6*** *Results of Net-KDE on road network from AS' Seeb City to Muscat International Airport through Burj AS' Sahwah roundabout (the biggest roundabout in Muscat from which drivers are commuting to other adjacent Governorates)*

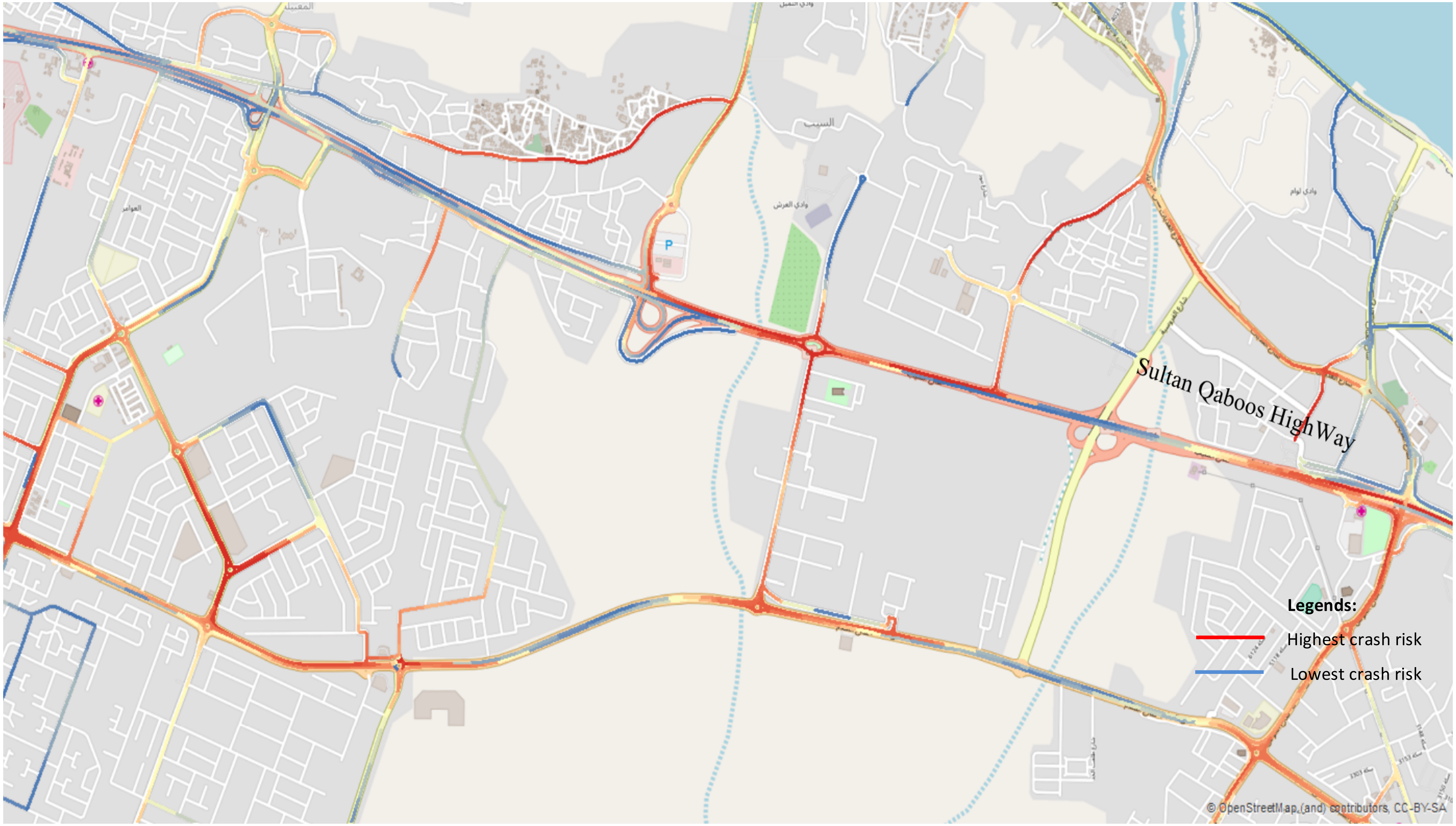


***Figure 5.7*** *Results of Net-KDE on road network in AS' Seeb Wilayat.*

### 5.3.2 Net-NND

As mentioned earlier, in order to evaluate the significance of Net-KDE of detecting the RTC hot-zones, both Net-NND and Net-K-function should be conducted to summarise the spatial dependence (clustering or dispersion) over a range of distances.

In this study, the Net-NND test was applied using the Monte Carlo simulation using a cell size of 200 meters and a confidence interval of 95% to determine the statistical level of significance. ***Table 5.1*** and ***Figure 5.8*** summarise the results of the Net-NND test (in meters):

***Table 5.1*** *Spatial dependency of RTCs in Muscat based on the Net-NND results*

| | |
|---|---|
| **Average observed Net-NND** | 54.371 |
| **Lower critical value for one-sided significance level** | 115.615 |
| **Upper critical value for one-sided significance level** | 119.074 |
| **Average expected Net-NND** | 117.327 |
| **P-value** | <0.000 |
| **Clark-Evans index= Average observed Net-NND/ Average expected Net-NND** | 0.463 |

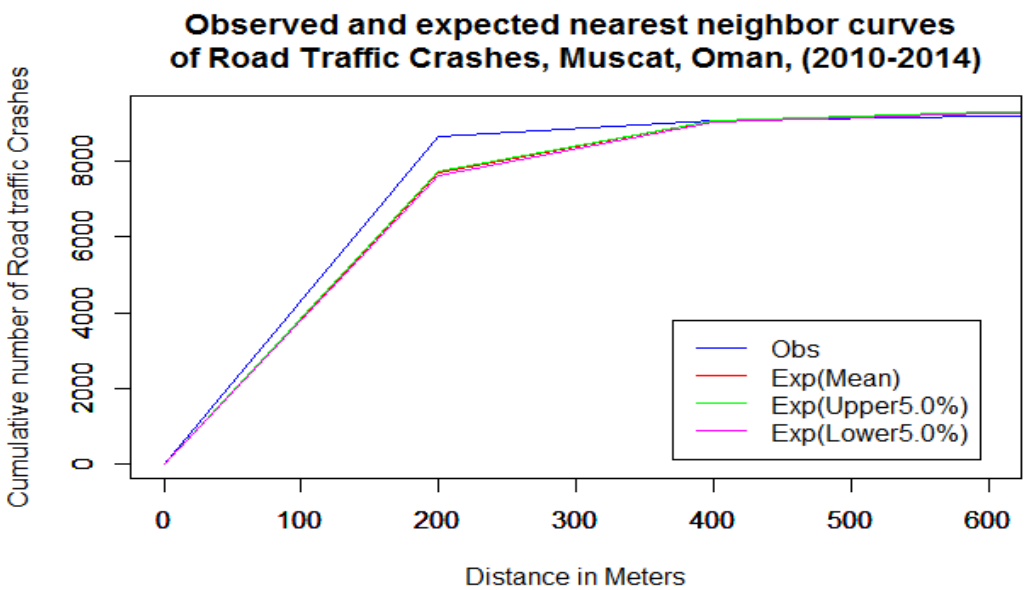


***Figure 5.8*** *Observed and Expected Nearest Neighbour curves of RTCs in Muscat based on Net-NND test*

Figure 5.8 displays four different curves: the observed curve (in blue), the expected curve under CSR hypothesis (in red) and the upper and lower envelop curves (in green and pink respectively) for one-sided 5% significance level. If the observed curve lays between the upper and lower envelop curve, the CSR hypothesis cannot be rejected, and if it lays above the upper envelop curve then the data exhibits clustering (Okabe and Sugihara, 2012). As it is clear from the Table, the Clark-Evans index=0.463 and the observed curve is above the upper envelop curve for distances less than 450 meters, the CSR hypothesis is rejected with 0.95 confidence level. This confirmed the significance of clustering patterns of RTCs along road network.

### 5.3.3 Net-K-Function

The K-Function method was applied in this study using Monte Carlo simulation to find the upper and lower critical values of a significance level α=5%. As mentioned in **5.2.2 part (c)**, the graphical presentation of the observed Net-K-function and the expected Net-K-function together with the upper and lower confidence envelops helps to conclude at a confidence level of 1-α (i.e. 95%) whether the RTCs tend to cluster (the graph of the observed Net-K-functions is above the upper confidence envelop) or be dispersed (the graph of the observed Net-K-functions is under the lower confidence envelop (Okabe and Sugihara, 2012). ***Figure 5.9*** summarises the results of the Net-K-Function method. The univariate spatial patterns of the Net-K-Function show significant deviations from the CSR hypothesis and indicate the clustering patterns (the graph of the observed K-functions is above the upper confidence envelop) of RTCs along the road network confirming the results obtained from the Net-KDE analysis. Therefore, we can conclude that the detected hotspots are significant as both the Net-NND and Net-K-Function methods reject the null hypothesis of random distribution.

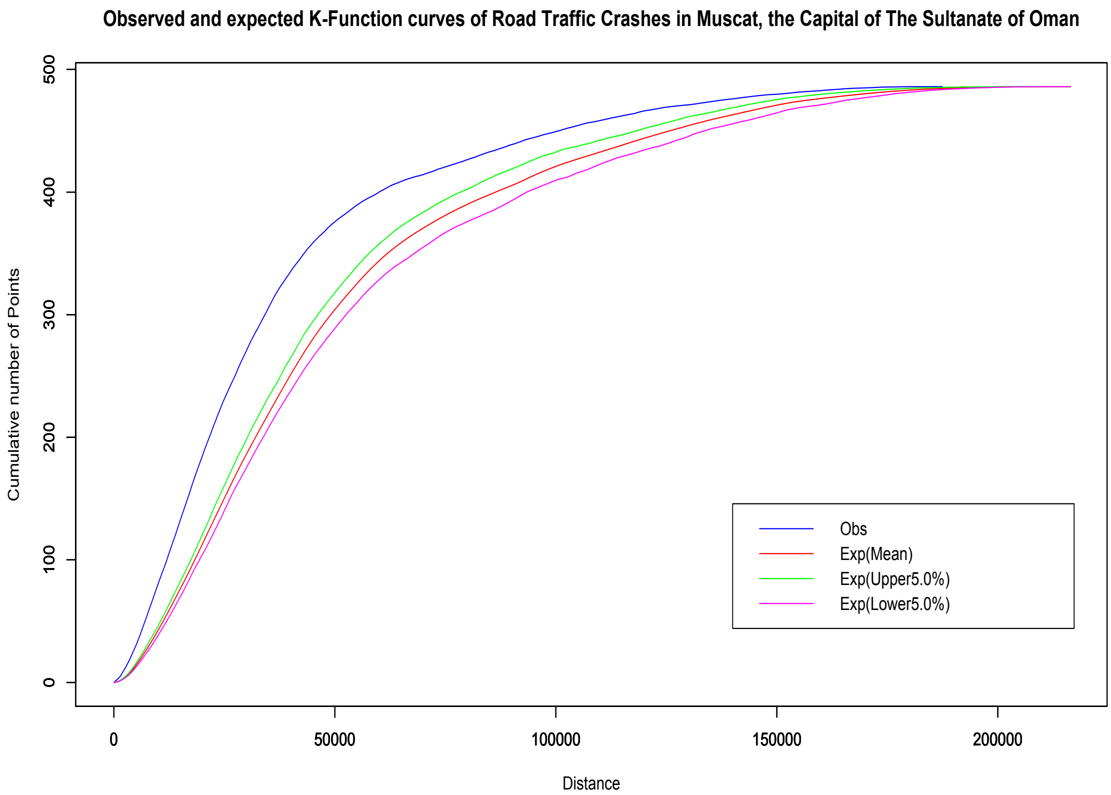


***Figure 5.9*** *Observed and Expected Net-K-function curves of RTCs in Muscat based on Net-k-function method*

### 5.3.4 RF Algorithm

Road geometry related attributes and road traffic related attributes are used in the construction of the RF Algorithm. The kernel density of every selected zone was found by summing the value of Net-KDE of all road segments located on that given zone. The average Net-KDE of all selected zones was 1128. A series of random forest models were fitted to explore the characteristics of cold-zones, normal-zones and hot-zones. Results of two models which produced the lowest percentages of classification error are presented here.

The first RF model was built using all the 82 intersections and they were classified into 2 classes (Hot-Zones= Net-KDE>800, Normal-Zones=Net-KDE <=800). A total of 500 trees with two split at each node were used to construct this model. The results of this model are summarised in ***Table 5.2*** and ***Figure 5.10***:

***Table 5.2*** *Out of Bag error for Random Forest Algorithm to classify Hot- and Normal-Zones*

| **Actual Class** | **Internal Test/Out of Bag estimate** | | | |
|---|---|---|---|---|
| | **N-Cases** | **N-accurately classified** | **N-misclassified** | **Prediction error** |
| **Normal-Zone** | 39 | 26 | 13 | 0.3333 |
| **Hot-Zone** | 43 | 32 | 11 | 0.2558 |
| **Average Out Of Bag estimate error** | | | | 0. 2927 |

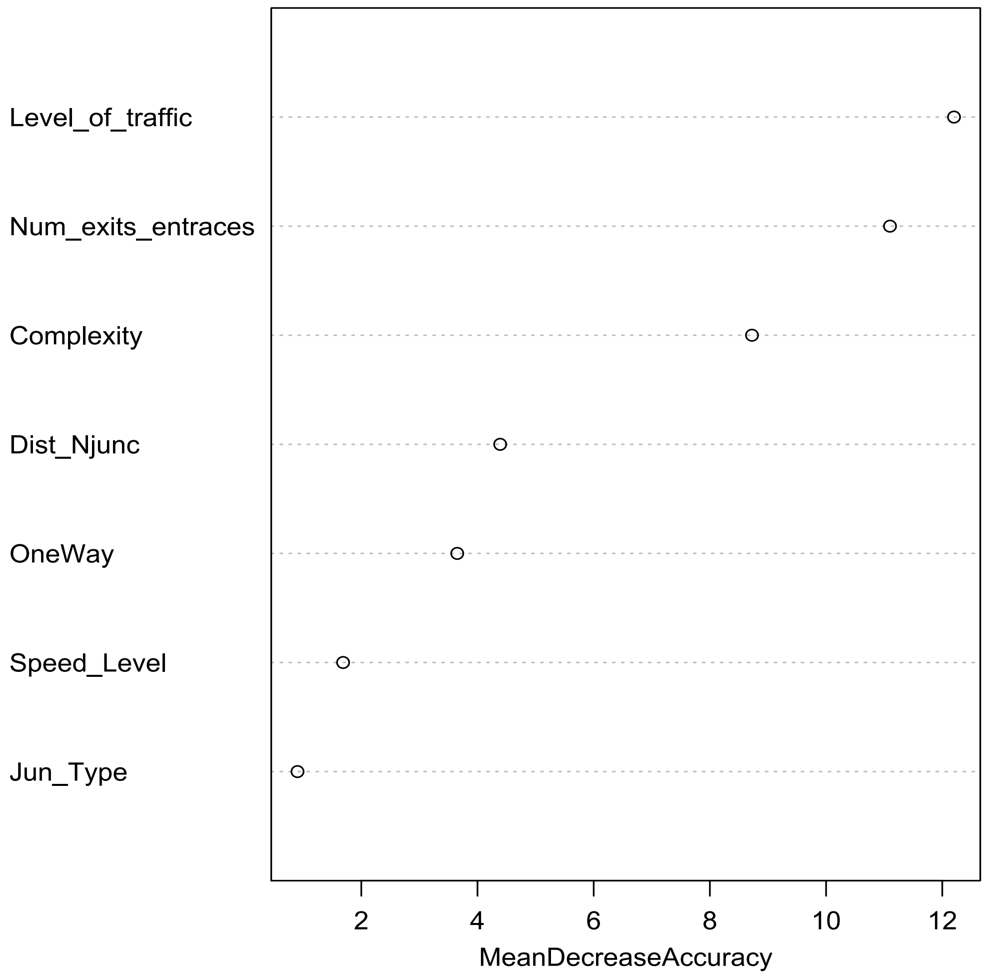


***Figure 5.10*** *Mean decrease in accuracy of Random Forest Algorithm to classify Hot- and Normal-zones*

Figure 5.10 shows the mean decrease in accuracy which described the decrease in model accuracy from permuting the values of each variable/feature, in other words it gives indication about the variable importance in the model. The Figure indicates that level of road traffic, number of entrances and exits (num_exits_entrances) in the intersection/zone, complexity, and distance to nearest junction (Dist_Njunc) are the most important factors affecting the accuracy of classifying normal and hot-zones. Conversely, maximum level of speed (Speed_level), junction type (Jun_Type), and type of road (one-way or two-way directions) do not affect the accuracy of classification of normal and hot-zones. As it is clear from Table 5.2, the model was able to accurately classify 26 out of 39 normal-zones and failed to classify 13 zones in their right class. Likewise, 32 out of 43 hot-zones (74.42%) were accurately classified into their right class. Overall more than 70% of all zones were accurately classified.

