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Driver influence on vehicle trajectory prediction

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A B S T R A C T

Drivers continually interact with other road users and use information from the road environment to make decisions to control their vehicle. A clear understanding of different parameters impacting this interaction can provide us with a new design approach for a more effective driver assistance system - a personalised trajectory prediction system. This paper highlights the influential factors on trajectory prediction system performance by (i) identifying driver behaviours impacting the trajectory prediction system; and (ii) analysing other contributing factors such as traffic density, secondary task, gender and age group. To explore the most influential contributing factors, we first train an interaction-aware trajectory prediction system using time-series data derived from the Second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS). Prediction error is then analysed based on driver characteristics such as driver profile which is subjectively measured through self-reported questions, and driving performance which is based on evaluation of time-series information such as speed, acceleration, jerk, time, and space headway. The results show that prediction error significantly increased in the scenarios where the driver engaged in risky behaviour. Analysis shows that trajectory prediction system performance is also affected by factors such as traffic density, engagement in secondary tasks, driver gender and age group. We show that the driver profile, which is subjectively measured using self-reported questionnaires, is not as significant as the driving performance information, which is objectively measured and extracted during each specific driving scenario.

1. Introduction

Driving is a complex activity whose safety is influenced by a wide range of factors such as driver behaviour, vehicle design and the road environment. Although many encouraging achievements have been made to improve road safety, annually 1.35 million people die and as many as 50 million are injured and experience long-term disability from road traffic crashes ("World Health Organisation report, 2018,"). The next frontier of crash prevention is in the technology space with an increasing presence of active safety technologies such as Advanced Driver Assistance Systems (ADAS). In this space, research shows that early detection of imminent hazards and the taking of corrective action through systems such as alerts and automatic braking could prevent or reduce the severity of road crashes (Harper et al., 2016).

A technical concept that has been increasingly suggested is the use of safety systems to inform the driver of imminent hazards or to initiate automated responses from the vehicle. Indeed, to avoid or mitigate collision risk, a reliable assistive safety system is needed which considers all contributing factors to accurately predict and warn about unsafe situations. Examples of these are the collision mitigation systems such as Lane-keeping and Lane-changing systems, Forward Collision Mitigation systems, and Adaptive Cruise Control. These can issue a warning to the driver, apply the brakes, or change the course of the vehicle by applying torque to the steering wheel. A timely and accurate prediction of vehicle trajectory prior to hazards in a traffic scene is a key for the development of all these technologies. Previous investigations have recommended that the optimal timing for forward warnings is at least 4 s prior to the imminent hazard for the driver to appropriately act instead of reacting Yan et al. (2015). There have been efforts to develop a variety of trajectory prediction methods, Lefèvre et al. (2014) classified prediction methods into three main categories; physics-based motion models (H. Guo et al., 2018; Zhao and Zhang, 2018), manoeuvre-based models (Lv et al., 2018; Xing et al., 2019a), and interaction-aware motion models (Das et al., 2020; Deo et al., 2018; Deo and Trivedi, 2018b; Khakzar

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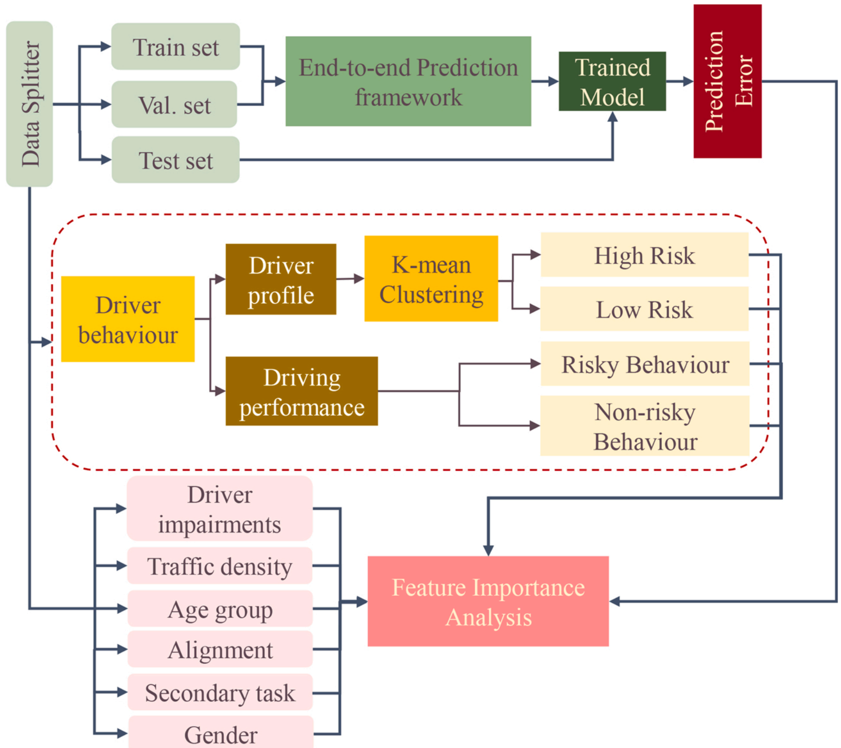

Fig. 1. Proposed framework.

et al., 2020). These approaches use vehicle kinematics to predict the up-coming trajectory of an ego-vehicle.[1] The main differences between these approaches are the prediction horizon and the interaction level which is considered by the system. The physics-based model considers the lowest level of interaction where a vehicle performs a series of manoeuvres that are considered independent of other vehicles on the road network. The interaction-aware models consider the trajectory of each vehicle as mutually influenced by surrounding vehicle trajectories and have a high-level of interaction. Considering mutual pairwise dependencies between vehicle trajectories increases the complexity of the prediction system. To solve this problem, Deep Neural Network (DNN) techniques, specifically Recurrent Neural Networks (RNNs), have been proven to work effectively (Dai et al., 2019; Deo and Trivedi, 2018a; Khakzar et al., 2020; Park et al., 2018). The DNN methods use the past trajectory values (e.g., 3 s) to predict how the system will evolve in the near future (e.g., 5 s). There is inherent error in all prediction systems making them a challenging task. Vehicle trajectory is associated with the interaction of three major factors; vehicle kinematics, driver profile, and environment parameters (Arbabzadeh et al., 2019). Reviewing literature has revealed that the common limitations in the majority of existing prediction systems are ignoring the driver profile and driving environment. These are two important considerations where their neglect may decrease system performance (Ba et al., 2017; Iranmanesh et al., 2018). Several studies have tried to identify driving styles and show risky driver behaviours and crash involvement that are influenced at the individual level (i.e., determined by the decisions of individuals) (Arbabzadeh and Jafari, 2017; Büyükyildiz et al., 2017; King and Parker, 2008; Li et al., 2019; Oviedo-Trespalacios and Scott-Parker, 2018). We consider driver behaviour from two distinct aspects; driver profile and driving performance. The driver profile is subjectively measured using self-reported questionnaires such as a risk-taking questionnaire and a driver demographic questionnaire. Driving performance is objectively measured during each specific scenario. Generally, it is defined as a distribution of time series driving information such as speed, acceleration, jerk, time, and space headway (Hoermann et al., 2017; Xing et al., 2019b)..

Doshi and Trivedi (2010) used kinematic metrics such as lateral and longitudinal acceleration and jerk to categorise drivers into non-aggressive and aggressive drivers and then evaluated the correlation of these metrics with the predictability of different driver categories. The results indicated that aggressive drivers are more consistent in behaviour and significantly more predictable than non-aggressive drivers. In Cai, Hu, Chen, and Zhu (2018), the effectiveness of considering driving performance for driver identification is evaluated. It confirmed that each driver uniquely engages in the driving task and this engagement may differ from person to person. F. Guo and Fang (2013) have conducted research on a 100-Car Naturalistic Driving Study (NDS) (Dingus et al., 2006) to recognise factors associated with individual driver risk and prediction of high-risk drivers. This study reported that driver age, personality, and critical incident rate had significant impact on crash and near-crash risk. Following these investigations, Ba et al. (2017) added driver profiles to the vehicle dynamics and distance metrics features and established a binary classifier to classify crashes and examine the effectiveness of considering driver profiles on system performance. The results demonstrated significant improvements in accuracy and specificity (i.e., lower false alarm) by adding driver profiles. In (Wang and Xu, 2019), drivers were categorised into three groups of high-, moderate- and low-risk drivers then logistic regression models were used to investigate correlation between the driver profile (i.e., self-reported risky driving behaviour questionnaire) and crash and near-crash risk in the Shanghai Naturalistic Driving Study. Findings showed there is a connection between driver profiles and individual driver crash risk. It was also stated that high-risk drivers are more likely to engage in inattention errors and violation behaviours compared with other drivers.

