# Understanding the discretionary lane-changing behaviour in the connected environment

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## Abstract

Discretionary lane-changing (DLC) is one of the complex driving manoeuvres that requires surrounding traffic information for efficient and safe manoeuvring. The connected environment not only provides such information but also increases situational awareness, which is useful for DLC decision-making. However, the literature is devoid of any concrete evidence of such impact of the connected environment on DLC decision-making. As such, this paper analyses the effects of the connected environment on DLC behaviour. Seventy-eight participants from a diverse background performed DLCs in randomised driving conditions using the CARRS-Q advanced driving simulator. These driving conditions are: baseline (without driving messages), connected environment with perfect communication (fully functioning and uninterrupted supply of driving messages), and connected environment with communication delay (impaired communication). Various key driving behaviour indicators are analysed and compared using a linear mixed model. To analyse the effects of the connected environment on DLC decision-making, two Generalized Estimation Equation (GEE) models are developed for gap acceptance and DLC duration. In addition, a Weibull accelerated failure time hazard-based duration model is developed to investigate the impact of the connected environment on safety associated with DLC manoeuvres. We find that drivers in the connected environment have a larger spacing, larger lead and lag gaps, a longer DLC duration, and a lower acceleration noise compared to the baseline condition. The GEE model on gap acceptance reveals that drivers tend to select relatively bigger gap sizes when the connected environment offers them the subsequent gap information. Similarly, the GEE model for DLC duration suggests that the connected environment increases DLC durations by 2.22 s and 2.11 s in perfect communication and communication delay driving conditions, respectively. Finally, the hazard-based duration model provides insights into the probability of avoiding a lane-changing collision, and indicates that the probability of a lane-changing collision is less in the connected environment driving conditions than in the baseline scenario. Overall, the connected environment improves the DLC driving behaviour and enhances traffic safety.

## 1. Introduction

Lane-changing has a significant impact on traffic flow characteristics and is an indispensable part of a microscopic traffic simulation package. Generally, lane-changing is of two types: mandatory lane-changing (MLC) and discretionary lane-changing (DLC). The former is compulsory and needs to be performed to reach the planned destination whilst the latter is voluntary and mainly carried out to achieve better driving conditions. DLC, compared to MLC, is more complex since drivers tend to evaluate its necessity, desirability, and safety, whilst for

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MLC, drivers only need to evaluate its safety (Toledo et al., 2005). This study is focussed on the DLC behaviour of drivers.

As one of the primary driving tasks that drivers frequently perform on the road, the importance of analysing and modelling lane-changing behaviour is widely acknowledged in the literature due to its negative impact on traffic flow efficiency, road safety, environment, etc. (Zheng et al., 2013, Zheng et al., 2011b, Pande and Abdel-Aty, 2006). Lane-changing modelling is generally classified as lane-changing decision-making and lane-changing impact (Zheng, 2014). This study concentrates on DLC decision-making behaviour in a connected environment.

The connected environment provides information via vehicle-to-vehicle and vehicle-to-infrastructure communications. The connected environment has shown promise to assist in solving massive transport issues related to traffic safety, mobility, efficiency, and the environmental impact (Kim, 2015). The connected environment provides information about surrounding traffic, which is essential whilst performing a DLC manoeuvre. More specifically, the connected environment provides information such as the distance from the preceding vehicle on the current lane, subsequent gaps on the target lane, and advanced warning on upcoming traffic situations. These driving messages are presumed to reduce drivers' workload and uncertainty associated with DLC, and thus make DLC manoeuvres more efficient and safer. Moreover, the impact of these driving messages is expected to be more pronounced at the operational stage of DLC decision-making including gap acceptance and duration of DLC execution (DLC duration hereafter). The former is an integral part of lane-changing modelling and has received lots of attention in the literature (Toledo et al., 2003a, Toledo et al., 2005, Bham and Goswami, 2007, Choudhury et al., 2007, Bham, 2009, Marczak et al., 2013) whilst the latter is an important aspect of lane-changing execution and has been rarely studied (Toledo and Zohar, 2007). DLC duration is often modelled as an instantaneous event, which contradicts the findings reported in the literature that suggests that DLC duration varies from 1 s to 16.5 s (Toledo and Zohar, 2007). This ignorance might result in: (a) unrealistically mimicking negative impact of a DLC manoeuvre, such as shockwaves on both the initial and the target lanes, capacity drop, and traffic safety hazards, during the DLC execution; and (b) biased estimates of traffic flow parameters. To this end, a DLC duration model can: (i) successfully predict how long a DLC manoeuvre would last; (ii) be a useful tool to develop comprehensive DLC impact models; and (iii) help in evaluating existing DLC impact models, aiming to fully characterise the impact of a DLC manoeuvre on surrounding traffic.