Only zones which have Net-KDE above (1128) or under (326) included as hot-zones and cold-zones respectively in building the second RF model.  A total of 44 zones were eligible to include in building this model and the results of this model are summarised in ***Table 5.3*** and ***Figure 5.11***. Similar to the results in Figure 5.10, Figure 5.11 indicates that level of traffic, the number of entrances and exits in the zone and type of junction are the most important factors in classifying cold and hot-zones. Unlike the first model, in this model the distance to the nearest junction and complexity level of the zone appear not affecting the accuracy of classifying cold- and hot-zones. Table 5.3 shows that the model was able to accurately recognise about 90% and 80% of hot- and cold-zones respectively. Interestingly, the model has an overall internal error rate of 13.64 % in classifying zones as cold or hot-zones and accordingly, more than 86.36% of these zones were correctly identified.

***Table 5.3*** *Out of Bag error for Random Forest Algorithm to classify Hot- and Cold-Zones*

| Actual Class | Internal Test/Out of Bag estimate | | | |
|---|---|---|---|---|
| | **N-Cases** | **N-accurately classified** | **N-misclassified** | **Prediction error** |
| **Cold-Zone** | 15 | 12 | 3 | 0.2000 |
| **Hot-Zone** | 29 | 26 | 3 | 0.1034 |
| **Average Out Of Bag estimate of error** | | | | 0.1364 |

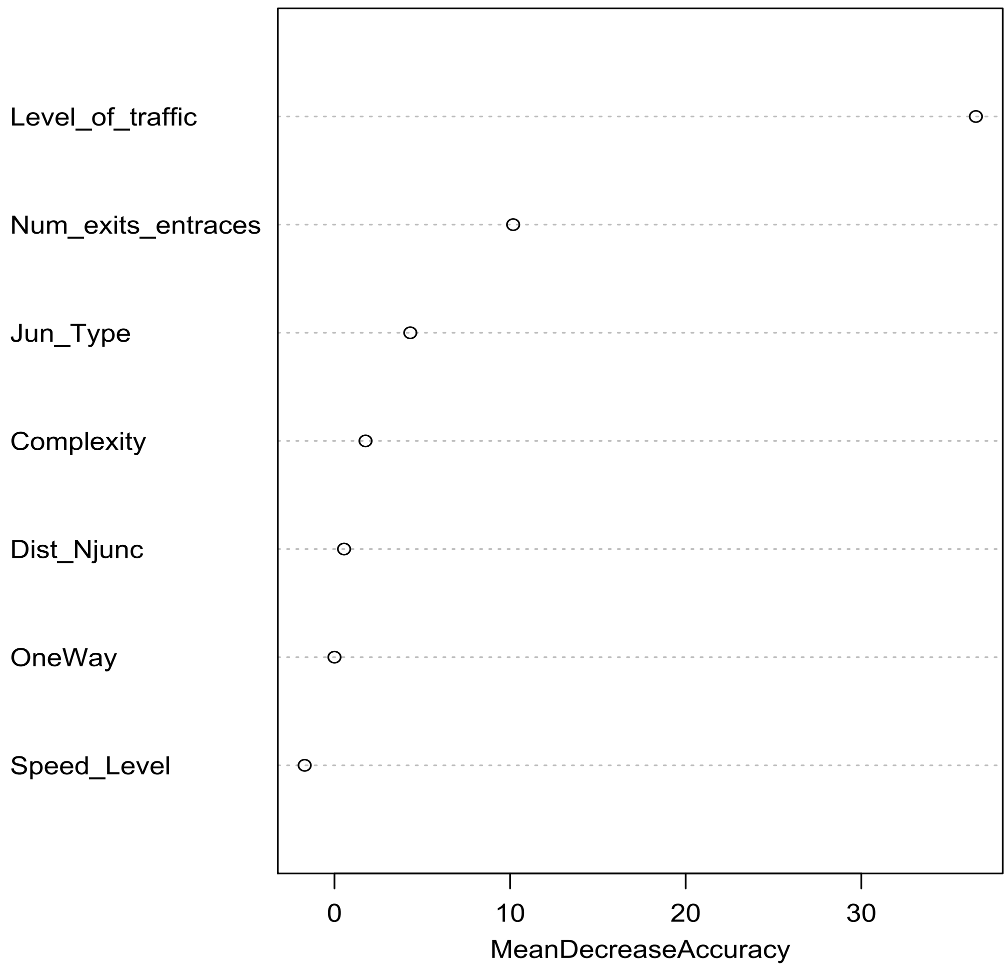


***Figure 5.11*** *Mean decrease in accuracy of Random Forest Algorithm to classify Hot- and Cold-zones*

### 5.3.5 Wilcoxon Test (Mann-Whitney U Test)

Wilcoxon tests applied in this study to quantitatively understand the different effect of each variable on hot-zones and normal-zones. Results from Wilcoxon tests are shown in ***Table 5.4.*** Overall, it is clear that most of the features are significantly different between normal- and hot-zones. More precisely, there is a difference in the mean of ranks of normal- and hot-zones in the number of exits and entrances, distance to nearest junction, complexity of the intersection and level of traffic at a significance level of $\alpha = 0.01$. However, it is clear that there is no significant difference between the two types of zones when considering type of junction (i.e. roundabout, cross, bridge or set of junctions), maximum level of speed, and type of road (i.e. one-way direction road, or two-ways). The highest difference can be seen in the number of exits and entrances; hot-zones appear to have higher number of exits and entrances compared with normal-zones. Likewise, hot-zones are characterised by having shorter distances to their nearest junction as compared to normal-zones. Similarly, higher level of traffic seems to increase the crash risk on road network and thus increasing the likelihood of having hot-zones. It is also clear that hot-zones are more likely to appear on areas where complex structure of road network exist when compared with normal-zones.

***Table 5.4*** *The effects of road and traffic related feature on classifying Hot- and Normal-Zones based on Wilcoxon Test*

| **Factor** | **Hot-Zones (N=43)** | | **Normal-Zones (N=39)** | | **Sig. Level** |
|---|---|---|---|---|---|
| | Mean Rank | Sum of Ranks | Mean Rank | Sum of Ranks | |
| Number of exits and entrances | 50.90 | 2188.50 | 31.14 | 1214.50 | <0.000 |
| Distance to nearest junction | 34.37 | 1478.00 | 49.36 | 1925.00 | 0.004 |
| Type of junction | 44.50 | 1913.50 | 38.19 | 1489.50 | 0.211 |
| Complexity | 48.57 | 2088.50 | 33.71 | 1314.50 | <0.000 |
| Level of traffic | 49.73 | 2138.50 | 32.42 | 1264.50 | <0.000 |
| Maximum level of Speed | 40.98 | 1762.00 | 42.08 | 1641.00 | 0.814 |
| Type of road | 44.59 | 1917.50 | 38.09 | 1485.50 | 0.029 |

The effects of road and traffic related feature on classifying Hot- and Cold-Zones summarised in ***Table 5.5*** and it shows that there is a difference in the mean of ranks of cold- and hot-zones in the number of exits and entrances, level of traffic and complexity of the intersection at a significance level of $\alpha = 0.01$. However, there is no significant difference with the type of road, type of junction, distance to nearest junction, and maximum level of speed.

***Table 5.5*** *The effects of road and traffic related feature on classifying Hot- and Cold-Zones based on Wilcoxon Test*

| **Factor** | **Hot-Zones (N=29)** | | **Cold-Zones (N=15)** | | **Sig. Level** |
|---|---|---|---|---|---|
| | Mean Ranks | Sum of Ranks | Mean Ranks | Sum of Ranks | |
| Number of exits and entrances | 27.81 | 806.50 | 12.23 | 183.50 | <0.000 |
| Distance to nearest junction | 20.00 | 580.00 | 27.33 | 410.00 | 0.072 |
| Type of junction | 21.91 | 635.50 | 23.63 | 354.50 | 0.662 |
| Complexity | 25.90 | 751.00 | 15.93 | 239.00 | 0.004 |
| Level of traffic | 28.88 | 837.50 | 10.17 | 152.50 | <0.000 |
| Maximum level of Speed | 21.05 | 610.50 | 25.30 | 379.50 | 0.239 |
| Type of road | 22.74 | 659.50 | 22.03 | 330.50 | 0.631 |

### 5.3.6 Spatio-Temporal Patterns

After estimating the annual crash density for each zone on road network, the densities should be analysed temporally to identify road zones which represent persistent problem areas for road traffic crashes in the study area. The visual comparison of maps by year reveals the dependency of high-crash-density locations, however, due to limited space, these results are presented in Appendix C and D. However, the temporal analysis was conducted by applying Pearson correlation for each pair of years to assess whether there is a consistency in the locations of hot-zones or not. ***Table 5.6*** displays the results of the spatio-temporal Pearson correlation for each pair of years during the study period. Similarly, ***Figure 5.12*** shows an example of this spatio-temporal dependency, and it indicates that RTCs are inclined to cluster in the same locations within the study period. It is also clear that the crash risk had increased gradually from 2010 to 2014 in the area shown in Figure 5.12.

***Table 5.6*** *The spatio-temporal correlation for each pair of years during the study period (2010-2014) of RTCs in Muscat Governorate*

| **Year of crash** | **correlation** | | | | |
|---|---|---|---|---|---|
| | **2010** | **2011** | **2012** | **2013** | **2014** |
| **2010** | | 0.828** | 0.627** | 0.524** | 0.409** |
| **2011** | 0.828** | | 0.665** | 0.581** | 0.574** |
| **2012** | 0.627** | 0.665** | | 0.753** | 0.541** |
| **2013** | 0.524** | 0.581** | 0.753** | | 0.769** |
| **2014** | 0.409** | 0.574** | 0.541** | 0.769** | |

**. Correlation is significant at the 0.01 level (2-tailed).

Results from the Pearson correlation Table indicates that there is a strong positive correlation (Pearson correlations are above 0.5) between most pairs of the study period except the pair representing the years 2010 and 2014. However, it is important to mention that for the year 2014 we have data for 10 months only (1st January-2nd November). It is also clear that the correlation becomes stronger when the pair represents two subsequent years (i.e. 2010 and 2011, 2011 and 2012 and so on). These results indicate that RTCs are more likely to cluster over the same road zones during the five years of the study period.