This research explores the influence of different driver profile and driving performance on trajectory prediction performance. Although the concept of assessing different driver behaviour on crash risk has been adopted in several studies, there is limited research conducted on the

[1] Ego-vehicle corresponds to the vehicle where the main observations take place.

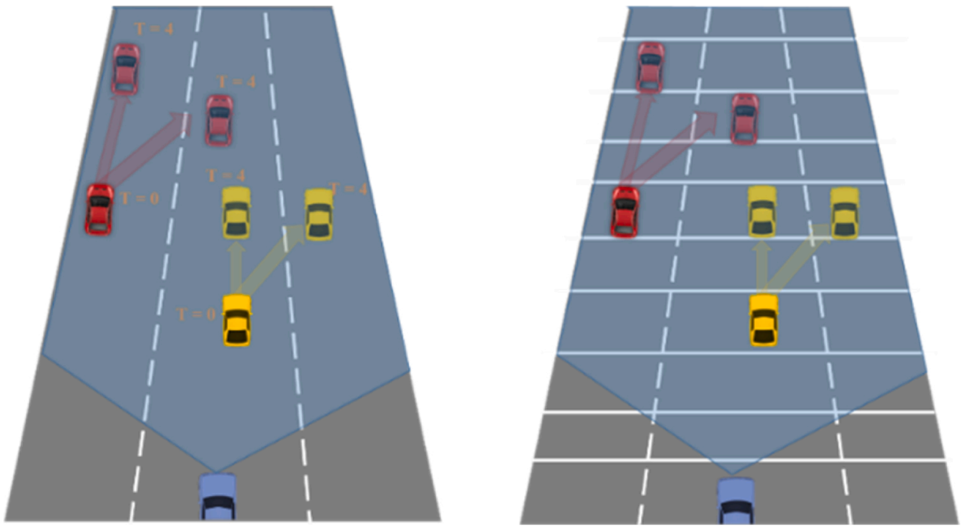

Fig. 2. Grid map representation of the traffic scene by using two adjacent ego-vehicle lanes.

concurrent effects of driver profile and driving performance on trajectory prediction accuracy. The hypothesis of this investigation is that there is a correlation between vehicle trajectory prediction error and driver profile and driving performance. Awareness of each factor's influence may provide us with a new approach to develop the next generation of safety systems where the prediction system is personalised for a particular driver.

2. Assessment methodology

As stated earlier, sufficient information about drivers and the driving environment can assist us in designing a personalised system and consequently improving system performance. Therefore, the focus of this study is to investigate the influence of driver profile, driving performance and other contributing factors such as traffic density, secondary task, gender and age group on trajectory prediction system performance. The methodology assessment is based on how driver profiles and driving-related factors have impact on trajectory prediction system performance. Fig. 1 illustrates a summary of the proposed framework including (i) end-to-end prediction method, (ii) driver profile classification into Low Risk and High Risk and driving performance into Risky Behaviour and Non-Risky-Behaviour clusters, and (iii) important analysis of other contributing factors. In the first step, a prediction model is trained using a set of driving samples extracted from (SHRP2., 2013) and then system performance is assessed for further analysis. The difference between actual and predicted values for each driving scenario were reported as prediction error. Later, this prediction error is used to evaluate the relevance and influence of driver profile, driving performance and contributing factors such as driver impairments, traffic density, and secondary task on the trajectory prediction system accuracy. In each driving sample, associated driver information (i.e., age, gender, experience) is linked to the predication error.

The participants are clustered into High Risk (HR), and Low Risk (LR) driver profiles based on their response to pre-driving questionnaires (i.e., risk-taking questionnaire and driver demographic questionnaire summarised in Appendix A) and their driving performance in the selected driving sample is classified as Risky Behaviour (RB) and Non-Risky Behaviour (NRB) based on observed driving behaviour provided by SHRP2 (2013). The list of risky behaviour used in this study is summarised in Appendix A. This information, along with prediction error, facilitates the third step of the assessment methodology where the relationship between prediction error and other parameters are analysed. A random forest important feature analysis is used to investigate the relationship between prediction error and selected factors related to the driver profile and driving performance A more detailed explanation of each step is described and discussed in the following sub-sections.

2.1. Prediction framework, error metrics and data preparation

The trajectory prediction system used in this study is inspired by the interaction-aware method described in Khakzar et al. (2020). This method has been chosen due to its performance in term of prediction accuracy compared with existing approaches. The trajectory prediction method that we have adopted comprises kinematic inputs (i.e. displacement, lateral/longitudinal velocity and acceleration) and a Long Short-Term Memory (LSTM) encoder-decoder structure for time series prediction as well as a convolutional LSTM mechanism on top of the base model to extract risk features and models the possible risk interaction among vehicles in the traffic scene. The model maps the trajectory information and risk associated with the traffic scene through the Occupancy Map (OM) and the Risk Map (RM), respectively. We utilised LSTM with 128 units for the encoder and decoder module with a batch size of 32. Models are trained using the Adam optimiser (Kingma and Ba, 2014) with a learning rate of 0.001 and ReLU activation with $\alpha = 0.1$. The loss function of the training process adopts MSE and we set 20 % dropout in the training process. Two ConvLSTM layers are stacked, where each layer has 128 hidden states with 2×2 kernels. The decoder consists of the 128 LSTM cell followed by an FC layer.

The scope of this study is focused on car-following scenarios where at least one adjacent lane and surrounding vehicle exists. Some manoeuvres, such as lane deviation and swerving, are out of the scope of this paper since lane marking coordinates are not reported in the dataset. We also acknowledge the limitation of considering other scenarios such as intersections and roundabouts since the prediction model limited to the scenarios with adjacent lanes.

Fig. 2 illustrates a driving scene and its associated grid map in a time horizon consisting of information from right adjacent, left adjacent, and occupied lanes to observe surrounding vehicle behaviour. If one of the adjacent lanes does not exist, the corresponding values are set to zero in the occupancy grid map. All the trajectory segments in this paper are 8 s long. For each trajectory, the prediction algorithm has insight into the 3 s of the track history of the ego-vehicle and all the surrounding vehicles in the grid map to predict the next 5 s of the ego-vehicle trajectory. Each column of grid map corresponds to adjacent lanes and the rows are separated by a length of approximately one standard vehicle (i.e. 5 m).

The grid map provides the prediction system with information about the traffic scene to consider the impact of surrounding-vehicle trajectories on the ego-vehicle. For more details on the prediction method, the interested reader is referred to (Khakzar et al., 2020). The prediction error in the literature is reported as a Root Mean Square Error (RMSE) or Final Displacement Error (FDE) given by,

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_{i,t}^{pred} - x_{i,t}^{obs}\right)^2} \tag{1}$$

$$FDE_i = \sqrt{\left(x_{i,t}^{pred} - x_{i,t}^{obs}\right)^2}\ , t = T_p \tag{2}$$

where n is the number of trajectories, $x_{i,t}^{pred}$ is the predicted position and $x_{i,t}^{obs}$ is the respective observed positions for the trajectory i at t^{th} time instance. The RMSE is used to evaluate the performance of the prediction system by having an average error factor for each time step of the horizon T_p. The FDE is used to assess the general performance of each prediction scenario. We used the SHRP2 Naturalistic Driving Study (NDS) since it provides a wide range of rich real-life data in several categories including event details, driver profile, time series, and vehicle attributes, each encompassing several to many individual data items. This dataset provides a unique opportunity to investigate the role of driver performance and behaviour across time and different locations. Table A1 (Appendix) provides detailed information about SHRP2 data used in this study. The SHRP2 NDS is the largest and most comprehensive study of its kind and includes data of about 5.5 million trips for over 3000 drivers in six states throughout the United States (Blatt et al., 2015). To the best of the authors' knowledge, this study is the first use of SHRP2 NDS for trajectory prediction. We used a) the risk-taking questionnaire and driver demographic questionnaire to categorise drivers into two classes of Low Risk (LR) and High Risk (HR) drivers, b) information provided about event details including traffic density, pre-incident manoeuvre, secondary task, and driver alignment, c) time series data has been used to train and examine the vehicle trajectory prediction system. The prediction method used in this study is designed for the places where adjacent lanes for ego-vehicles exist. Hence, the scenarios such as roundabouts and intersections are out of scope for this study.

