

**HUMAN PERCEPTIONS OF VEHICLE TURNING INTENTION:  
OVERALL PERFORMANCE AND CONTRIBUTORY FACTORS**

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## ABSTRACT

All pedestrians, drivers and cyclists regularly make predictions on where they think an oncoming vehicle is intending to travel, so that they can successfully and safely navigate road systems. Despite the importance of these predictions, the effectiveness of this process is currently poorly understood with all existing research being focused on predictions from in-vehicle technologies. This paper therefore investigates how well observers are able to predict a vehicle's turning intention as it approaches an intersection and explores the explanatory variables involved in the success of this process through a logistic regression analysis. An interactive touch screen experiment was developed so that people's predictions about turning intention could be investigated. The data set has been created with over 100 participants attempting to predict a number of vehicles' turning intention.

The key findings of this study are that people are very good overall at predicting turning intention with approximately 90% median success rate when vehicles are between 0 and 20 meters (0-21.9 yards) away from the intersection, but with a substantial fall to approximately 70% median success rate when the vehicle is between 30 and 50 meters (32.8-54.7 yards) away. Other key explanatory variables include both vehicle specific factors (e.g. use of indicator lights) and crucially the intersection layout, providing valuable information on the relationship between intersection design and road safety.

Key words: Turning Intention, Prediction, Human Perception, Road Safety

## INTRODUCTION

Crossing the road safely is a part of most pedestrians' everyday routine which doesn't seem to require too much conscious thought. Drivers also are (usually) able to safely merge into traffic through their perception of what other vehicles are intending to do. However while both crossing and merging behavior are frequently studied, the idea of predicting a vehicle's turning intention, which is central to both these situations, is relatively un-researched. New technologies are still in the early stages of development and implementation for predicting a driver's intentions from within the vehicle (*I*), but these usually rely on sensors being installed in the vehicle. For people to be able to perceive where vehicles are going when they are driving or crossing the road they must be able to equivalently 'sense' what the vehicle is doing and extrapolate (or pattern match) this into an expected future behavior. An understanding of the overall correctness of these predictions and the factors that influence the correctness will enable a better understanding of the impacts of both intersection design and potentially driver behavior on perceptions (or dangerous misperceptions) of turning intention.

This paper therefore aims to investigate how good people are at predicting the turning intentions of oncoming vehicles and the contextual variables which influence the correctness of those predictions. Key questions which need to be answered to advance research in this area include:

1. How well can people predict a vehicle's turning intention as it approaches an intersection?
2. Is there a relationship between the distance the vehicle is from the intersection and the predictions made about turning intention?
3. What are the most influential variables in predicting turning intention?
4. What role do demographic variables play in predicting turning intention?
5. What do people perceive as the most important variables which help them to predict a vehicle's turning intention?

## PREDICTING TURNING INTENTION

Throughout this paper, 'turning intention' is defined as how a driver is planning to travel through an upcoming intersection, e.g. are they intending to turn left, right or travel straight on at a typical 4-arm intersection. While little research has been undertaken in the past focusing on the human perception of turning intention, understanding turning movements is important for: traffic signal control systems (improved turning proportion accuracy could enable more efficient signal stage determination and calibration of intersection signal timings), highway safety and design (designing roads to help pedestrians cross the road safely and to make it easier for merging traffic) and in-vehicle driver support systems (e.g. emergency braking and crash avoidance) has meant that the subject has often been considered from the technology viewpoint. In general, turning intention can currently be determined (technologically) through two key methods:

- Real time detection within vehicles (in-vehicle sensors)
- Pre-defined route choices (satellite navigation systems)

Previous work on both of these methods is explored in this section to develop a thorough understanding of existing turning intention prediction research, to identify issues that could also be being considered by humans considering the same situation.

Firstly, there have been a number of studies carried out for predicting a driver's turning intention within advanced driver assistance systems to improve safety on the road. If the behavior of a driver can be used to help predict which way they are intending to turn, then this information would be very useful for lane departure warning systems. Hence there has been research carried out to investigate the relationship between turning movements and the driver's eye movement, accelerator and brake usage, indicator activation, steering wheel angle, lane position and many other variables (1).

Lidstrom and Larsson investigated proactive vehicle alert systems which warn the driver about hazardous situations in the near future (2). A speculation in this study is that passengers are often able to predict where drivers are intending to turn at an intersection because of the surrounding environment and a common set of 'conventions' which drivers typically adhere to. For example, the speed approaching an intersection, a driver's gaze towards other roads and the position of the vehicle in the lane will help to indicate a driver's

turning intention. Therefore by monitoring both in-vehicle movements, such as using the indicators, a driver turning their head, use of brakes or accelerator, and by observing a vehicle's speed and position within the lane, then it is possible to predict what a driver intends to do at the next intersection.