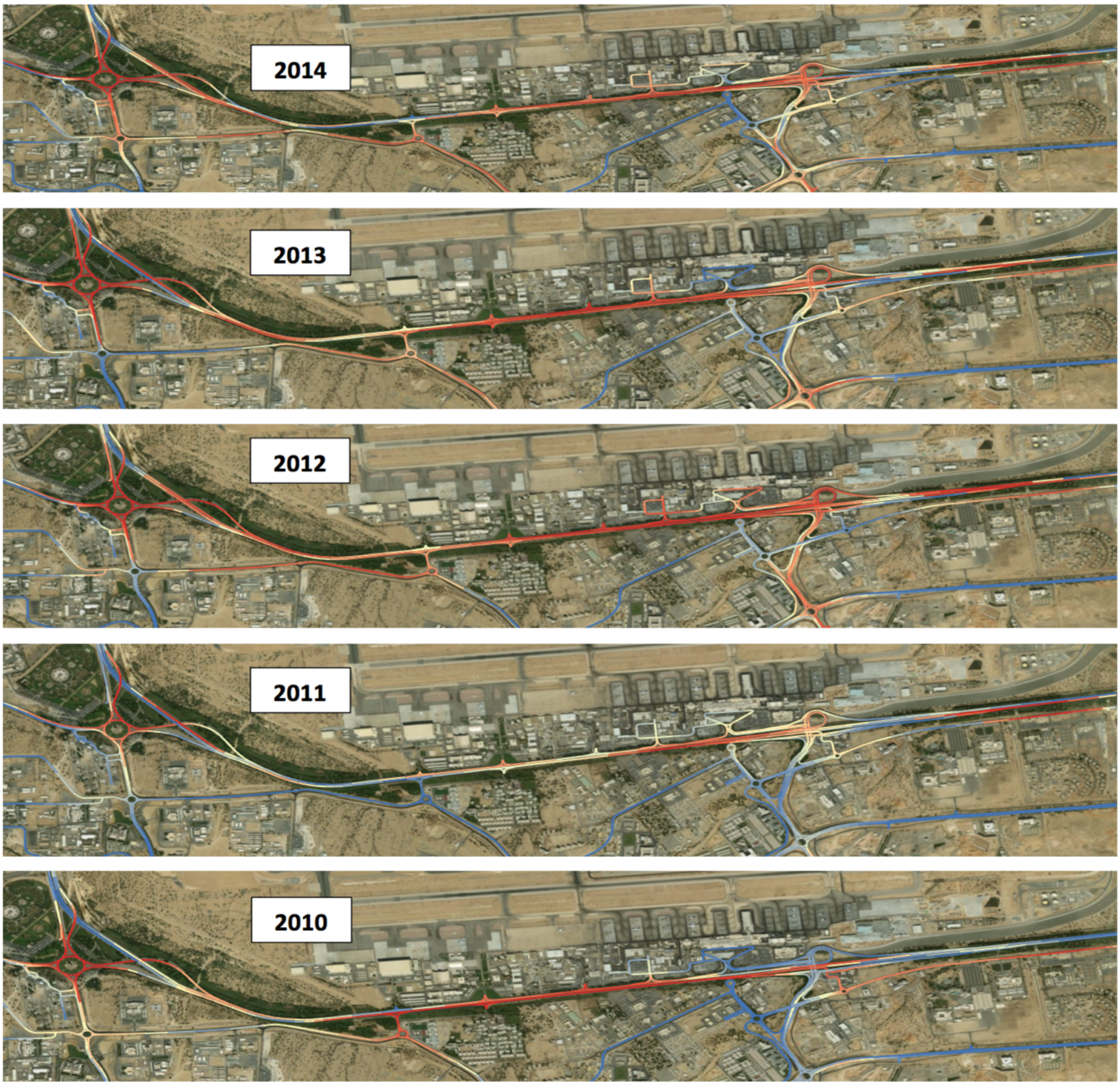


***Figure 5.12*** *Spatio-temporal patterns of RTCs next to Muscat Airport in AS'Seeb City*

To identify the road zones which represent persistent problem areas for road traffic crashes, the values of the annual Net-KDE of the zones are listed in descending order and each zone is assigned a rank based on its position in the list. Then, the sum of the annual rankings, mean of annual ranking, variance and standard error (SE) of annual ranking for each zone are calculated. This step is repeated using the Olympic average approach in assigning mean annual rank for each zone. Following the Olympic average approach, the lowest and highest ranks of each zone are removed, and the remaining three ranks are used to calculate the sum, mean, variance and SE. ***Figure 5.13*** shows the scatter plot of mean of annual ranking of each zone resulting from both methods. The scatter plot and the variances resulting from the Olympic average approach show that this is a more robust approach and has smaller variance compared with results of using all 5-years ranks. ***Table 5.7*** presents the results drawn from the Olympic average, the variance and SE indicate the homogeneity of hot- and cold-zones locations. In other words, it is clear that most hot-zones have small variance and SE indicating that these locations are always having the highest densities of RTCs, and consequently, this confirms the consistency of hazardous locations over time. Although cold-zones appear to have low SE in their ranking, however, these zones are more likely to experience higher fluctuation in their annual ranking (which could also mean there is a heterogeneity in crash risk over these zones) compared with hot-zones.

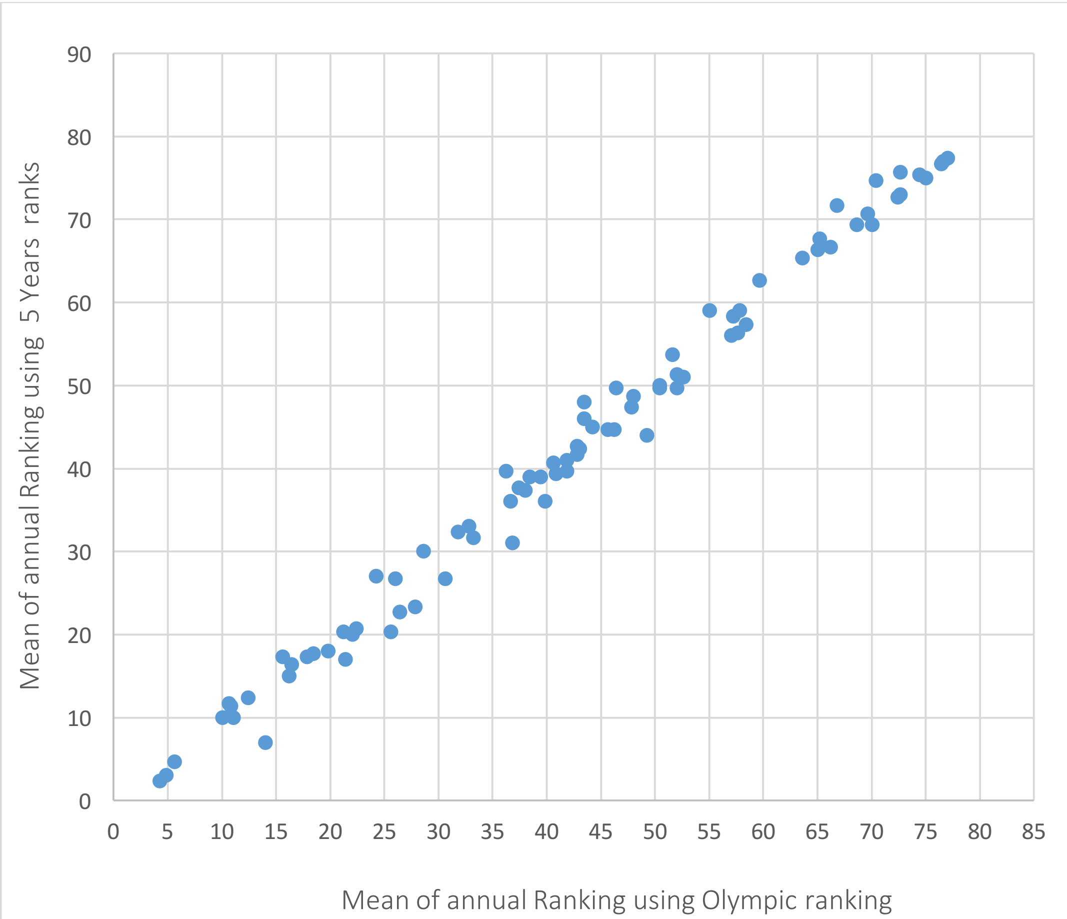


***Figure 5.13*** *Scatter plot of mean of annual ranking using the 5-year and the Olympic average approach*

***Table 5.7*** Variance of ranking of road hot-zones and cold-zones based on the sum of annual ranking using Olympic average approach

| Hot-Zones (10 with lowest sum of annual ranking) | | | | | Cold-Zones (10 with highest sum of annual ranking) | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Zone_ID | Sum of annual Ranking | Mean of annual ranking | Variance of annual ranking | S.E. | Zone_ID | Sum of annual Ranking | Mean of annual ranking | Variance of annual ranking | S.E. |
| 12 | 7 | 2.333 | 5.333 | 2.309 | 2 | 232 | 77.333 | 41.333 | 6.429 |
| 22 | 9 | 3.000 | 3.000 | 1.732 | 42 | 231 | 77.000 | 7.000 | 2.646 |
| 19 | 14 | 4.667 | 14.333 | 3.786 | 15 | 230 | 76.667 | 25.333 | 5.033 |
| 21 | 21 | 7.000 | 1.000 | 1.000 | 39 | 227 | 75.667 | 10.333 | 3.215 |
| 10 | 30 | 10.000 | 4.000 | 2.000 | 60 | 226 | 75.333 | 25.333 | 5.033 |
| 17 | 30 | 10.000 | 13.000 | 3.606 | 41 | 225 | 75.000 | 9.000 | 3.000 |
| 14 | 34 | 11.333 | 40.333 | 6.351 | 37 | 224 | 74.667 | 8.333 | 2.887 |
| 24 | 35 | 11.667 | 4.333 | 2.082 | 51 | 219 | 73.000 | 52.000 | 7.211 |
| 79 | 37 | 12.333 | 20.333 | 4.509 | 3 | 218 | 72.667 | 12.333 | 3.512 |
| 76 | 45 | 15.000 | 4.000 | 2.000 | 33 | 215 | 71.667 | 25.333 | 5.033 |

### 5.3.7 Validation of Net-KDE results using iMAAP pilot data

This section compares the results of Net-KDE using RTC data of year 2014 with pilot data drawn from iMAAP, network based crash analysis system developed by the UK Transport Research Laboratory. iMAAP is implemented by ROP and supported by The Research Council under the National Road Safety Research programme. In 2015, ROP used iMAAP in documenting a sample of RTCs in two areas in **Muscat** namely: **Al-Khoudh** and **Othaiba** and both of these areas are located in AS' Seeb Wilayat. The iMAAP pilot data includes information about the sex, age and nationality of drivers, number of casualty killed, number of casualty injured, type and number of vehicles involved, crash date, time, day of week, severity of the crash, primary and secondary cause of crash, latitude of longitude of the crash location, landmark, type of collision, type of road, type of road, road name, number of lanes, carriageway width, shoulder width, light condition, street light, weather conditions, and crash description. The pilot data has details of 255 incidents collected between January 2015 and August 2015.

***Figures 5.14*** shows the scatter plot of the Net-KDE of randomly selected locations in Al-Khoudh and Othaiba using iMAAP data and a sample of 269 observations from 2014 dataset. The scatter plot clearly indicates that there is a strong positive correlation between the density of RTCs in both datasets. However, it is important to highlight that these two dataset are not covering the same time period (i.e. iMAAP data is a sample of crashes occurring between January 2015 and August 2015). ***Figure 5.15*** confirms the result of the scatter plot and it provides a visual comparison of the Net-KDE values produced from both datasets using maps. The maps clearly indicate that the Net-KDE cached similar spatial patterns identifying almost the same hot-zones in both dataset, and both Figures provide evidence about the accuracy of the geo-coded data generated by the author of this thesis.

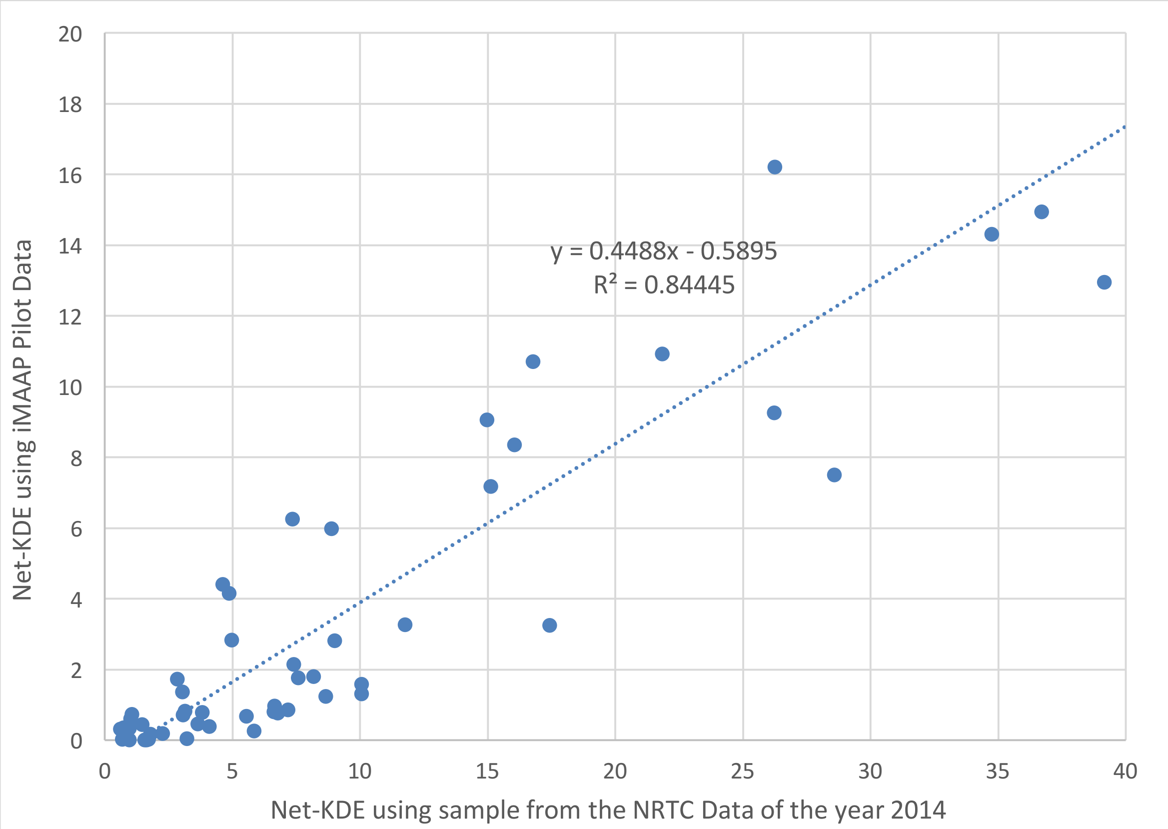


***Figure 5.14*** *Scatter Plot of Net-KDE using iMAAP Pilot Data and a sample from the NRTC Data of the year 2014*

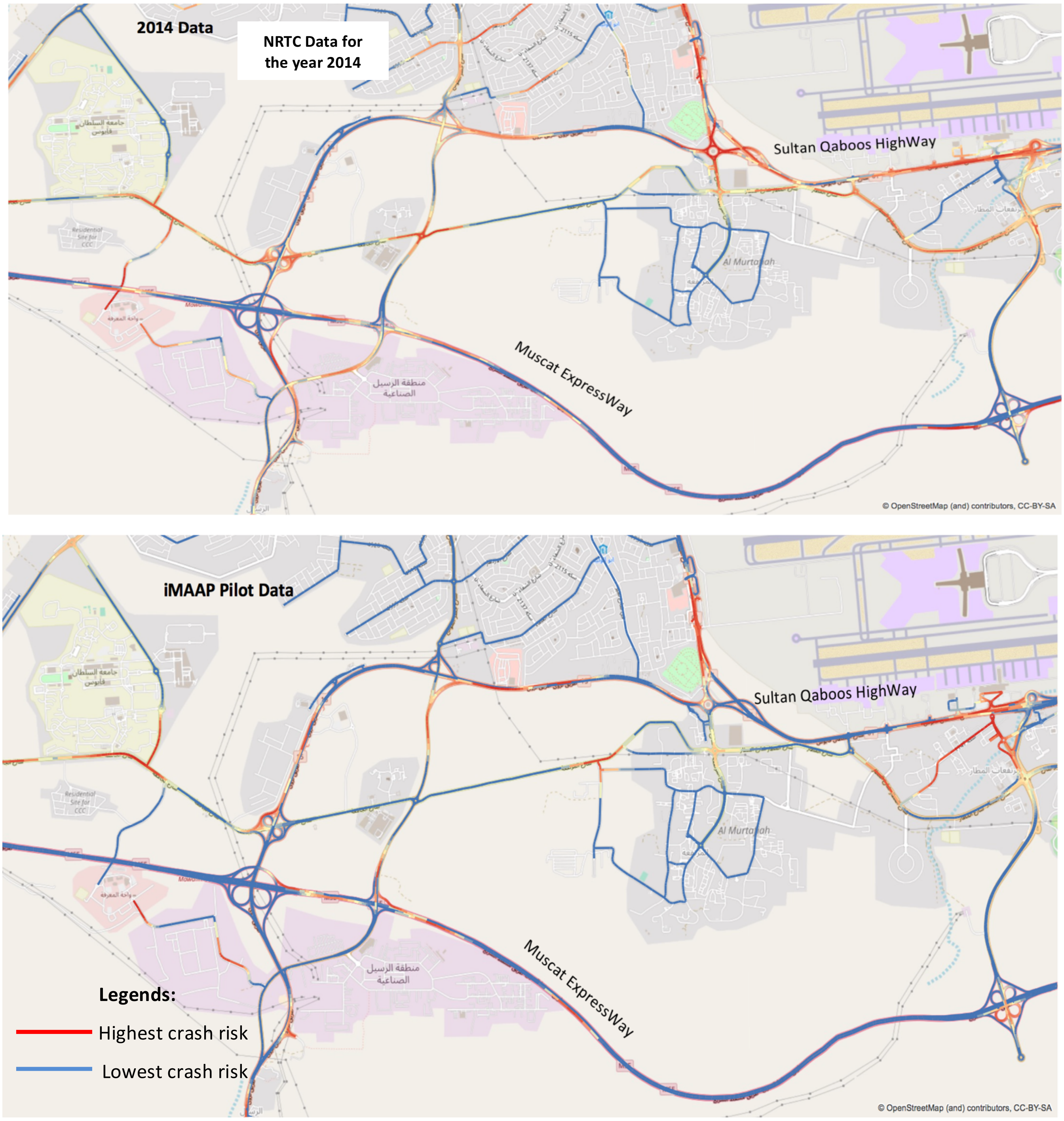


***Figure 5.15*** *Comparison of Net-KDE results using the NRTC Data of the year 2014 and pilot data drawn from iMAAP System*

## 5.4 Discussion and conclusions

The identification of road crash hot-zones is a key to introduce the most effective strategies to reduce the crash density on high-risk areas. The foci of this study were to: (1) identify high density crash zones in the Muscat Governorate (2) explore the characteristics of crash hot-zone, and (3) examine the spatio-temporal patterns of RTCs in the study area. This study has exemplified the use of GIS in detecting hot-zones by employing a wide range of statistical techniques using data of five yeas (2010-2014) of RTCs in Muscat Governorate. To the best of the researcher knowledge, this study is of its first type in Oman in analysing the spatial patterns of RTCs.