2.2. Driver behaviour

In this paper, we consider driver behaviour from two distinct aspects; driver profile and driving performance. Driving performance consists of demonstrated driver behaviour during each specific driving scenario which is classified into two classes of Risky Behaviour (RB) and Non-Risky Behaviour (NRB). Table A2 in Appendix A summarises risky behaviour annotated by SHRP2[2] NDS where the label "None" represent the scenarios without risky behaviour and other labels represent the type of risky behaviour performed. Detail about how SHRP2 labelled driving behaviour data is reported in SHRP2 (2013). The driver profile is extracted from a number of attitudinal and perceptual self-reported measures of risk and crash experiences. Due to the significant variances and complex interaction between these factors, it is challenging to combine all of them in a single analytical model. To address this matter, we adopted K-mean cluster analysis to cluster drivers into two classes of High-Risk (HR) and Low-Risk (LR) drivers. K-mean clustering is an approach to classify multidimensional data into groups with certain patterns which has been used in the analysis of the naturalistic driving study due to several advantages such as algorithmic simplicity, calculation speed, and good clustering effect to classify each individual driver into different risk level groups (F. Guo and Fang, 2013). In total, 2781 drivers were clustered into two categories of LR and HR drivers based on their profiles where each driver maps to the cluster with the nearest mean. As described in Eqs. (3) and (4), we measured the within-cluster sum of squares (WCSS) and average silhouette ($s_{(i)}$) to evaluate the clustering effect,

$$\text{WCSS} = \sum_{i=1}^{k}\sum_{x_j \in s_i}\left\|X_j - \mu_i\right\|^2 \tag{3}$$

$$S_{(i)} = \frac{b(i) - a(i)}{\max[a(i),\ b(i)]} \tag{4}$$

where X_j is the observations data which is the risk-taking tendency rate for each observation; $S = (S_1, S_2)$ is the set of 2 clusters; and μ_i is the mean number of observations in set S_i, where S_i is the silhouette of observation i. The average distance between i and all other observations within the same cluster is shown with $a(i)$; and $b(i)$ is the average distance of i to the observations in neighbouring clusters. The range of $s_{(i)}$ changes from -1 to $+1$ and the average silhouette over all observations of the entire dataset is a measure of how appropriately the data has been clustered.

2.3. Importance analysis

We assess the influence of other contributing system performance factors using Random Forests (RF). It has been regarded as one of the prediction methods, having advantages such as an ability to determine variable importance, ability to model complex interactions among independent variables, and flexibility to perform several types of statistical data analysis (i.e., including regression, classification and unsupervised learning).We fit RF to the data to rank factors by their relevance to a regression problem in order to reduce the number of model inputs in high-dimensional data sets and consequently increase computational efficiency. Briefly, RF is a random approach to generate a forest by combining multiple decision trees to decrease overfitting problems and the inaccurate judgment of a single decision tree. RF uses a variation of bagging whereby many independent trees are learned from the same training data. The Out-of-Bag (OOB) samples are those not used for training a specific tree and as such can be used as an unbiased measure of performance. When the forest is obtained, each decision tree in the forest is judged separately to see which category is chosen most and the sample is predicted for that category while there is no correlation between each decision tree. This step is performed to discover variables that do not contribute to model performance either because they do not play an important role in error reduction or because they have minimal effect on the system. Variables with high importance are drivers of the outcome and their values have a significant impact on the outcome values. By contrast, variables with low importance might be omitted from a model, making it simpler and faster to fit and predict. In the fitting process, the OOB error for each data point is recorded and averaged over the forest. After training, the values of the i^{th} feature are permuted among the training data and the OOB error is again computed on this perturbed data set to measure the importance of the i^{th} feature. The importance score for the i^{th} feature is computed by averaging the difference in OOB error before and after the permutation over all trees. The score is normalized by the standard deviation of these differences. We will discuss the result of importance analysis in the 4. Discussion section.

3. Results

The dataset which is used in our study involves 9215 driving sample from 2781 individual drivers. Each driver may have one or more driving samples which are between 16–20 s long. We have applied a moving window within 16–20 s trajectories to obtain 8 s trajectory samples. Driving samples which are used in train, test and validation should be 8 s long (i.e., 3 s history to predict 5 s ahead). To consider different traffic density situations, we have randomly separated the data into non-

[2] Labels were entered by data reductionist during manual event analysis.

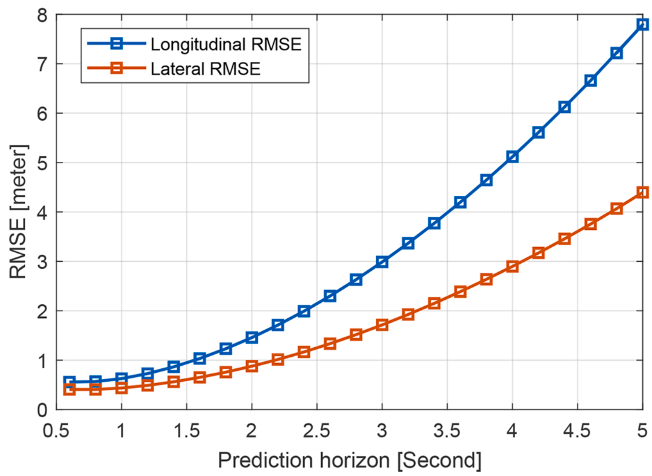

Fig. 3. System performance for lateral and longitudinal trajectory prediction.

overlapping sets of 70 % train, 10 % validation and 20 % test dataset and trained 15 prediction models which provide us 487,292 test driving sample. The use of traffic density in trajectory prediction systems is vital; therefore, the training process needs to consider traffic density. Since traffic density is proportional to grid occupancy in Fig. 2, we have carefully selected training samples that reflect sufficient diversity in the occupancy grid and thus provide a diversity of traffic densities.

Fig. 3 depicts the lateral and longitudinal RMSE performance of the prediction method for up to a 5 s horizon. Results show that the prediction horizon has a direct relation with system uncertainty. When the prediction horizon increases, the prediction error increases. In order to visualise the system, three examples of

trajectory prediction results using SHRP2 NDS are provided, see Fig. 4. In Fig. 4, a 3 s trajectory is given to the system (i.e., black line) and the next 5 s of trajectory is predicted (i.e., red line) while the blue line shows the actual trajectory of the ego-vehicle (i.e., target). Since red and blue lines are aligned, the system could accurately predict the trajectory of the ego-vehicle.

The prediction error for lateral and longitudinal movement is illustrated in Fig. 5(a and b) as a histogram of displacement error for each driving scenario. Displacement error has a normal distribution with a -0.47 (m) average, standard deviation of 5.1 for longitudinal and 0.027 (m) average, standard deviation of 0.31 for lateral displacement, see Fig. 5(a) and (b). The Final Displacement Error (FDE) is obtained from the lateral and longitudinal displacement depicted in Fig. 5(c) with 3.33 average and 3.9 standard deviation. The rest of the paper uses FDE as a performance indicator for each driving sample.