Similar to Lidstrom and Larsson, Liu and Pentland stated that most passengers in a car would be able to infer what a driver intends to do simply by watching them (3). The passenger would be able to determine what the driver intends to do through eye movements, posture change, velocity of the vehicle and lane position; therefore it is not inconceivable that sensors in the car would be able to conclude the movements also. They carried out an experiment to test if driver intention could be determined in real time, and the results showed that left turns could be recognized 60-70% of the time and right turns were recognized over 60% of the time; it should be noted that this was within three seconds of being given a command to turn left or right, which does not represent reality as drivers could take longer than three seconds to change their driving behavior. However, Hidden Markov Models were developed (3, 4) to predict when a vehicle was going to change lane to the left based on in-vehicle data and driver gaze information, with varying degrees of success. However, the problem was that the maneuver was predicted only a very short period of time before the event (5), and the accuracy was 50% at best. Also, these predictive algorithms were based on small sample sizes and were carried out in simulators (1), which could reduce the accuracy of prediction due to the fact that it was a simulated environment.

Henning et al used an instrumented vehicle to help recognize any patterns for when drivers are about to change lanes (1). This research identified a very strong correlation to when drivers look at the left mirror and indicate which is understandable as this is the driving procedure taught in driving lessons. However, the problem is that during the experiment people tended to indicate more frequently than what other research has suggested. Olsen stated that only 64% of people actually use their turning signals (6) and therefore a prediction model could not rely solely on the driver's use of a turning signal.

The overall high performance of these prediction algorithms is confirmation that the approach of vehicles to intersections is not merely a random process, instead that different turning intentions do lead to different approach characteristics. Critical for this study however is that all this existing research relies on detailed monitoring of the driver to make predictions (e.g. head movements or eye glances). This type of information would generally not be available to an external observer and is therefore of limited wider application.

Alternatively, a study carried out by Ito et al. (aimed at developing a new navigation system which interacts with the driver and attempts to determine turning intention), showed that turning intention could be predicted up to 94% of the time by using in-vehicle data (7). However this experiment was based in a driving simulator and not all of its assumptions were stated in the paper therefore reduces its reliability in comparison to real world data. The experiment also attempted to determine a distance from the intersection when the turning intention could be predicted, stating that it could recognize a driver's intention at 80 meters (87.5 yards) away from the intersection at 60 kilometers per hour (37.3 mph). While this prediction may be specific to the particular intersection that was investigated, it hypothesizes that there may be a cut-off threshold on approach to intersection before which turning

154 intention may not be predictable. Whether the threshold value is fixed spatially (80 meters –  
155 87.5 yards) or temporally (about 4.8 seconds) will be investigated in this research.

156 Naito et al. highlights that there is a crucial stage in the driver's preparations on  
157 approach to an intersection, when all the participants carried out very similar actions with the  
158 brakes, accelerator and velocity for a turning maneuver (5), which was around three seconds  
159 away from the intersection. One important difference between Naito's experiment and the  
160 research in this paper is that 'left' and 'right' movements need to be distinguished here.

161 Prediction models do not solely have to rely on in-vehicle data sources. Ziebart et al.  
162 states that future satellite navigation systems will likely learn drivers' preferences, habits and  
163 will be able to provide the driver with up to date information on the traffic network (8). With  
164 this additional data source, it could be fed into an algorithm which is attempting to predict the  
165 turning intention of an approaching vehicle with a relatively high confidence value for  
166 repeated journeys.

167 While most of the existing research for predicting a vehicle's turning intention has  
168 utilized direct vehicle or driver data such as accelerator, brakes, steering angle and eye  
169 movements, it is clear that very little research has been completed on externally observing a  
170 vehicle when it is approaching an intersection. It does however provide some insight into  
171 how external observers may perceive an approaching vehicle, especially the possible  
172 existence of an approach threshold before which predictions may be little more than educated  
173 guesses based for example on overall turning proportions at the intersection.

174

## 175 **METHODOLOGY**

176 It is clear therefore that there is little existing evidence on how well people can predict  
177 turning intention or on how contextual factors such as use of indicators influence these  
178 perceptions. To create a dataset which enabled analysis of such questions, an interactive  
179 touch screen experiment was developed to determine how well a person can predict a  
180 vehicle's turning intention as it approaches an intersection.

181 The experiment was designed to act in a standalone manner, i.e. making it self-  
182 contained without the need for anybody present to guide the participant through the  
183 experiment. This was done to prevent the presence of an experimenter biasing the responses  
184 by the participant feeling the pressure of someone watching, and also because this maximized  
185 both the number and variety of participants. The experiment was placed at various locations  
186 around the main campus of the University of Southampton over a period of three weeks so  
187 that any passers-by (both staff and students, representing a wide demographic of people)  
188 could be reached.

189 In the experiment participants watched ten videos of different vehicles approaching an  
190 intersection and had to predict which way they thought the vehicle was intending to turn.  
191 Each video would pause with the vehicle at various distances from the intersection and the  
192 user predicted where the vehicle was intending to turn, with the options of 'Left', 'Straight',

‘Right’ or ‘Don’t Know’. The vehicle was highlighted to the participant through an information box on screen but they were also informed before each video started which vehicle they would be considering. As identified above, a key aspect of the research is how far away from the intersection a vehicle’s turning intention can be accurately predicted. Therefore during the experiment, the videos were paused at specific locations (unknown in advance to the participant) which were 0, 10, 20, 30, 40 or 50 meters (0, 10.9, 21.9, 32.8, 43.7, 54.7 yards) from the intersection. For usability purposes, it was decided to only pause the video twice each time so that the user could make an initial guess when the vehicle was far away and then they would always get the chance to change their mind as the vehicle got closer. Naito et al. stated that turning intention could be accurately predicted when a vehicle was approximately three seconds away from the intersection (5). Therefore all of the videos were created with at least three seconds of viewing before the intersection to ensure that users could have sufficient time to observe the vehicle before making a decision.