Analysis of hot-zone identification done with the help of Net-KDE and the significance of the results from kernel density evaluated using the Net-NND and Net-K-function methods. Findings from the Net-KDE demonstrate evidence of spatial clustering of RTC hot-zones on roads demarcated by high number of intersections, complex bridges and roundabouts. Hot-zones appear to be more dominant on road segments where highest level of traffic interactions exists, especially along Sultan Qaboos highway. Conversely, low crash densities observed along roads locating outward from the core market and workplace areas, and Muscat Expressway is one example of such roads. Likewise, findings from the Net-NND and Net-K-function methods confirm the significance of clustering patterns of RTCs along road network in Muscat. These findings provide statistical evidence and confirm the research hypothesis that that road intersections (roundabouts, crosses and bridges) represent higher risk of causing RTCs than other road geometric features. These results are statistically validated using the pilot data from iMAAP network based crash analysis system.

Findings from RF algorithm and Wilcoxon tests indicate that road and traffic related features play a key role in determining locations of high crash risk. Based on the results from Wilcoxon tests, hot-zones are associated with higher level of road traffic. This result is in line with findings from past studies, which have proven that traffic level is a key factor associated with higher crash risk (Abdel-Aty and Radwan, 2000; Caliendo et al., 2007; Jiang et al., 2016). Hot-zones also appear to be associated with the higher number of exits and entrances and shorter distance between junctions. This is consistent with results from previous literature, which concluded that higher density of intersections positively influences the number of crashes on such road sections (Siddiqui et al., 2012; Jiang et al., 2016). Conversely, although past studies indicated that lower levels of posted speed limits associated with low crash-risk (Abdel-Aty et al., 2011; Jiang et al., 2016), results of the current study indicate that posted speed limits had no significant effect in determining the crash risk on road zones. This could be due to the low percentage of road sections with small posted speed limits (i.e. most of the road sections included in the study have posted speed limit>100 km/m) or it could be associated with existence of higher proportions of cyclists and pedestrians on road with low speed limits which in turn increase the likelihood of crash occurrence. However, the current study could not explore the interaction between speed limit and data related to number of cyclists and pedestrians due to lack of data. Overall, these findings offer new insights for road safety specialists to understanding the difference between hot-zones and other zones in Muscat Governorate, and thus helping them in adopting effective planning strategies and allocating proper resources to reduce the crash risk on these high density crash.

The spatio-temporal analysis provides evidences of the consistency in the positions of crash hot-zones in the study area. Comparing the mean of ranking of the same locations over five years of the study period, the results indicate that RTCs are inclined to cluster in the same locations within the study period. The inference of such result could be attributed to the same road and traffic related features existing on these zones. Therefore, further safety inspections and engineering studies should be carried out to investigate the possible contributing factors, and identify the potential countermeasures such as engineering improvements to reduce the crash risk at these sites.

It is important to highlight the data limitations of the present study. Unfortunately, the study could not disentangle other factors such as factors related to socio-economic, population, and land use factors due to lack of data. Socio-economic factors such as socioeconomic status, school enrolment density, number of automobile per households, number of non-retired workers per household, number of hotels are found to be significantly affecting the level of crash risk (Ng et al., 2002; Loukaitou-Sideris et al., 2007; Huang et al., 2010; Siddiqui et al., 2012; Wang et al., 2012). Having these data could help validate and improve our understanding of the spatial characteristics and the crash risk over different zones in the road network. However, the present study could not explore these factors because of lack of data.

Despite these limitations, our study demonstrates systematic quantitative evidence of spatio-temporal patterns associated with the crash risk over different locations on road network in Muscat. More importantly, the findings clearly pinpoint the importance and influence of the road and traffic related feature in road crash spatial analysis. It is recommended that future research should systematically address potential effects of the socio-economic, population, and land use factors in identifying road crash hot-zones in Oman.

# Chapter 6

## Improving Efficiency and Quality of Data Collection on Road Crashes: Recommendations Based on Statistical Analysis of NRTC Database

The ***aim*** of this chapter is to undertake a critical appraisal of existing data collection procedures and recording systems, reflecting on the strengths and weaknesses of NRTC database, and suggesting coherent ways to record, monitor and analyse road crash data.

**Key messages**

- The crash reporting form should include full details of the incident, demographic data of all persons and other involved, vehicle condition, road and weather conditions.
- Proper linkage of RTC data using civil identification numbers to other relevant sources (e.g. Ministry of Health, Ministry of Transportation and Telecommunications, database of vehicle registration unit at ROP, and Insurance companies) is important to enhance the accuracy, and monitor, and update the crash records.
- Electronic systems (mobile apps or tablets) with essential back-up services (e.g. online data transmission facility) are recommended to record crash data.

**Keywords:** Road traffic crashes, injuries, Oman, NRTC database, iMAAP, crash records, crash reporting form, data quality, data accuracy, data linkage, severity, fatal and nonfatal outcomes

## 6.1 Introduction and background

The ***overarching aim*** of this Chapter is to evaluate the quality of NRTC data and propose recommendations for improvements in data recording and processing for research and policy use. The proposed recommendations are based on the evaluation and analysis of NRTC data, where appropriate reflecting on the strengths and limitations of existing data recording and processing for research use. Reliable RTC data and statistical evidence are fundamental to identifying the risk factors more accurately, identifying priority areas for policies and interventions, monitoring performance and evaluating intervention programmes (Peden, 2004; WHO, 2010). Policy decisions not based on accurate data and scientific analysis could be potentially misleading for resources allocation and could result in limited or even negative impact on the outcomes of interventions and policies (Peden, 2004).

Although most countries have national road traffic crash database based on police or/and health records, there are differences between different surveillance systems in terms of the reliability and quality of such data collection within the same country (Peden, 2004). This is especially the case in Oman where road traffic crashes continue to exert significant challenges on national and family resources. Lack of appropriate database on RTCs is a common challenge in many countries around the world (Peden, 2004; Grimm and Treibich, 2010). Completeness and accuracy are the two main challenges in RTC databases (Imprialou and Quddus, 2017). Moreover, effective counter-measures to improve road safety largely rely on the accuracy of crash analyses and the quality of RTC data (WHO, 2010; Imprialou and Quddus, 2017).

The quality and reliability of any data depend on who collects the data, how the data are collected (tools and methods), how information is recorded and processed for various purposes (Peden, 2004; WHO, 2010; Imprialou and Quddus, 2017). Road traffic crashes are complex in nature and different institutes need these data for different purposes (WHO, 2010; Imprialou and Quddus, 2017). For example, road crash and vehicle data are usually collected by police, health institutions, insurance companies, private and public institutions (e.g. transport companies and government departments specialized on collecting data for national planning) and other special interest groups (e.g. victim support agencies, research institutes and organisations involved in road safety actions) (Peden, 2004). Although this could be seen as an advantage, it could make road traffic data problematic in terms of harmonisation and linkage with other relevant database (Peden, 2004). Data collection activities need to be better coordinated for ensuring quality, reliability and comparability (Peden, 2004). Such harmonisation and regularity of data collection could greatly improve the assessment of road safety indicators of any country (Grimm and Treibich, 2010).

The objectives of this chapter are three-fold: (i) undertake a critical evaluation of the NRTC database and the method of data collection and recording systems, reflecting on the analysis presented in Chapters 3-5; (ii) propose coherent ways to record, monitor and analyse data on road crashes and (iii) assess the extent of use and feasibility of alternative systems such as iMAAP crash recording system. The main question addressed in this chapter is: How can we improve the existing data collection systems to better understand and measure road traffic crashes and related injury outcomes?

## 6.2 NRTC database: strengths and limitations

NRTC database is maintained and published by the Directorate of Road Traffic of the ROP. It has to be noted that the NTRC data collection is not designed for road safety research but to record and store national level RTC data (OECD/ITF, 2015). However, NRTC database is the only source of RTC data in the Sultanate. The database has basic information of RTCs such as crash date, time, severity level, gender, age and nationality of drivers and his/her related injury outcomes, number of causalities, number of fatalities, type and number of vehicles involved, cause of crash, type of collision, location, type of road, weather conditions and crash description.

Ordinal scales are usually used to record the severity level of RTCs (Yamamoto et al., 2008). In Oman, the following five categories are used to record the severity level of crash outcomes: property damage only, slight injury, medium injury, serious injury, and fatal injury. Underreporting of RTCs is a common problem globally, especially for lower levels of injury severity (Aptel et al., 1999; Alsop and Langley, 2001; Yamamoto et al., 2008; Watson et al., 2015; Janstrupet et al., 2016). To examine the underreporting problem of RTCs, many studies have compared the police records with data from medical sources, and they have found that 85-100% of fatal injuries are recorded in the police database, whereas only 30-75% of nonfatal outcomes recorded by the police (Aptel et al., 1999; Alsop and Langley, 2001; Yamamoto et al., 2008; Watson et al., 2015; Janstrupet al., 2016).

Underreporting rates of crash data have been found to vary by type of road user (e.g. drivers, pedestrians, bicyclists, motorcyclists), number and type of vehicle involved, place of the crash (urban verse rural), and severity level of crash outcome (Aptel et al., 1999; Alsop and Langley, 2001; Yamamoto et al., 2008; Abay, 2015; Watson et al., 2015; Janstrupet al., 2016). Motorcyclist crashes more likely to be underreported, while injury outcomes of crashes involving multiple vehicles and crashes of severe outcomes and injuries of long periods of stay at hospital found to be more likely to be reported (Aptel et al., 1999; Alsop and Langley, 2001).

Although NTRC database provides information on serious crashes, there could be bias and misclassification of injury outcomes, especially minor crashes. According to ROP (2006), serious crashes are those crashes involving an injury, public property damage or an inability of the involved vehicles' drivers to resolve between themselves who was at fault. Whereas, minor crashes are those crashes that not having the three above criteria so that insurance companies can resolve the situation without the involvement of ROP, and thus these type of crashes are not recoded in the ROP database (AL-Bulushi et al., 2015). Due to copyright and data protection reasons, we could not include a sample of NRTC reporting form. Therefore, due to the difference in classifying RTCs to serious and minor crashes, lower severity outcomes are more likely to be underreported (e.g. slight or medium injuries) (Yamamoto et al., 2008) and can be classified as minor crashes and not recorded in the ROP database. Underreporting of RTC data can lead to misleading results of the accurate effects of different variables on the severity of crash injuries (Abay, 2015). For example, the results of analysis based on underreported RTC data can underestimate the effectiveness of seat belt and other safety measures in reducing the severity of crash injury (Abay, 2015). Therefore, this necessitates the importance of linkage between police database and health institution or hospital database and use of capture-recapture to compare both datasets to overcome the reporting bais in police data. The following sections summarise a few limitations of the NRTC database.

### 6.2.1 Manual reporting system

The manual recording system of crashes data is one of the main limitations of NRTC database. With manual reporting system, data are to prone to recording errors. For example, due to time restriction, especially when one or more of the crash casualties is seriously/fatally injured, police officer at crash site could randomly make errors while recording details of numerical data such as driver civil id, date of birth and age. To reduce these errors, existing data collection protocols and guidelines could be improved, and provide supportive supervision to ensure that police officers are following the correct protocols for reporting RTCs. It is also important to put in place routine in-service training programmes and periodic (online) assessment of related learning outcomes. Inconsistency in data entry by accidently switching details, for example switching the details of driver at fault and other involved driver or details of drivers and passengers, is also one of the main limitations of the manual reporting system. This inconsistency can make data unsuitable for research, analysis and policy decisions. Unlike automated systems, longer time is needed to generate written reports, and duplication of data entry are more likely to occur when manual reporting system is used. Physical space is also needed to store paper documents for future reference, and this requires longer time and security systems. Similarly, manual reports are difficult to update when corrections or changes in the report are required. Using manual reporting system makes it harder to recover from unexpected natural or manmade disasters such as fire and water.

### 6.2.2 Challenges with the definition and classification of RTC related deaths

The definition of deaths related to road traffic crashes in Oman[21] differs from definition used in the international level[22] according to the WHO, and this makes it difficult to determine the extent of accuracy of the direct comparison with other countries using the WHO definition (AL-Bulushi et al., 2015). There is also lack of documentation of severe injuries, eventually leading to deaths. It is likely that some of the severe injuries could lead to fatal outcomes during hospitalization or post-discharge from the hospitals, which could be potentially missed out in the ROP register. Yet another challenge is related to reporting the cause of death. If a death from a crash incident occurs at the hospital, then potential misclassification of the cause of death is likely. For example, if a crash victim dies at the hospital following haemorrhage or myocardial infraction, then the cause of death recorded could be those conditions and crash becomes the reason why the victim was admitted to the hospital. Using civil identification number, it is possible to establish whether the crash victim who died or suffered serious injuries have other prevailing health conditions such as allergies, diabetes, hypertension, cancers or cardiac problems. The identification of conditions for the latter would help expedite the treatment options. Therefore, the follow-up process of the crash, especially when the victims are transferred to the hospital, should be carefully investigated to explore how the crash database is updated according to the changes in the health conditions of the victims.