As stated earlier, risk taking behaviours vary substantially among drivers. To precisely explore and analyse the impact of this variation on system performance, we analyse trajectory prediction system performance for both driver profile and driving performance. K-means clustering is used to cluster driver profiles in different classes based on driver responses to the self-reported Risk-Taking Questionnaires. To identify the optimised number of clusters, we run the k-mean algorithm for different cluster numbers and evaluate the error. The results shows that having low-risk (LR) and high-risk (HR) classes of drivers has the lower clustering error, see Fig. 6. To evaluate how K-mean clustering separates participant according to question, we rank each question with a unique

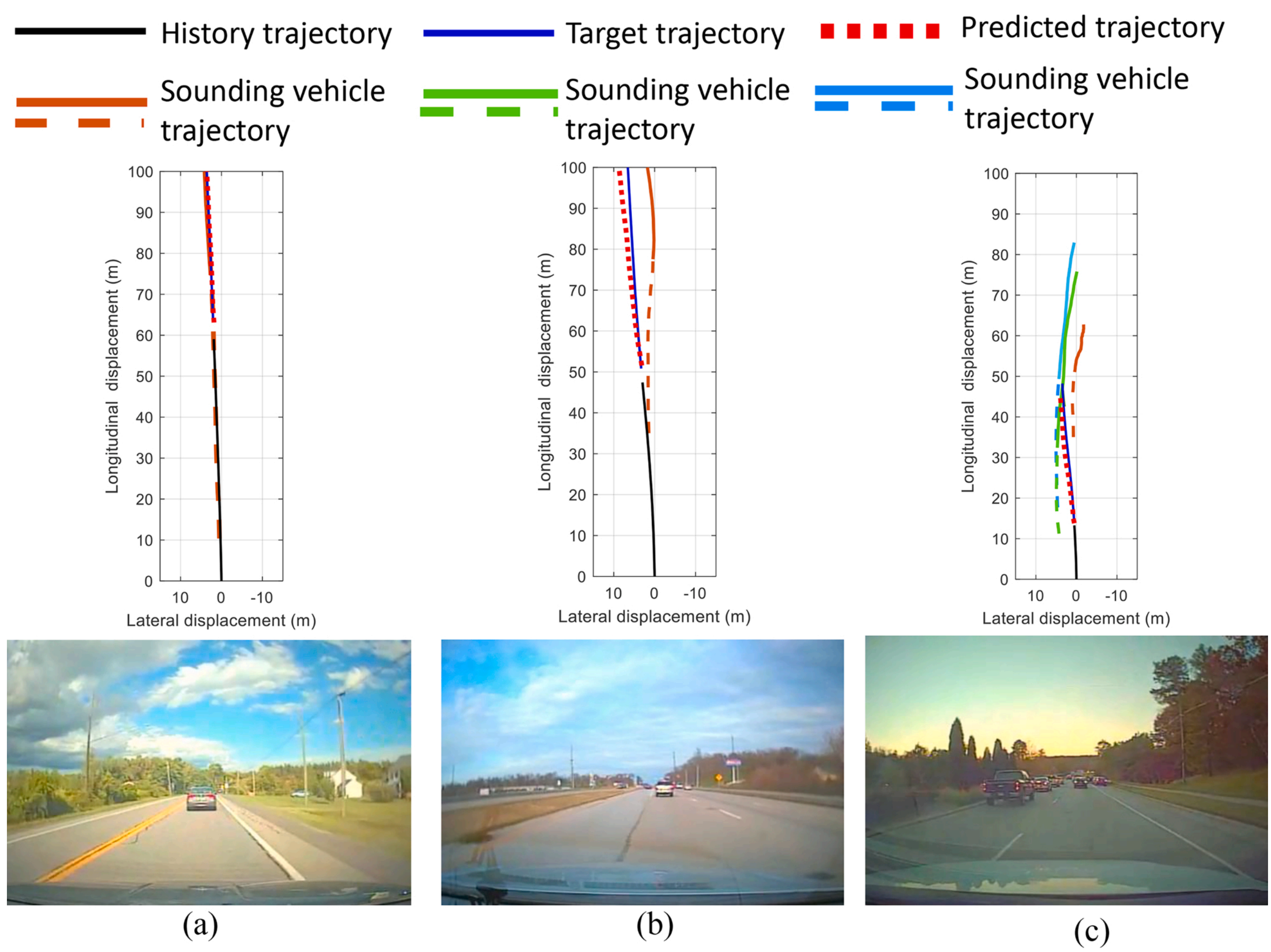

Fig. 4. Qualitative Examples of using the trajectory prediction method for SHRP2 NDS. (a) Decelerating in traffic lane. (b-c) Lane change manoeuvre.

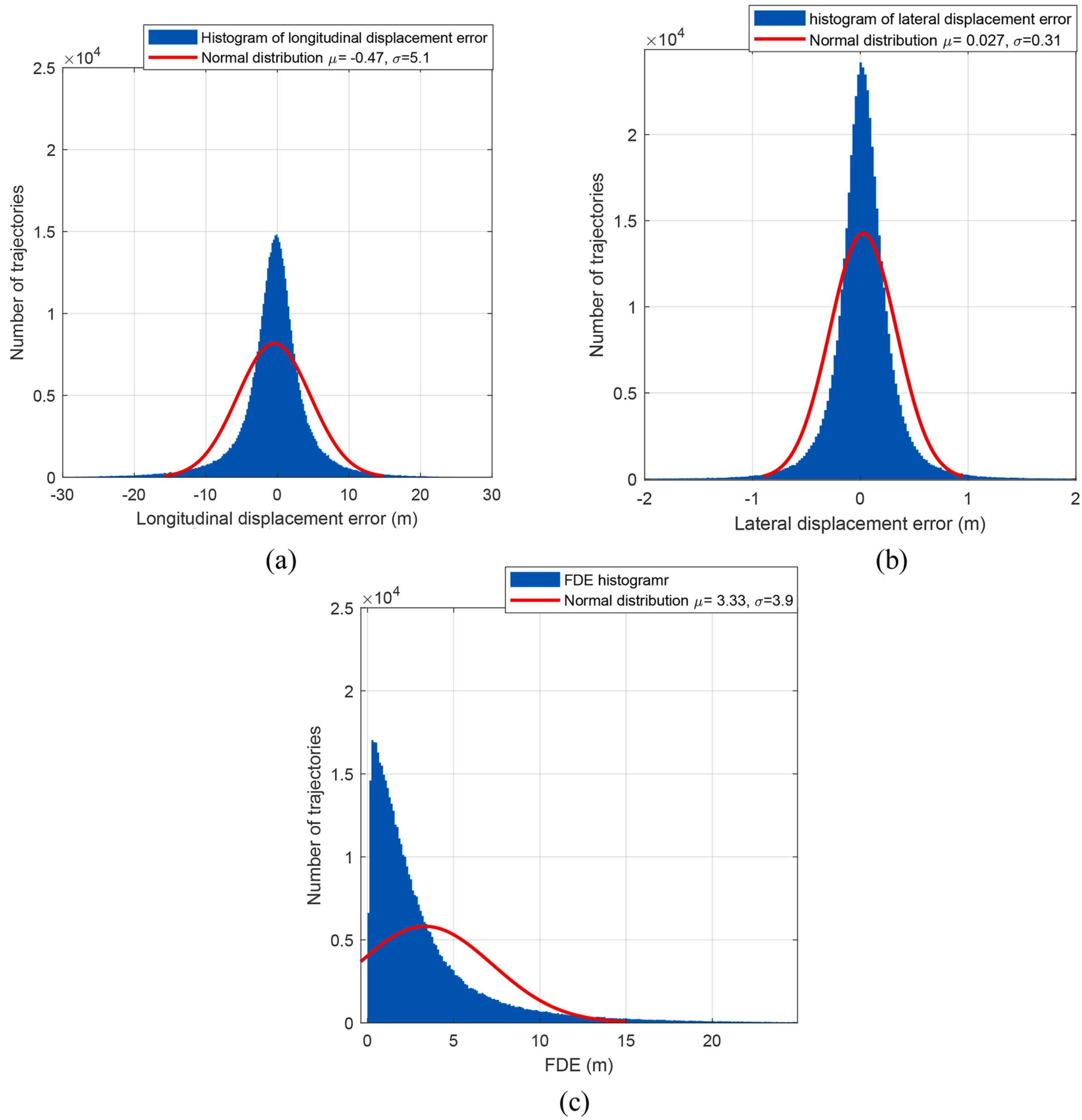

Fig. 5. The histogram of displacement error distribution for Lateral (a) and Longitudinal (b) movement (blue curve) with fitted normal distribution (red line). Final displacement error, (c), for test trajectories with fitted normal distribution.

score and the sum of all question responses is considered as the participant score. Fig. 6(a) shows how K-mean clustering separates participants based on their score. The output of cluster analysis WCSS $= 0.28$ and $s_{(i)} = 0.415$ confirms that the clusters have a distinct clustering effect. Cluster analysis in Fig. 6(b) indicates that about 20 % of the drivers were HR and about 80 % of the drivers were LR (i.e., four times lower than the HR group).