Although the ‘pause’ approach is in some ways unrealistic as vehicles approaching an intersection rarely stop in this way, this approach was used to ensure that the participant (a) could only consider information up to that point in time and (b) did not miss visual information between the first and second pauses in each video while they made their selection for the first pause. However this does mean that the second decision will have been influenced by data from the first decision. In reality decision-making of turning intention is a continual process, with people prepared to reassess their prediction at any point if the vehicle appears to not be behaving as expected by their current prediction.

There were three different types of 4-way intersection (FIGURE 1) that were used in the experiment to determine whether intersection layout had any effect on a person’s ability to predict turning intention. It was decided to only consider 4-way intersections to reduce the chances of users simply guessing the correct answer at a T-intersection. Intersection 1 was an un-signalized intersection with a single lane approach, very low traffic flow and clear visibility. Intersection 2 was a signalized intersection with high traffic flow, clear visibility and a two lane approach, where one was a dedicated right turn lane and the other lane was only for straight and left turning traffic. Intersection 3 was a signalized intersection with a two lane approach where the right lane was for right and straight turning traffic and the left lane was for left and straight turning traffic; there was a high traffic flow and only ground level visibility (see FIGURE 1). For the signalized intersections, all the vehicles were approaching when the lights were green. All of the videos were filmed at 1080p quality, in the United Kingdom where vehicles drive on the left.

The selection of ten videos for each intersection was chosen because they appeared to be representative examples of the observed traffic; however each turning movement was chosen at least three times for each intersection. This ensured that all turning movements would have an equal opportunity of being predicted.

The user was able to complete as many videos as they wanted to, however to improve the quality of the dataset being generated, all of the results which are analyzed only show completed experiments to remove potential bias of any learning effects that may occur. For each intersection selected by the participant, the videos were shown in a random order so that learning effects would be minimized over the whole dataset. Users would potentially become

236 better at the experiment as they attempted more videos, and therefore the video order was  
237 randomized to remove this effect.



238 **FIGURE 1 The three intersection options**  
239  
240

At the end of each intersection (set of ten videos), the user was then asked to indicate what they thought the influential variables were that helped them determine a vehicle's turning intention. The user was given twelve options and was able to choose as many (or as few) as they thought were applicable. Some of the possible answers were thought unlikely to be helpful, but these were included to (a) ensure that people would take the experiment seriously (i.e. if they chose 'vehicle color' as a useful variable then it would be unlikely that their answers were serious) and (b) to prevent participants simply ticking all the options (in the mistaken impression that it was a list of things that we as researchers thought was useful and therefore they would have been wrong if they hadn't actually considered all of the options to be important). The twelve options that were available were:

- Indicators
- Speed
- Position in the road
- Lane choice
- Trajectory
- Vehicle type
- Distance to other vehicles
- Braking distance
- Vehicle color
- Driver age
- Size of engine
- Don't know

In order to create a small competitive element to the experiment, a brief score screen was presented at the end of each intersection (after ten videos). This displayed the user's result, average score and the highest score achieved by all participants. As each video paused twice, a point was awarded if the user predicted the movement correctly, and therefore the maximum score possible was 20 for each intersection. No prize or other incentive was offered to participants, either to participate at all or to reward a high score.

Although all participation in the experiment was anonymous, some basic demographic data was collected at the beginning of each experiment to enable potential demographic impacts on correctness of prediction to be investigated. The following questions were asked (all of which had an opt-out option for participants who did not want to give the information):

- Gender
- Age Range (12-22, 23-30, 31-50, 50+)
- Did they drive or cycle in a typical week (or 'both')?
- Were they a car passenger in a typical week?

While not directly considering turning intention, significant amounts of research have been carried out in the wider field of pedestrian safety when crossing a road and it is evident from this research that different age groups can have very different perceptions of a vehicle's speed of approach which could correlate with predictions of future vehicle intention. Child safety had been of particular interest for a number of decades, where studies have found that