To overcome this problem, linkage between police database and health institution or hospital database and use of capture-recapture to compare both datasets are recommended (WHO, 2010;

[21] in Oman, ROP identifies road traffic deaths as those deaths that take place between the time of the crash and the closure of the case file on 31st of January of next year.

[22] At the international level, the World Health Organisation (WHO) identifies RTCs' death as a death occurring within 30 days of being involved in a RTC.

Imprialou and Quddus, 2017). Other circumstantial evidence might also prove useful for research and legal investigations. For example, analysis of reports from the witnesses of the incident could be compared to authenticate the police judgement of the incident.

### 6.2.3 Challenges with recorded data

#### a. Driver at fault, co-passengers

There is a lack of data related to drivers at fault such as driving experience, licence status, traffic offenses, previous incidents, education and type of profession. There is no information about the demographic details and injury outcomes of co-passengers. Data related to drivers of other involved vehicles are missed in the database used in this thesis. Ideally, it would be useful, for both documentation and legal perspectives, to create a case file with a comprehensive documentation of the incident, damages and human/animal injury outcomes. Availability of such data would improve the understanding of drivers' risk behaviours, especially young drivers, the most dominant group at risk of all types of RTCs in Oman.

#### b. Other road users

Although the details of other road users are not directly associated with the cause of RTCs, however, these details are of critical importance for road safety analysis especially if they belong to specific group (e.g. children and elderly people) (Imprialou and Quddus, 2017). There is a lack of demographic data related to other road users such as passengers and pedestrians in the ROP database. Due to the lack of data, the present analyses could not explore the crash outcomes of road users other than drivers at fault. It is recommended that ROP should record details, at least retrospectively if not at the time of incident, of the personal characteristics of all road user involved in the crash in order to systematically analyse and understand the types of injury outcomes of passengers including children and elderly people. This will also help to measure the effects of various types of road user with different age/sex groups of drivers (i.e. behavioural studies). For example, past studies found that young drivers, especially teenage drivers, have higher crash risk when carrying passengers compared with drivers aged 30 years and above (Keall et al., 2004; Williams, 2003). Likewise, having a male co-passenger could lead to higher level of risk taking behaviours among male drivers, whereas having a female passenger or parents found to lead to more careful and safe driving (Rolls and Ingham, 1992 and Arnett et al., 1997 cited in Doherty et al., 1998).

#### c. Data related to features of the involved vehicles

The vehicle features can represent risk to its driver and also impose risk for the driver of other vehicles and other non-motorised road users (Wenzel and Ross, 2005). The existing database has limited information about the features of the involved vehicles, type of the vehicle whose driver is at fault is the only information available in this database. However, other information such as the design and mass of the vehicle, braking system, lighting system, safety technology such as frontal height, air bags, and Antilock Braking System (ABS) are not available in this database. Integration with other sources such as the database of vehicle registration unit at ROP and linkage to the database of Insurance companies can help in recording this information.

#### d. Geocoded locations of RTCs

Geocoded locations of RTCs are fundamental elements for spatial analysis to identify the high risk areas where RTCs are more frequent and this is crucial for the enforcement authorities to take effective measures to reduce the risk of RTCs (Yu et al., 2014; Benedek et al., 2016). One of the main challenging tasks the author of this thesis faced was to generate geocoded locations for RTCs based on the description of the crash. Due to the long time required to achieve the task as well as the technical difficulty to determine the geocoded locations of crashes outside Muscat, the researcher generated locations of RTCs only in the Muscat Governorate, examining 12,436 individual case records. The information given in the crash description field offered a good source for the researcher to generate the geocoded data using Google-Maps.

The first step to improve RTC database is to develop an official base-map storing all road-related attributes including road geometric feature, road networks, and traffic volume (Imprialou and Quddus, 2017). In order to have accurate and direct linkage with RTC database, common indexes between these data sources are required, and this can be achieved by using GPS-based applications in reporting crash locations (Brown et al., 2015; Imprialou and Quddus, 2017). Distance to the nearest speed camera facility or important road signs prior to the incident might be useful in improving the accuracy of the RTC locations.

### 6.2.4 Inaccuracy

#### a. Crash severity level

Data on RTCs based on police judgement might be subject to bias and misclassification, although these records are cross-verified or validated by the legal and insurance systems. Crash severity is determined based on the maximum injury severity of all involved casualties in crash (WHO, 2010; AL-Bulushi et al., 2015). The police could use their own criteria to specify severity of the crash based on their experience and judgement leading to potential misclassifications especially if compared to hospital records (Yannis et al., 2014; Watson et al., 2015; Mandacaru et al., 2017). Although, fatal and no-injury crashes are more straightforward to be identified, the misclassifications are more likely to occur when reporting other levels of crash severity (i.e. severe/serious, moderate/medium and mild/slight injuries) (Watson et al., 2015; Imprialou and Quddus, 2017). To overcome this problem, linkage between police database and health records is recommended (Mandacaru et al., 2017; Weijermars et al., 2018).

**b. Crash contributing factors**

The crash preventive measures are mainly developed based on data related to crash causation factors. The form used by ROP has a fixed list of the potential factors contributing to the crash including factors related to driver-fault, vehicle defects, road-related factors and weather conditions. The police officers need to prioritise the factors that seem more relevant to the crash circumstances, and as it is clear from the NRTC database used in this thesis, they are mostly pre-determined factors related to drivers (more than 95% of crashes attributed to drivers-related factors and more than 55% attributed to overspeeding behaviour). However, it is challenging to capture all features of the crash incident, especially when attributed to only one prioritised factor as it is the case of the database used in this thesis, because of the complexity associated with a range of human, vehicle and environmental factors. The police officers at crash site need to understand and report the cause of crash and other attributes in a minimal time especially when one or more of the crash casualties is/are seriously/fatally injured (Imprialou and Quddus, 2017). Time restriction along with potential of lack of experience could influence judgement and understanding of the crash causation factor and could sometimes lead to incomplete or erroneous crash report (Imprialou and Quddus, 2017). Also, due to lack of data relating to the secondary contributing factor to RTC, the author of this thesis could not analyse the influence of combination of risk factors (we have only the primary contributing factor) such as overspeeding and negligence or drink driving because of lack of detailed (subjective) data.

In-depth crash investigation is one of the effective approaches used in many countries to improve the quality of determining the crash contributory factors, where team of transport experts visit the crash site and independently of police officers to evaluate and report the potential contributory factors (Beanland et al., 2013; Flannagan et al., 2015; Imprialou and Quddus, 2017). A significant difference was found when comparing contributory factor identified by transport specialist team and those independently identified by police (Montella, 2011). Police reports were found mainly focus on driver-related factors, while specialist team reports mainly give more attention to the interaction between the vehicle and road-related factors.

There is also lack of objective and inconsistency in the description of many contributory factors especially those related to drivers' faults (Michalaki et al., 2015; Imprialou and Quddus, 2017). For example, it is difficult to assess how fatigue and negligence are determined at the crash spot or later in the police investigations leading to underreporting of fatigue-related crashes (in this research, less than 0.5% of the crashes were attributed to fatigue) especially when the involved drivers have fatal injury (Michalaki et al., 2015). Self-reported contributory factor is one of the solutions used to overcome this problem, although it would be inappropriate for situations when contributory factors related to unlawful behaviours such as drinking alcohol (Imprialou and Quddus, 2017). However, identifying impaired drivers is not difficult task as this can be objectively assessed using breath test (OECD/ITF, 2015; Imprialou and Quddus, 2017).

There is also under-reporting of alcohol or substance abuse related crash in the NRTC database (only 2% of crash attributed to this factor). It is also unclear how police officers gather this data, especially when one of the involved drivers had alcohol or drugs but died immediately after the crash. It is possible that even if the alcohol test takes place, then for religious, social and legal reasons, it could be possible that the result may not be included in crash report.

#### c. Time of the crash

Time of the day found to play a significant role on the level of alertness and wakefulness of the drivers. For example, Lenné et al. (1997) found that early morning and early afternoon hours are the times at which impaired driving performance and sleep propensity occur. Accurate reporting of crash time is crucial for identifying the effects of different times of day on the outcomes of road traffic crashes. It also helps to explore the association between time of the day and the contributory factors of RTCs, for example, the association between time of the crash and fatigue-related crashes, the association between time and alcohol-related crashes.

The reported crash time in the NRTC database does not contain precise time information at the minute-level, it has only the hour-level which means that the time is rounded. This inaccuracy in crash time reporting has significant impact in exploring the effects traffic volume have on predicting the real-time of crash occurrence (Golob and Recker, 2003; Imprialou and Quddus, 2017) and it has the same impact on the accuracy of the spatiotemporal analyses. The accuracy of reporting time of the crash can be improved by automatically calling the nearest police unit using in-vehicle systems (this method is used in the European Union), or alternatively reporting the time when the police receive the call about the crash (Altwaijri, 2013; Imprialou and Quddus, 2017). Improved accuracy of reporting crash time would enhance the integration between RTC database and road-related data (e.g. road geometry, weather condition and real-time traffic).

### d. Use of mobile phone

Technology has made significant changes on transportation system including vehicles, road infrastructure and communication system among different road users. In-vehicle technology, dashboard entertainment systems and mobile phones, can be a source of distraction to the driver's attention taking him/her away from the driving task. Talking on a phone, typing and reading emails, texting and searching or changing CDs while driving have been found to be more common among young drivers and they increase the likelihood of collision or near collision by 23 times when compared with driving without distraction (Beanland et al., 2013; Ontario Agency for Health Protection and Promotion, 2014; Tucker et al., 2015).

Only 6 cases out of 35,785 crashes attributed to the use of mobile phone in the NRTC database, which means there is possible gross underreporting in the recording the use of mobile phones. Although it is difficult for the police officer to judge whether the driver was using the mobile phone prior to crash, the conjunction with telecommunication database would help to overcome this problem by consulting the driver phone records immediately before the crash (Beanland et al., 2013).

### e. Wearing of seatbelt

Wearing seatbelts/helmets found to play important role in reducing the severity of RTCs (Lipovac et al., 2015). Although the national seat belt law in Oman stated that both front and rear seats occupants should wear the seatbelt (WHO, 2015), however, the enforcement of using the seat belt for the rear seat passengers is questionable. Likewise, although national helmet law applied for all drivers and passengers of motorcycles, however, it is not clear whether this law is applied for all road types and all engine types of motorcycles. A noticeable observation is the inaccuracy of reporting the wearing of seatbelt in the NRTC database, less than 5% of drivers at fault in the NRTC database were reported not wearing seatbelt/ helmet.

### 6.2.5 Lack of linkage with other data sources

While it is pertinent to collect internationally comparable data, it is essential to collect (link) data relevant to the local context. For example, the characteristics of the expatriate non-Omani population, the duration of their stay, license status etc. are important to document for policy and legislation interventions.

In addition, due to lack of data (e.g. traffic volume, average annual daily distance travelled by sex and age group and driver population by age, sex and nationality group), the exposure effect was not explored in the analyses of this study. Linkage to these data will help to examine the effects of different types of exposure on the crash involvement rate.

Similarly, the high burden of mortality and disability resulting from RTCs has considerable economic, social and health care implications for the left-behind families, as most victims of RTCs are usually the primary breadwinners. The lives of the left-behind families could adversely affect by these tragedies and millions of people are subject to coping with the death or disability of their primary breadwinners (Al- Mazruii et al., 2015; Kamruzzaman et al., 2013; Majdan et al., 2013; WHO, 2015). Therefore, data collected by insurance companies, health institutions and victim support agencies are important source especially for determining the economic cost of the crashes and enable policies and decision makers in designing suitable remedial measures and effective strategies.

However, recently ROP piloted ***iMAAP system*** developed by the UK Transport Research Laboratory to collect RTC data and with an attempt to help improving the NRTC database in Oman. TRL, a leading Transport Research Laboratory in the UK, has developed useful road safety software including Microcomputer Accident Analysis Package (MAAP), MAAPcloud and iMAAP. These software packages are used in the UK and worldwide including Saudi Arabia and United Arab Emirates (TRL, 2017).

## 6.3 Reflection on the strengths and weaknesses of iMAAP System

iMAAP (integrated) is the new generation of MAAP and is characterised by providing better design with the latest new generation technologies (TRL, 2017). It is a flexible web based system and has the capability of handling a number of database platforms and GIS-based systems along with enhancing IT and security standards (TRL, 2017). According to the director of road safety programme in Oman, a connection to the internet is required to record the crash details and automatically save the records in the main server. However, in the case of no connectivity available, these details will be saved in the tablet device used at the crash site and will be transferred to the main server when connecting the tablet to any computer within which the iMAAP is installed. In 2015, ROP used iMAAP in documenting a sample of RTCs in two areas in Muscat namely: Al-Khoudh and Othaiba.

***Figure 6.1*** and ***Figure 6.2*** show the prototype of screen-shots adapted from iMAAP crash recording system. There are five different windows: crash-related, vehicle-related, casualty-related, Ministry of Health MoH-related, and Emergency Medical Service EMS-related data. iMAAP is a GIS based system which enhance the accurate recording of crash locations. It also has the capability to import and export data to other software format. It has details from a range of data sources including data related to drivers, passengers, pedestrians, vehicle features, road features and detailed information of casualty health conditions. However, the big number of health details could lead to incomplete reporting of data. The key stakeholders should agree on the essential details needed in these two platforms.

However, road traffic related data are missed in this system, and it is not clear if has the feasibility of adding new fields to include traffic data without requirement of redevelop the whole system. It is also unclear whether iMAAP has the capability of automatically sketching the crash scene and to produce user-defined reports and queries. Linkage to other data sources such as insurance companies and victim support agencies is important for determining the economic cost of the crashes. It is also worth pointing out that the generation of geocodes for crashes in the NRTC database helped to validate the consistency of recording crash locations in iMAAP database and NRTC database in chapter 5 of this thesis.


***Figure 6.1*** *Prototype of screen-shots adapted from iMAAP crash recording system, Police-reporting*


***Figure 6.2*** *Prototype of screen-shots adapted from iMAAP crash recording system, Hospitals–reporting task*

## 6.4 Coherent ways to record, monitor and analyse road crash data.

In this chapter, the quality of NRTC database was evaluated by reflecting on the strengths and limitations of existing data recording and processing for research use. The following are the recommendations to improve the RTC data recording and processing system:

1. NRTC database should be improved for ensuring accuracy and reliability of recording and updating RTCs. Linkage to other relevant sources is also important to enhance the accuracy, and monitor, and update the crash records. The reporting form used by ROP should collect full details of the incident. For example, demographic data of all persons involved including drivers, co-passengers, those from other vehicles and significant others (e.g. other road users, pedestrians, other vehicles). In addition, there should be accurate recording of the vehicle condition (extent of damage, year of manufacture, safety measures), road (type of road, distance between the crash spot and vehicle) and weather conditions. Where appropriate, include pre-designed diagrams to aid completion of the incident details.