Table 1 compares the headway time, Time to Collision (TTC), lateral/longitudinal acceleration and velocity for each group of LR and HR drivers. Since the time to collision by itself does not indicate a safety-critical situation (Vogel, 2003), we consider TTC in tailgating situations (i.e., headway less than one second). It is observed that the average TTC value is slightly higher for LR compared to the HR cluster. The mean headway of LR drivers is greater than HR drivers while the mean of velocity and acceleration for HR drivers are higher in both lateral and longitudinal directions. The results show that HR drivers are more likely to drive at higher speeds and with shorter following distances in relation to the proceeding vehicle. To see how significant the differences between groups are, we have used an unpaired *t*-test. It reveals significant differences for LR and HR categories (t= -294.1; $p < 0.01$) where the t score is a ratio of the difference between the two groups and the difference within the groups. The larger the t score, the larger the difference between groups.

In Table 2, we compare the driving performance (i.e., driving behaviour observations clustered in RB and NRB categories) with the clustering result of what drivers declared about their risk tendency (i.e., driver profile which clustered in LR and HR groups). It shows that 64.5 % of drivers belong to the same driver profile and driving performance

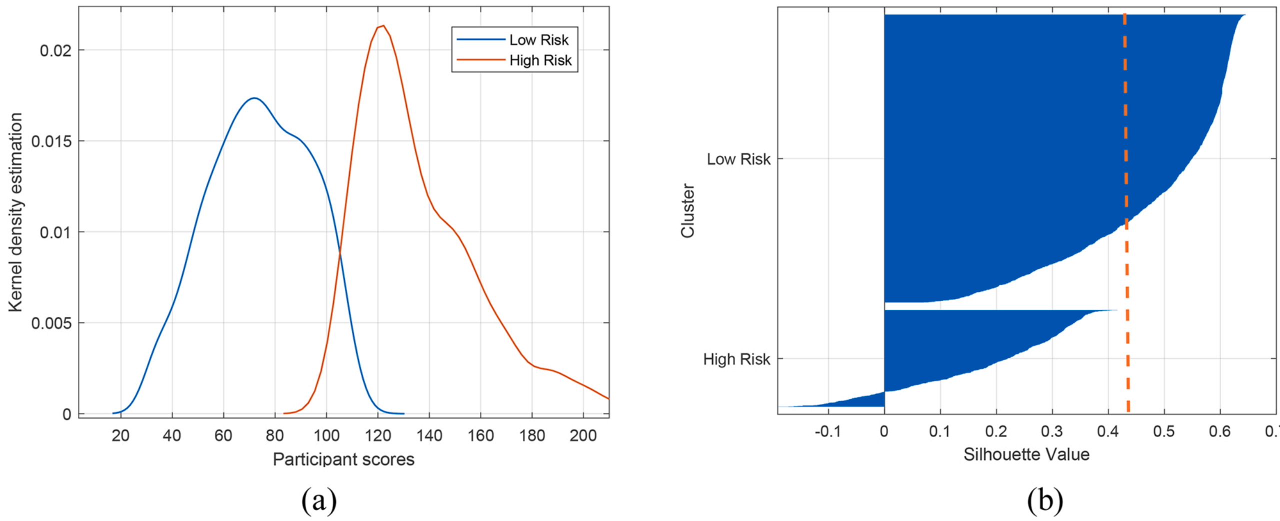

Fig. 6. K-mean clustering results (a) Kernel density estimation of distribution for LR (blue line) and HR (red line) clusters based on participant scores from the self-report questionnaire (lower value indicates a lower risk tendency); (b) silhouette value (blue curve) and average s_i (dotted line) for LR and HR clusters.

Table 1
Comparison of headway, TTC, acceleration and velocity for low- and high-risk drivers.

	Headway (s)		TTC when Headway $<=1$ (s)		Lateral acceleration (m/s^2)		Longitudinal acceleration (m/s^2)		Lateral velocity (m/s)		Longitudinal velocity (m/s)	
	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
LR Driver	**2.7**	2.8	2.97	1.51	**0.86**	0.84	**0.73**	1.02	**11.9**	7.5	**0.73**	13.32
HR Driver	**2.1**	2.8	2.78	1.44	**0.89**	0.90	**0.78**	1.13	**12**	7.49	**0.87**	14.15

Table 2
Comparison of driver profile and driving performance clustering.

		Driving performance			
		NRB		RB	
driver profile	**LR**	278,399	57.13%	58,720	12.05%
	HR	113,860	23.36%	36,313	7.45%

cluster while 35.5 % of drivers behaved differently compared with what they declared. As this proportion is limited to the current study, it does not generalise to other databases or other data samples.

Table 3 shows the average FDE for different observation categories including

- Low Risk (LR) driver with Risky Behaviour (RB)
- Low Risk (LR) driver with Non- Risky Behaviour (NRB)
- High Risk (HR) driver with Risky Behaviour (RB)
- High Risk (HR) driver with Non-Risky Behaviour (NRB)

The results show the trajectory prediction performance for both Low-Risk and High-Risk driver profiles while performing Risky Behaviour have a higher average FDE and variance compared to the Non-Risky Behaviour cluster. The lowest average prediction FDE belongs to the NRB cluster where the driver declares a LR tendency. Therefore, the error distributions for both LR and NRB clusters are expected to be lower than HR and RB clusters, respectively.

The error distribution based on driver and driving performance clustering is shown in Fig. 7(a) and (b), respectively. Fig. 7(b) shows the error distribution based on driving performance clustering demonstrating a significant difference between RB and NRB clusters while the driver profile clustering error distribution for LR and HR drivers is slightly different which contrasts with the expectation of low prediction errors for LR drivers concluded from Table 3. A one-way ANOVA test follows by a multiple comparison test is used to evaluate the impact of driver profile and driving performance on FDE. The means of each group is depicted in Fig. 7(c) showing that the differences in system performance for LR and HR drivers is not statistically significant compared to the NRB and RB clusters. Hence, for the rest of the paper, we will focus on the driving performance data cluster. The other contributing factors which have been used to evaluate importance to system performance are summarised in Table 4.

We performed a variable importance analysis to assess the average decrease in node impurity measured by the Out-of-bag (OOB) feature importance. This analysis provides information on the variables that need to be considered to improve system performance. The number of tree sets and minimum leaf size for training the random forest is obtained by analysing the regression. Fig. 8 shows the regression error for

Table 3
FDE for different observation clusters.

		Driving performance	FDE				
			Count	Mean	Variance	Stdev	95^{th} Percentile
driver profile	LR driver	RB	58,720	4.095	17.67	4.20	13.12
		NRB	278,399	2.933	10.64	3.261	9.478
	HR driver	RB	36,313	4.32	18.58	4.31	13.54
		NRB	113,860	3.02	11.64	3.41	9.94