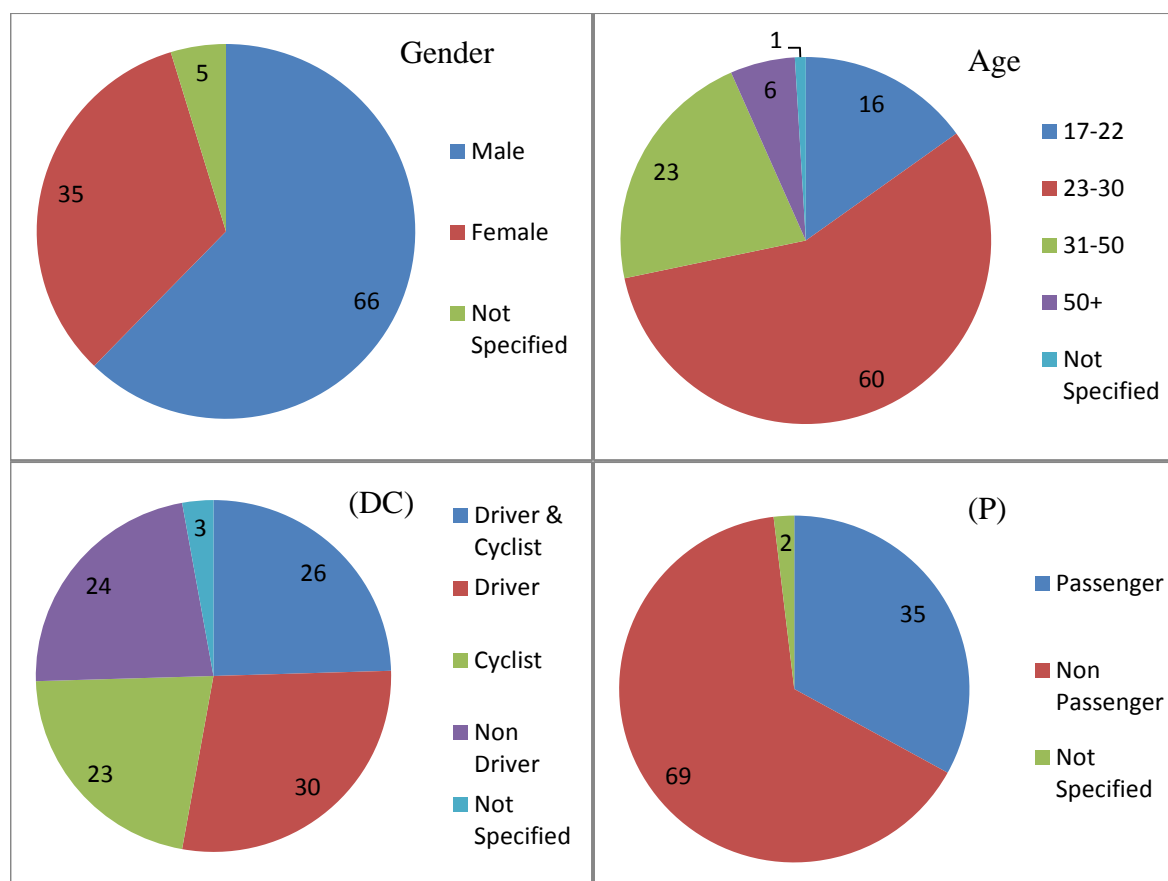


young children (5-9 years old) struggle with determining a vehicle's speed (9), but there also exist studies (10) on adults and elderly people which suggest that age and gender continue to have a significant impact on a pedestrian's perception of approaching vehicles.

The questions about driving/cycling and being a passenger were included to understand whether higher levels of experience related to improved correctness of prediction. While it is expected that all participants would have experience of crossing roads and predicting turning intentions as a pedestrian, a greater amount of experience of predicting turning movements at a greater closing speed either as a driver or cyclist may mean a higher level of accuracy in the predictions. As it is very difficult to quantify quickly and simply how much experience of predicting turning intentions in reality a participant has, these questions, along with age group are included as a possible proxy for an overall experience measure.