2. Revisit the crash spot recording mechanisms and ensure that at least one of the officers assigned is responsible for recording all crash related details at the spot. If circumstances are critical, then back-up system should be arranged to ensure that spot data are properly collected.

3. Ensure logical flow and consistency of details recorded using built-in filter or skip questions. It is recommended that the effective way to record crash data is to use electronic systems (mobile apps or tablets) with essential back-up services (e.g. online data transmission facility).

4. Provide a customized classification table to record injuries and signs of life of all victims, in consultation with the emergency ambulance services at the spot. In the absence of emergency ambulance services, record the injuries using the customized form. For example, the classification table could consider either pre-written statements or images of injuries that are common in RTCs.

5. Ensure follow-up of injured or deceases victims, where appropriate in hospitals or home through preferably face-to-face interaction or online/postal post-incident details form. The follow-up process of the crash, especially when the victims are transferred to the hospital, should be carefully investigated to explore how the crash database is updated

according to the changes in the health conditions of the victims. Therefore, linkage between police database and health institution or hospital database and use of capture-recapture to compare both datasets are recommended.

6. Ensure proper supervision for recording crash data, validation and subsequent editing of data collected from the crash spot and cross-verify personal details of affected persons using a unique identifier linking the Civil ID registration systems. Strengthen multi-sectoral coordination to ensure that the data collected are linked to Civil IDs.

7. Provide access to RTC data to researchers and experts in anonymous format. Engage researchers in the analysis and interpretation of RTC data.

8. Data related to average annual daily distance travelled by sex and age group and driver population by age, sex and nationality group, driving experience, personal factors (e.g. license status, mobile phone use, stress, health conditions, previous incidents) are impotant indicators of road safety in Oman and should be documented in the NRTC database. Having these data is important to examine the effects of different types of exposure on the crash involvement rate and to determine the accurate risk associated with a particular sex-age group.

9. Similarly, information such as the design and mass of the vehicle, braking system, lighting system, safety technology such as frontal height, air bags, and Antilock Braking System (ABS) should be be documented in the NRTC database. Integration with other sources such as the database of vehicle registration unit at ROP and linkage to the database of Insurance companies can help in recording this information.

10. Data collected by insurance companies, health institutions and victim support agencies are important source especially for determining the economic cost of the crashes and enable policies and decision makers in designing suitable remedial measures and effective strategies. Therefore, linkage to these sources is recommended.

## 6.5 Conclusion

Improving the quality of RTC data is the first step to develop effective counter-measures and enhance the efforts road safety in any country. This chapter evaluates the quality of existing data collection procedures and recording systems, reflecting on the strengths and weaknesses of both NRTC and iMAAP databases. These reflections were developed based on the analyses presented in Chapters 3-5 of this thesis. The chapter ended with proposing recommendations for improving data recording and processing for research and policy use.

# Chapter 7

## Conclusions and Recommendations

This Chapter provides a summary of findings and key contributions with a discussion on the implications and limitations of the present research. The Chapter concludes with a brief outline of future research priorities for strengthening RTC evidence-base.

### 7.1 Main contribution of the thesis

The thesis contributed to a systematic understanding of the sociodemographic and behavioural factors and spatial patterns underlying high burden of RTCs and related injury outcomes in the Sultanate of Oman. Additionally, the thesis evaluated the quality of NRTC data, and proposed a set of recommendations for improvements in data recording and processing RTC data for research and policy use.

### 7.2 Key findings

The overarching **aim** of this research is to apply robust statistical techniques to identify and evaluate the *multi-dimensional* social, demographic, spatial and technological factors associated with the likelihood of RTCs and associated outcomes in Oman. This section provides a summary of key findings reflecting on the main research questions and hypotheses:

1. *What are the social, demographic, economic, spatial and technological factors associated with the likelihood of traffic crashes and fatalities in Oman?*

Reviews of previous literature and data from national RTC database have indicated that fatal road traffic crashes are a routine public health emergency. Findings from this thesis demonstrated evidence that one in three of the road crash victims had a mild or moderate injury, and one in ten had a fatal injury in Oman. The findings also demonstrated compelling evidence that young male drivers are at higher risk of road traffic crashes and fatal outcomes than their female counterparts, mainly attributed to personal and behavioural risk factors such overspeeding, overtaking, lack of driving experience, violation of traffic rules, carelessness, fatigue, and sleepiness.

With regards to spatial terms, the findings showed that although more than one third of the total RTCs occurred in the most populous capital city of Muscat, which accommodates more than a third of total population in Oman, fatal injuries are more likely in Al-Wusta and Dhofar, and the highest proportion of fatal crashes occurred in Al-Batinah Governorate. Road and traffic related features appear to play a key role in determining locations of high crash risk. Findings from the spatial analysis demonstrate evidence of spatial clustering of RTC hot-zones on long roads demarcated by intersection and roundabouts. RTC hot-zones appeared to be associated with higher level of road traffic.

***2.*** *What are the patterns of fatal and non-fatal injury outcomes of road traffic crashes in Oman? How do these vary and interact by age and sex of the drivers?*

This question was addressed in the first paper of this thesis. Findings from this analysis provided statistical evidence that the odds of severe incapacitating and fatal injuries are significantly higher for young males than their older and female counterparts. Overspeed driving behaviour of young males in the 20–29 years age range was the primary factor associated with severe and fatal road injuries in Oman. The findings also provide evidence of negligence and fatigue in causing severe and fatal road injuries in Oman. In addition, the data showed that about 2% of the drivers had alcohol while driving the vehicle, though legally, alcohol is prohibited in Oman.

***3.*** *Is there any statistical association between the severity of motor vehicle crash and timing of the incident? More specifically, does the intensity of crash severity vary during certain hours of the day?*

This was the main question for the second paper of this thesis. The present study confirmed statistical evidence that the severity of road injuries varied by the peak hours of congestion with fatal RTCs peaking around 1800 hours, while the peak hour for nonfatal crashes occurred around 1500 hours. Driver fatigue and drowsiness are the potential dominant factors for early evening fatal crashes, while the high density of traffic volume during the rush hours could be the potential factor for the high density of nonfatal RTCs at 1500 hours. The findings also indicate that age and sex of the driver, day of the week and crash location are critical factors in mediating the association between the density and severity of RTCs and time of day. Overall, compared to other sex-age groups, young males aged 21-30 years are more likely to cause higher number of fatal and non-fatal crashes as moving from the minimum point of the off-peak hours to the maximum point of the peak hours during both weekday and weekend.

4. *Where are the high risk or hot-zone areas for road crashes in Muscat Governorate where crashes are more frequent?*

This was the main question addressed in the third paper of this thesis. The findings demonstrated evidence of spatial clustering of RTC hot-zones on roads demarcated by high number of intersections, complex bridges and roundabouts. Hot-zones appear to be more dominant on road segments where the highest level of traffic interactions exists, especially along Sultan Qaboos Highway, the primary route linking most main areas and workplaces in Muscat Governorate. Conversely, roads locating outward from the core market with low crash risks such as Muscat Expressway have low densities of RTCs. These findings were statistically validated using the pilot data from iMAAP network based crash analysis system, thus confirming similar spatial patterns based on the analysis of NRTC database.

5. *How can we use the spatial analysis to understand and model the patterns of road crashes integrating relevant predictors such as road geometry and traffic related features?*

This question was part of the third paper of this thesis. The findings showed that road and traffic related features play a key role in determining locations of high crash risk. The results confirm that hot-zones are positively associated with higher level of road traffic. Hot-zones also appear to be associated with the higher number of exits and entrances, and shorter distance between junctions. Interestingly, the present study provided fresh evidence that speed limits signs seem to have no significant effect in increasing crash risk on road zones in Muscat. This could be due attributed to high proportions of cyclists and pedestrians on roads with low speed limits, which in turn increase the likelihood of crash occurrence.

To identify the road zones with persistent risks of road traffic crashes, the values of the annual Net-KDE of the zones were listed in descending order and each zone was assigned a rank based on its position in the list. Then, the sum of the annual ranking, mean of annual ranking, variance and standard error (SE) of annual ranking for each zone was calculated. Comparing the mean of annual ranking and the correlation between the densities of RTCs over the same locations during the five years of the study period, the spatio-temporal analysis showed consistency in the positions of crash hot-zones in the study area.

6. *How can we improve the existing data collection systems of the of National Road Traffic Crash (NRTC) database to better understand and measure road traffic crashes and related injury outcomes in Oman?*

To answer this question, a critical appraisal of existing data collection procedures and recording systems was undertaken in chapter 6, reflecting on the strengths and weaknesses of NRTC database, and suggesting coherent ways to record, monitor and analyse road crash data. The key recommendations based on the review of NRTC database and findings presented in Chapters 3-5 are: (i) the crash reporting form should include full details of the incident, demographic data of all persons and others involved, vehicle conditions, road and weather conditions; (ii) proper linkage of RTC data using civil identification numbers to other relevant sources (e.g. Ministry of Health, Ministry of Transportation and Telecommunications, database of vehicle registration unit at ROP, and Insurance companies) is important to enhance the accuracy, and monitor, and update the crash records; and (iii) use of electronic systems (mobile apps or tablets) with essential back-up services (e.g. online data transmission facility) to record onsite crash data.

## 7.3 Implications of findings

**a. Scientific**

The thesis contributed to generating systematic evidence of the patterns and factors associated with RTC in the Sultanate of Oman based on statistical modelling of data from the NRTC database. The research focused on sociodemographic, behavioural and spatial factors associated with RTCs and related injury outcomes. Previous studies on road injuries focused mainly on trends and behavioural risk factors, and a few included age and gender as control variables without systematically analysing their joint or interactive effects.

The first paper of this thesis generated systematic quantitative evidence of complex age–sex interactions associated with the severity of RTI outcomes. More importantly, the findings clearly pinpointed the significance and influence of age and sex in road crash analyses recommending that future research should systematically address potential age–sex interactions in predicting risk behaviours associated with RTC outcomes.

The second paper generated statistical evidence of the association between the timing of road crashes highlighting the peak hours of traffic congestion and the severity of fatal and non-fatal road injuries. Findings from this analysis clearly showed that time of the day significantly influence the severity of RTC outcomes and the magnitude of this association varies by age and sex of the driver, day of week and location of the crash. Future research should address the potential effect of the peak hours of traffic congestion (in 24 hours) and controlling for demographic, environmental and spatial factors in predicting the recurrence and outcomes of RTCs. To identify sleep and fatigue related crashes, police database should collect information on how long drivers have been awake, how many hours did their last sleep last and the length of the duration of being driving prior to the crash.

The third paper demonstrated systematic quantitative evidence of spatio-temporal patterns associated with the crash risk over different locations on road network. More importantly, the findings clearly pinpoint the importance and influence of the road and traffic related feature in road crash spatial analysis.

Findings from the spatio-temporal analysis of the consistency of the hot-zone locations clearly pinpoint the importance of carrying out safety inspections and engineering studies to investigate the possible contributing factors, and identify the potential countermeasures such as engineering improvements to reduce the crash risk at these sites. In addition, locations of hot-zones would help in selecting one long zone of a specific length as surveillance zone which can be proposed for a minimum of 36 months for pilot testing a range of road safety interventions and surveillance of crash monitoring, as well as generating high quality data for research.

The researcher independently generated the geographical coordinates (latitude and longitude) for the Muscat governorate based on transcripts recorded within the NRTC database and using Google maps, which was then linked to the Muscat road network and statistically validated using the pilot data from iMAAP network based crash analysis system. Furthermore, the quality of NRTC database was evaluated followed by recommendations for improvements in data recording and processing for research and policy use.

**b. Policy and programmes**

The findings offer new insights to understanding the demographic, behavioural, spatial, and temporal effects of RTCs in Oman, where evidence-based interventions for road safety are critical to tackling the high burden of injuries. Interventions promoting road safety awareness should focus on enabling behavioural changes in drivers particularly in RTC hot-zones near road intersections where crashes are recurrent as well as impose control measures and penalty to restrict over speeding. The policies and programme interventions should target both natives and expatriates particularly new drivers, families, educational institutions and work places. It is also equally important to initiate policies to address and document the broader social and human consequences of road crashes and related injury outcomes in public health promotion and road safety awareness campaigns.

The high risk of fatal and severe injuries among young males has considerable long-term impact on the left-behind families such as emotional, economic and social well-being impacts. In addition, managing disability and chronic conditions comprise high-cost healthcare expenditures and this can be catastrophic for health systems and families in Oman.

Findings from the second analysis firms statistical evidence of peak hours of crash confirming that peak hours of traffic congestion have significant effect on the outcomes of traffic crashes in Oman, suggesting that fatigue and drowsiness are possible dominant factors for both early afternoon non-fatal and early evening fatal crashes respectively. Drivers should be aware that sleepiness represents a high risk for their safety and the safety of other road users. Road safety campaigns should focus at encouraging drivers to stop driving when feel sleepy and to use alternate between drivers as a countermeasure when the driver feel sleepy and have a passenger who is able to take over driving. Additionally, roads should be designed to enhance driver alertness and education campaigns should target countermeasures that are most appropriate for a particular situation such as reducing driver sleepiness and risky behaviour towards young drivers. Introducing nighttime driving restrictions for the young adult drivers can have considerable impact in reducing the magnitude of RTCs in the country. Equally important is to strengthen the provision and use of public transport systems across Oman. This can have measurable impact in reducing both traffic flows and crashes as well as other lifestyle-related chronic and non-communicable diseases.

Findings from the third paper of this thesis offer new insights for road safety specialists to understanding the difference between hot-zones and other zones in Muscat Governorate, and helping them in adopting effective planning strategies (e.g. road safety measures should be given priorities in the land use planning strategies) and allocating proper resources to reduce the crash risk on those high density crash locations. Routine traffic surveillance and risk reduction measures would be beneficial to reduce the high crash risk on these hot-zones. These routine surveillance measures could be designed for targeting drivers violating the recommended speed-limit and other traffic rules such as not wearing seat-belts and alcohol drinking on high-crash-risk zones.

## 7.4 Study limitations and data challenges

This thesis had the advantage to systematically explore and make the best use of the NRTC dataset. However, the analyses are not exempt from limitations. There are a number of data limitations in this study. The manual recorded crash data with limited number of variables were one the main challenges of this study. The database has only simple details of crashes, which suggest that there could be other potential factors that are not captured in the NRTC database, the availability of such data could have strengthened our understanding of the RTC phenomenon in Oman.

Although the data recorded serious crashes, it is still possible that minor crashes have been misinterpreted or wrongly coded as serious crashes and vice versa. In addition, these data are based on police judgement and more likely to subject from bias and misclassification especially when classifying non-fatal RTCs. For example, it is difficult to assess how fatigue and negligence are determined at the crash spot or later in the police investigations. In addition, the influence of combination of risk factors such as overspeeding and negligence or drink driving was not explored in this study because of lack of detailed (subjective) data. It is also likely that some of the severe injuries could lead to fatal outcomes during or after hospitalisation.