The anticipated benefits of connected environment are a function of drivers' compliance to the information. Ignoring the information would nullify such benefits (Sharma et al., 2017). Thus, the role of a driver is of the utmost importance during a decision-making in the connected environment, and it is more important and critical in DLC, which is voluntary and depends on drivers' perception about the current driving conditions. The synthesis of the literature suggests that most of the studies evaluating the connected environment's impact at a macroscopic level are either based on hypothesis (Kim, 2015) or using numerical simulations (Guériau et al., 2016, Reina and Ahn, 2015). A main problem with numerical simulations is the lack of human factor, which is critical for the success of the connected environment (Sharma et al., 2017). A sound understanding of the connected environment's impact on DLC behaviour and its association with human factor is important for developing more realistic DLC models, which can be used for operating and controlling vehicles in the connected environment, and for designing a safer and more efficient connected driving environment. Unfortunately, the literature is devoid of evidences of the connected environment's impact on DLC decision-making and its association with human factors, mainly because of the novelty of the connected environment and the consequent scarcity of the relevant data. To better analyse and understand the impact of the connected environment on DLC decision-making behaviour, high-quality vehicle trajectory data along with detailed information of human factors are required. As such, this study aims to fill this research gap. More specifically, the objective of this study is twofold: (a) to evaluate the impact of the connected environment on DLC decision-making; and (b) to understand the association of human factors with DLC decision-making in the connected environment.

To this end, this paper is organised as follows: Section 2 summarises the relevant literature related to gap acceptance, DLC duration, and DLC safety. Section 3 describes the data collection process including the advanced driving simulator, the experiment design, and data pre-processing. Section 4 presents results of our descriptive analysis on the experimental data. Section 5 develops statistical models for gap acceptance, DLC duration, and safety. Section 6 discusses the main findings. Finally, Section 7 concludes the study.

## 2. Literature review

This section describes literature related to: (a) gap acceptance behaviour; (b) DLC duration; and (c) safety related to DLC.

### 2.1 Gap acceptance behaviour during DLC

In general, DLC behaviour is modelled in two steps: target lane selection and gap acceptance. Since this study empirically analyses the impact of the connected environment on gap acceptance in DLC decision-making, studies related to DLC gap acceptance behaviour are reviewed herein.

Gap acceptance, an integral part of DLC decision modelling, is modelled using the gap acceptance theory, which states that a driver will never reject a gap larger than the critical gap. According to this theory, if a driver does not find a gap larger than the critical gap, the driver will continue travelling on the current lane (Marczak et al., 2013). To determine factors affecting gap acceptance behaviour, a thorough literature review is carried out and Table 1 summarises some representative studies related to DLC gap acceptance behaviour. Many factors have been considered for DLC gap acceptance behaviour, which can be classified as: factors in the current lane and factors in the target lane. Some of the common factors considered for the current lane are the speed of the subject vehicle, spacing, density, and relative speed, etc. Some common factors for the target lane are lead and rear gaps, the speed of the leading and the following vehicles, relative speeds, density, and heavy vehicle in front, etc. Personality traits such as aggressiveness and sensation seeking are reported to influence MLC behaviour (Bham and Goswami, 2007), but a little is known on the effect of such factors on DLC behaviour.

Notably, all of the studies reported in Table 1, have mainly focussed on the traditional environment (without driving assistance system) and mostly neglected human factors such as age, and gender, which are critical for the success of the connected environment. No gap acceptance model for DLC in the connected environment is found in the literature.

