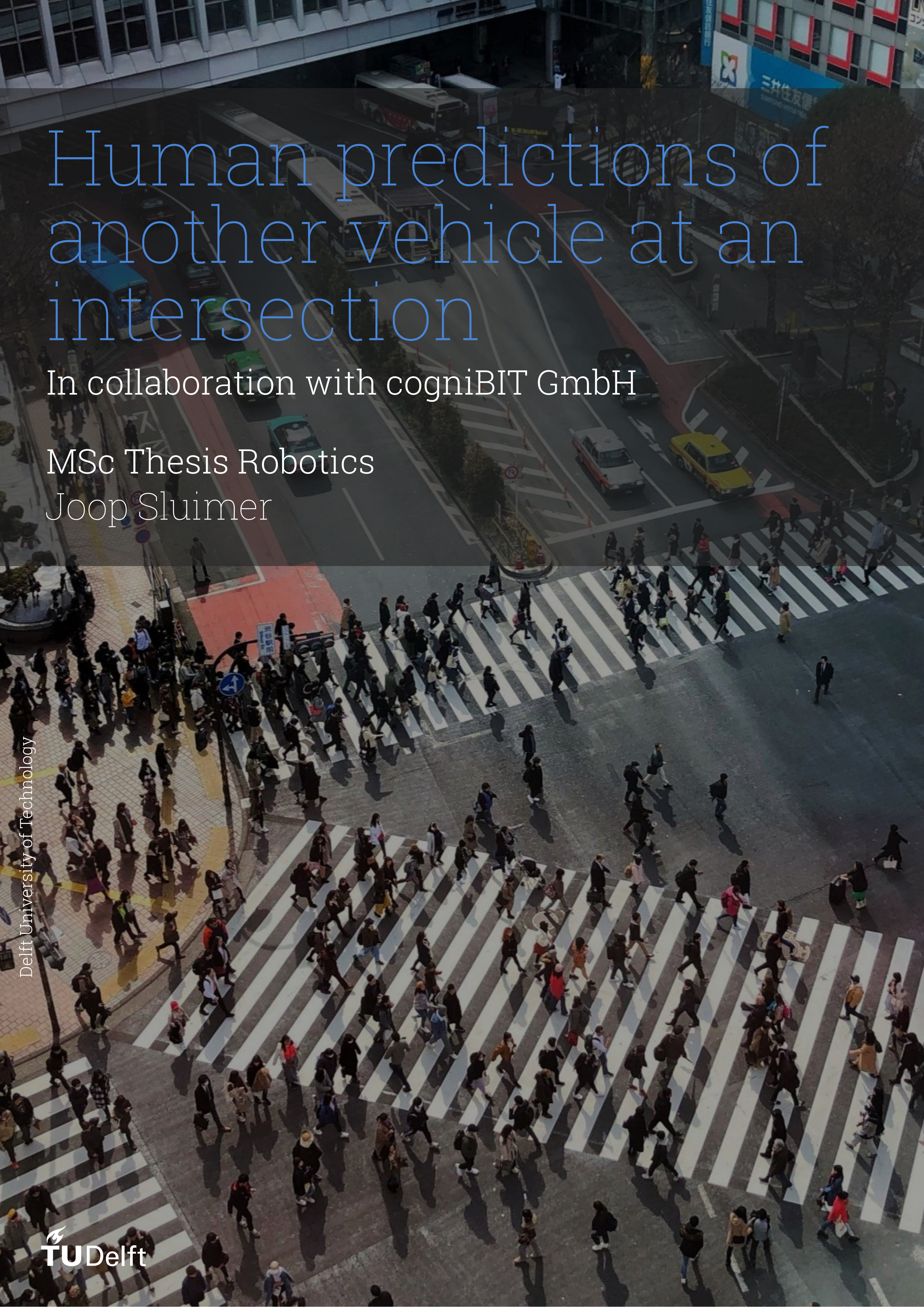

Human predictions of another vehicle at an intersection

In collaboration with cogniBIT GmbH

MSc Thesis Robotics

Joop Sluimer

Delft University of Technology

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by

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Cover: Highly realistic traffic simulation image from CogniBIT. Found at `https://cognibit.de/` (Modified)

TU Delft

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Abstract

Annually, thousands of lives are lost to traffic accidents. To improve the safety of all traffic participants, the understanding and modelling of the limitations of human behaviour in traffic have continuously been researched. Currently, there is a lack of existing research on human predictions of other vehicles in traffic beyond binary decisions, such as whether the pedestrian will cross or whether another vehicle will accept the gap. This study conducted a human factors experiment with a novel response method where 30 participants viewed 168 unique scenarios for 5 seconds and then had to predict the intended direction the other vehicle would continue at the intersection. The direction predictions are a measure of how likely humans think the observed vehicle will go forward, left or right at the intersection. Analysis of the results showed that the heading angle and the relative position of the other vehicle had the greatest influence on the predicted direction and confidence of the response. Blinker use and deceleration had a lesser impact on prediction direction but significantly affected confidence. The lateral offset showed no statistical significance on the responses. The results highlight the limitations and inconsistencies in human predictions for other vehicles, particularly when the observed vehicle was positioned on the left or right side of an intersection, even when participants could focus solely on the other vehicle and no other distractions were present. Accounting for these inconsistencies when developing driving systems or testing autonomous vehicles can significantly enhance the safety and awareness of all traffic participants involved in an intersection.

1. Introduction

In 2023, over 2800 fatal car crashes happened in Germany alone [1]. Traffic accidents could be caused by several factors, including human factors such as drunk driving, being distracted while driving, or speeding [2]. Human drivers constantly have to perform a varying number of complex driving manoeuvres safely while remaining aware of their surroundings, other traffic participants, and reaching their destination within a given time. Continued research has been done to make the road safer for all users. Automotive developments such as autonomous vehicles (AVs) and advanced driving-assistance systems (ADAS) are among the many fields. As long as human drivers and AVs coexist in traffic, to ensure safe traffic interactions between humans and AVs, understanding and modelling the limitations of the underlying human cognitive mechanics allows for a better understanding of expected human behaviour in all traffic scenarios.

The current state of the art in human behaviour modelling includes data-driven approaches, which learn from large traffic datasets, and cognitive models, which try to replicate human perception, decision-making, and attention patterns. While data-driven models, such as those used by leading AV developers, perform well in everyday scenarios, they often struggle to perform reliably in critical traffic scenarios due to the scarcity of such scenarios during model training [3, 4]. To address this, recent research has emphasised incorporating human cognitive constraints, such as limited perception, lapses in attention, or reaction time variability, into traffic simulation agents [5, 6]. These more human-like agents enable more robust testing, closer to reality, which contributes to better generalisation and safer human-AV interactions.

While incorporating human cognitive constraints has improved the realism of traffic agents, one key feature is still not fully understood: how humans predict the behaviour of other traffic participants. Human drivers continuously form expectations about the intentions and future movements of others, such as whether a cyclist will yield, whether a car will turn, or whether a pedestrian will cross the street. These predictive processes are essential for safe and coordinated traffic interactions. However, current behaviour models often treat human traffic agents as reactive rather than predictive. Understanding how humans predict the actions of others is essential for both modelling human behaviour more accurately and ensuring autonomous systems can safely coexist with them.

Several studies have sought to understand how humans predict the behaviour of other traffic participants. For example, Sripada et al. [7] and Tian et al. [8] examined changes in autonomous vehicle driving behaviour as a form of implicit communication for crossing pedestrians. Sripada et al. assessed whether lateral lane deviations affected pedestrians' willingness to cross the road in front of the AV through an online experiment in a simulated environment. Participants in the experiment held a button as long as they felt safe crossing the road. Results showed lateral movement towards the pedestrian, and blinkers were effective signs of yielding behaviour. Tian et al. assessed how pedestrians perceived different forms of decelerations as yielding behaviour. Within a simulation environment brought to life using projectors, participants had to decide whether to cross the road or not. Early braking resulted in more pedestrian crossings; however, low constant speeds were often also interpreted as yielding behaviour, resulting in more dangerous pedestrian crossings compared to the other decelerations.

Other studies, such as Miller et al. [9], Werkene et al. [10], and Zgonnikov et al. [11], created simulation experiments to study driver behaviours at an intersection. Miller et al. investigated deceleration and lateral movement to communicate yielding or insisting behaviour when approaching a bottleneck from opposite sides of the road. Participants rated the distinctiveness and cooperativeness of the other vehicle in the shown scenario on a Likert scale. For AVs, early lateral vehicle movement is recommended. Werkene et al. analysed the influence of intersection complexity on driver attention when making right turns into oncoming traffic, through a simulation-based experiment. Less complex scenarios resulted in more accidents due to inadequate allocation of attention. Zgonnikov et al. looked into driver left-turn gap acceptance in simulated intersection scenarios. Results showed that participants were more likely to accept the gap when given larger time gaps, but not distance gaps.

As an alternative to simulation-based experiments, Hamilton et al. [12] and Hensch et al. [13] used real-world traffic videos. Hamilton et al. had participants predict the intended turning direction of an observed vehicle approaching an intersection. The distance from the observed vehicle, blinker use and the intersection layout had a significant influence on the predicted directions. Hensch et al. assessed different modes of transport approaching the driver's vehicle in left turn scenarios. Participants had to indicate a comfortable time gap for making a left turn in front of the other mode of transport. Younger participants accepted narrower gaps more often.

Lastly, Colombo et al. [14] experimented to analyse human predictions of bicycle trajectories within a Virtual Reality (VR) environment and then developed a cognitive model to replicate these predictions. Similar models could be generalised to describe the limitations in driver predictions. This could enable ADAS and other AVs to compensate for the lack of drivers' situational awareness.

While prior studies have examined how drivers make predictions about the intentions of other traffic participants, these studies often focus on isolated scenarios with binary responses such as pedestrian crossings or gap acceptance. Moreover, few studies attempt to measure or quantify how humans predict directionality in these situations, relying instead on inferred choices or response durations. No known previous work has directly quantified directional predictions in intersection scenarios using explicit human responses. By incorporating key behavioural cues such as heading angle, blinkers, and deceleration into the shown scenarios, this study contributes not only new data but also a novel response method that quantifies how humans make direction predictions about other vehicles at intersections. This enables a deeper understanding of the predictive processes critical for human-human and human-AV traffic interaction, bridging the gap between cognitive theory and practical AV/ADAS design.

A human factors experiment was created to assess and quantify human direction prediction responses of another vehicle at an intersection. This novel method measured participants' response trajectories for changes in observed vehicle heading angle, relative position, blinker use, declaration and lateral offset. The observed vehicle's intended behaviour cues were based on prior human prediction studies and intuitive differences in driving behaviour when approaching an intersection. Mixed-effect models were used to analyse the statistical importance of each cue in the obtained prediction responses. Results suggest that the observed vehicle heading angle and relative position are the most statistically significant factors for predicting direction. Random Forest Regressors were trained and tested to replicate the participants' prediction behaviour with a 70.9% accuracy.

2. Methodology

The experiment done during this study consisted of several components. The chosen method and decisions made for each component are included in the following sections.

2.1. Participant selection criteria

Thirty healthy adults (mean age of 32.2 years (SD = 14.6); 23 male, 7 female) were recruited to participate in the simulated experiment in Munich, Germany, and Delft, the Netherlands. The following selection criteria were used when asking participants to join in the experiment.

- Must be at least 18 years old.
- Must have a driver's license.
- Must be comfortable driving on the right-hand side of the road.

This guarantees that participants are familiar with driving scenarios that closely mirror those in the experiment. Before participating in the experiment, participants provided written informed consent about the procedure and the use of their recorded data.

2.2. Equipment used

To ensure all experiments were completed under identical experimental conditions, all experiments were done in person on the same laptop. The laptop has a 1536x960 screen resolution. Participants used the same Logitech mouse set at 1600 dpi (dots per inch) sensitivity on the same 27 x 31.5 cm mouse pad. Participants were allowed to position the laptop in a way that allowed them to view the screen comfortably. The scenarios were created in Carla version 0.9.15 [15] in Unreal Engine 4 [16]. All scenarios were recorded in the simulation environment and played back at 30 frames per second in a Pygame Graphical interface.

2.3. Intersection scenarios

The virtual intersection environment was an urban four-way intersection connected by standard German 3.5-meter-wide two-lane roads. The participant's perspective was from within a car with a large, open windscreen, driving at 5 m/s towards the intersection. Another (observed) vehicle would drive towards the same intersection at 10 m/s, reaching the intersection before the (ego) participant's vehicle. After approximately 5 seconds, the scenario freezes, and participants must predict the direction they think the observed vehicle will continue directly after the freeze. The ego vehicle was always the same, but several variables influenced the observed vehicle in the traffic scenarios. The independent variables (IVs) during the experiment were designed as follows:

- *Relative position*: With a 4-way intersection, there were four positions the observed vehicle could be relative to the ego vehicle: Following, Left, Opposite or Right. Depending on where the observed vehicle was would affect what was visible to the participants. For example, when the ego vehicle followed the observed vehicles, brake lights were much easier to see than in other relative positions.

(a) -10° (b) -5° (c) 0° (d) +5° (e) +10°

Figure 1. Observed vehicle heading angles shown at the end of each scenario when the ego vehicle followed the observed vehicle with a left lateral offset. The observed vehicle relative positions, lateral offset, and blinkers are shown in Figures 9, 10, and 11 in the Appendix.