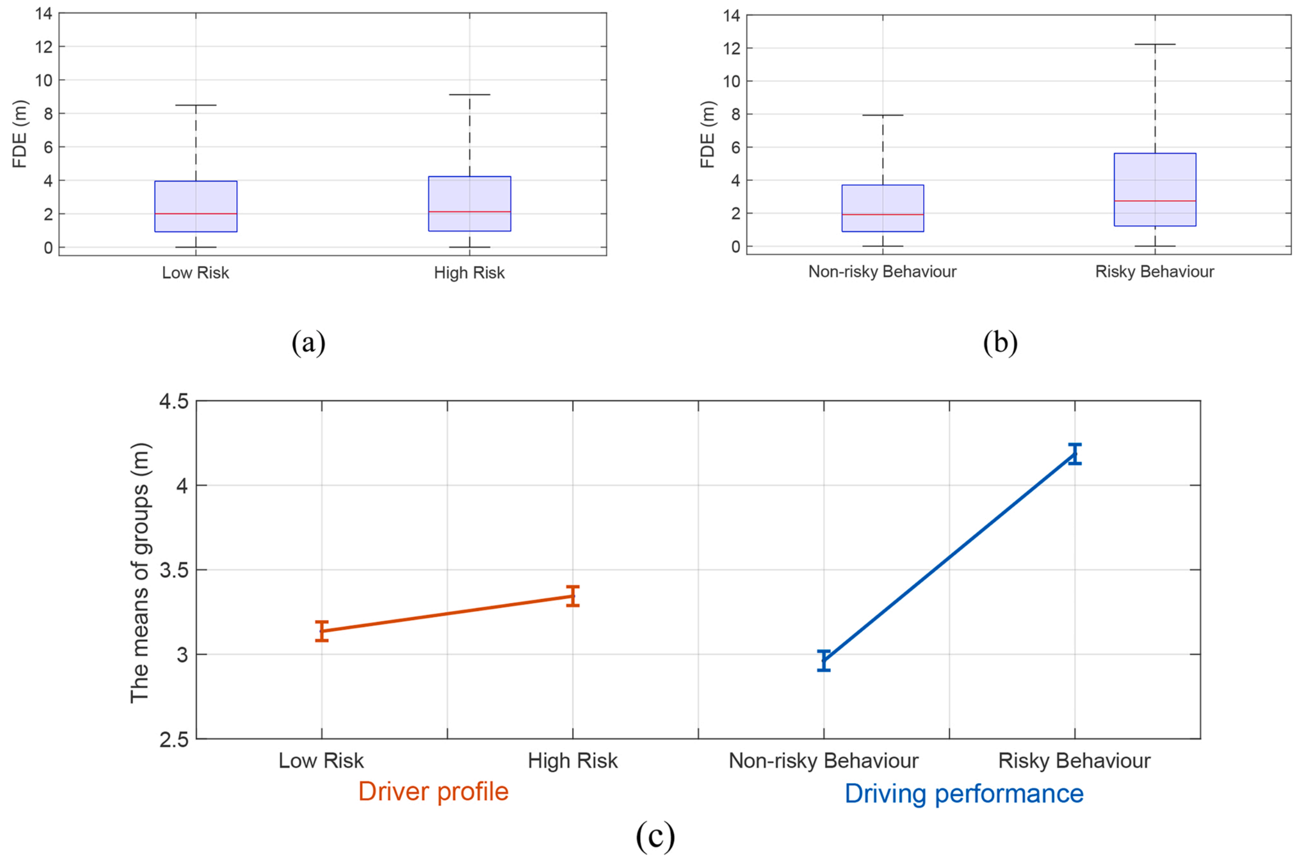

Fig. 7. Distribution of error for (a) driver profile, (b) driving performance clustering and c) the means of each group obtained from one-way ANOVA test followed by a multiple comparison test.

Table 4
Contributing factor categories.

		FDE			
		Mean	Stdev	Var	95th Percentile
Gender	F	3.17	3.498	12.23	10.40
	M	3.23	3.59	12.891	10.725
	between_25_55	3.237	3.620	13.117	10.878
Age Group	Grater_55	2.97	3.29	10.82	9.491
	Under_25	3.262	3.590	12.890	10.760
	Level-of-service A1	3.58	3.69	13.670	11.20
	Level-of-service A2	2.588	2.849	8.121	8.078
	Level-of-service B	3.194	3.583	12.840	10.6158
Traffic Density	Level-of-service C	3.99	4.182	17.493	13.1338
	Level-of-service D	3.92	3.829	14.668	11.687
	Level-of-service E	3.178	3.200	10.24	9.304
	Level-of-service F	2.96	3.055	9.3346	9.1718
Secondary task	No Secondary Tasks	3.139	3.460	11.977	10.33067
	Secondary Tasks	3.239	3.603	12.981	10.691
	Curve left	3.164	3.580	12.817	10.636
Alignment	Curve right	3.707	3.946	15.576	12.143
	Straight	3.160	3.499	12.247	10.398
	Angry;	4.245	4.035	16.281	12.821
	Drowsy; sleepy; asleep; fatigued	3.101	3.709	13.762	10.989
	Drowsy; sleepy; asleep; fatigued; Angry	3.108	3.443	11.860	10.085
	Drugs; alcohol	3.166	2.696	7.2704	6.545
Driver Impairments	Impaired due to previous injury	3.377	3.649	13.315	11.315
	None apparent	3.190	3.529	12.458	10.506
	Other emotional state	4.570	5.426	29.450	16.337
	Other illicit drugs	4.560	5.085	25.857	16.123
	Other	5.936	5.753	33.106	18.780

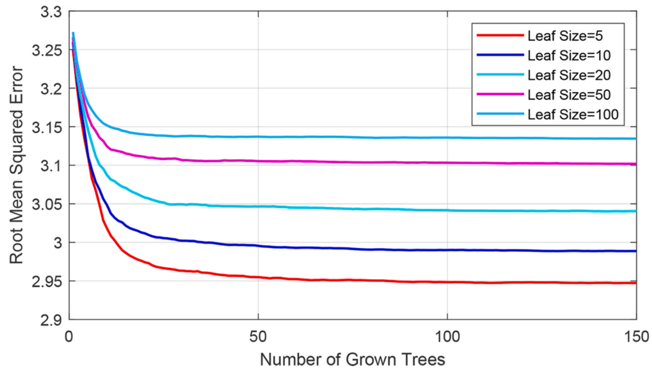

Fig. 8. Comparison between minimum leaf size and number of grown in tree in random forest.

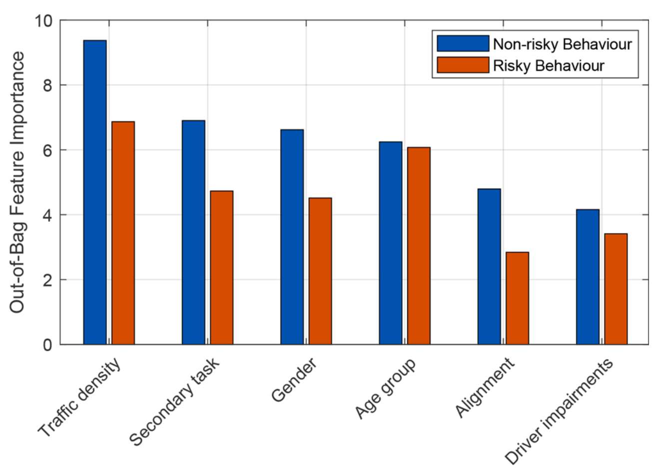

Fig. 9. Variable importance analysis of contributing factors for driving performance clustering.

different minimum leaf sizes by increasing the number of trees. It is observed that the minimum regression error is obtained when the minimum leaf size is set to 5. The error is not significantly improved by selecting more than 50 tree sets. Hence, in this study, 50 tree sets with minimum leaf size equal to 5 were used to fit the FDE parameters of the trained trajectory prediction system with the aim of ranking factors by their relevance to the regression problem. After training the RF, we analysed which variables have a significant impact on the outcome values.

Fig. 9 shows the result of variable importance analysis for two groups of RB and NRB with the variables ranked by their OOB feature importance. The four most important variables for trajectory prediction performance are traffic density, secondary task, gender and age group for NRB. For RB, the order of factor importance is traffic density, age group, secondary task and gender, since they are associated with the highest OOB feature importance. Traffic density is the most important factor for both RB and NRB, while the importance of traffic density for NRB clusters is more pronounced compared with the RB cluster.

Fig. 10 illustrates the trajectory prediction system FDE for the four most importance variables including traffic density, secondary task, age group and gender. Fig. 10(a) shows the system performance for different levels of traffic density for both RB and NRB clusters. It can be seen that for both clusters, as the traffic density level increases from Free Flow with the presence of leading vehicles (i.e., level A2) to Stable Flow (i.e., level C), system error increases and then when the traffic flow is unstable or there is a temporary restriction or stoppages, it decreases. Fig. 10(b & c) shows the FDE for different genders and age groups. The system has lower performance for the RB cluster regardless of driver gender or age. However, the prediction system is less accurate at predicting RB drivers between 25 and 55 years of age. Fig. 10(d) shows the FDE of "engaging secondary task" status for RB and NRB clusters showing that the NRB cluster, regardless of engaging a secondary task, has the same performance, while the RB cluster has lower system performance compared to NRB.