**Table 1**. A summary of representative DLC studies

| Study | Variables considered in DLC | Analyses/modelling methodologies |
|---|---|---|
| McDonald et al. (1997) | Lead time-to-collision and speed | Fuzzy logic |
| Zhang et al. (1998) | Relative distance between the subject and leading vehicles, relative speed of the subject and leading vehicles, heavy vehicles, and aggressiveness of the follower | Multiregime traffic simulator |
| Ahmed (1999) | Lead and lag gaps, front gap/spacing, current and target lane densities, speeds of lead and lag vehicles, front vehicle, relative speed in current and target lanes | Utility theory |
| Das and Bowles (1999) | Front gap, rear gap, and speed of the subject vehicle | Fuzzy logic |
| Toledo et al. (2003b) | Subject vehicle speed, relative front and lag vehicle speeds, spacing, and tailgate variable | Utility theory |
| Rakha and Zhang (2004) | Distance headway and speed differential between the leading and following vehicles | INTEGRATION model |
| Toledo et al. (2005) | Lane density, average speed in lanes, spacing, relative front vehicle speed, and tailgate variable | Utility theory |
| Hidas (2005) | Front gap, rear gap, and speed of the subject vehicle | Fuzzy logic |
| Yeo et al. (2008) | Speed of the subject vehicle and relative speed | Macroscopic model |
| Moridpour et al. (2008) | Speed and acceleration of the subject vehicle, front vehicle speed, space headway, rear vehicle speed, and target lead and lag vehicle speeds | Empirical analysis |
| Kan et al. (2009) | Speed disadvantage, speed advantage, and speed gain | Empirical analysis |
| Feng et al. (2009) | Speed difference between the subject vehicle and leader in the current lane | Utility theory |
| Moridpour et al. (2010) | Front vehicle speed, rear and lead vehicle speeds in target lane, lead and lag gaps in target lane | Empirical analysis |
| Sun and Elefteriadou (2011) | Slow vehicle, queue advantage, heavy vehicle, and tailgating | Focus group and empirical analysis |
| Moridpour et al. (2012) | Front and rear space gaps, right lag space gap, and average speed in the current lane | Fuzzy logic |
| Schakel et al. (2012) | Speed, lead time-to-collision, lag time-to-collision | Embedded in car-following |
| Sun and Elefteriadou (2012) | Congestion, Queue length, Location stop, Distance to bus, driver type | Utility theory |
| Hill et al. (2014) | Front and rear gaps, and speed of the subject vehicle | Empirical analysis |
| Wang et al. (2014) | Lateral positions and speed of the subject vehicle | Empirical analysis |
| Balal et al. (2014) | Front and rear gaps before and after lane change, lead and lag time-to-collisions before and after lane change | Empirical analysis |
| Zheng et al. (2014) | Instantaneous speed of the subject vehicle, type of vehicle, relative speed between lead vehicle and subject vehicle, space gap between lead vehicle and subject vehicle, and relative speed between lead vehicles | Neural network |
| Zeng and Yang (2015) | Spacing, speed of the subject and leading vehicles and following vehicles in the target lane | Discrete dynamic game |
| Park et al. (2015) | Speed differences | Logistic regression |
| Talebpour et al. (2015) | Speed differences between the subject and leader and follower vehicles in the target lane, change in speed | Game theory |
| Wang et al. (2015) | Distance between the subject vehicle and preceding vehicle, speed of front vehicle, and maximum braking deceleration | Analytic hierarchy process |
| Nie et al. (2016) | Speed differences between: subject vehicle and leader and follower in the target lane; subject vehicle and leader in | Support vector machine |