- *Heading angle*: Just before the freeze, the heading angle shown by the observed vehicle was: +10, +5, 0, -5 or -10 degrees. See Figure 1. Positive heading angles were right, and negative angles were left. The ±10 heading angles should have been an obvious turn in the same direction from all relative positions, but the ±5 could have been mistaken for a natural vehicle oscillation or the driver creating space to turn the other direction.
- *Blinkers*: As the observed vehicle approached the intersection, its blinkers were on or off. The blinkers were always in the turning direction, and off when going straight over the intersection. Initially, the blinker could have been left, right, or off, but due to the variable space being too large, the blinkers were simplified to on or off. This means that no "fake" blinkers (e.g., indicating left but turning right) are included; however, participants were not explicitly informed about this during the experiment.
- *Deceleration*: As the observed vehicle approached the intersection, the observed vehicle showed three types of deceleration behaviour: Constant speed, hard braking, and soft braking. With a constant speed, the observed vehicle maintained a speed of 10 m/s until the scenario froze. Hard braking is a late braking action close to the intersection, with the braking lights activated and decelerating quickly to 5.5 m/s. Soft braking is an earlier braking action, slowing down to 4.5 m/s over a greater distance but less abruptly. See Figure 2 for a visualisation.
- *Lateral offset*: The observed vehicle was 0.2 m left or right relative to the centre of the lane. The offset could have been an implication for turning. When the ego vehicle follows the observed vehicle, and the observed vehicle is positioned to the left of the centre of the lane, the driver may be making space to turn right.

The variable space yields 240 unique scenarios; however, not all of these unique scenarios were included in the experiment. As mentioned previously, no blinkers were shown in the straight scenarios, removing 24 scenarios, resulting in 216 unique scenarios. The pilot experiment suggested that 216 scenarios were too many for participants; the entire process took approximately one hour to complete. Participants were rushing their final responses to finish the experiment. Thus, more scenarios had to be removed to get the experiment duration closer to a comfortable 30 minutes. The difference between the left and right lateral offset was unnoticeable when the observed vehicle was left or right relative to the ego vehicle. Therefore, half of these variable combinations were also excluded, ensuring all other variable combinations are preserved, resulting in 168 unique scenarios shown during the experiment.

Further experiment design choices for added realism included: The observed vehicle exhibited a slight natural lateral oscillation on top of the lateral offset, to prevent the observed

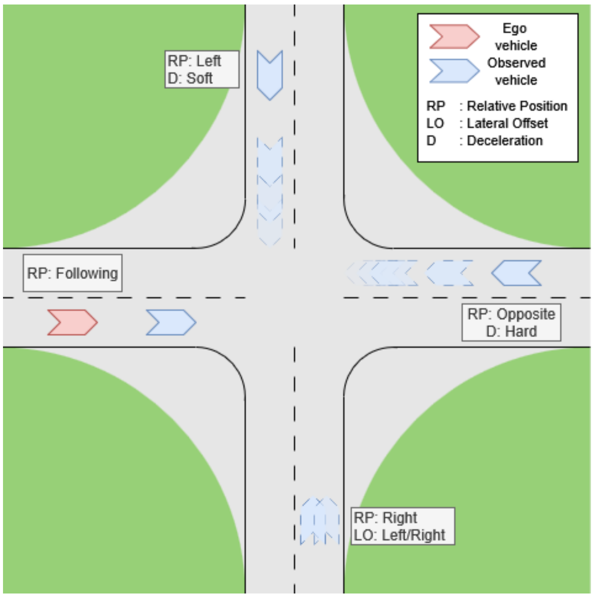

Figure 2. Top down visualisation of the intersection scenarios shown during the experiment. The graphic includes the relative positions of the ego vehicle to the observed vehicle, the difference between lateral offset, and a visualisation of hard and soft deceleration. See Figure 1 for the heading angles shown during the experiment.

vehicle from driving perfectly straight. The observed vehicle model was randomly chosen for each scenario. The model criteria for models to be included in the scenarios were:

- No special decals, such as taxi or police cars, to avoid unnecessary biases.
- Visually complete models with working blinkers and brake lights.
- All vehicles must have similar exterior dimensions to ensure the models take up roughly the same area on screen. SUVs and trucks are significantly larger than other car models and would block a greater portion of the intersection; therefore, they were excluded.

Given 22 existing vehicle models in the cogniBOT [17] driver model, the following 6 vehicle models met the criteria: 2021 Mini Cooper S, 2020 Dodge Charger, Audi TT, 2017 Lincoln MKZ, 2020 Mercedes Coupe, and 2020 Lincoln MKZ.

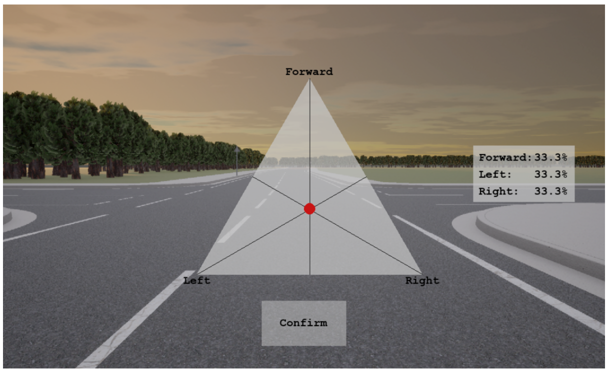

Figure 3. Response triangle when the ego vehicle followed the observed vehicle. The red dot indicating score, initialised at 33.3%, 33.3%, 33.3% for forward, left and right.

2.4. Responding to the scenario

Following the scenario freeze, all vehicles on screen disappear. This prevents participants from analysing the scenario further, forcing them to respond based on what they saw during each scenario shown. The participants had to predict the direction they thought the observed vehicle would continue directly after the freeze. All responses were to be given from the perspective of the other vehicle, resulting in three directions the observed vehicle could continue at the intersection: left, forward or right.

Given that not all scenarios would continue in one clear direction, responses consisted of a magnitude in each direction. The response triangle shown in Figure 3 was used during all experiments. The inverse relative distance to each direction vertex was used to score the predicted direction. The red dot, indicating the current score, always started in the centre of the triangle, which corresponds to all directions being equally likely. The participants could click or drag anywhere within the triangle to move the red dot to their desired score. The score percentages were also displaced to the right of the response triangle. To finalise their prediction, the participant had to press the confirm button below the triangle, stopping measurements and displaying the option to load the next scene. Examples of final prediction scores are shown in Figure 4.

To ensure participants could provide an intuitive response to each shown scenario, the response triangle would rotate such that the

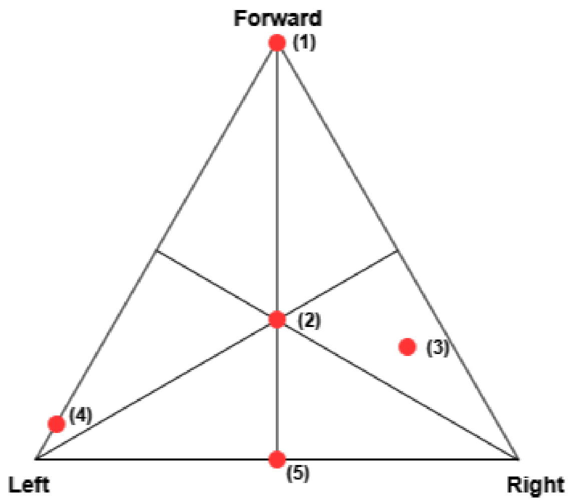

Figure 4. Examples of final prediction scores in the response triangle. (1) 100% Forward, very confident response. (2) 33.3% in all directions, completely unsure response. (3) Unsure response, likely to turn Right, but could still go Forward, with a small chance to turn Left. (4) 90% Left, most likely will turn left but small chance, 10%, that the observed vehicle could still go forward. (5) 50% Left and 50% Right, certain that the observed vehicle will not continue forward but not sure whether it will go left or right.

forward direction aligned with the direction the observed vehicle was approaching from. See all response triangle rotations in Figure 12.

2.5. Experimental procedure

The experiment session started with the potential participant reading and signing the informed consent form. Then the experimenter explained to the participant: *"You and another vehicle are driving towards an intersection, the other vehicle will move and look slightly different every time, and it is your task to predict what direction the other vehicle will go in at the intersection. It is important to give your response from the perspective of the other driver."* Expected responses when following, opposite, and right were then explained using visuals.

Next, how responses are given was explained: *"After about 5 seconds, the video will freeze and you will be shown the response triangle. You move the red dot in the direction you think the other vehicle will go."* A visual example is included.

Then the experimenter would demonstrate four scenarios with example responses. Thereafter, the participants had to participate in a brief test to confirm they understood how the response triangle works. Five scores were consequently displayed, and the participant was asked to replicate the scores in the response triangle, allowing for some margin of error. Only if they successfully matched the score could they proceed to the next score to replicate.

Finally, after completing the test, the participants had 10 scenarios to practice watching and giving responses. This allowed the experimenter to confirm that all participants responded with their expected response, but did not teach them the expected responses. In some scenarios where the observed vehicle was opposite, participants would respond 'left' when they meant 'right', which was then corrected by the experimenter, causing responses in the opposite direction to occur rarely during the actual experiment. It was essential for participants to respond with their predictions and not with what was expected. Thereafter, the participant could start the actual experiment.

Participant 1 was the pilot participant. The experiment was greatly improved by making the response method easier; their measurements were thus not included in the recorded data. Participants 2 to 16 took part in the improved experiment. During this experiment, the experimenter noticed that the video frame rate was slightly lower than expected. This issue was then fixed for participants 17 to 30. The improved framerate decreased the experiment duration and made the observed vehicle deceleration easier to see. The difference between the experiments was insufficient to invalidate all the previously acquired data. All obtained response data is analysed within the same group. The differences between the groups are illustrated in the Appendix.

2.6. Measurements

As soon as the response triangle is shown, measurements are recorded. The mouse position on the screen (x, y), the current score (f%, l%, r%), the number of clicks and the timestamps for each participant ID and scenario ID are recorded at a 100 Hz. The timestamp represents the difference between the current mea-

participant_id	scenario_id	timestamp	mouse_x	mouse_y	score_f	score_l	score_r	mouse_clicks
16	80	0.00	668	701	33.3	33.3	33.3	0
16	80	0.01	668	702	33.3	33.3	33.3	0
16	80	0.02	668	703	33.3	33.3	33.3	0
16	80	...	...	...	33.3	33.3	33F.3	0
16	80	2.31	469	545	2.4	94.1	3.6	1
16	80	...	...	...	2.4	94.1	3.6	1
16	80	3.82	614	658	2.4	94.1	3.6	2

Table 1. Example of measurements where participant 16 moved from some starting position to a left prediction at t = 2.31 s, then confirmed their score at t = 3.82 s to end recording.

surement time and when the response triangle was first displayed. Recordings continue until the participant presses the confirm button. The method for saving measurements is illustrated in Table 1.

2.7. Data preprocessing

During some responses, participants would choose their final prediction score but then wait to confirm their score due to some distraction. This resulted in a significant increase in the total time required to respond to this scenario. To mitigate the impact of these outliers on the statistical data, any measurement samples with the same final score 10 seconds after the final score was chosen would be truncated, and the response confirming sample would be overwritten to reflect the final score 10 seconds after it was decided. Out of all recorded scenarios, 19 outliers were identified. The truncation method significantly reduces the number of redundant measurement samples, but could cause a sudden jump in mouse positions. During most distractions, the participant would have their hand off the mouse with the cursor near the confirm button; therefore, this potential jump is justifiable to reduce the redundant measurement samples.

2.8. Metrics for analysis

The final prediction score, response entropy and response duration will all be grouped by the IVs for analysis. The trend between variables will indicate the importance of each variable in predicting the direction and confidence in the prediction. The response duration is the time between the response triangle shown on screen and the participant confirming their prediction.

Response entropy is a simple measure of confidence in one's score. The entropy ranges from 0: a fully confident choice (100% in any direction), to 1: complete uniform uncertainty (33.3% in all directions). Any response with an entropy value below 0.4, approximately equal to a prediction of 85% in any direction, will be considered a confident response. All entropy was calculated using the Shannon entropy:

$$H = -\sum_i p_i \log_2(p_i) \tag{1}$$

2.9. Statistical analysis

Mixed-effect (ME) models were used to analyse the influence of the observed vehicle variables (see Section 2.3) on the final prediction score, response entropy and response duration. The ME models were implemented using the Python package statsmodels linear mixed effect model [18].

Standard linear analysis models could not be used to model the prediction score, as the score is multidimensional and interdependent on a total score of 100%. The additive log-ratio (alr) transformation was applied to the scores to create log ratios between left/forward and right/forward, which can be analysed with two separate ME models. Analysis was done relative to forward, as unless the driver takes another action, any vehicle driving over an intersection will continue straight through it. The magnitude of the coefficients reflects the influence of conditions on the log-ratios; larger magnitudes indicate that left or right predictions become more likely compared to forward predictions, depending on the model.

As the variables are all categorical, the values are compared to a reference scenario. The chosen scenario involves the ego vehicle following, with a 0° heading angle, blinkers off, hard deceleration, and a left lateral offset.

The null hypothesis used in analysis is that "variable value X does not affect the outcome". Therefore, any obtained p-values above 0.1 have no evidence against the null hypothesis, and any p-values less than 0.001 provide strong evidence against the null hypothesis, meaning that variable value X strongly influences the prediction score, entropy or response duration compared to the reference scenario.