## RESULTS AND DISCUSSION

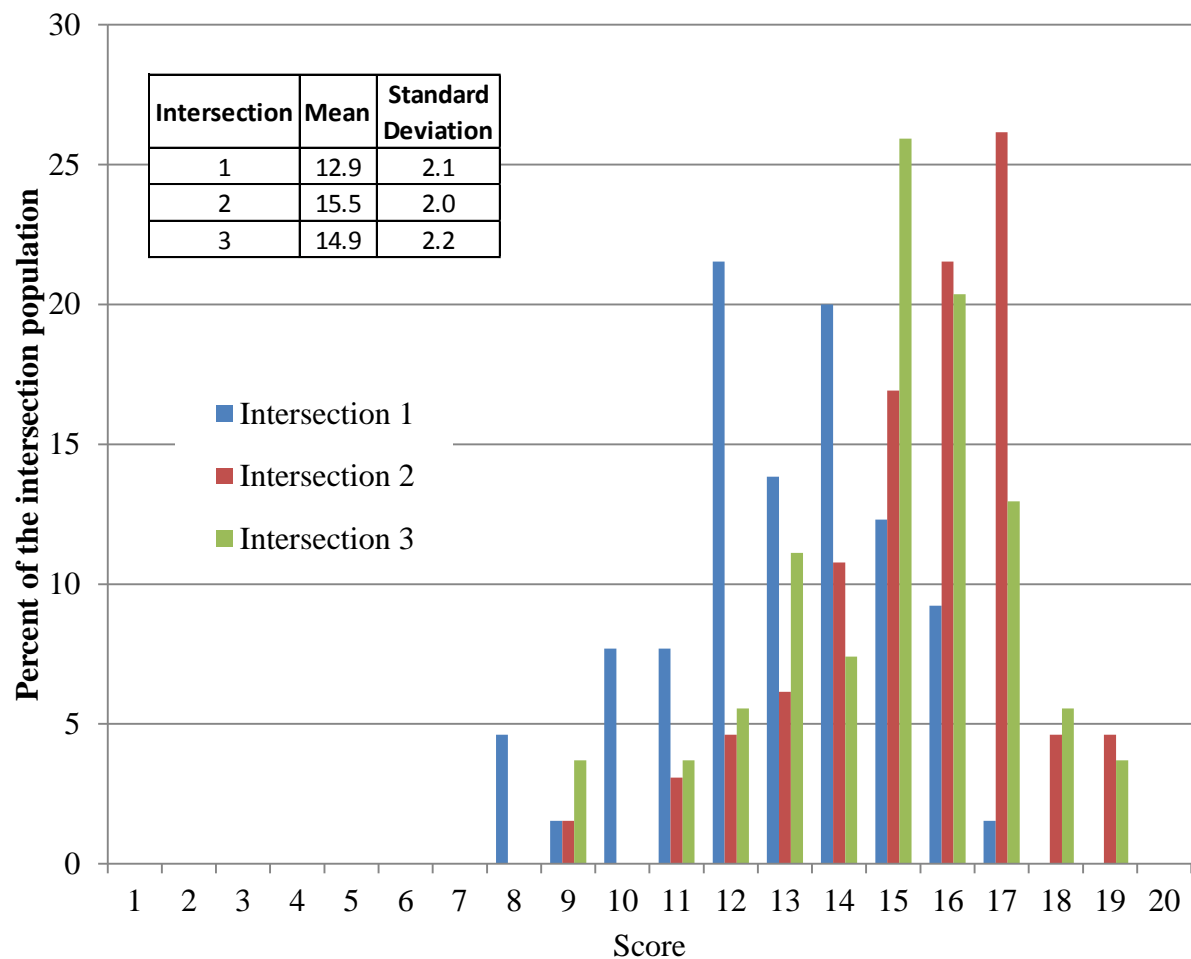
A total of 128 participants over a three week period at the University started the experiment, with the results presented here being from the 106 participants who completed at least one intersection. The summary demographic data of participants is given in FIGURE 2, confirming that a broad range of participants were included in the dataset.



**FIGURE 2 Summary demographic data (where ‘DC’ represents the Driver and or Cyclist in a typical week and ‘P’ represents the Passenger in a typical week)**

As there were three intersections to choose from and participants could attempt more than one intersection (in any order), there were varying numbers of participants for each intersection – Intersection 1 and 2 had 65 participants and Intersection 3 had 54 participants. FIGURE 3 shows the overall scores achieved by each participant for each intersection, suggesting a high level of correctness in predictions (overall mean score 14.4/20 substantially higher than the 6.7/20 which would have been achieved by random guesses – ignoring the effect of lane choice), but also a negative skew (especially with Intersection 2 and 3) with Shapiro-Wilk tests confirming that all three intersections do not therefore deviate from Normality ( $p = 0.030, 0.002$  and  $0.016$  for intersections 1, 2 and 3 respectively).

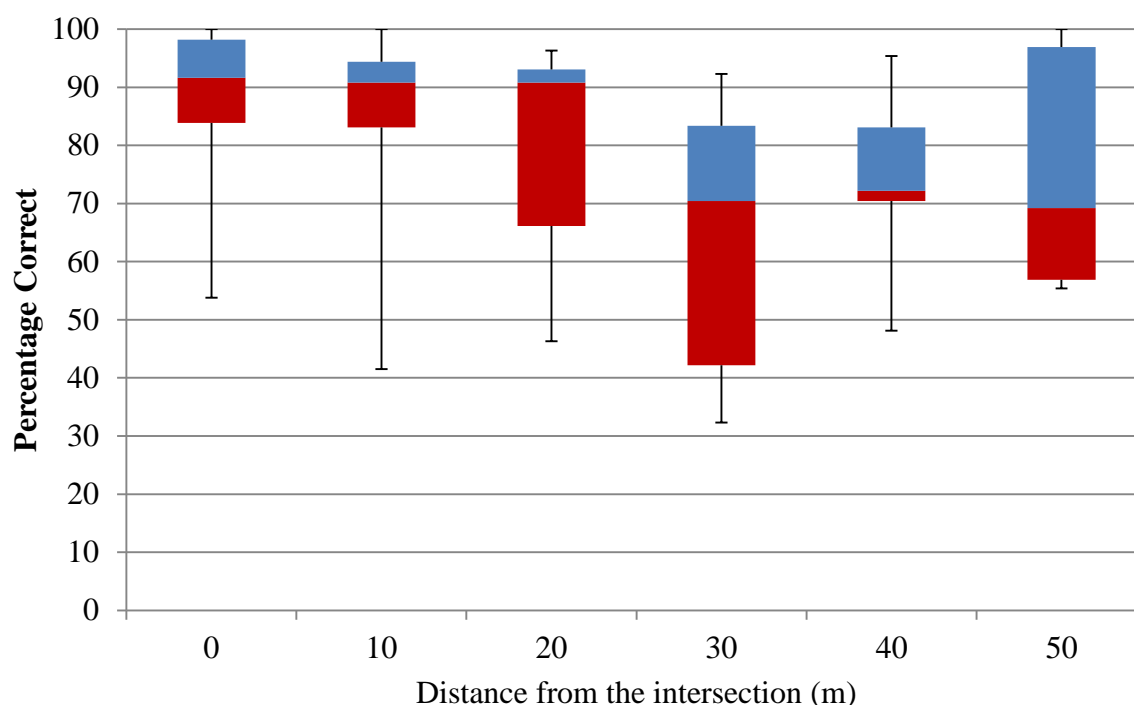
FIGURE 3 clearly displays that Intersection 1 was the most difficult level to predict, whereas the scores for Intersection 2 and 3 were very comparable. One possible reason for this is that Intersection 1 only had a single approach lane, and the vehicles started in the middle of the lane due to parked cars at the sides of the road (see FIGURE 1). At this intersection, all three maneuver choices were always possible, whereas in the other two intersections, a lane choice would mean that the vehicle would only have at most two turning options available (assuming rules of the road were obeyed).