4. Discussion

The purpose of our research is to explore the role of driver profile and driving performance on trajectory prediction system performance. Specifically, we aimed to analyse associations among driver profile and driving performance and other contributing factors such as age, gender, traffic density, driver impairment, secondary task, manoeuvre judgment, and alignment to the performance of the trajectory prediction system (see Appendix A). The study uses an interaction-aware trajectory prediction system to predict ego-vehicle trajectory using the SHRP2 NDS. Prediction performance was evaluated based on different driver profiles and driving performance to identify factors which may minimise prediction error. To the best of our knowledge, this is one of the few studies that assesses the impact of driver and environment factors on prediction system performance. This study provides new information for designing personalised trajectory prediction systems considering driver profile, driving performance and environment situation. Future ADAS need to consider the impact of individual driver differences in their performance.

We evaluated the trajectory prediction performance in term of RMSE and FDE for both lateral and longitudinal manoeuvres. The trajectory prediction method described in Khakzar et al. (2020) was used to predict trajectories within the SHRP2 database for scenarios where at least one adjacent lane exists. The RMSE values for lateral and longitudinal manoeuvres demonstrated system performance for predicting 5 s ahead, showing the relationship between the horizon of prediction and system performance. The FDE distribution shows 3.2 (m) average with standard deviation 3.5 for longitudinal and 0.21 (m) average with standard deviation 0.23 for lateral displacement error. Despite the satisfactory performance of this prediction method for SHRP2 NDS, the overall performance of the system compared with its performance on structured databases such as NGSIM (Colyar and Halkias, 2006, 2007) and HighD (Krajewski et al., 2018) was slightly lower (Khakzar et al., 2020). Since this was the first time that SHRP2 NDS has been used for trajectory prediction purposes, we were not able to benchmark it against other trajectory prediction methods using the same dataset.

We evaluated the impact of driver profile and driving performance on the trajectory prediction system. We used K-means clustering to classify drivers into two groups based on the information provided by drivers. The analysis of driver profile showed that high risk (HR) drivers tend to keep a shorter headway with other vehicles on the road and showed higher velocity and acceleration compared with low risk (LR) drivers. The lateral velocity and maximum acceleration in lateral movement for HR drivers compared with LR drivers was more pronounced, revealing that HR drivers have a higher tendency to perform lane change manoeuvres. These findings are consistent with research by Wang and Xu (2019) reporting that HR drivers are more likely to engage in inattention errors and risky behaviours compared with other drivers. We have also compared the performance of the system based on driving performance (i.e., Non-Risky Behaviour - NRB and Risky Behaviour - RB)

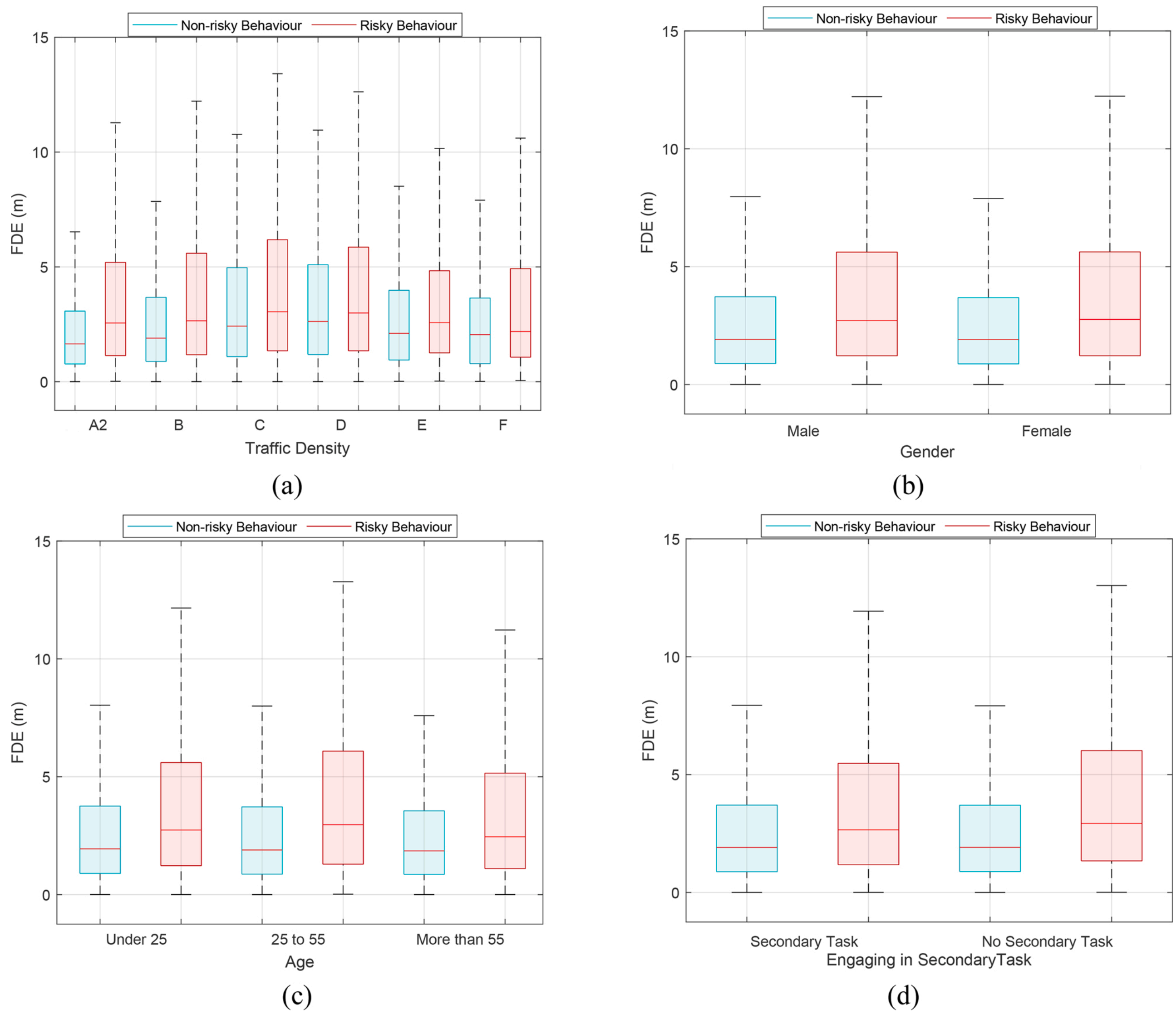

Fig. 10. FDE distribution for the four most important factors.

and driver profile (LR and HR) clusters. This comparison showed that trajectories which belong to the LR drivers who were also in the NRB category resulted in the lowest FDE while trajectories which were driven by HR drivers who also performed RB had the highest error rate. It can also be seen that drivers who were categorised as HR drivers and performed NRB had a lower FDE mean compared with HR drivers with RB and LR drivers with RB. In order to assess the error distribution for driving performance and driver profiles, we looked at the system error distribution for each driver cluster. The results confirmed a relationship between driving performance and system performance. In comparison, the results showed that driver profile does not have a significant impact on system performance. However, the driving performance has a relationship with trajectory prediction performance. Indeed, the prediction error distribution is 1.5 times higher in RB compared with NRB. This suggests that considering the driving performance of a driver influences the performance of the system. This finding is consistent with research by Cai et al. (2018), who found that each driver uniquely engages in the driving task so considering driving performance for drivers can effectively describe driving characteristics. Our findings, however, are contrary to Doshi and Trivedi (2010) which found that aggressive drivers are more predictable than non-aggressive drivers which may happen due to different methods of driver clustering. Our investigation has highlighted that engaging in risky behaviour can increase prediction error.