The standard ME models look into the average effect caused by a change in variable value across all values of the other variables. The model with interaction effects included examines the impact of one variable compared to the chosen baseline scenario, which is a combination of variables. In this study, both models are created and used in the analysis of prediction score and response entropy. Analysis of response duration will only include the standard ME model.

2.10. Modelling responses

Random Forest Regressors (RFRs) were used to replicate the prediction responses based on the observed vehicle variables. The RFRs were implemented with version 1.6.1 of the scikit-learn Python package [19].

All prediction response data, with an 80/20 train/test split, was used to train and test the model. Max tree depths of 4 to 15 were tested for model accuracies and Mean Squared Error (MSE), see Table 9 in the Appendix. The model accuracy and MSE did not improve past a depth of 8. Therefore, a max depth of 8 is optimal to prevent overfitting on the data. Then, the RFRs were trained on all prediction responses, as well as on the data grouped by relative position. The obtained accuracies will be discussed.

3. Results

Before the experiments, it was hypothesised that participants mainly used blinkers as the most significant indicator of observed vehicle direction. The observed vehicle variables, grouped by score, response entropy, and response duration, can be seen in Figures 5, 6, and 7, respectively. Every graph visualises the difference in responses between observed vehicle variable values. The graph analysis is supported by statistical analysis of the categorical variables. The interaction effect of relative position and every other variable will also be discussed.

3.1. Prediction score grouped by observed vehicle variables

The prediction score was the participant's response during the experiment, representing their observed vehicle direction prediction. Figure 5 shows boxplots of all obtained responses grouped by the variables. Table 2 presents the ME model results, while Tables 6 and 7 in the Appendix provide the interaction effect results. Given that the direction predictions are interdependent, the interquartile range (IQR) will mainly be analysed for response consistency. Large IQRs, spanning from 0% to 100%, could suggest that the majority confidently predict that the vehicle will (100%) or won't (0%) continue in this specific direction. Similarly, narrow IQRs, spanning from 60% to 100%, for example, suggest consistent predictions among participants in this direction. Trends between variables reveal potential reasons for participants predicting in the chosen direction when predicting another vehicle's direction at an intersection.

3.1.1. Relative Position

The relative position had a significant influence on the prediction responses. As per Figure 5a, when the observed vehicle was followed or opposite, most of the direction predictions were to the left or right. The large IQRs show that participants often predicted fully in one direction. However, when the observed vehicle was left or right, the majority of predictions were forward.

The narrow IQRs for left and right predictions when the observed vehicle was left or right of the ego vehicle suggest consistent prediction responses. For the left scenarios, the IQR for left predictions was [2.8%, 33.5%] (=30.6%), and for the right scenarios, the IQR for left predictions was [2.9%, 36.3%] (=33.4%) and for right predictions was [3.5%, 33.3%] (=29.9%). Implying that participants were unsure at best or confident that the observed vehicle would not go left or right. Only when the observed vehicle was left, right predictions had an IQR of [4.1%, 65.2%] (=61.1%), suggesting participants predicted the observed vehicle would most likely turn towards them.

When the ego vehicle was positioned left or right of the observed vehicle, the predictions for left and right turns decreased significantly.

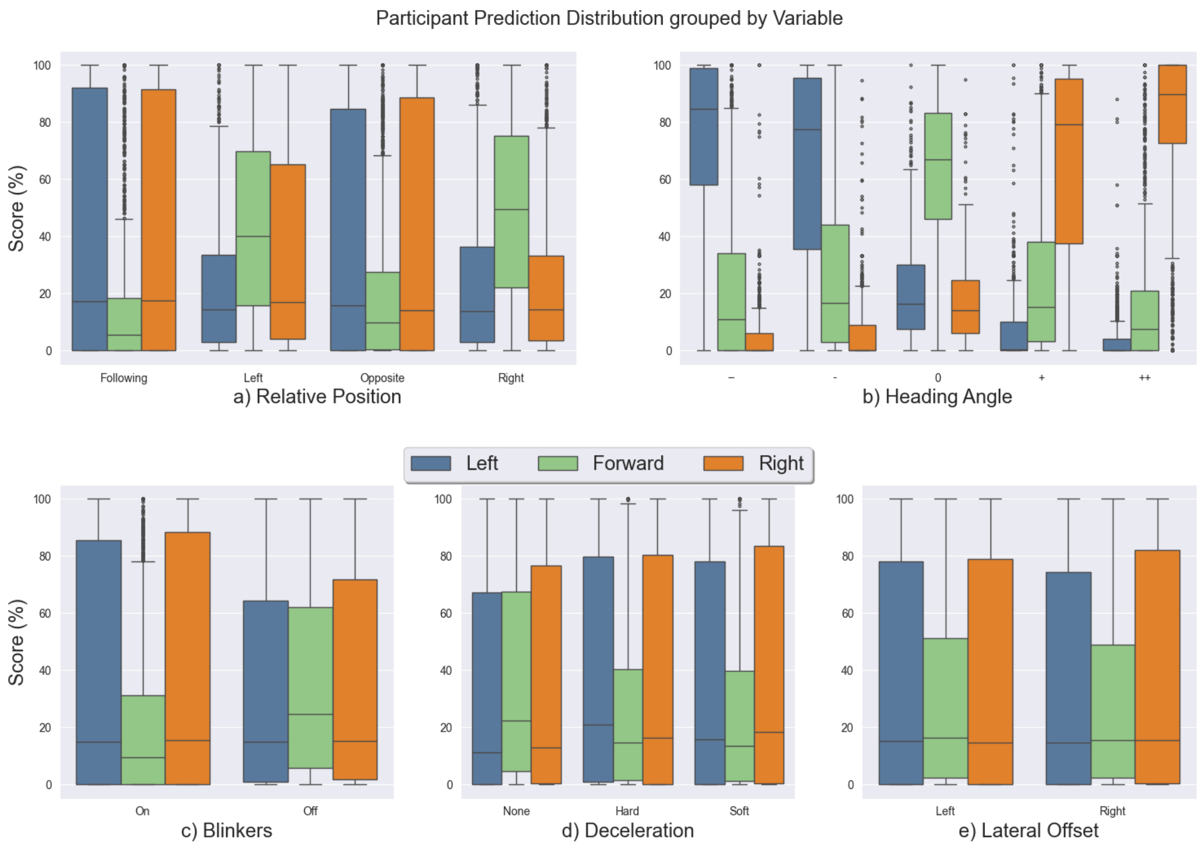

Figure 5. Scores grouped by variable, discussed in Section 3.1. The prediction score is an array of percentages ranging from 0 to 100 for left/forward/right, quantifying the prediction of the observed vehicle direction directly after the shown scenario.

This is confirmed by the ME models in Table 2. The significant negative coefficients (-4.990, -5.605, -4.306, and -5.864, all with $p < 0.001$) when the observed vehicle was left or right of the ego vehicle suggest a significant decrease in left and right predictions compared to forward predictions; forward predictions were more likely when all other variables were constant. This is most likely due to the other variable changes being harder to see when the observed vehicle was left or right of the ego vehicle at the intersection. This claim will be assessed through the interaction effect between the relative position and all other variables in the following subsections.

3.1.2. Heading Angle

Participants generally relied on the heading angle when predicting a direction as per Figure 5b. The left and right prediction scores follow similar mirrored sigmoid functions when compared to the heading angle.

For left predictions, the IQR decreased from [58.1%, 99.1%] (=40.9%) to [35.6%, 95.6%] (=59.9%), [7.6%, 30.0%] (=22.4%), [0.0, 9.9%] (=9.9%) and [0.0%, 4.2%] (=4.2%) from -10° to -5°, 0°, +5°, and +10° respectively. The ME model also reflects this trend in the left/forward predictions in Table 2. The negative (left) heading angles have large positive coefficients: 7.352 and 5.968 for -10° and -5°, thus significantly increasing the left predictions, whereas the positive heading angles have large negative coefficients: -4.675 and -5.038 for -5° and -10°, decreasing the left predictions.

The trend is mirror for right predictions, the IQR decreased from [72.6%, 100%] (=27.4%) to [37.5%, 95.3%] (=57.8%), [6.1%, 24.6%] (=18.5%), [0.0%, 9.9%] (=9.9%) and [0.0%, 6.0%] (=6.0%) from +10° to +5°, 0°, -5°, and -10° respectively. Again, this trend is confirmed by the ME model results for right/forward predictions in Table 2. The positive (right) heading angles have significant positive coefficients: 7.134 and 9.881 for +5° and +10°, thus significantly increasing the right predictions, whereas the negative head-

	Model for log(p_left/p_forward)						Model for log(p_right/p_forward)					
	Coef.	**Std.Err.**	**z**	**P>|z|**	**[0.025,**	**0.975]**	**Coef.**	**Std.Err.**	**z**	**P>|z|**	**[0.025,**	**0.975]**
Intercept	1.534	0.791	1.939	0.053	-0.017	3.085	0.033	0.696	0.047	0.962	-1.330	1.396
Rel.Position:Left	-4.990	0.611	-8.170	3.1e-16	-6.187	-3.793	-4.306	0.543	-7.929	2.2e-15	-5.370	-3.241
Rel.Position:Oppo	-2.131	0.566	-3.767	1.7e-4	-3.240	-1.022	-2.191	0.495	-4.423	9.7e-6	-3.161	-1.220
Rel.Position:Right	-5.605	0.608	-9.211	3.2e-20	-6.797	-4.412	-5.864	0.541	-10.844	2.1e-27	-6.924	-4.804
Head.Angle:-10	7.352	0.792	9.286	1.6e-20	5.800	8.904	-3.949	0.697	-5.644	1.5e-8	-5.315	-2.582
Head.Angle:-5	5.968	0.793	7.522	5.4e-14	4.413	7.524	-4.242	0.700	-6.053	1.3e-9	-5.613	-2.870
Head.Angle:+5	-4.675	0.791	-5.912	3.4e-9	-6.225	-3.125	7.134	0.697	10.234	1.4e-24	5.768	8.501
Head.Angle:+10	-5.038	0.791	-6.372	1.9e-10	-6.587	-3.488	9.881	0.697	14.185	1.1e-45	8.516	11.246
Deceleration:None	-2.471	0.524	-4.712	2.5e-6	-3.499	-1.443	-1.363	0.464	-2.938	0.003	-2.273	-0.454
Deceleration:Soft	-0.626	0.522	-1.199	0.231	-1.649	0.397	0.205	0.462	0.444	0.657	-0.700	1.111
Blinkers:On	1.500	0.456	3.288	0.001	0.606	2.395	1.060	0.405	2.619	0.009	0.267	1.853
Lat.Offset:Right	-0.374	0.427	-0.876	0.381	-1.210	0.462	-0.206	0.378	-0.545	0.586	-0.947	0.535
Group Var	5.695	0.111					3.604	0.085				

Table 2. Mixed effects model coefficients and 95% confidence intervals for variable effect on prediction score, discussed in Section 3.1. Statistical analysis of categorical variables relative to the reference scenario. Two separate models are required for the interdependent score as mentioned in Section 2.9.

ing angles have significant negative coefficients: -3.949 and -4.242 for -10° and -5°, decreasing the right predictions.

The forward predictions follow a Gaussian-like distribution around the 0° heading angle. The IQR was greatest at [46.2%, 83.1%] (=36.9%) at 0°, then decreased to [2.9%, 44.2%] (=41.2%), [3.1%, 38.0%] (=34.9%), [0.0%, 34.0%] (=34.0%) and [0.0%, 21.0%] (=21.0%) for -5°, +5°, -10°, and +10° respectively. Notably, left predictions were slightly greater than right predictions for the 0° heading angle. This matches expectations as left turns are feasible for longer compared to right turns when any vehicle approaches an intersection. The ME models in Table 2 show that the smaller heading angles have less influence on making a left or right prediction over a forward prediction, given the smaller magnitude of the coefficients compared to the larger heading angles.

The interaction effect between the relative positions and the heading angle in Tables 6 and 7 confirms the prior claim that participants often missed changes in the other variables when left or right of the observed vehicle. The large left (-10°) heading angle, when compared to the reference scenario (notably following with a 0° heading angle), has a significant influence on left predictions: left/forward predictions increased by 10.710 ($p < 0.001$). However, when the observed vehicle is left and the same large left heading angle is shown, the left/forward predictions decreased by 7.628 ($p < 0.001$). Similarly, large right heading angles compared to the reference scenario increased right/forward predictions by 10.830 ($p < 0.001$), but with a right relative position, the right/forward predictions decreased by 7.378 ($p < 0.001$). Suggesting that heading angles turning away from the ego vehicle were rarely spotted, resulting in lower prediction scores in the same direction as the heading angle. This is also true for the observed vehicle turning towards the ego vehicle: when the observed vehicle was right with a large left heading angle, the left/forward predictions decreased by 6.409 ($p < 0.001$), a significant decrease in left predictions. When the observed vehicle was left with a large right heading angle, the results were not statistically significant ($p = 0.234$). Overall, participants relied less on the heading angle when making predictions about the vehicle's direction when it was left or right of them.

When the observed vehicle was opposite the ego vehicle, the left and right predictions decreased compared to the following scenario, however, not as significantly as in the left or right scenarios. When the observed vehicle was positioned opposite and showed a large left heading angle, the left/forward predictions decreased by 0.340 ($p = 0.804$) compared to the following scenario; however, this difference was not statistically significant. Similarly, when shown a large right heading angle, the right/forward predictions increased by 1.543 ($p = 0.228$), but again, this was not statistically significant.