**FIGURE 3 Correct predictions for each intersection**

### Impact of Physical and Demographic Factors

As the videos were paused when the highlighted vehicle was at a specific distance from the intersection, FIGURE 4 displays a box plot of how accurately people predicted turning intention at different varying distances from all three intersections combined. The box plot shows a substantial step change between 20-30m (21.9-32.8 yards) with around a 20% reduction in prediction accuracy. At 0 meters from the intersection, the median percentage of people that predicted correctly was 91.7% (falling slightly to 90% by 20m), whereas at 30m (32.8 yards) only 70% of people were able to predict correctly (falling slightly to 69.2% when distance is increased to 50 meters (54.7 yards)).



**FIGURE 4 Percentage of people predicting correctly for varying distances**

The speed limit for each of the intersections is 30 miles per hour (mph) and estimating from the times at which the videos are paused suggests that vehicles are typically travelling approximately 20 mph when approaching the intersections. This equates to approximately 9m/s (9.8 yards/s) and therefore the vehicle is roughly 27 meters (29.5 yards) away at three seconds before the intersection. This agrees strongly with the findings of Naito et al. (5) who concluded that three seconds before an intersection is when a vehicle's turning intention can be accurately predicted from in-vehicle monitoring, but is less than that identified by Ito et al. who stated that they could predict a driver's turning intention from inside the vehicle when they were 4.8 seconds away from the intersection (7). This study did not consider further than 50 meters (54.7 yards) as the proximity of other intersections would have become an issue or visibility of approaching vehicles would have been too occluded, but it does not appear that people are able to predict turning intention from outside the vehicle as accurately as Ito achieved through in-vehicle technology. Ito managed to predict 80-94% of the vehicles correctly during the experiment, whereas the median percentage of people predicting correctly at 50 meters (54.7 yards) here was only 69.2%; this implies that it is more challenging to predict turning intention without the help of in-vehicle data sources, however Ito et al did not specify all of the correct predictions for varying distances so some assumptions have been made when reviewing their work.

FIGURE 4 clearly demonstrates that people find it harder to predict turning intention when the vehicle is further away, but not included in FIGURE 4 are a small number of videos which people appeared to find very difficult to predict regardless of distance. These 'challenging' vehicles were included as part of a representative sample of vehicles from the video footage and included vehicles straddling two lanes and examples of poor observer

visibility due to the presence of surrounding vehicles. Predicting turning intention is never going to be a perfect science and there will always be challenging drivers who change their direction at the last moment. One of the intentions of this study is to determine what variables help people most in predicting turning intention, and the videos which people achieved the lowest scores were when the vehicles did not perform a ‘text book’ turn at the intersection.

While distance has a clear impact on correctness of prediction, to assess how all the physical variables interact to impact the predictive capabilities of people, a logistic regression analysis was undertaken. Variables (and two-factor interactions) were added sequentially in order of greatest improvement in log-likelihood, with the resulting sequence of models and their corresponding Nagelkerke  $R^2$  values given in TABLE 1. Although the  $R^2$  values may appear low in comparison to the overall level of correct predictions in FIGURE 3, it should be noted that this analysis is attempting to identify the important factors in variation in correctness, not the overall level of correct predictions.

- Indicator – whether the vehicle indicated before the video paused
- Turning\_Direction – did the vehicle actually turn left, right or travel straight on
- Distance\_Threshold – the vehicle is more than 25m from the intersection
- Intersection\_Type – to allow for the variations in lane layouts

**TABLE 1 Logistic Regression Analysis**

Factor Type	Factor/Interaction	$R^2$
Physical	Indicator	0.147
Physical	Turning_Direction	0.270
Physical	Intersection_Type	0.307
Physical	Distance_Threshold	0.327
Physical	Turning_Direction * Intersection_Type	0.348
Physical	Indicator * Intersection_Type	0.359 <sup>#</sup>
Physical	Distance_Threshold * Turning_Direction	0.362 <sup>#</sup>
Physical	Distance_Threshold * Intersection_Type	0.364 <sup>#</sup>
Demographic	Age	0.371
Demographic	Driver_Cyclist	0.373 <sup>#</sup>
Demographic	Age * Driver_Cyclist	0.377 <sup>#</sup>