Additionally, the present analyses did not explore the fatal and non-fatal injury outcomes of passengers including children and elderly people due to lack of data. There was no data on injury outcomes of co-passengers or others involved in the incident, which suggests that the health outcomes analysed in this thesis are biased and under-estimated. The availability of such data would help to develop a better understanding of the differential effects of various types of passengers on drivers, particularly young male drivers. Furthermore, the definition of deaths related to road traffic crashes in Oman differs from definition used in the international level according to the WHO, and this would make the comparison to other countries to be inaccurate.

Other information such as distance travelled, driving experience, personal factors (e.g. license status, mobile phone use, stress, health conditions, previous incidents) could help validate and improve our understanding of the risk behaviours. Behavioural factors other than risky driving were not disentangled due to data limitations. Similarly, there is lack of data related to road traffic volume data, daily travelled distance and number of driving license holders for each sex-age group which prevented exploration of the accurate risk associated with a particular sex-age group. The availability of these data could have resolved the exposure group or the population at risk, and offer insights on why males aged 21-30 years had the highest risk of being involved in both fatal and nonfatal crashes.

Although the NRTC database has a field describing the location where the crash occurred, the longitude and latitude of these locations were not available. Generating the geocoded locations of RTCs was one of the main challenges, and the researcher invested four months to extract the spatial codes, which later proved useful and informative in validating the iMAAP data. Due to the long time required to achieve the task as well as the technical difficulty to determine the geocoded locations of crashes outside Muscat, the researcher generated geocodes of RTCs only in the Muscat Governorate.

## 7.5 Future research priorities

Due to lack of data, the present study could not disentangle behavioural factors other than risky driving. Likewise, the influence of combination of risk factors such as overspeeding and negligence, fatigue or drink driving was not explored due to lack of detailed (subjective) data. Future research should systematically address the potential effect of other behavioural factors, such as fatigue, using mobile phone and drunk-driving, and combination of two or more risk factors on the outcome of RTCs.

The present study could not explore the fatal and non-fatal injury outcomes of other passengers including those for vulnerable populations such as children and elderly due to lack of data. This is an important area in road safety research in Oman.

The lack of information of the traffic volume, daily travelled distance as well as the number of driving license holders has precluded an investigation of the exposure or actual population at risk of RTCs by age and sex. Further research is needed to examine the effects of different types of exposure on the crash involvement rate.

The present study also could not disentangle factors such as factors related to socio-economic, population, and land use factors in identifying road crash hot-zones due to lack of data. Having these data could help validate and improve our understanding of the spatial characteristics and the crash risk over different zones in the road network. Therefore, it is recommended that future research should systematically address potential effects of the socio-economic, population, and land use factors in identifying road crash hot-zones in Oman.

Due to lack of linkage to other sources of data such as health-related and crash-cost related data, the present study could not investigate the impacts of RTCs on the injured victims and could not explore the economic implications of RTCs on the country, victims and their families. For example, it is likely that some of the severe injuries could lead to fatal outcomes during or after hospitalisation, which could be potentially missed out in the ROP register. Follow-up data of injured or deceases victims was not explored in this thesis due to lack of data, and future research should systematically address the impact of RTCs on the injured victims and on their left behind children and other family members. In addition, health and wellbeing related data are not only important for quantifying short and long-term consequences of RTCs, but these data could be also used to explore the association between the driver health conditions and RTCs.

Finally, although a number of intervention measures have been introduced to reduce RTCs in Oman; however, few systematic evaluation has been undertaken to assess the effectiveness of these interventions. Therefore, future research should evaluate these interventions to explore their usefulness in reducing the burden of RTCs and their related injuries.

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***Appendix A*** *The multivariate analyses (Negative Binomial Model): (Fatal RTCs) (Model selection)*

| **Parameter** | ***Model (1)*** | | | | ***Model (2)*** | | | | ***Model (3)*** | | | | ***Model (4)*** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** |
| *Intercept* | 2.134680 | 0.156 | [1.829, 2.441] | <0.000 | 1.5173700 | 0.111 | [1.299, 1.735] | <0.000 | 1.660069 | 0.114 | [1.437, 1.883] | <0.0000 | 1.9768220 | 0.086 | [1.808, 2.929] | <0.0000 |
| *Time* | 0.028379 | 0.011 | [0.007,0.050] | 0.01 | 0.0300543 | 0.005 | [0.020, 0.040] | <0.000 | 0.029976 | 0.005 | [0.020,0.040] | <0.0000 | 0.0295183 | 0.004 | [0.023, 0.036] | <0.0000 |
| *Time$^2$* | | | | | | | | | | | | | | | | |
| *Time$^3$* | | | | | | | | | | | | | | | | |
| *Time$^4$* | | | | | | | | | | | | | | | | |
| *Driver's Sex* | | | | | | | | | | | | | | | | |
| *Female* | | | | | -2.817386 | 0.082 | [-2.98, -2.65] | <0.0000 | -5.23718 | 0.718 | [-6.64, -3.83] | <0.0000 | -5.212180 | 0.712 | [-6.61, -3.82] | <0.0000 |
| *Male (ref )* | | | | | - | - | - | - | - | - | - | - | - | - | - | - |
| *Driver's Age group* | | | | | | | | | | | | | | | | |
| *15-20 years* | | | | | 0.6511080 | 0.119 | [0.418,0.884] | <0.000 | 0.654460 | 0.128 | [0.403, 0.906] | <0.0000 | 0.6902767 | 0.093 | [0.508, 0.873] | <0.0000 |
| *21-30 years* | | | | | 2.1815070 | 0.115 | [1.956, 2.406] | <0.000 | 1.951386 | 0.124 | [1.708, 2.195] | <0.0000 | 1.9965220 | 0.087 | [1.826, 2.167] | <0.0000 |
| *31-40 years* | | | | | 1.4730010 | 0.119 | [1.240, 1.706] | <0.000 | 1.171409 | 0.126 | [0.925, 1.418] | <0.0000 | 1.1987200 | 0.090 | [1.022, 1.375] | <0.0000 |
| *41-50 years* | | | | | 0.6229675 | 0.122 | [0.384, 0.862] | <0.000 | 0.462161 | 0.129 | [0.209, 0.716] | <0.0000 | 0.4898040 | 0.095 | [0.304, 0.676] | <0.0000 |
| *50+ years (ref)* | | | | | - | - | - | - | - | - | -- | - | - | - | - | - |
| Age*Sex group | | | | | | | | | | | | | | | | |
| *15-20 years female* | | | | | | | | | 1.288531 | 0.775 | [-0.23, 2.807] | 0.096 | 1.2644070 | 0.765 | [-0.23, 2.763] | 0.0980 |
| *21-30 years female* | | | | | | | | | 2.649276 | 0.730 | [1.218, 4.080] | <0.0000 | 2.5790030 | 0.719 | [1.169, 3.989] | <0.0000 |
| *31-40 years female* | | | | | | | | | 2.894184 | 0.733 | [1.458, 4.330] | <0.0000 | 2.8653540 | 0.722 | [1.450, 4.281] | <0.0000 |
| *41-50 years female* | | | | | | | | | 2.514042 | 0.745 | [1.054, 3.974] | 0.0010 | 2.4894310 | 0.735 | [1.050, 3.929] | 0.0010 |
| *50+ years female (ref))* | | | | | | | | | - | - | - | - | - | - | - | - |
| *Day of the week* | | | | | | | | | | | | | | | | |
| *Weekend* | | | | | | | | | | | | | -0.842000 | 0.049 | [-0.94, -0.75] | <0.0000 |
| *Weekday (ref.)* | | | | | | | | | | | | | - | - | - | - |
| *Negative Binomial Parameter α* | 2.525108 | 0.173 | [2.208, 2.887] | | 0.3212159 | 0.035 | [0.258, 0.399] | | 0.293129 | 0.032 | [0.236, 0.363] | | 0.0999657 | 0.015 | [0.074, 0.135] | |
| *Likelihood Ratio test of α = 0* | 8466.86 | | Prob. >=chibar$^2$ = 0.0000 | | 881.81 | | Prob. >=chibar$^2$ = 0.0000 | | 857.13 | | Prob. >=chibar$^2$ = 0.0000 | | 222.68 | | Prob. >=chibar$^2$ = 0.0000 | |
| *Comparisons of model (N) and Model (N+1)* | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** |
| | 6.57 | 0.010 | 3183.008 | 3195.5 | 728.32 | <0.000 | 2464.686 | 2498.076 | 58.34 | <0.0000 | 2414.344 | 2464.429 | 208.18 | <0.0000 | 2208.167 | 2262.43 |

| Parameter | Model (5) | | | | Model (6) | | | | Model (7) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** |
| *Intercept* | 1.694641 | 0.106 | [1.488, 1.902] | <0.0000 | 2.2448624 | 0.1104 | [2.232, 2.8665] | <0.0000 | 2.53607 | 0.141 | [2.260, 2.812] | <0.0000 |
| *Time* | 0.091752 | 0.014 | [0.064, 0.120] | <0.0000 | -0.237296 | 0.0314 | [-0.299, -0.176] | <0.0000 | -0.29907 | 0.070 | [-0.435, -0.163] | <0.0000 |
| *$Time^2$* | -0.00252 | 0.106 | [-0.004, -.001] | <0.0000 | 0.0294807 | 0.0029 | [0.024, 0.035] | <0.0000 | 0.040053 | 0.011 | [0.018, 0.062] | <0.0000 |
| *$Time^3$* | | | | | -0.000851 | 0.00008 | [-0.001, -0.0007] | <0.0000 | -0.00150 | 0.001 | [-0.003, -0.0002] | <0.0000 |
| *$Time^4$* | | | | | | | | | 0.000012 | 0.00001 | [-0.00001, 0.00003] | |
| *Driver's Sex* | | | | | | | | | | | | |
| *Female* | -5.19938 | 0.712 | [-6.595, -3.804] | <0.0000 | -5.206955 | 0.7105 | [-6.600, -3.814] | <0.0000 | -5.20685 | 0.711 | [-6.600, -3.814] | <0.0000 |
| *Male (ref)* | - | - | - | - | - | - | - | - | - | - | - | - |
| *Driver's Age group* | | | | | | | | | | | | |
| *15-20 years* | 0.710940 | 0.091 | [0.532, 0.890] | <0.0000 | 0.6991103 | 0.0784 | [0.546, 0.853] | <0.0000 | 0.699025 | 0.078 | [0.545, 0.852] | <0.0000 |
| *21-30 years* | 2.011755 | 0.085 | [1.844, 2.179] | <0.0000 | 1.997142 | 0.0716 | [1.857, 2.137] | <0.0000 | 1.997540 | 0.072 | [1.857, 2.138] | <0.0000 |
| *31-40 years* | 1.206912 | 0.088 | [1.034, 1.380] | <0.0000 | 1.198925 | 0.0747 | [1.053, 1.345] | <0.000 | 1.199194 | 0.075 | [1.053, 1.346] | <0.0000 |
| *41-50 years* | 0.494529 | 0.093 | [0.312, 0.677] | <0.0000 | 0.4947388 | 0.0803 | [0.337, 0.652] | <0.000 | 0.495025 | 0.080 | [0.337, 0.653] | <0.0000 |
| *50+ years (ref)* | - | - | - | - | - | - | - | - | - | - | - | - |
| *Age*Sex group* | | | | | | | | | | | | |
| *15-20 years female* | 1.240856 | 0.764 | [-0.257, 0.890] | 0.1050 | 1.248144 | 0.7614 | [-0.244, 2.740] | 0.1010 | 1.248821 | 0.761 | [-0.244, 2.741] | 0.1010 |
| *21-30 years female* | 2.554872 | 0.719 | [1.146, 3.964] | <0.0000 | 2.582982 | 0.7158 | [1.180, 3.986] | <0.0000 | 2.582088 | 0.716 | [1.179, 3.985] | <0.0000 |
| *31-40 years female* | 2.851209 | 0.722 | [11.437, 3.964] | <0.0000 | 2.864038 | 0.7185 | [1.456, 4.272] | <0.0000 | 2.863347 | 0.719 | [1.455, 4.272] | <0.0000 |
| *41-50 years female* | 2.480088 | 0.734 | [1.041, 3.919] | <0.0000 | 2.479954 | 0.7309 | [1.047, 3.913] | 0.0010 | 2.479702 | 0.731 | [1.047, 3.912] | 0.0010 |
| *50+ years female (ref)* | - | - | - | - | - | - | - | - | - | - | - | - |
| *Day of the week* | | | | | | | | | | | | |
| *Weekend* | -0.83418 | 0.048 | [-0.928, -0.740] | <0.0000 | -0.828302 | 0.0401 | [-0.907, -0.750] | <0.0000 | -0.82790 | 0.040 | [-0.907, -0.749] | <0.0000 |
| *Weekday (ref.)* | - | - | - | - | | - | - | - | - | - | - | - |
| *Negative Binomial Parameter $\alpha$* | 0.091529 | 0.015 | [0.067, 0.125] | | 0.041693 | 0.0092 | [-3.611, -2.744] | | 0.042017 | 0.009 | [0.027, 0.065] | |
| *Likelihood Ratio test of $\alpha = 0$* | 187.20 | | Prob. >=chibar$^2$ = 0.0000 | | 65.15 | | Prob. >=chibar$^2$ = 0.0000 | | 65.53 | | Prob. >=chibar$^2$ = 0.0000<br>Prob. >=chibar$^2$ = 0.0000 | |
| *Comparisons of model (N) and Model (N+1)* | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** |
| | 19.92 | <0.0000 | 2190.247 | 2248.68 | 103.89 | <0.0000 | 2088.356 | 2150.963 | 1.00 | 0.3179 | 2089.359 | 2156.139 |