3.1.3. Blinkers

Blinkers were a significant indicator for predicting direction; however, a greater influence on predicted direction was expected. With blinkers on, participants predicted the observed vehicle to go left or right more often than when the blinkers were off, as reflected by the coefficients in 2: 1.500 ($p = 0.001$) for left/forward predictions and 1.060 ($p = 0.009$) for right/forward predictions, suggesting blinkers have a statistically significant influence on the predicted direction but less so compared to heading angle and relative position. Furthermore, the IQRs in Figure 5c visualise the difference in predictions with blinkers on and off. When the blinkers were on, left predictions had an IQR of [0.0%, 85.4%] (= 85.4%), and right predictions had an IQR of [0.0%, 88.4%] (= 88.4%). The large range is expected as a majority of left predictions have an insignificant right prediction, and vice versa. The IQRs of all directions with the blinkers turned off are all approximately equal at 60%, suggesting nearly equal direction predictions despite the other changes in observed vehicle variables.

Blinkers should have had a larger influence on predictions; however, the participants could not always see the blinkers, replicating real driving scenarios. For example, when the observed vehicle is to the right of the ego vehicle and wants to turn right, the right blinker may not always be spotted. The decreased influence of blinkers when the ego vehicle was not following the observed vehicle is proven by the interaction effect between blinkers and the relative positions in Tables 6 and 7. Left, Opposite and Right relative positions all had less left/forward and right/forward predictions as per the negative coefficients, notably in the exact aforementioned scenarios where the blinker is away from the ego vehicle: -3.822 ($p < 0.001$) when left regarding left/forward prediction and -3.730 ($p < 0.001$) when right regarding right/forward predictions. Furthermore, opposite scenarios showed a statistically significant decrease in both left/forward and right/forward predictions with coefficients: -2.631 ($p = 0.001$) and -2.473 ($p < 0.001$). All this behaviour is most likely due to the limited screen resolution in the experiment and visibility of the blinkers in the Carla simulation. Reducing the potential impact of blinkers on prediction scores.

3.1.4. Deceleration

The only significant influence deceleration had on the prediction score was whether the observed vehicle decelerated. Participants predicted forward more when the observed vehicle did not decelerate compared to when it showed hard or soft deceleration, resulting in more left or right predictions. This is shown in Figure 5d and Table 2. The score distributions for hard and soft deceleration are nearly identical, suggesting insufficient difference between the two types of deceleration. No deceleration showed an increase in forward predictions and a slight decrease in left/right predictions. The negative coefficients of left/forward: -2.471 ($p < 0.001$) and right/forward: -1.363 ($p = 0.003$) show the increase in forward predictions. Soft deceleration had no statistically significant difference on the prediction score.

The interaction effect between relative position and deceleration had no statistically significant influence, given all interactions had a p-value greater than 0.05.

3.1.5. Lateral Offset

Lateral offset had no statistically significant influence on scores, and the distributions in Figure 5 appear identical.

Lateral offset could have been used as an indication of turning behaviour if the prediction was tested at different times leading up to the turning point, freezing the scenario at 4.0, 4.5 and 5.0 seconds, for example. Within this study's experiment, participants rarely noticed the difference between the lateral offsets or ignored it when seeing changes in the other variables at the end of the scenario.

3.2. Response entropy grouped by observed vehicle variables

Response entropy is a measure of participants' confidence in their predictions. Figure 6 shows violin plots of all response entropies grouped by the variables. Table 3 is the ME model results, and Table 8 in the Appendix is the interaction effect results. Violin plots with wide bases and narrow tips suggest many confident responses, near 100% in any direction, for the given group. Broad middle areas suggest less confident responses, with an average of 75% in one direction. Trends between variables reveal variable influence on the prediction confidence of another vehicle's direction at an intersection.

	Coef.	Std.Err.	z	P>|z|	[0.025,	0.975]
Intercept	0.522	0.025	20.839	1.9e-96	0.473	0.572
Rel.Position:Left	0.241	0.019	12.526	5.4e-36	0.203	0.278
Rel.Position:Oppo	0.052	0.018	2.868	0.004	0.016	0.087
Rel.Position:Right	0.258	0.019	13.443	3.4e-41	0.220	0.295
Head.Angle:-10	-0.221	0.025	-8.822	1.1e-18	-0.270	-0.172
Head.Angle:-5	-0.154	0.025	-6.154	7.5e-10	-0.204	-0.105
Head.Angle:+5	-0.152	0.025	-6.092	1.1e-9	-0.201	-0.103
Head.Angle:+10	-0.264	0.025	-10.546	5.3e-26	-0.313	-0.215
Deceleration:None	-0.024	0.017	-1.474	0.140	-0.057	0.008
Deceleration:Soft	-0.014	0.016	-0.873	0.383	-0.047	0.018
Blinkers:On	-0.061	0.014	-4.227	2.4e-5	-0.089	-0.033
Lat.Offset:Right	0.002	0.013	0.138	0.890	-0.025	0.028
Group Var	0.006	0.004				

Table 3. Mixed effects model coefficients and 95% confidence intervals for variable effect on response entropy, discussed in Section 3.2. Statistical analysis of categorical variables relative to the reference scenario. Same notation as in Table 2.

3.2.1. Relative Position

Compared to when the observed vehicle was followed by the ego vehicle, all other observed vehicle relative positions significantly increased the entropy and thus decreased response confidence. In Figure 6a, the distribution for all following scenarios is widest at the base, with a narrow middle and narrower peak, suggesting a majority of low-entropy, high-confidence responses. Similarly, the opposite scenarios had a majority of confident responses, being widest at the base, but the middle and peak were wider compared to the following scenarios. This is reflected in the increase in response entropy, with a coefficient of 0.052 ($p = 0.004$) in Table 3; overall, the opposite scenarios had higher entropy values compared to the following scenarios.

The entropy distributions for the left and right scenarios showed very few low-entropy responses, with a majority of responses around an entropy of 0.6, roughly representing a [50%, 50%, 0%] response. The higher entropy values are confirmed by the coefficients in Table 3: 0.241 ($p < 0.001$) for left scenarios and 0.258 ($p < 0.001$) for right scenarios. Overall, predictions are more uncertain when the vehicle isn't directly in front of the participant.

3.2.2. Heading Angle

The Gaussian-like distribution present in forward predictions in Figure 5b is also present in the response entropy distributions when grouped by heading angle: the distributions for the larger ±10° heading angles are widest near 0 entropy, indicating a higher concentration of confident responses, then as the heading angle decreases in magnitude so does the concentration of confident responses. The narrow tips, when shown a non-zero heading angle, exhibit few completely unsure responses, which supports the prior claim that predictions rely on the heading angle shown. Furthermore, the distribution for the 0° heading angle is widest at the peak with a narrow base. When no heading angle was shown, participants were rarely fully confident in making a prediction 100% in one direction, regardless of the other variables. This is further reflected in Table 3, where all heading angles significantly decrease the entropy. When shown the -10° heading angle (−−), on average, participants responded with an entropy of 0.301, corresponding to 90% in one direction, most likely left in this example. Whereas, when shown no heading angle, participants, on average, responded with an entropy of 0.522, corresponding to 75% in one direction. The shown heading angles significantly influence the response entropy and, consequently, the prediction confidence.

3.2.3. Blinkers

Blinkers contributed significantly to the response entropy distribution. The response entropy distribution in Figure 6c with blinkers on is widest at the base, mainly suggesting confident responses, 100% in one direction.

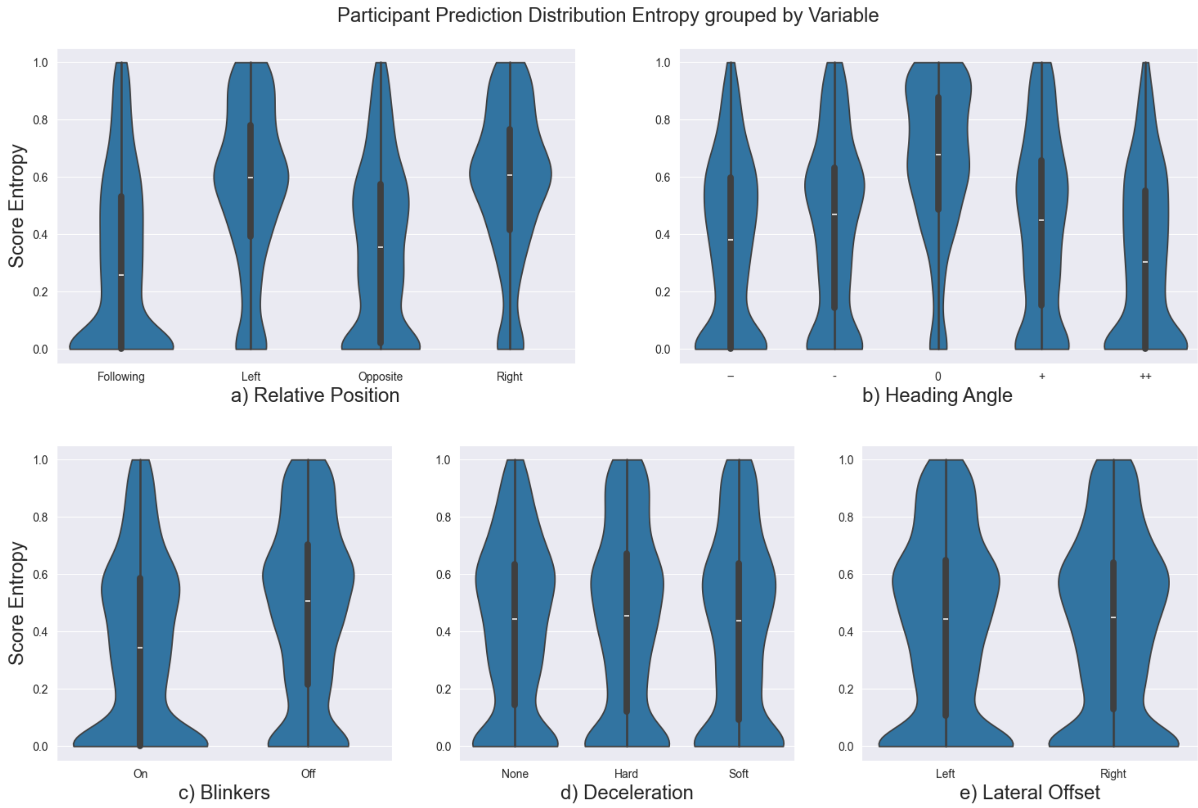

Figure 6. Response entropy grouped by variable, discussed in Section 3.2. Entropy ranges from 0 (fully confident) to 1 (complete uniform uncertainty).

The distribution of predictions when no blinkers were shown is widest near the top half, suggesting more uncertainty in the prediction responses. Table 3 confirms that blinkers in general decrease the response entropy with a coefficient of -0.061 ($p < 0.01$). However, when the observed vehicle was not followed, the effect of blinkers was weaker, as shown by the positive interaction effect coefficients in Table 8: 0.096 ($p = 0.003$), 0.093 ($p = 0.002$) and 0.085 ($p = 0.009$). Further emphasising that blinkers were often missed by participants when the observed vehicle was left/opposite/right of the ego vehicle.

3.2.4. Deceleration

Although the prediction score showed different distributions in Figure 5d, the entropy distributions are similar for all forms of deceleration, revealing insufficient change in prediction confidence based solely on the deceleration shown. The entropy distributions in response to scenarios with hard and soft deceleration were virtually identical, reinforcing the prior comment about a lack of difference between the types of deceleration shown during the experiment. No significant difference in response entropy was found when considering the different relative positions, with all p-values greater than 0.05.

3.2.5. Lateral Offset

There was no significant difference in response entropy when shown different lateral offsets, suggesting no change in prediction confidence. The distributions in Figure 6e are nearly identical, and the change in lateral offset had no significant influence ($p = 0.890$) on the response entropy in Table 3.

3.3. Response duration grouped by observed vehicle variables

The response duration is the time between the video scenario ending and the participant confirming their prediction. Figure 7 shows violin plots of all response durations grouped by the variables. Table 4 is the ME model results. Notably, the initial ME model failed to converge. Therefore, the heading angles had to be simplified to left, zero, and right to reduce model complexity. Furthermore, the interaction effect was removed to ensure model convergence and to facilitate the interpretation of the impact of the different variables on response duration.

In general, short response durations may suggest decisive responses; conversely, longer responses may suggest hesitation. Trends between variables reveal potential reasons for participants' hesitation when predicting the direction of another vehicle at an intersection.

	Coef.	Std.Err.	z	P>|z|	[0.025,	0.975]
Intercept	3.872	0.194	19.92	2.97e-88	3.491	4.253
Rel.Position:Left	0.577	0.154	3.74	1.9e-4	0.275	0.880
Rel.Position:Oppo	0.431	0.138	3.14	1.7e-3	0.162	0.701
Rel.Position:Right	0.466	0.154	3.03	2.5e-3	0.164	0.767
Head.Angle:Left	-0.200	0.178	-1.13	0.26	-0.549	0.149
Head.Angle:Right	-0.321	0.178	-1.80	0.071	-0.670	0.028
Deceleration:None	0.067	0.131	0.51	0.61	-0.189	0.323
Deceleration:Soft	0.050	0.130	0.38	0.70	-0.206	0.306
Blinkers:On	-0.170	0.114	-1.49	0.14	-0.394	0.054
Lat.Offset:Right	-0.041	0.107	-0.39	0.70	-0.250	0.167
Group Variance	0.169	0.036				

Table 4. Mixed effects model coefficients and 95% confidence intervals for variable effect on response duration, discussed in Section 3.3. Statistical analysis of categorical variables relative to the reference scenario. Heading angles are reduced to left and right to allow for model convergence.