Unsurprisingly, the most important indicator amongst the physical is the presence of an indicator. This was closely followed by the actual turning direction and intersection type, which together can be seen as a partial proxy for lane choice. The clear non-linear relationship with distance in FIGURE 4 is then represented by the Distance\_Threshold factor being included in the model rather than a linear effect of the actual distance (all effects of which are insignificant once the threshold factor has been included). Although the three physical factor interactions denoted # in TABLE 1 are formally significant due to the amount

of data available, their presence in the model does not increase the predictive accuracy of the model beyond the 79.5% of correct/incorrect predictions forecast by the inclusion of only Indicator, Turning\_Direction, Intersection\_Type, Distance\_Threshold and the Turning\_Direction × Intersection\_Type interaction.

The demographic data collected was also investigated in this analysis, by adding it to the final physical factors model, to determine if the characteristics of the participant had any additional influence on their ability to predict correctly.

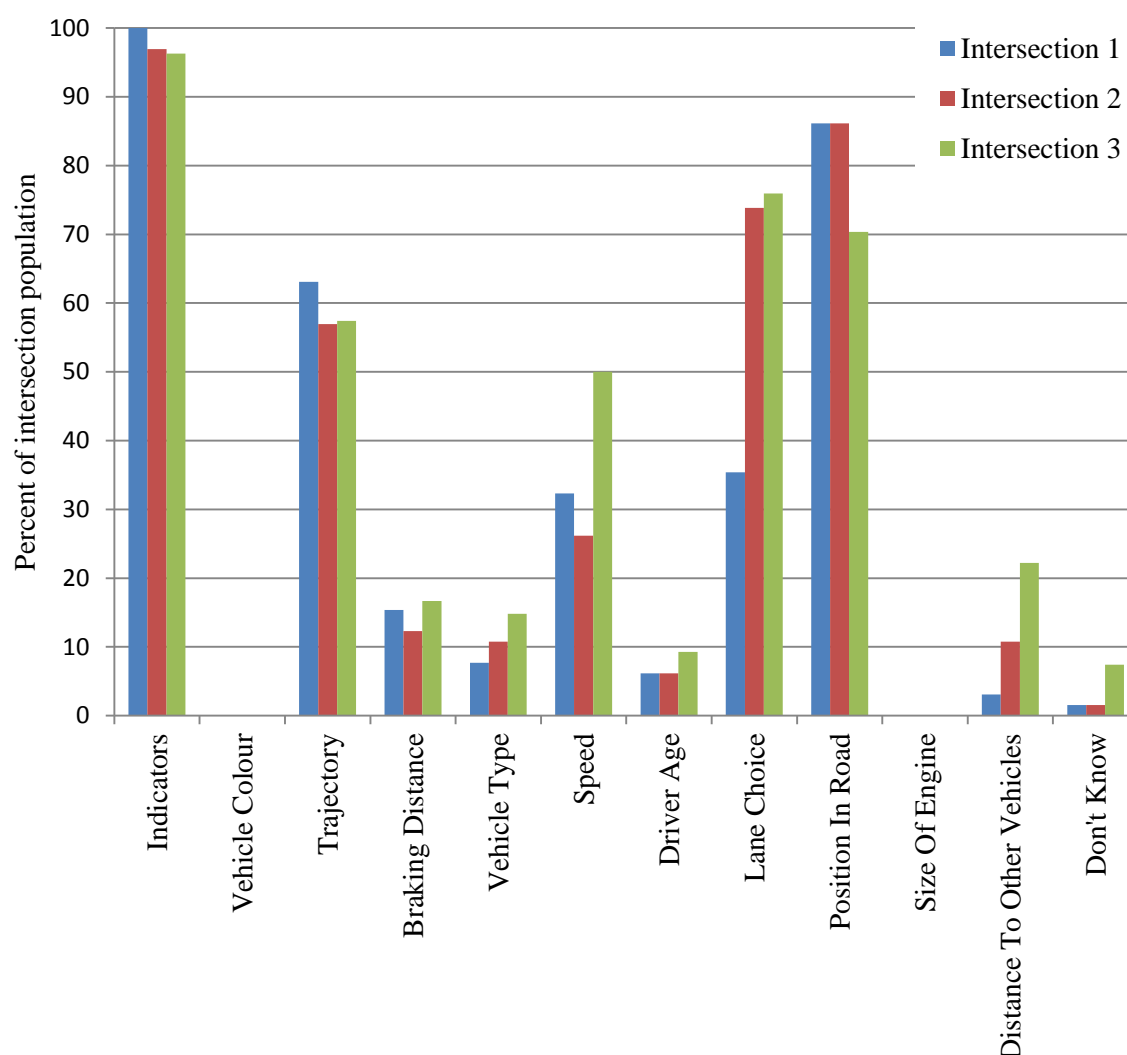
- Age – the age group
- Gender – the gender group
- Driver\_Cyclist – Did they drive or cycle in a typical week?
- Passenger – Were they a car passenger in a typical week?