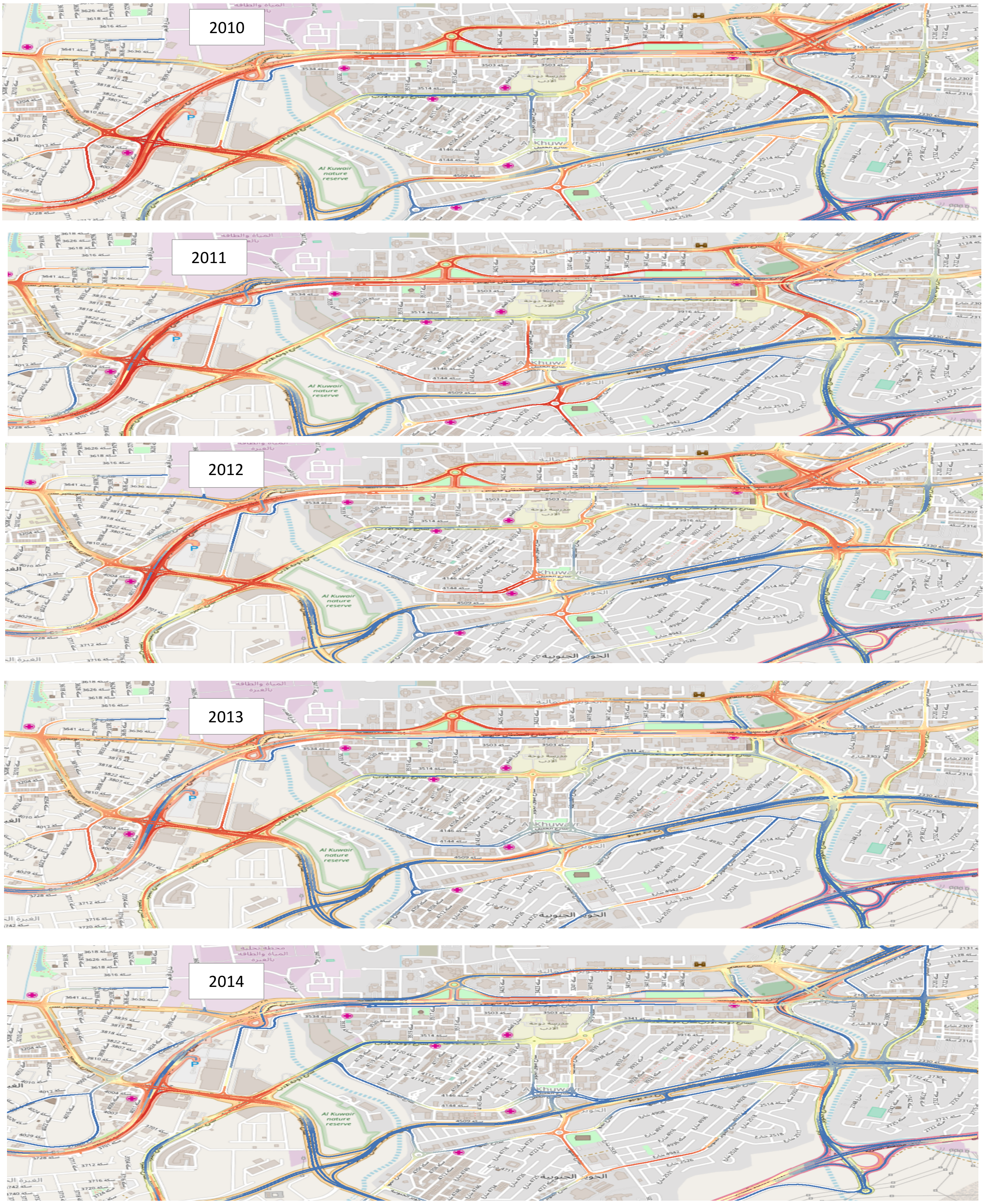
**Appendix B** *The multivariate analyses (Negative Binomial Model): (non-fatal RTCs) (Model selection)*

| ***Parameter*** | ***Model (1)*** | | | | ***Model (2)*** | | | | ***Model (3)*** | | | | ***Model (4)*** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** |
| *Intercept* | 3.83208 | 0.1413 | [3.555, 4.109] | <0.000 | 3.0435140 | 0.1125 | [2.823, 3.264] | <0.000 | 3.308752 | 0.126 | [3.062, 3.556] | <0.0000 | 3.7031350 | 0.0940 | [3.519, 3.887] | <0.0000 |
| *Time* | 0.02309 | 0.0101 | [0.003, 0.043] | 0.022 | 0.0252429 | 0.0058 | [0.014, 0.037] | <0.000 | 0.025123 | 0.0056 | [0.014, 0.036] | <0.0000 | 0.0253884 | 0.0041 | [0.017,0.033] | <0.0000 |
| *Time$^2$* | | | | | | | | | | | | | | | | |
| *Time$^3$* | | | | | | | | | | | | | | | | |
| *Time$^4$* | | | | | | | | | | | | | | | | |
| *Driver's Sex* | | | | | | | | | | | | | | | | |
| *Female* | | | | | -2.259198 | 0.0745 | [-2.41, -2.11] | <0.0000 | -3.12864 | 0.1850 | [-3.49, -2.77] | <0.0000 | -3.142862 | 0.1562 | [-3.45, -2.84] | <0.0000 |
| *Male (ref)* | | | | | - | - | - | - | - | - | - | - | - | - | - | - |
| *Driver's Age group* | | | | | | | | | | | | | | | | |
| *15-20 years* | | | | | 0.6010422 | 0.1168 | [0.372, 0.830] | <0.000 | 0.461024 | 0.1481 | [0.171, 0.751] | <0.0000 | 0.506617 | 0.1062 | [0.298, 0.715] | <0.0000 |
| *21-30 years* | | | | | 2.451386 | 0.1162 | [2.224, 2.680] | <0.000 | 1.957293 | 0.1471 | [1.669, 2.246] | <0.0000 | 1.993452 | 0.1046 | [1.789, 2.198] | <0.0000 |
| *31-40 years* | | | | | 1.723185 | 0.1171 | [1.494, 1.953] | <0.000 | 1.201001 | 0.1474 | [0.912, 1.490] | <0.0000 | 1.230625 | 0.1051 | [1.025, 1.437] | <0.0000 |
| *41-50 years* | | | | | 0.624480 | 0.1175 | [0.394, 0.855] | <0.000 | 0.380049 | 0.1481 | [0.090, 0.670] | 0.0100 | 0.386559 | 0.1064 | [0.178, 0.595] | <0.0000 |
| *50+ years (ref)* | | | | | - | - | - | - | - | - | - | - | - | - | - | - |
| *Age*Sex group* | | | | | | | | | | | | | | | | |
| *15-20 years female* | | | | | | | | | 0.560152 | 0.2453 | [0.080, 1.041] | 0.0020 | 0.4914575 | 0.2001 | [0.099,0.884] | 0.0140 |
| *21-30 years female* | | | | | | | | | 1.294838 | 0.2362 | [0.832, 1.758] | <0.0000 | 1.2311770 | 0.1875 | [0.864, 1.599] | <0.0000 |
| *31-40 years female* | | | | | | | | | 1.350703 | 0.2374 | [0.885, 1.816] | <0.0000 | 1.2925290 | 0.1894 | [0.921, 1.664] | <0.0000 |
| *41-50 years female* | | | | | | | | | 0.824839 | 0.2438 | [0.347, 1.303] | 0.0010 | 0.8108285 | 0.1982 | [0.422, 1.199] | 0.0010 |
| *50+ years female (ref)* | | | | | | | | | - | - | - | - | - | - | - | - |
| *Day of the week* | | | | | | | | | | | | | | | | |
| *Weekend* | | | | | | | | | | | | | -1.04959 | 0.0521 | [-1.15, -0.95] | <0.0000 |
| *Weekday (ref.)* | | | | | | | | | | | | | - | - | - | - |
| *Negative Binomial Parameter α* | 1.970892 | 0.1133 | [1.761, 2.206] | | 0.5527085 | 0.0400 | [0.480, 0.637] | | 0.503855 | 0.0369 | [0.437, 0.582] | | 0.2424814 | 0.0203 | [0.206, 0.286] | |
| *Likelihood Ratio test of α = 0* | $4.5*10^4$ | | Prob. >=chibar$^2$ = 0.0000 | | 9663.75 | | Prob. >=chibar$^2$ = 0.0000 | | 9372.47 | | Prob. >=chibar$^2$ = 0.0000 | | 3767.23 | | Prob. >=chibar$^2$ = 0.0000 | |
| *Comparisons of model (N) and Model (N+1)* | **LR chi$^2$ ($df_{N+1}$-$df_N$)** | **P-value** | **AIC** | **BIC** | **LR chi$^2$ ($df_{N+1}$-$df_N$)** | **P-value** | **AIC** | **BIC** | **LR chi$^2$ ($df_{N+1}$-$df_N$)** | **P-value** | **AIC** | **BIC** | **LR chi$^2$ ($df_{N+1}$-$df_N$)** | **P-value** | **AIC** | **BIC** |
| | 5.19 | 0.023 | 4766.308 | 4778.829 | 656.07 | <0.000 | 4120.241 | 4153.632 | 43.50 | <0.0000 | 4084.74 | 4134.825 | 289.54 | <0.0000 | 3797.20 | 3851.459 |

Appendix B

| Parameter | Model (5) | | | | Model (6) | | | | Model (7) | | | | Model (8) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** | ***Coef.*** | ***Std. Err*** | ***95% CI*** | ***P-value*** |
| *Intercept* | 3.17242 | 0.1014 | [2.974, 3.371] | <0.0000 | 3.8524410 | 0.1101 | [3.637, 4.068] | <0.0000 | 4.56080 | 0.1334 | [4.299, 4.823] | <0.0000 | 4.799 | 0.4612 | [3.895, 5.703] | <0.0000 |
| *Time* | 0.14356 | 0.0135 | [0.117, 0.170] | <0.0000 | -0.186975 | 0.0315 | [-0.25, -0.13] | <0.0000 | -0.70016 | 0.0668 | [-0.83, -0.57] | <0.0000 | -1.903 | 0.3307 | [-2.551, -1.255] | <0.0000 |
| *Time*$^2$ | -0.0049 | 0.0005 | [-0.01, -0.003] | <0.0000 | 0.0286777 | 0.0030 | [0.023, 0.035] | <0.0000 | 0.11743 | 0.0107 | [0.096, 0.138] | <0.0000 | 0.419 | 0.0780 | [[0.838, 1.219] | <0.0000 |
| *Time*$^3$ | | | | | -0.000913 | 0.0001 | [-0.001, -0.0007] | <0.0000 | -0.00637 | 0.0006 | [-0.008, -0.005] | <0.0000 | -0.037 | 0.0077 | [-0.052, 0.022] | <0.0000 |
| *Time*$^4$ | | | | | | | | | 0.00011 | 0.00001 | [0.00008, 0.0001] | <0.0000 | 0.001 | 0.0003 | [0.001,0.002] | <0.0000 |
| *Time*$^5$ | | | | | | | | | | | | | $-2.10 \times 10^{-5}$ | $5.369 \times 10^{-6}$ | [$-3.15 \times 10^{-5}$, $-1.05 \times 10^{-5}$] | <0.0000 |
| *Driver's Sex* | | | | | | | | | | | | | | | | |
| *Female* | -3.1256 | 0.149 | [-3.42, -2.83] | <0.0000 | -3.137061 | 0.1412 | [-3.41, -2.86] | <0.0000 | -3.13699 | 0.1368 | [-3.41, -2.87] | <0.0000 | -3.165 | 0.2442 | [-3.64, -2.68] | <0.0000 |
| *Male (ref.)* | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| *Driver's Age group* | | | | | | | | | | | | | | | | |
| *15-20 years* | 0.54812 | 0.0967 | [0.359, 0.738] | <0.0000 | 0.5392098 | 0.0837 | [0.375, 0.703] | <0.0000 | 0.53267 | 0.0766 | [0.383, 0.683] | <0.0000 | 0.566 | 0.2075 | [0.159, 0.973] | 0.0060 |
| *21-30 years* | 2.03563 | 0.0948 | [1.850, 2.221] | <0.0000 | 2.0250160 | 0.0815 | [1.865, 2.185] | <0.0000 | 2.02430 | 0.0742 | [1.879, 2.170] | <0.0000 | 2.071 | 0.2066 | [1.667, 2.476] | <0.0000 |
| *31-40 years* | 1.26467 | 0.0954 | [1.078, 1.452] | <0.0000 | 1.2570800 | 0.0822 | [1.096, 1.418] | <0.000 | 1.25127 | 0.0750 | [1.104, 1.398] | <0.0000 | 1.302 | 0.2069 | [0.560, 1.820] | <0.0000 |
| *41-50 years* | 0.40206 | 0.0967 | [0.213, 0.592] | <0.0000 | 0.4015106 | 0.0837 | [0.237, 0.566] | <0.000 | 0.39920 | 0.1677 | [0.471, 1.129] | <0.0000 | 0.427 | 0.2077 | [0.020, 0.834] | 0.0400 |
| *50+ years (ref.)* | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| *Sex*Age group* | | | | | | | | | | | | | | | | |
| *15-20 years female* | 0.43983 | 0.1899 | [0.068, 0.812] | 0. 0200 | 0.4533011 | 0.1770 | [0.106, 0.800] | 0.0100 | 0.45143 | 0.1700 | [0.118, 0.785] | 0.0080 | 0.375 | 0.3300 | [-0.272, 1.022] | 0.2560 |
| *21-30 years female* | 1.16288 | 0.1764 | [0.817, 1.501] | <0.0000 | 1.1876720 | 0.1626 | [0.869, 1.506] | <0.0000 | 1.18962 | 0.1551 | [0.886, 1.494] | <0.0000 | 1.146 | 0.3197 | [0.519, 1.772] | <0.0000 |
| *31-40 years female* | 1.22820 | 0.1785 | [0.878, 1.578] | <0.0000 | 1.2465110 | 0.1648 | [0.923, 1.570] | <0.0000 | 1.24720 | 0.1575 | [0.939, 1.556] | <0.0000 | 1.190 | 0.3212 | [0.560, 1.820] | <0.0000 |
| *41-50 years female* | 0.78570 | 0.1877 | [0.418, 1.154] | <0.0000 | 0.8015455 | 0.1747 | [0.459, 1.144] | <0.0000 | 0.80002 | 0.1677 | [0.471, 1.129] | <0.0000 | 0.781 | 0.3278 | [0.139, 1.424] | 0.0170 |
| *50+ years female (ref)* | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| *Day of the week* | | | | | | | | | | | | | | | | |
| *Weekend* | -1.0108 | 0.0478 | [-1.10, -0.92] | <0.0000 | -1.013681 | 0.0418 | [-1.096, -0.932] | <0.0000 | -1.00514 | 0.0385 | [-1.08, -0.93] | <0.0000 | -1.029 | 0.0973 | [0.838, 1.219] | <0.0000 |
| *Weekday (ref.)* | - | - | - | - | | - | - | - | | | | | - | - | - | - |
| *Negative Binomial Parameter α* | 0.19433 | 0.0170 | [0.164, 0.231] | | 0.1379262 | 0.0130 | [0.115, 0.166] | | 0.11083 | 0.0109 | [0.092, 0.134] | | | | | |
| *Likelihood Ratio test of α = 0* | 2712.23 | | Prob. >=chibar$^2$ = 0.0000 | | 1728.79 | | Prob. >=chibar$^2$ = 0.0000 | | 1240.50 | | Prob. >=chibar$^2$ = 0.0000 | | 988.575 | | Prob. >=chibar$^2$ = 0.0000 | |
| *Comparisons of model (N) and Model (N+1)* | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** | ***LR chi$^2$ ($df_{N+1}$-$df_N$)*** | ***P-value*** | ***AIC*** | ***BIC*** |
| | 73.67 | <0.0000 | 3725.526 | 3783.959 | 115.67 | <0.0000 | 3611.858 | 3674.47 | 69.95 | <0.0000 | 3543.904 | 3610.69 | 95.726 | 0.206 | 3977.358 | 3978.53 |

**Appendix C** The Spatio-temporal patterns of RTCs on the road from Othaiba to Al-Khuwair



**Apppendix D** The Spatio-temporal patterns of RTCs on the road from Al-Khuwair to Al-Qurum