The relative position is the only variable with a statistically significant influence on the response duration. Compared to the following scenarios, all other relative positions resulted in an average longer response duration. Left scenarios increased the response duration by 0.577 seconds (p = 1.9e-4), right scenarios increased the response duration by 0.466 seconds (p = 2.5e-3), and opposite scenarios increased the response duration by 0.431 seconds (p = 1.7e-3). A potential reason for this could be the complexity of interactions required between the participant and the observed vehicle. Within the created scenarios, when following, regardless of the decision made by the other vehicle, the ego vehicle driver only needs to ensure that they maintain a safe distance from the other vehicle. When the observed vehicle approached the intersection from any other position, the participant had to consider more possible actions. Will the other driver's path intersect with the ego's path, requiring the participant to avoid a collision? Will the other driver stop and let them pass? Will the other driver try to go over the intersection before the ego vehicle? Interestingly, the left scenarios increase the response duration the most, possibly because the participant expected to be given priority by the other driver, but then the observed driving behaviour conflicted with the participant's expected behaviour.

3.4. Response modelling

The RFR aims to replicate the prediction responses based on each unique combination of observed vehicle variables per scenario. The final model consisted of 100 decision trees in the random forest, with a maximum depth of 8. The model obtained an accuracy of 70.9% and an MSE of 352.1. Figure 16 includes a visualisation of truncated tree 0 from the final model. The decision trees created or a similar decision flow chart could be implemented into the prediction module of a cognitive human model to replicate human prediction responses for an observed vehicle approaching an intersection.

The model's feature importance [20] in Figure 8 aligns with prior analysis. The decisions are replicated using the heading angle and relative position, and then refined using the remaining variables to best replicate the responses shown during each scenario.

The RFR model was trained on all prediction samples obtained during the experiments. The same parameters were used to train and test the RFR model on the data grouped per relative position. Table 5 includes the number of samples, accuracy and MSE of each model. All models, except the one trained on the following dataset only, perform worse than the model trained on the entire dataset. The following dataset includes most prediction responses with 0 entropy, 100% in one direction, and therefore the easiest to replicate. The model trained on opposite scenarios achieved results similar to those of the model trained on the entire dataset. However, the models trained only on left and right scenarios perform significantly worse. This is most likely due to a combination of low training sample size and inconsistent responses, resulting in the models being unable to replicate the human prediction

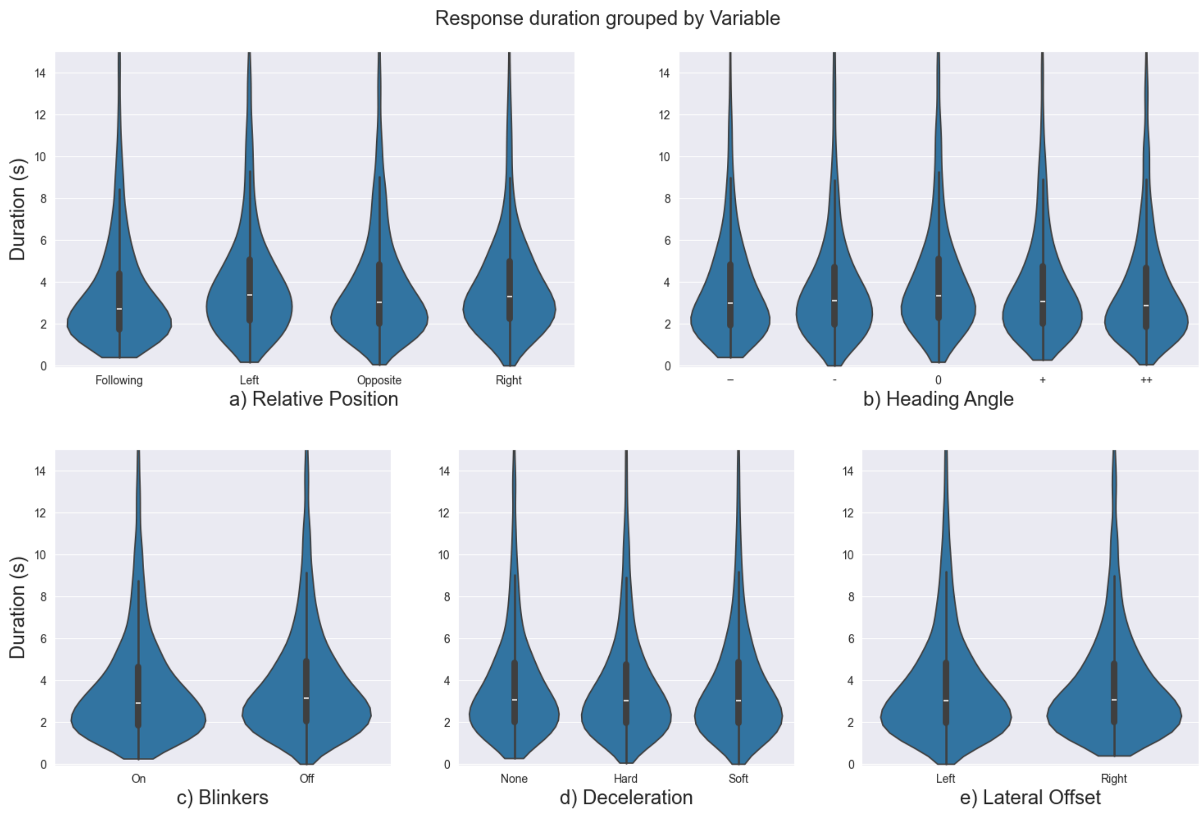

Figure 7. Response duration grouped by variable, discussed in Section 3.3. Plots truncated to [-0.05, 15.05] to better visualise the differences between distributions.

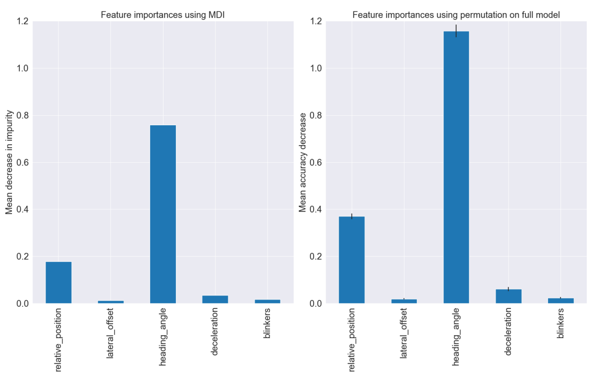

Figure 8. RFRs feature importance plotted based on mean decrease in impurity and permutation on full model. Relative position, lateral offset, heading angle, deceleration and blinkers are respectively on the x-axes.

	# Samples	Accuracy (%)	MSE
All	4948	70.9	352.1
Following	1543	69.2	271.5
Left	925	51.6	397.8
Opposite	1537	66.8	375.2
Right	943	35.9	593.8

Table 5. RFR model samples, accuracy and MSE.

responses.

4. Discussion

From this study, it can be concluded that the relative position and heading angle of the observed vehicle had the most significant influence on the predictions. The heading angle was consistent with the predicted direction scores in the same direction. When the observed vehicle was left or right of the ego vehicle, participants, on average, predicted the car to continue forward more than when the vehicle was following or opposite. When the observed car did not decelerate, on average, participants predicted forward more often than with the other two forms of deceleration shown. Blinkers resulted in more left and right predictions, but not as significantly as expected. Lastly, lateral offset had no significant influence on the predicted direction. The prediction confidence followed similar trends between the variables; the heading angle and relative position had the most significant influence on the prediction confidence, followed by blinkers and whether the observed car decelerated. The relative position was the only variable with a statistically significant influence on the response duration. Any position not following, on average, increased response duration.

This study contributes to a deeper understanding of how humans form predictions about other vehicles at intersections, an essential aspect of traffic behaviour modelling for safe human-automated vehicle (AV) interactions that was previously underexplored. This study obtained 4948 human prediction responses to simulation-based intersection scenarios. Through analysis of responses to various cues, such as blinkers, deceleration, and vehicle positioning, the findings clarified which variables had the most decisive influence on prediction scores, confidence, and response duration. Furthermore, the responses to the shown scenarios quantify how humans predict the intended direction of another vehicle approaching an intersection. Intersection traffic scenarios in the real world are too complex to be described by binary direction predictions. This study demonstrated that predictions are rarely 100% or 0% in one direction. Human drivers constantly anticipate the behaviour of others and are wary of potentially dangerous scenarios. This knowledge can be applied when designing cognitively plausible traffic agents for use in AV testing simulation environments. Traffic agents' prediction modules, trained on the responses collected during this study, can better replicate human-like limitations in perception and predictions, such as the low confidence in predictions when drivers encounter ambiguous cues from other drivers at intersections. This brings testing environments closer to real-world complexity and ultimately enables more robust evaluation of AV behaviour in shared spaces. Beyond testing in simulation, the results highlight the role of AVs and ADAS in compensating for, or at least being aware of, human prediction errors. Signalling strategies or motion planning that communicate intent support safer and more intuitive interactions between autonomous and human-driven vehicles. By exploring how different cues influence prediction, this study fills a key gap in current models of human traffic behaviour.

Prior studies on human behaviour prediction in traffic agree with the findings in this study. Hamilton et al. [12] reported that human observers are generally very good at predicting a vehicle's turn intent at close range, with 90% accuracy when a car is within 0–20m of the intersection, falling to around 70% at 30–50m. Crucially, they found that explicit blinkers were "the most important cue" in these judgments. In this study, it was also observed that participants relied on blinkers when confidently predicting a vehicle to turn, which aligns closely with Hamilton's results. Although this study had no correct responses, as the videos never continued past the point when a response was requested, the decrease in accuracy at larger distances can be correlated with the reduction in confidence when participants in this study made predictions for non-following relative positions. When the observed vehicle was left/opposite/right of the ego vehicle at the intersection, the response entropy and response duration increased. Both studies agree that observed vehicles with blinkers on strongly disambiguates the driver's intent, whereas a decrease in response confidence was shown when blinkers were off or distant. This consistency reinforces the idea that explicit direction communication through blinkers is a primary factor in predicting a driver's intended direction.

Other researchers have emphasised lateral motion cues to communicate intended behaviour. Sripada et al. [7] showed that pedestrians use a vehicle's lateral deviation within the lane as an implicit signal of yielding: an AV steering toward the pedestrian to indicate yielding was found to be intuitive and highly effective. In a different context, Miller et al. [9] presented drivers with two vehicles meeting at a bottleneck, varying each vehicle's lateral (toward centre or edge) and longitudinal (speed changes) behaviour. They found that lateral shifts were interpreted the fastest and most distinctly, and that people required less time to infer intent from lateral movement than from longitudinal cues. Although the contexts differ between the studies, parallels can be drawn between lateral motion cues and their influence on human predictions. However, the results of this study do not agree with these findings: lateral offset had no significant influence on the responses. During the experiment, participants often verbally made predictions before the entire video was shown. Scenarios without blinkers shown were frequently ambiguous until the heading angle was revealed at the end of the video. The lateral lane position of the observed vehicle influenced the early predicted directions; however, as soon as the heading angle was revealed, the lateral offset was disregarded in favour of relying on the heading angle for predicting the intended direction. The conflict between lateral offset and other cues was also noted by Sripada et al. and Miller et al., resulting in less response confidence. If responses were taken over the entire video duration during this study, then lateral offset could have had a significant influence on the predicted directions.

Deceleration and braking patterns have also been identified as communicative cues. Miller et al. [9] reported that purely longitudinal manoeuvres (decelerating, stopping, or maintaining speed) were generally less decisive than lateral ones. Tian et al. [8] examined pedestrian crossing decisions and similarly found that people aligned their behaviour with the observed deceleration: pedestrians recognised different braking profiles and chose crossings accordingly. They further observed that pedestrians crossed earlier and judged yielding more accurately when braking started early rather than late. Although both these studies examined yielding behaviour, their findings broadly align with those of this study. Whether the observed vehicle decelerated or not had a significant influence on the predicted direction, but not as significantly for the response entropy or duration. Deceleration can signal intent, but humans cannot rely solely on it for confident predictions of intended direction, such as when using blinkers or significant changes in heading angle.

Finally, several studies note human limitations even when cues are present. Werneke and Vollrath [10] demonstrated that drivers often overlook parts of the intersection scene, resulting in missed information and increased crash risk. Colombo et al. [14] demonstrated that drivers systematically misjudge short-term trajectories of cyclists, implying cognitive biases in prediction. These studies focus on various aspects of human prediction in traffic, but they reinforce a common theme: humans often fail to predict others' motions accurately. Although this study does not examine prediction accuracy, the decrease in response confidence when presented with ambiguous scenarios compared to scenarios with explicit direction cues (such as blinkers or large heading angles) can be related to the prediction errors reported by Werkene and Vollrath or Colombo et al.

Despite the contribution made within this study, several limitations constrain the extent to which this study fully understands how humans make predictions about other vehicles at intersections. While the experimental setup was made to replicate realistic driving situations, certain decisions inherently constrain the participants. These design choices may have introduced biases or limitations to the results. The decision was made to maintain a constant perspective during the experiment; participants were unable to look around the scenario to scan for additional information. Although the cognitive load when giving responses was low during this experiment, a similar experiment in virtual reality (VR) with a steering wheel would allow participants to scan the scenario as they would when driving in the real world, thereby obtaining more realistic prediction data. The results showed low prediction confidence when the observed vehicle was left or right of the observer. This is most likely due to the ego vehicle frame partially blocking the observed vehicle when it approached from the left, adding reasonable doubt that not all intended direction cues were spotted, possibly causing the participants to predict differently if they had seen the deceleration or blinkers, for example. If the experiment had been conducted in VR, participants could have looked around the frame to observe the other vehicle more clearly.