To further identify factors influencing prediction performance, we performed a random forest importance analysis to rank the importance of different factors on system performance. The final variable ranking in descending order of importance as provided by RF's variable importance analysis suggests that the main variables impacting system performance are related to traffic density for both groups followed by secondary task, gender and age group for NRB drivers and age group, secondary task and gender for RB drivers. Regarding the results of variable importance analysis, we only discuss the four most relevant variables. The analysis revealed that the age group for RB drivers is the second most important factor impacting trajectory prediction performance, while for NRB drivers it is the fourth most important factor. Among three driver age groups, the 25–55 year old drivers who classified in the RB cluster had a higher prediction error while there were no differences identified between age groups of NRB drivers. While considering different levels of traffic density associated with system performance, some patterns were found between RB and NRB driver performance. Overall, RB drivers present higher error in all levels of traffic density compared with NRB. This error in both categories is minimum for free flow traffic density. As the traffic density level increases with leading vehicles present (i.e., Level A2), the FDE slightly increases until the point that manoeuvre ability and speed are both restricted (i.e., Level C). The system experienced the highest level of prediction error for both RB and NRB drivers at this level. Moving on from stable flow (i.e., level C) to unstable flow (i.e., level D), there is a slight improvement in system performance which is maintained until traffic density reaches levels E & F. This reduction may be due to the very slow movement of traffic or temporary vehicle stoppages in the traffic scene. Though not directly comparable, the patterns observed between traffic density and prediction error showed that when external restrictions are applied in the traffic scene, the system cannot perform predictions as accurately as in other situations. While the system has lower performance for the RB cluster, the findings further confirmed that the gender of drivers does not show a significant relationship to prediction error. The prediction system is less confident with predictions for RB drivers between 25–55 years of age. The last variable we analysed is engaging or not engaging with secondary tasks. This is consistent with previous research confirming changes in lateral and longitudinal vehicle control among drivers engaging in secondary tasks such as mobile phones (Onate-Vega et al., 2020; Oviedo-Trespalacios et al., 2018). Although there are similarities between these the two groups of drivers, the result showed that system performance for the RB cluster is lower than NRB. These results confirm that human factors such as distraction could interact negatively with the performance of ADAS using trajectory prediction performance.

Recent advances in trajectory prediction systems have been incremental, however there are still barriers to their widespread implementation, such as timing, accuracy, ability to work based on different driver profiles and driving performance. Well-designed trajectory prediction provides an opportunity to reduce or mitigate crash risk and save drivers and other road users. Although previous investigations have demonstrated the effectiveness of considering different driver profiles in improving trajectory prediction performance, it was not clear which sort of information needed to be considered in the design of a new generation of trajectory prediction systems. The finding of this research using driver profile and driving performance identified important variables which can be considered for a new generation of trajectory prediction systems with the aim of improving performance through design of a personalised trajectory prediction system. In addition, this investigation identified the consideration of external restrictions such as traffic density that can improve the accuracy of future trajectory prediction systems. This new information can lead to the design of an attention-based mechanism in prediction frameworks to distinguish between different data distributions while training a model (Xing et al., 2020, 2019b). A more accurate prediction model with better performance (less False-Alarms or Missed-Alarms) improved driver's technology acceptance and reduces the likelihood that the driver ignores correctly generated alarms in crash situations as well as detracting from long-term system use. Ultimately, this research can increase adoptions and correct us of ADAS.

The present study has some important limitations that need to be considered. The driver profile was based on the scales developed by the SHARP2 team, but its broader validity has not been tested. Perhaps validated questionnaires such as the driver behaviour questionnaire or Behaviour of Young Novice Drivers Scale (Oviedo-Trespalacios and Scott-Parker, 2017; Tosi et al., 2020) or the Driver Behaviour Questionnaire (Özkan and Lajunen, 2005) would have produced different findings for the driver profile. The analysis was limited to the scenarios where at least one adjacent lane exists so the variables influencing the performance of an ADAS may be different in other scenarios such as roundabouts, T-intersections, and driving in roads without lane markings.

5. Conclusions and future work

This manuscript explores vehicle trajectory prediction performance according to individual differences based on driver profile and driving performance. The investigation showed that driver profile, based on self-reported questionnaires, did not influence performance of the system. Driving performance, however, influenced trajectory prediction performance. In particular, among drivers who exhibited a riskier profile (i.e., driving too close, or engaging in risky behaviour), trajectory prediction showed more error than among drivers who exhibited safer behaviour. This highlights an important issue. Namely, trajectory performance prediction is less effective among drivers who present more risky driving tendencies and arguably, need more protection from transport infrastructure. Technology alone may not be sufficient to increase road safety due to different human-systems integration issues that need to be addressed. Future research can address these issues by adding information which may influence the performance of trajectory prediction systems and developing technology- or education-based interventions to improve the performance of ADAS. Future research also needs to consider the use of driving behaviour in the vehicle trajectory prediction system. The use of categorical data with the same distribution and analysing specific patterns will lead to the design of a personalised trajectory prediction system that improves system performance and road safety.

Authorship contributions

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Acquisition of data: M.K. Khakzar

Analysis and/or interpretation of data: M.K. Khakzar, A.B. Bond, A.R. Rakotonirainy, S.G.D. Dehkordi.

Category 2

Drafting the manuscript: M.K. Khakzar, A.B. Bond, A.R. Rakotonirainy, O.O.T. Oviedo-Trespalacios, S.G.D. Dehkordi;

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Category 3

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Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A

Table A1
SHRP2 data used in this study.

	variables	
Risk Taking Questionnaire	Run Red Lights Past 12mo	Adjust CD Player
	Drive Sleepy	Eyes off Road to Passenger
	Take Risks for Fun Often	Race Other Cars Past 12mo
	Change Lane Suddenly	Merge without Checking Rear-view Mirror
	Run Stop Sign Often	Speed 10–20 MPH Over
	Speed for Thrill Often	Speed 20 + MPH Over
	Fail to Yield	Not Yield to Pedestrians
	Make Illegal Turns	Not Use Belt
	Tailgate	Not Use Signal
	Follow Emergency Vehicles	Use Worn Tires Often
	Take Risks Because of Hurry	Pass When Visibility Obscured
	Failure to Adjust	Roll Through Stop Sign
	Pass on Right	CARDS Frequency of Risky Behaviour Score
	First Off Line Past 12mo	Modified CARDS Frequency of Risky Behaviour Score
	Accelerate at Yellow Light	Adjust CD Player
	Drive after Drugs	Eyes off Road to Passenger
	Using Drugs While Driving	Race Other Cars Past 12mo
	Road Rage Past 12mo	Merge without Checking Rear-view Mirror
	Drive for Enjoyment	Speed 10–20 MPH Over
	Secondary Tasks While Driving Often	Speed 20 + MPH Over
Driver Demographic Questionnaire	Gender	Male Female
	Age group	Under_25 Between 25 and 55 Grater_55
Time Series Data	Velocity	Acceleration
	Position	Radar
	Angular velocity	
Event Details	Driver impairment	Angry; Drowsy; sleepy; asleep; fatigued Drowsy; sleepy; asleep; fatigued; Angry Drugs; alcohol Impaired due to previous injury None apparent Other emotional state Other illicit drugs Other
	Traffic density	service A1: Free flow; no lead traffic Level-of-service A2: Free flow; leading traffic present Level-of-service B: Flow with some restrictions Level-of-service C: Stable flow; manoeuvrability and speed are more restricted Level-of-service D: Unstable flow - temporary restrictions substantially slow driver Level-of-service E: Flow is unstable; vehicles are unable to pass; temporary stoppages; etc. Level-of-service F: Forced traffic flow condition with low speeds and traffic volumes that are below capacity
	Secondary task	No Secondary task Engaging in secondary task
	Alignment	Curve left Curve right Straight

Table A2
Risky behaviour in this study used in driving performance.

Aggressive driving	Other Specific- directed menacing actions	
Violation	Stop sign violation	Rolling stop Intentionally ran stop sign at speed
	Crossing violation	Non-signed crossing violation
	Other sign violation (e.g. Yield)	Intentionally disregarded Apparently did not see sign
Improper braking or turn	Backing	Did not see Other
	Turn	Cut corner on left cut corner on right wide right turn wide left turn
Signal	Violation	Apparently did not see signal Intentionally disregarded signal Tried to beat signal change
	Failed to signal	
Cutting in	Too close behind other vehicle Too close in front of other vehicle	
Right-of-way error	In relation to other vehicle or person	Apparent decision failure Apparent recognition failure other or unknown cause
Speed	Exceeded	Exceeded safe speed but not speed limit Exceeded speed limit Speeding or other unsafe actions in work zone
	Slowly	In relation to other traffic, not below speed limit Below speed limit
Apparent general inexperience driving		
Apparent unfamiliarity with roadway		
Avoiding other vehicle		
Avoiding pedestrian		
Did not see other vehicle during lane change or merge		
Drowsy- sleepy- asleep- fatigued		
Following too closely		
Distracted		
Driving in other vehicle's blind zone		
Driving without lights or with insufficient lights		
Passing	Other improper or unsafe passing Illegal passing Passing on right Wrong side of road- not overtaking	

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