The inclusion of age group in the model in addition to the physical factors (Table 1) seems to be sufficient to represent a level of experience effect, increasing the predictive accuracy of the model slightly to 80.3% or correct/incorrect responses. Although the effect of regular driving/cycling did have additional significant effect on the fit of the model, as with the later interactions of the physical factors it does not contribute to an increase in the predictive ability. The impact of the age factor, while small, suggests that correctness of prediction may rise from the 17-22 group to the 23-30 group, before falling back slightly in the groups over 30 years of age.

Allowing for all two-way interactions within the physical and within the demographic factors produces an overall logistic regression model with a Nagelkerke  $R^2$  value of around 0.4 (which is typical for a human behavior experiment), already sufficient to predict the correctness of participants' decisions in over 80% of the data. This suggests that while more subtle explanatory factors such as approach speed profiles and precise lane positioning may be having an impact on perceptions in borderline cases (and may also be the reason why the overall correct rate of predictions by participants was only around 75%), the correctness of external observer predictions of turning intention can usually be forecast by the limited range of explanatory factors considered in this paper.

## Perceived Important Variables

While the preceding section investigated which physical and demographic variables were significant in determining the correctness of turning intention predictions, the counterpoint to this is to consider which variables were perceived to be useful by the participants. FIGURE 5 highlights the perceived important variables which influenced users to predict turning intention at each intersection. As expected given the actual result above, almost everybody selected indicators for each of the three intersections, with lane choice, trajectory and position in the road also highly rated variables. It should be noted that nobody selected vehicle color or size of engine which helps to demonstrate that even though no experimenter was present, participants were still selecting their answers realistically.



**FIGURE 5 Participants perceptions of important factors**

FIGURE 5 shows a strong degree of agreement between the intersections, even though in many cases different participants attempted different intersections. The exception to this is Intersection 3 where speed of approach and distance to other vehicles was considered as comparatively more beneficial, with fewer participants suggesting they felt they used the vehicle's position in the road. This could be because the position in the road was much harder to see in Intersection 3 due to the lower angle of view and therefore participants were much more dependent on other variables.

A number of participants wanted to discuss the experiment further after they had completed it (contact details for the researchers were provided at the end of the experiment to facilitate this), and a key aspect of their feedback was that they did not trust 'white van' drivers whereas they expected emergency service vehicles to obey the rules of the road. Even with this response, the vehicle type variable was seldom selected and this suggests that

different participants may have been interpreting the vehicle type option in different ways. This vehicle specific effect may also be being represented by participants feeding back that local knowledge may have played some part in their decision making, especially when local buses were included in the video as participants may have been able to use their (known) trajectories as a guide to the turning intentions of other vehicles.

## CONCLUSIONS

Overall, it appears that people are very good at predicting the turning intention of a vehicle on its approach to an intersection as the average score overall was 14.4 out of 20. Previous research has considered the problem of predicting turning intention from within the vehicle, but this research shows that high levels of correctness can also be achieved when turning intention is being predicted from outside of the vehicle (a 'passive' approach as opposed to expensive 'active' approaches that rely on having specific technologies installed in every vehicle). Considering that there were four possible options for users to select (don't know was included as an option, but rarely selected), this demonstrates how good people really are at predicting turning intention. These prediction rates are significantly better than both a random guess and using overall historical average turning proportions for the intersections.

When considering how distance influences people's ability to predict turning intention, it was found that a substantial step change occurs between 20 and 30 meters (21.9 – 32.8 yards) away from the intersection. There was a median value of approximately 90% success when the vehicle is between 0 and 20 meters (21.9 yards); and 70% success when between 30 and 50 meters (32.8 – 54.7 yards) upstream. The sudden step change can be compared to research carried out by Naito et al., where people were able to predict the turning intention very accurately (over 90%) when the vehicle was only three seconds away from the intersection when observing variables from inside the vehicle; therefore the threshold value appears to be temporally fixed as opposed to spatially constrained.

This paper has investigated the most influential variables in the correctness of predicted turning intentions through a logistic regression analysis. While physical factors dominate the relationships, demographics of the participant also appear to be affecting the prediction, with age group providing a significant and important effect. When asked to indicate the variables that they thought they were using to make their decisions, participants were in general in agreement with the physical factors identified in the logistic model, but also perceived a number of other variables such as the position in the road and trajectory. The issue with including these into the model is that it is difficult to quantify what aspects of position and trajectory are being used and how these might vary between participants. One key aspect of this research is that unlike a computer algorithm, human brains cannot be interrogated to understand precisely how all the factors are combined to produce the end result, nor are participants likely to be able to consistently explain exactly what it is about each variable that is important to them. While these variables are potentially important in borderline cases therefore, the overall success rate of participants of 72% correct predictions and overall success rate of 80% for the logistic regression model in forecasting whether the



participants would predict correctly suggest that their effect is less important than simpler factors such as overall lane choice.

Very little previous work has been carried out on the correctness of predicted turning intention from outside of the vehicle and therefore this research shows for the first time that while external predictions by people are generally correct, the physical variables related to the intersection design and vehicle operation can influence how well turning intention can be predicted. Understanding these influences is the first step to reducing the potential impacts of dangerous misperceptions of turning intention, which can be applied to highway design, traffic signal calibration and road safety.

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