| | | |
|---|---|---|
| | the current lane, lead and lag gaps in the target lane, and spacing in the current lane | |
| Bi et al. (2016) | Speed of the subject vehicle, distance to leader and follower in the target lane, speed difference to leader and follower in the target lane, and lateral distance to the target lane | Back-propagation neural network |
| Balal et al. (2016) | Speed and gaps in the current and target lanes | Fuzzy logic |
| Lee et al. (2016) | Relative speed and spacing advantage | Exponential probability model |
| Zhao et al. (2017) | Spacing, lead and lag gaps | Empirical analysis |
| Vechione et al. (2018) | Spacing, lead and lag gaps | Empirical analysis |
| Guo et al. (2018) | Speed difference, space headway, time headway, speed difference between two adjacent lane, and density difference between two adjacent lanes | Empirical analysis |
| Jin et al. (2018) | Speed of the subject vehicle and leader in the current lane, lead and lag gaps in the target lane, and spacing | Empirical analysis |
| Edrisi and Askari (2018) | Mean vehicle speed in the current and target lanes, number of vehicles in all lanes | Count regression model |
| Wang et al. (2017) | Relative distance and speed between target vehicle and surrounding vehicles | Fuzzy many-person multi-objective non-cooperative game |
| Wang et al. (2018) | Relative distance and speed between target vehicle and surrounding vehicles | Phase-Field coupling and multiplayer dynamic game |
| Wang et al. (2019) | Relative distance and speed between target vehicle and surrounding vehicles | Multi-player dynamic game |
| Yang et al. (2019) | Speeds of leaders in the current and target lane | Prospect theory |

## 2.2 DLC duration

DLC duration, an important aspect of DLC execution and impact, is defined as the time taken by the subject vehicle to complete the DLC manoeuvre from the current lane to the target lane. DLC duration is often reported to have a significant impact on surrounding traffic in a congested traffic (Moridpour et al., 2010). Thus, it is important to develop models that can properly describe important traffic characteristics (e.g., DLC duration) of DLC execution.

Among many problems in modelling DLC duration reported in the literature, the foremost important issue is to properly and accurately measure DLC duration as most of the databases do not directly provide such information. As a result, various studies use different techniques such as an observer method (Hetrick, 1997), and self-reporting technique (Salvucci and Liu, 2002). However, these methods are subject to memory bias and are likely to induce biasedness and error. In contrast, Toledo and Zohar (2007) utilised lateral profiles to measure DLC duration and neglected failed lane-changing attempts and noise in the data. Thus, a robust and sound methodology is required to accurately pinpoint the DLC starting point and subsequently, DLC duration.

Although the magnitude of DLC duration has been reported in previous studies, DLC duration models are rare. Toledo and Zohar (2007) developed a lane-changing duration model for the traditional environment and identified factors affecting lane-changing duration such as the speed of the subject vehicle and spacing in the current lane, relative speed in the target lane, density, etc. However, this model does not incorporate any human factors, which are important for DLC execution. A separate model is needed for the connected environment that can cater for flow of information and its impact on DLC duration coupled with human factors, which is critical for describing driving behaviour in the connected environment, as reported by Sharma et al. (2017).

### 2.3 Safety during DLC

Inaccurate and risky DLC decisions are likely to increase crash risk and could result in rear-end or sideswipe collisions (collectively referred as lane-changing collisions). Many factors are reported to increase the probability of lane-changing crashes such as traffic speeds, volumes, and the differences in occupancies on the adjacent lane (Pande and Abdel-Aty, 2006). Similarly, Jun et al. (2007) found that lane-changing crashes are associated with higher speeds and hard decelerations. Using naturalistic data, Fitch and Hankey (2012) reported that drivers involved in lane-changing crashes do not frequently use turn signals and make decision errors such as improper estimation of gaps and surrounding traffic speed.

Due to the inherent complexity of crashes and the scarcity of detailed information on crash data, studying the safety aspect of DLC along with detailed human factor information is difficult. As such, surrogate measures of safety are used to understand crash risks. A wide range of surrogates are presented in the literature and can be utilised for evaluating safety critical events during DLC such as minimum time-to-collision, maximum deceleration required to avoid a collision, minimum post-encroachment time, and many others. These factors also have the potential to quantify the impact of the connected environment on DLC. The literature till date is devoid of studies that focus on safety associated with DLC manoeuvres in the connected environment.

### 2.4 A review of studies related to road user behaviour in the connected environment

Due to novelty of the connected environment and the consequent scarcity of the relevant data, many studies have reported different benefits of the connected environment using numerical simulations (McGurrin et al., 2012, Zeng et al., 2012). For instance, a microsimulation-based study has presented a modelling framework for vehicles operating in the connected environment and has found that these vehicles can improve traffic mobility, enhance safety, and reduce greenhouse gas emissions at a network level (Olia et al., 2016). Similarly, Rahman and Abdel-Aty (2018) analysed vehicle platooning in the connected environment and have observed an increased safety, measured in terms of safety surrogates. Using infrastructure-to-vehicle communication, Park et al. (2011) provided merging advisory information to vehicles in a simulation framework and reported 6.4% increase and 5.2% decrease in average speed and emissions, respectively. In align with Park’s study, Ahmed et al. (2017) reported that drivers in the connected environment can collaborate and improve safety during merging.