The consistent scenarios allowed for testing of a large quantity of unique variable combinations. However, the simple scenarios enabled the participants to focus solely on the observed vehicle at the intersection. When humans drive towards an intersection in the real world, they must remain vigilant of their position on the road, the road structure, multiple other traffic participants, and potentially more [21, 22]. Moreover, even though the observed vehicle always reached the intersection before the ego vehicle, priority rules at intersections could have decreased confidence in participant predictions. In most right-hand-side driving European countries, a "right before left" priority rule exists for intersections. When the observed vehicle approached from the left, the driver should expect the observed vehicle to slow down and give priority to the driver; however, this was not always the case during the experiment, causing conflicts between expectation and reality, leading to more "unsure" predictions. Creating an experiment with defined traffic scenarios, rather than focusing on a large, unique variable space, could provide more insight into human predictions at an intersection.

The observed vehicle variables were designed to be consistent, allowing for the creation of unique scenarios by combining changes in variables; however, the specific changes in variable values may have influenced the representativeness of the results across broader traffic scenarios. Some effects may be dependent on how the variables were defined. Analysis of responses showed that the heading angle of the observed vehicle had the most significant influence on prediction direction. The decision was always to show approximately 5 seconds of video before the scenario froze and the participant could respond. The obtained heading angle results could be interpolated to estimate how the predicted direction and confidence could change as the observed vehicle approaches the intersection. Researching a larger range of heading angles or trajectory durations, for prediction score confidence, could lead to a better understanding of human prediction of another traffic participant over time, which could then be considered in ADAS and AV system design. Furthermore, the lateral offset had no statistically significant influence on the responses; the lateral offset was a constant distance from the centre of the lane for the shown scenario, but had the lateral offset been a change over time from the centre of the lane to left or right, as what was done by Sripada et al [7], then it might've had a more significant influence on responses.

Furthermore, the methods of analysis used in this study focused solely on the final predicted score and response duration. The response triangle provides novel human responses for cognitive modelling by measuring the response trajectory. However, this study underanalysed the differences between participants and their response trajectories. Further analysis of the response trajectories could lead to a better understanding of differences between participants and the effect of the cues on the responses. For example, swift mouse movements to the final predicted score could suggest high response confidence, or large swings in direction could signify hesitation and thus low response confidence.

Another potential extension of this research will be to explore implicit driver-driver communication at an intersection. The effect of deceleration and lateral offset was analysed as a form of implicit communication of intended behaviour; however, no human driver was included in the observed vehicle during the experiment. Forms of implicit communication, such as eye contact or head movement, most likely increase the confidence humans have when predicting the direction another traffic participant would go at an intersection [13, 23].

By continuing the research through these insights, researchers and developers can create predictive systems and AV agents that are not only more human-like in behaviour but also more supportive of safe, coordinated interactions in complex, shared traffic environments.

5. Conclusion

This study aimed to discover the influence of differences in intended behaviour cues of another vehicle on human-predicted direction. Results show that the pose of the observed vehicle is the primary indicator for human prediction of the intended driving direction at an intersection. Participants of the experiment were able to consistently and confidently predict similar directions when the ego vehicle was following or opposite to the other vehicle, and were shown a $\pm 10°$ heading angle in either direction. However, struggled to give responses with similar confidence or consistency when no large heading angle was shown, or when the observed vehicle was left or right at the intersection. As autonomous technologies continue to be researched and developed, incorporating the human prediction patterns discovered in this study can support the creation of safer and more human-aware ADAS and AV systems.

Ethics Statement

This study was conducted with the consent of the TU Delft research ethics committee. The ethical approval was granted under the condition that the data protection regulations were adhered to. The participants provided their informed consent to participate in the study by signing the informed consent form before their participation.

Dataset

Sluimer, J., and Zgonnikov A., "Data underlying the MSc project: Human predictions of another vehicle at an intersection." 4TU.ResearchData, Jul. 16, 2025, doi: 10.4121/77747CFA-F219-4211-AA77-80F7D75CA017.V1.

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References

[1] Bundesamt, S., "Number of deaths in road traffic accidents in Germany from 1950 to 2023 [Graph]," , 2023. URL `https://www-statista-com.tudelft.idm.oclc.org/statistics/1331134/road-traffic-fatalities-germany/`.

[2] Forum, I. T., "Germany: Road Safety Country Profile, 2021," , 2021. URL `https://www.itf-oecd.org/sites/default/files/germany-road-safety.pdf`.

[3] Stoler, B., Navarro, I., Jana, M., Hwang, S., Francis, J., and Oh, J., "SafeShift: Safety-Informed Distribution Shifts for Robust Trajectory Prediction in Autonomous Driving," , 2024. URL `https://arxiv.org/abs/2309.08889`.

[4] Gauthier, M., "Tesla's FSD Runs Over Child Mannequin, But It's Not To Blame," Carscoops, Jun. 13 2025. URL `https://www.carscoops.com/2025/06/teslas-fsd-botches-another-test-but-its-not-to-blame/`, online; accessed 2025.

[5] Lu, H., Zhu, M., Lu, C., Feng, S., Wang, X., Wang, Y., and Yang, H., "Empowering safer socially sensitive autonomous vehicles using human-plausible cognitive encoding," *Proceedings of the National Academy of Sciences*, Vol. 122, No. 21, 2025, p. e2401626122. doi: 10.1073/pnas.2401626122, URL `https://www.pnas.org/doi/abs/10.1073/pnas.2401626122`.

[6] Schumann, J. F., Srinivasan, A. R., Kober, J., Markkula, G., and Zgonnikov, A., "Using Models Based on Cognitive Theory to Predict Human Behavior in Traffic: A Case Study," , 2023. URL `https://arxiv.org/abs/2305.15187`.

[7] Sripada, A., Bazilinskyy, P., and de Winter, J., "Automated vehicles that communicate implicitly: Examining the use of lateral position within the lane," *Ergonomics*, Vol. 64, 2021, pp. 1–15. doi: 10.1080/00140139.2021.1925353.

[8] Tian, K., Tzigieras, A., Wei, C., Lee, Y. M., Holmes, C., Leonetti, M., Merat, N., Romano, R., and Markkula, G., "Deceleration Parameters as Implicit Communication Signals for Pedestrians' Crossing Decisions and Estimations of Automated Vehicle Behaviour," *Accident Analysis & Prevention*, Vol. 190, 2023, p. 107173. doi: 10.1016/j.aap.2023.107173, URL `https://www.sciencedirect.com/science/article/pii/S0001457523002208`.

[9] Miller, L., Leitner, J., Kraus, J., and Baumann, M., "Implicit intention communication as a design opportunity for automated vehicles: Understanding drivers' interpretation of vehicle trajectory at narrow passages," *Accident Analysis Prevention*, Vol. 173, 2022, p. 106691. doi: https://doi.org/10.1016/j.aap.2022.106691, URL `https://www.sciencedirect.com/science/article/pii/S0001457522001270`.

[10] Werneke, J., and Vollrath, M., "What does the driver look at? The influence of intersec-

tion characteristics on attention allocation and driving behavior," *Accident Analysis Prevention*, Vol. 45, 2012, pp. 610–619. doi: https://doi.org/10.1016/j.aap.2011.09.048, URL https://www.sciencedirect.com/science/article/pii/S0001457511002855.

[11] Zgonnikov, A., Abbink, D., and Markkula, G., "Should I Stay or Should I Go? Cognitive Modeling of Left-Turn Gap Acceptance Decisions in Human Drivers," *Human Factors*, Vol. 66, No. 5, 2024, pp. 1399–1413. doi: 10.1177/00187208221144561, URL https://doi.org/10.1177/00187208221144561, pMID: 36534014.

[12] Hamilton, A., Waterson, B., and Snell, I., "Human Perceptions of Vehicle Turning Intention: Overall Performance and Contributory Factors," *Transportation Research Record*, Vol. 2458, No. 1, 2014, pp. 8–15. doi: 10.3141/2458-02, URL https://doi.org/10.3141/2458-02.

[13] Hensch, A.-C., Beggiato, M., Schömann, M. X., and Krems, J. F., "Different Types, Different Speeds – The Effect of Interaction Partners and Encountering Speeds at Intersections on Drivers' Gap Acceptance as an Implicit Communication Signal in Automated Driving," *HCI in Mobility, Transport, and Automotive Systems*, edited by H. Krömker, Springer International Publishing, Cham, 2021, pp. 517–528.

[14] Colombo, A., Depaola, M., Ferrise, F., Dozio, N., and Rodrigues de Campos, G., "Predicting Mispredictions: A Model of Human Misjudgment About Vulnerable Road Users' Trajectories," *IEEE Transactions on Intelligent Transportation Systems*, Vol. 26, No. 1, 2025, pp. 157–168. doi: 10.1109/TITS.2024.3484004.

[15] CARLA Simulator Team, "CARLA Simulator 0.9.15 Release," , November 2023. URL https://carla.org/2023/11/10/release-0.9.15/, accessed: 2025-05-30.

[16] Epic Games, "Unreal Engine 4," , 2025. URL https://www.unrealengine.com/, accessed: 2025-05-30.

[17] cogniBIT Team, "driveBOT: Realistic AI-based Driver Model for Autonomous Vehicle Simulation," https://cognibit.de/drivebot/, 2025. Accessed: 2025-06-18.

[18] Perktold, J., Seabold, S., Taylor, J., and statsmodels developers, "Mixed linear model (MixedLM) [Software documentation]," , 2023. URL https://www.statsmodels.org/stable/generated/statsmodels.regression.mixed_linear_model.MixedLM.html, accessed: 2025-05-27.

[19] scikit-learn developers, 2025. URL https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html.

[20] scikit-learn developers, "Forest Importances Example," , 2025. URL https://scikit-learn.org/stable/auto_examples/ensemble/plot_forest_importances.html, accessed: 2025-06-07.

[21] Tice, P., Dey Tirtha, S., and Eluru, N., "Driver Attention And The Built Environment Initial, Findings From A Naturalistic Driving Study," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, Vol. 65, No. 1, 2021, pp. 1077–1081. doi: 10.1177/1071181321651271, URL https://doi.org/10.1177/1071181321651271.

[22] Choi, K., Byun, G., Kim, A., and Kim, Y., "Drivers' Visual Perception Quantification Using 3D Mobile Sensor Data for Road Safety," *Sensors*, Vol. 20, No. 10, 2020. doi: 10.3390/s20102763, URL https://www.mdpi.com/1424-8220/20/10/2763.

[23] Zhang, M., Dotzauer, M., and Schießl, C., "Analysis of Implicit Communication of Motorists and Cyclists in Intersection Using Video and Trajectory Data," *Frontiers in Psychology*, Vol. 13, 2022, p. 864488. doi: 10.3389/fpsyg.2022.864488, URL https://doi.org/10.3389/fpsyg.2022.864488.

Appendix

Observed vehicle relative positions

(a) Following (b) Opposite

(c) Left (d) Right

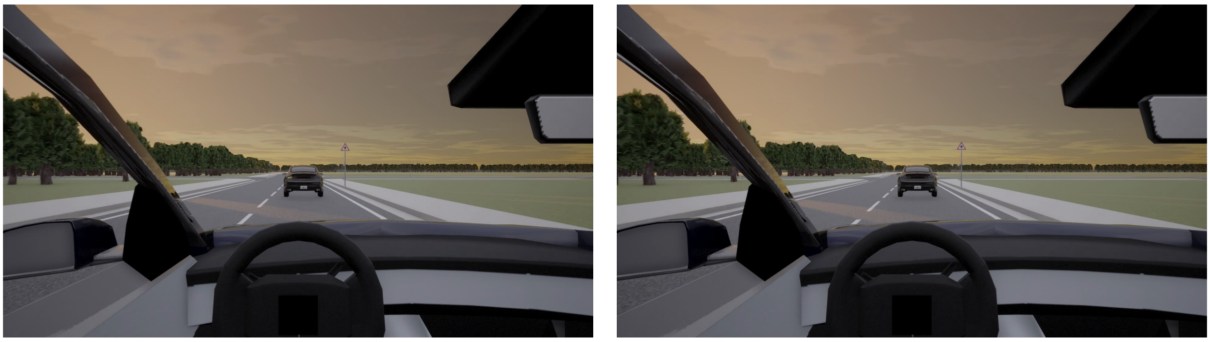
Figure 9. Observed vehicle relative positions visualised. The positions are relative to the ego vehicle.

Observed vehicle lateral offset

(a) Left (b) Right

Figure 10. Observed vehicle lateral offset visualised. The lateral offset distance started at 0.2 m from the centre of the lane.

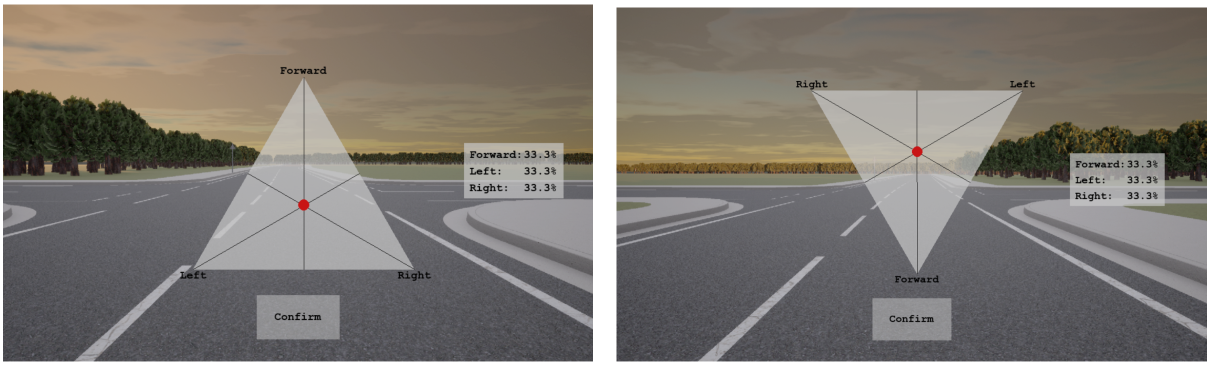
Observed vehicle blinkers



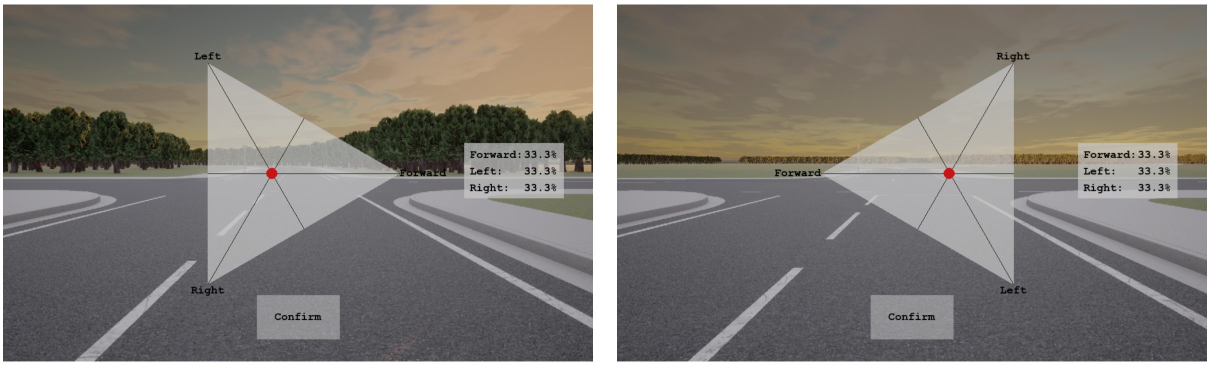
(a) Blinkers on to the left. (b) Blinkers off

Figure 11. Observed vehicle blinkers. They were more apparent during the experiment, when the scenario takes up the entire screen; however, the limited screen resolution did impact blinker visibility.

Response triangle rotations



(a) Following (b) Opposite



(c) Left (d) Right

Figure 12. The response triangle rotated based on the observed vehicle relative position. Rotating the triangle meant participants didn't have to think about the response from the observed vehicle's perspective, reducing cognitive load during the experiment.

Difference between experimental groups

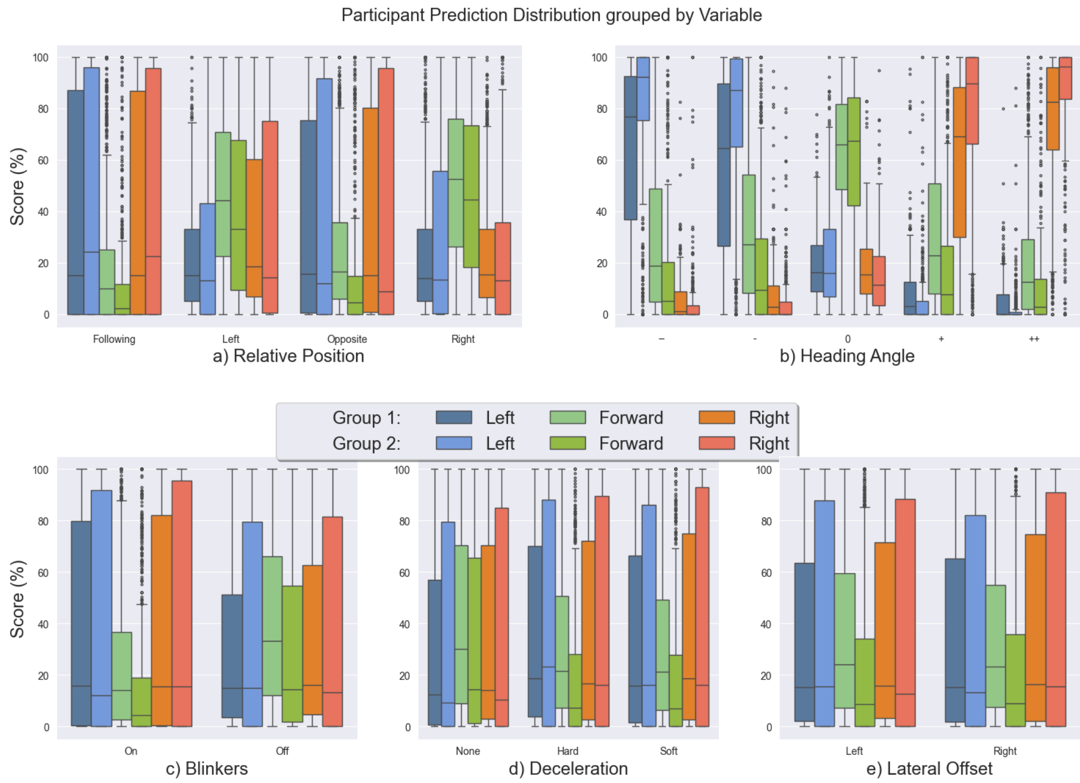


Figure 13. Scores grouped by variable, separated by experiment groups. Colours correspond to direction prediction. The difference between responses was insufficient to justify separating the groups.

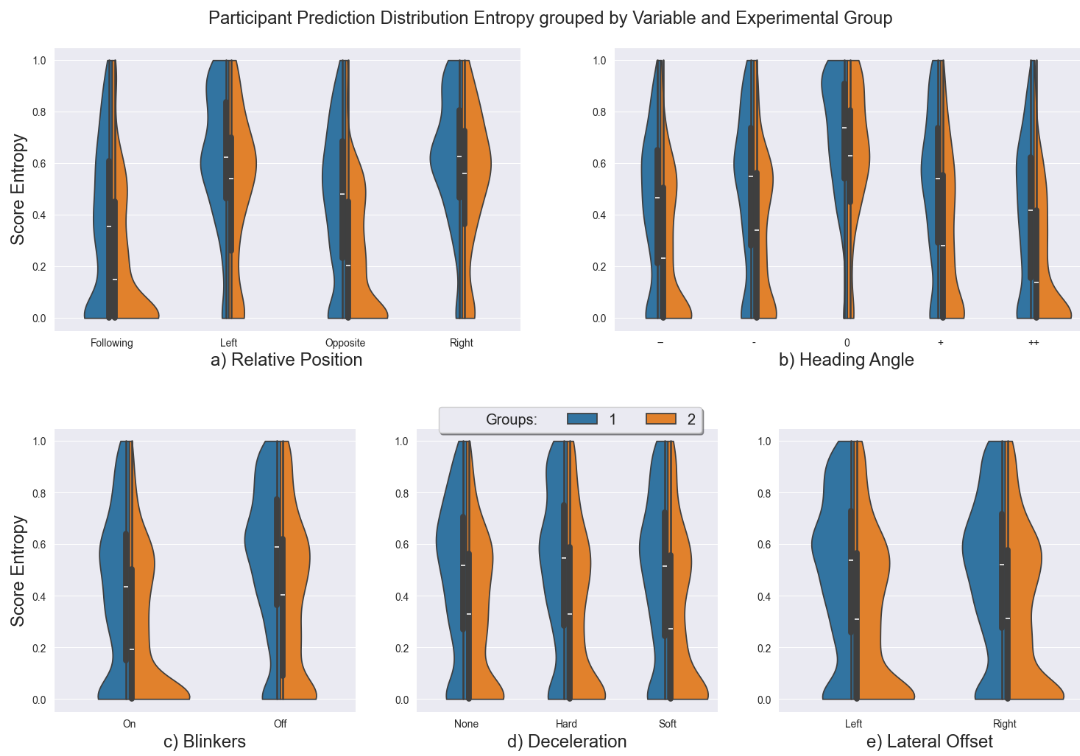


Figure 14. Response entropy grouped by variable, separated by experiment groups. The general trend between variables is consistent for both experiment groups, but the second group was, on average, more confident with their responses.

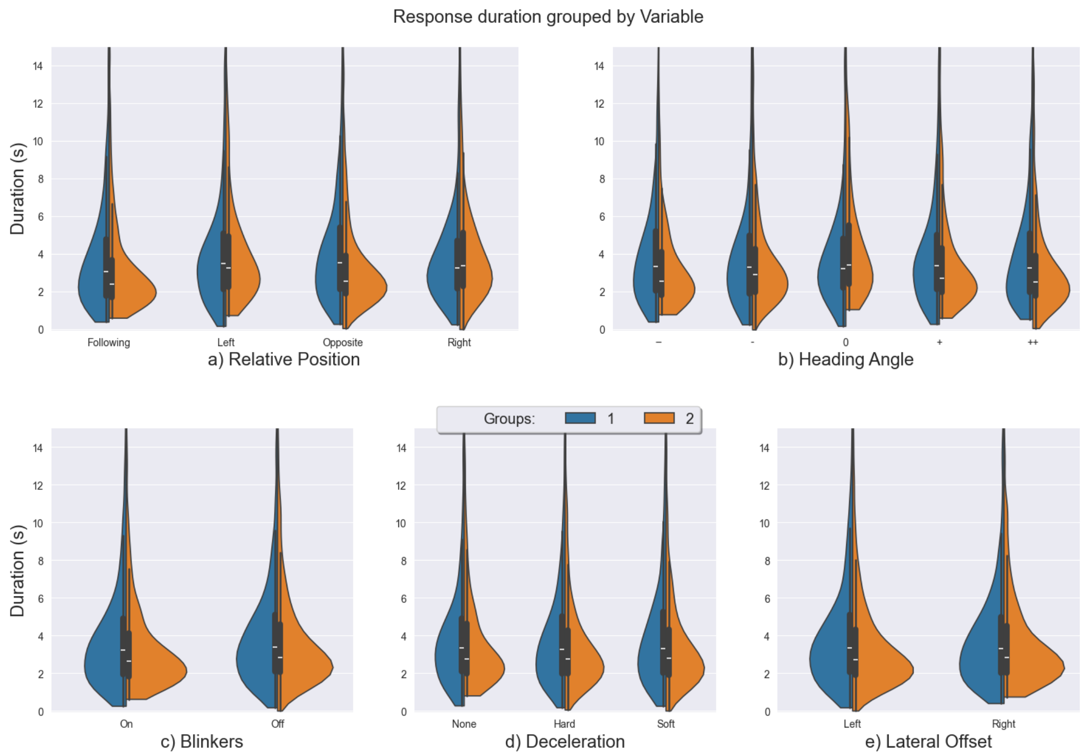


Figure 15. Response duration grouped by variable, separated by experiment groups. Again, the general trend between variables is consistent across groups, but the second group was, on average, quicker to respond.

The general trend between the variables is similar for both experiment groups. Figures 13, 14, and 15 show the data split per experiment group. Group 2, in general, was more confident in their prediction responses, as can be seen by the wider bases and narrower tips of the majority of entropy distributions in Figure 14, compared to group 1. This is most likely due to the second group being younger on average, with less driving experience. The interquartile range (Q1-Q3) for years of driving experience for group 1 was 5-27 years, and for group 2 was 1.25-5.75 years. Less experienced drivers are likely to be more trusting of signals shown by other drivers. In contrast, experienced drivers generally remain cautious and consider multiple possibilities when making predictions, as reflected in the differences between the experimental groups. However, the differences between the experimental groups were insufficient to warrant splitting the data for analysis in this study; therefore, all responses were considered as part of the same group.

Mixed-Effect Model interaction effect of relative position on the other variables for prediction score.