Apart from lane-changing, the connected environment has also shown a promise in improving driving behaviour in general. For instance, Sharma et al. (2019) reported increased response times of drivers in the connected environment compared to when they are driving without the connected environment. Lee and Park (2012) proposed an intersection control algorithm based on the connected environment that does not require a traffic signal at an intersection. This study with the help of microsimulations showed that the proposed intersection algorithm reduces stop delay and travel time by 99% and 33%, respectively, compared to a conventional actuated intersection. Hashimoto et al. (2016) proposed a probabilistic model for pedestrian crossing behaviour at signalised intersections for connected vehicles (vehicles operating in the connected environment) and have reported that the model can capture rushing behaviour of pedestrians, who can be in a blind spot of a turning driver.

He et al. (2017) proposed a generalised simulation framework using vehicle-to-pedestrian communication and suggested that vehicle-to-pedestrian communication can improve pedestrian safety. Using infrastructure-to-vehicle communication, Kamalanathsharma and Rakha (2016) showed improved fuel consumption of vehicles in the range of 5 to 30%.

## 3. Experiment methodology and data collection

To observe the impact of the connected environment on DLC behaviour, an innovative driving simulator experiment was designed. Participants drove in three randomised driving conditions including baseline (without driving messages), connected environment with perfect communication, and connected environment with communication delay. The first condition serves as the default driving condition to which the driving performance is compared. The second condition enables the comparison of driving behaviour in the connected environment without any interruption whilst the third condition allows the evaluation of differential effect of the connected environment where the information provided by the connected environment is delayed.

### 3.1 Advanced driving simulator

To collect high-quality trajectory data in the connected environment, the Centre for Accident Research and Road Safety-Queensland (CARRS-Q) advanced driving simulator was used (Figure 1). The participants were asked to drive a fully functioning Holden Commodore car that is attached to three front-view projectors providing a high-resolution 180° field of view. The simulator has a rotating base, providing six-degrees-of-freedom along with moving and twisting in *x*, *y*, *z* space, mimicking driver cues for acceleration, deceleration, breaking, cornering, road surface, and integration with other road features. The simulator uses SCANeR$^{TM}$ studio software linked with eight computers that control vehicle dynamics in a virtual road environment. An audio system is also attached to the simulator for producing engine noises, vehicle-road interaction noises, and noises of other traffic interactions, creating an enhanced realism of the driving experience. The simulator provided vehicle trajectory data, such as speeds, accelerations and positions, at a rate of 20 Hz.

**Fig. 1.** CARRS-Q advanced driving simulator

## 3.2 Participants

Seventy-eight participants from a diverse background were recruited for participation in the simulation experiment, which were self-selected through advertising at various public places and social media platforms. The average age of the participants is 30.8 years (standard deviation [SD] 11.7). The average age for male and female participants is 34.1 (SD 12.6) and 24.9 (SD 6.7) years, respectively. About 64% of the participants are males. All of the participants held a valid Australian driving licence, and the average driving experience of the participants is 12.2 (SD 11.5) years. Each participant received AU $75 as a compensation of their time upon completion of the study.

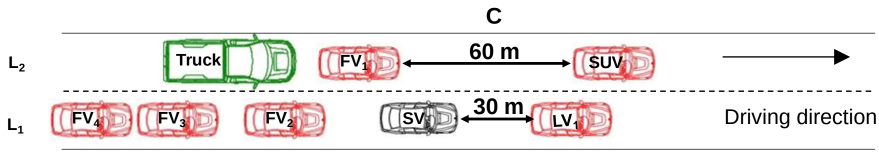
## 3.3 Experiment design

A 3.2 km four-lane motorway with two lanes in each direction is designed for the simulator experiments. The posted speed limit on the motorway is 100 km/h. Roadway geometric features, lane markings, and road signs along the motorway in the simulator experiments were designed according to a typical Australian motorway to the extent possible. Note that the driving in the Australia is on the left side of the road. Although the simulated route includes both MLC and DLC events, the scope of this paper is limited to analysing driving behaviour during a DLC manoeuvre. Our work and subsequent modelling on MLC can be found in (Ali et al., 2018, Ali et al., 2019a, Ali et al., 2019b). To avoid driving sequence bias, the driving conditions are randomised for each participant. The three driving conditions in the experiments are described below.

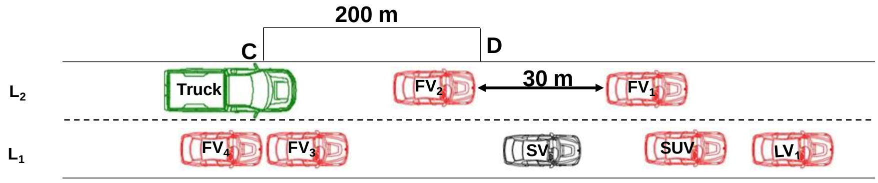
*Baseline driving condition*

Each participant drives the simulator vehicle without driving assistance system (i.e., no driving messages provided by the connected environment). The roadway section for DLC events was created in a way that the current lane had a congested driving condition, and each participant had the opportunity to change lanes to the adjacent lane to achieve better driving conditions. Consistent with the real driving behaviour observed in the field, the following vehicles (FVs) accelerate, decelerate, and remain unaffected by the DLC action of the subject vehicle (SV)– the vehicle driven by the participants.

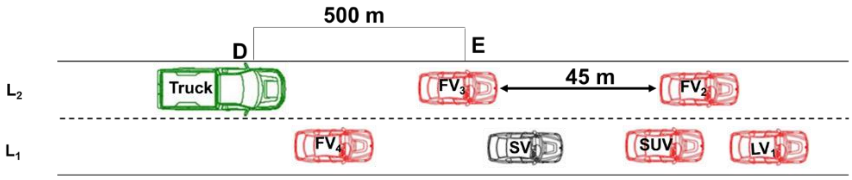
At the start of the scenario as shown in Figure 2(a), the distances between SV and the leading vehicle ($LV_1$) on the current lane ($L_1$) and SUV and $FV_1$ on the target lane ($L_2$) are respectively 30 m and 60 m. Both a smaller spacing on the current lane and a larger gap size on the adjacent lane trigger the DLC event, and present the first DLC opportunity (out of five opportunities), as the participants are likely to gain the speed advantage on the adjacent lane. If SV rejects this gap, SUV moves to the SV's lane ($L_1$) and starts moving at the speed of 50 km/h. Meanwhile, $FV_2$ moves to the adjacent lane ($L_2$) and creates the gap of 30 m from $FV_1$ (Figure 2b). This is the second DLC opportunity. After travelling 500 m from the point D (Figure 2c), $FV_2$ moves past SV and $FV_3$ changes lane to the adjacent lane from the SV's lane ($L_1$) and creates the gap of 45 m from $FV_2$. This presents the third DLC opportunity. If SV decides to remain on the current lane, $FV_4$ and Truck respectively create the gaps of 15 m and 90 m for DLC. After the gap of 90 m, there is infinite gap on the adjacent lane for DLC. Once a participant has changed lanes, all of the FVs will move at predefined speeds. At the end of motorway, the participants take an exit ramp to the city where the scenario ends. Note that the trigger/temptation for DLC is that all of the vehicles (FVs) on the adjacent lane are moving fast, giving an impression to SV that the current lane has congested driving conditions whilst the vehicles travelling on the adjacent lane has a higher speed than that of the current lane.