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	-0.372	0.877	-0.425	0.671	-2.092	1.347
Rel.Position:Left	-0.898	1.289	-0.696	0.486	-3.424	1.629
Rel.Position:Oppo	-2.330	1.241	-1.878	0.060	-4.763	0.102
Rel.Position:Right	-1.181	1.297	-0.911	0.362	-3.723	1.361
Head.Angle:-10	10.710	0.966	11.082	<0.001	8.816	12.604
Head.Angle:-5	8.904	0.968	9.199	<0.001	7.007	10.801
Head.Angle:+5	-6.697	0.966	-6.934	<0.001	-8.591	-4.804
Head.Angle:+10	-5.986	0.966	-6.194	<0.001	-7.881	-4.092
Deceleration:None	-2.419	0.618	-3.912	<0.001	-3.631	-1.207
Deceleration:Soft	-0.074	0.618	-0.121	0.904	-1.285	1.136
Blinkers:On	3.348	0.535	6.259	<0.001	2.299	4.396
Lat.Offset:Right	-0.078	0.505	-0.154	0.877	-1.067	0.911
Rel.Position:Left : Head.Angle:-10	-7.628	1.470	-5.190	<0.001	-10.508	-4.747
Rel.Position:Oppo : Head.Angle:-10	-0.340	1.369	-0.248	0.804	-3.023	2.343
Rel.Position:Right : Head.Angle:-10	-6.409	1.455	-4.406	<0.001	-9.260	-3.558
Rel.Position:Left : Head.Angle:-5	-6.126	1.474	-4.155	<0.001	-9.016	-3.237
Rel.Position:Oppo : Head.Angle:-5	0.200	1.369	0.146	0.884	-2.483	2.883
Rel.Position:Right : Head.Angle:-5	-7.174	1.469	-4.885	<0.001	-10.053	-4.296
Rel.Position:Left : Head.Angle:+5	3.730	1.467	2.543	0.011	0.855	6.604
Rel.Position:Oppo : Head.Angle:+5	1.952	1.368	1.427	0.154	-0.729	4.633
Rel.Position:Right : Head.Angle:+5	4.492	1.465	3.067	0.002	1.621	7.362
Rel.Position:Left : Head.Angle:+10	1.745	1.465	1.191	0.234	-1.126	4.617
Rel.Position:Oppo : Head.Angle:+10	2.190	1.369	1.600	0.110	-0.492	4.872
Rel.Position:Right : Head.Angle:+10	0.146	1.466	0.100	0.921	-2.727	3.020
Rel.Position:Left : Deceleration:None	-0.763	0.998	-0.765	0.445	-2.718	1.193
Rel.Position:Oppo : Deceleration:None	1.356	0.875	1.550	0.121	-0.359	3.070
Rel.Position:Right : Deceleration:None	-1.345	0.994	-1.353	0.176	-3.294	0.604
Rel.Position:Left : Deceleration:Soft	-1.359	0.997	-1.363	0.173	-3.313	0.595
Rel.Position:Oppo : Deceleration:Soft	0.245	0.875	0.280	0.780	-1.470	1.960
Rel.Position:Right : Deceleration:Soft	-1.724	0.991	-1.739	0.082	-3.667	0.219
Rel.Position:Left : Blinkers:On	-3.822	0.883	-4.331	<0.001	-5.552	-2.092
Rel.Position:Oppo : Blinkers:On	-2.631	0.757	-3.476	0.001	-4.115	-1.148
Rel.Position:Right : Blinkers:On	-1.381	0.877	-1.575	0.115	-3.101	0.338
Rel.Position:Left : Lat.Offset:Right	0.073	0.824	0.088	0.930	-1.543	1.688
Rel.Position:Oppo : Lat.Offset:Right	-0.112	0.714	-0.156	0.876	-1.511	1.288
Rel.Position:Right : Lat.Offset:Right	-1.546	0.818	-1.890	0.059	-3.150	0.057
Group Var	0.495	0.050				

Table 6. Mixed effects model log(p_left/p_forward) coefficients and 95% confidence intervals for the interaction effect between relative position and other variables on prediction score.

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	-0.728	0.821	-0.887	0.375	-2.337	0.881
Rel.Position:Left	-4.552	1.211	-3.760	<0.001	-6.925	-2.179
Rel.Position:Oppo	-2.468	1.162	-2.124	0.034	-4.744	-0.191
Rel.Position:Right	-2.292	1.219	-1.881	0.060	-4.681	0.096
Head.Angle:-10	-4.564	0.904	-5.048	<0.001	-6.336	-2.792
Head.Angle:-5	-5.884	0.906	-6.496	<0.001	-7.659	-4.108
Head.Angle:+5	8.720	0.904	9.651	<0.001	6.949	10.491
Head.Angle:+10	10.830	0.904	11.978	<0.001	9.058	12.602
Deceleration:None	-2.204	0.578	-3.811	<0.001	-3.338	-1.071
Deceleration:Soft	0.288	0.578	0.498	0.619	-0.845	1.420
Blinkers:On	2.919	0.500	5.837	<0.001	1.939	3.900
Lat.Offset:Right	0.037	0.472	0.079	0.937	-0.888	0.962
Rel.Position:Left : Head.Angle:-10	1.046	1.383	0.756	0.450	-1.666	3.757
Rel.Position:Oppo : Head.Angle:-10	1.219	1.281	0.951	0.342	-1.293	3.730
Rel.Position:Right : Head.Angle:-10	0.840	1.369	0.613	0.540	-1.844	3.524
Rel.Position:Left : Head.Angle:-5	3.449	1.390	2.482	0.013	0.726	6.173
Rel.Position:Oppo : Head.Angle:-5	1.915	1.281	1.495	0.135	-0.596	4.426
Rel.Position:Right : Head.Angle:-5	2.479	1.383	1.792	0.073	-0.233	5.190
Rel.Position:Left : Head.Angle:+5	-2.661	1.382	-1.925	0.054	-5.370	0.048
Rel.Position:Oppo : Head.Angle:+5	1.964	1.280	1.535	0.125	-0.544	4.472
Rel.Position:Right : Head.Angle:+5	-7.187	1.380	-5.208	<0.001	-9.892	-4.482
Rel.Position:Left : Head.Angle:+10	1.488	1.380	1.078	0.281	-1.217	4.192
Rel.Position:Oppo : Head.Angle:+10	1.543	1.281	1.205	0.228	-0.967	4.053
Rel.Position:Right : Head.Angle:+10	-7.378	1.382	-5.340	<0.001	-10.086	-4.670
Rel.Position:Left : Deceleration:None	1.499	0.943	1.589	0.112	-0.350	3.347
Rel.Position:Oppo : Deceleration:None	1.287	0.818	1.574	0.116	-0.316	2.891
Rel.Position:Right : Deceleration:None	0.869	0.940	0.925	0.355	-0.973	2.711
Rel.Position:Left : Deceleration:Soft	0.166	0.944	0.175	0.861	-1.685	2.016
Rel.Position:Oppo : Deceleration:Soft	-0.503	0.818	-0.615	0.538	-2.107	1.100
Rel.Position:Right : Deceleration:Soft	0.064	0.938	0.068	0.945	-1.774	1.903
Rel.Position:Left : Blinkers:On	-1.665	0.837	-1.989	0.047	-3.306	-0.024
Rel.Position:Oppo : Blinkers:On	-2.473	0.708	-3.492	<0.001	-3.860	-1.085
Rel.Position:Right : Blinkers:On	-3.730	0.831	-4.487	<0.001	-5.359	-2.100
Rel.Position:Left : Lat.Offset:Right	-0.433	0.781	-0.555	0.579	-1.964	1.098
Rel.Position:Oppo : Lat.Offset:Right	-0.718	0.668	-1.075	0.282	-2.027	0.591
Rel.Position:Right : Lat.Offset:Right	0.178	0.775	0.230	0.818	-1.340	1.697
Group Var	0.004	0.045				

Table 7. Mixed effects model log(p_right/p_forward) coefficients and 95% confidence intervals for the interaction effect between relative position and other variables on prediction score.

Mixed-Effect Model interaction effect of relative position on the other variables for response entropy.

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	0.685	0.034	20.129	<0.001	0.619	0.752
Rel.Position:Left	0.007	0.049	0.148	0.882	-0.090	0.104
Rel.Position:Oppo	-0.084	0.048	-1.745	0.081	-0.178	0.010
Rel.Position:Right	-0.025	0.050	-0.506	0.613	-0.122	0.072
Head.Angle:-10	-0.386	0.038	-10.271	<0.001	-0.459	-0.312
Head.Angle:-5	-0.316	0.038	-8.423	<0.001	-0.390	-0.243
Head.Angle:+5	-0.311	0.038	-8.297	<0.001	-0.385	-0.238
Head.Angle:+10	-0.384	0.038	-10.235	<0.001	-0.458	-0.311
Deceleration:None	-0.009	0.024	-0.357	0.721	-0.056	0.039
Deceleration:Soft	-0.015	0.024	-0.621	0.535	-0.062	0.032
Blinkers:On	-0.127	0.021	-6.110	<0.001	-0.168	-0.086
Lat.Offset:Right	-0.006	0.020	-0.290	0.772	-0.044	0.033
Rel.Position:Left : Head.Angle:-10	0.299	0.056	5.345	<0.001	0.189	0.408
Rel.Position:Oppo : Head.Angle:-10	0.119	0.053	2.247	0.025	0.015	0.224
Rel.Position:Right : Head.Angle:-10	0.248	0.055	4.475	<0.001	0.139	0.356
Rel.Position:Left : Head.Angle:-5	0.285	0.056	5.099	<0.001	0.176	0.395
Rel.Position:Oppo : Head.Angle:-5	0.102	0.053	1.915	0.056	-0.002	0.206
Rel.Position:Right : Head.Angle:-5	0.265	0.056	4.745	<0.001	0.156	0.374
Rel.Position:Left : Head.Angle:+5	0.265	0.056	4.757	<0.001	0.156	0.374
Rel.Position:Oppo : Head.Angle:+5	0.066	0.053	1.237	0.216	-0.038	0.170
Rel.Position:Right : Head.Angle:+5	0.321	0.056	5.778	<0.001	0.212	0.430
Rel.Position:Left : Head.Angle:+10	0.088	0.056	1.582	0.114	-0.021	0.197
Rel.Position:Oppo : Head.Angle:+10	0.071	0.053	1.342	0.180	-0.033	0.175
Rel.Position:Right : Head.Angle:+10	0.314	0.056	5.647	<0.001	0.205	0.423
Rel.Position:Left : Deceleration:None	-0.042	0.037	-1.130	0.258	-0.116	0.031
Rel.Position:Oppo : Deceleration:None	0.023	0.034	0.684	0.494	-0.043	0.090
Rel.Position:Right : Deceleration:None	-0.055	0.037	-1.474	0.141	-0.128	0.018
Rel.Position:Left : Deceleration:Soft	-0.007	0.037	-0.183	0.855	-0.080	0.066
Rel.Position:Oppo : Deceleration:Soft	-0.003	0.034	-0.090	0.928	-0.070	0.064
Rel.Position:Right : Deceleration:Soft	0.001	0.037	0.017	0.986	-0.072	0.073
Rel.Position:Left : Blinkers:On	0.096	0.033	2.944	0.003	0.032	0.161
Rel.Position:Oppo : Blinkers:On	0.093	0.029	3.160	0.002	0.035	0.151
Rel.Position:Right : Blinkers:On	0.085	0.033	2.610	0.009	0.021	0.149
Rel.Position:Left : Lat.Offset:Right	0.003	0.031	0.108	0.914	-0.057	0.063
Rel.Position:Oppo : Lat.Offset:Right	0.016	0.028	0.574	0.566	-0.038	0.070
Rel.Position:Right : Lat.Offset:Right	0.021	0.030	0.685	0.493	-0.039	0.081
Group Var	0.003	0.003				

Table 8. Mixed effects model coefficients and 95% confidence intervals for the interaction effect between relative position and other variables on response entropy.

Random Forest Regressor Modelling results

Max Depth	Accuracy	MSE
4	0.648	425.358
5	0.690	374.773
6	0.700	362.503
7	0.704	357.450
8	0.709	352.083
9	0.707	353.900
10	0.706	355.209
11	0.706	355.210
12	0.706	355.210
13	0.706	355.210
14	0.706	355.210
15	0.706	355.210

Table 9. RFR Model Accuracy and MSE per Max Depth, all RFRs were trained on 80% of the prediction responses with 100 estimators in random state 0.

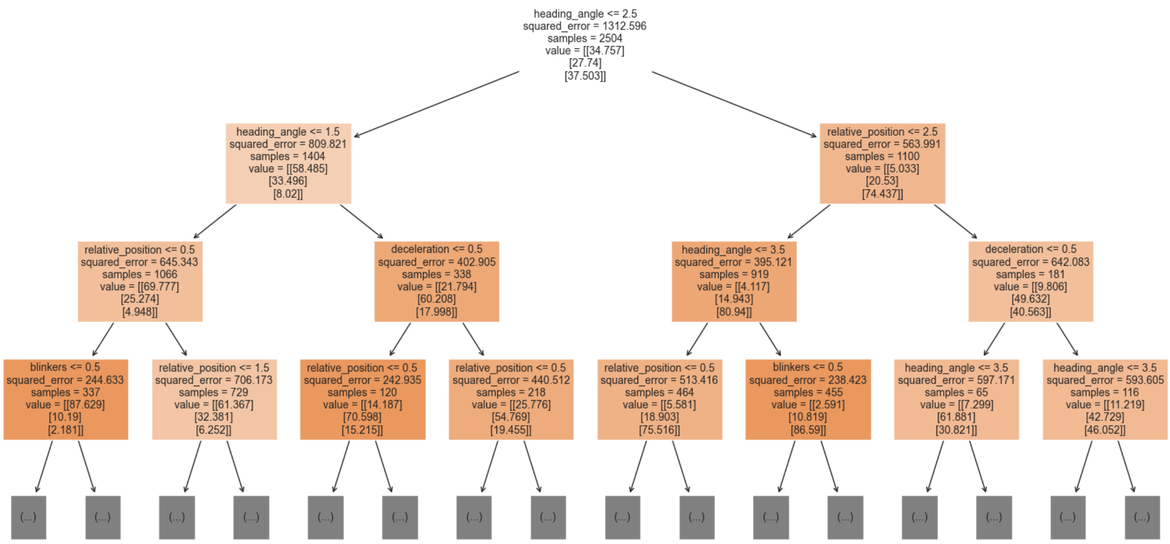


Figure 16. Truncated tree 0 from the final RFR model. Only showing the first 4 layers for node legibility and to illustrate the general trend for modelling the responses.