(a) Vehicular interactions at the start of the DLC scenario




(b) Vehicular interactions during the second available gap




(c) Vehicular interactions during the third available gap

**Fig. 2.** Design of the DLC scenario (not to scale); note that other gap sizes are not depicted in this diagram

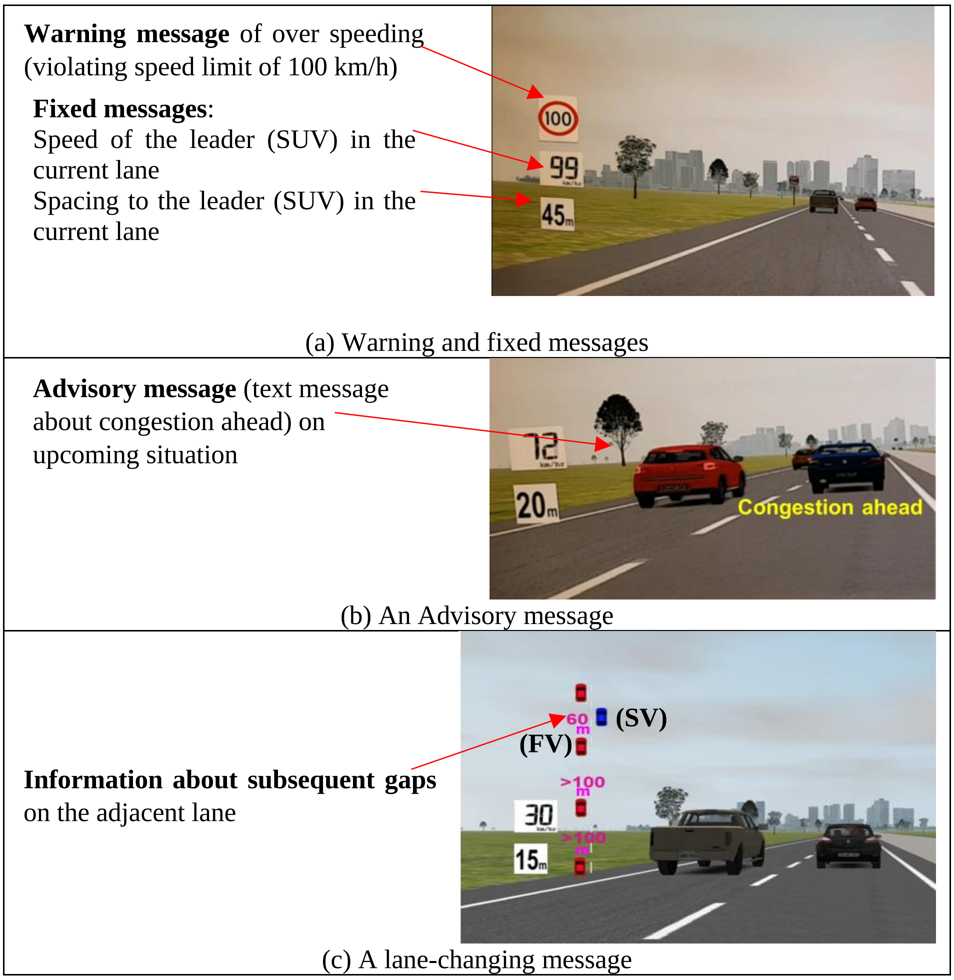
Five gap sizes were provided in the baseline driving scenario. A simple and pragmatic strategy was adopted to randomise the gap size: bigger and smaller gap sizes were mixed together so that participants should not be able to guess the next available gap from the trend of available gap sizes. Meanwhile, the gap size was mainly selected based on the existing literature, suggesting that a lane-changer and its immediate follower interact with each other when the distance between them is 60 m or less (Toledo et al., 2003b, Liu et al., 2007). Based on the literature, the gap sizes were provided at a regular interval in the baseline scenario.

We intentionally provide identical gap sizes to all the participants across three drives to objectively assess and model the connected environment's impact on DLC decision-making, DLC execution, and safety during a DLC manoeuvre. Randomising these gaps would result in: (a) complex vehicular interactions; (b) compromising the data quality due to increase in participants' workload; and (c) difficulty to distinguish the real reason of different driving performances as such the difference is caused by the connected environment's impact or due to randomised gaps. Thus, our experiment is intentionally designed to create similar vehicular interactions for all the participants and the same gaps to minimise confounding factors.

*Connected environment with perfect communication driving condition*

The vehicular interactions and roadway design in this driving condition remain the same as in the baseline driving condition. However, the participants receive the information from a fully functioning connected environment in the form of driving messages, mimicking vehicle-to-vehicle communication and vehicle-to-infrastructure communication. For an effective design of the connected environment (more specifically, driving messages), we have comprehensively reviewed the state-of-the-practice in the automobile industries on how major car manufacturers have designed their driving messages [e.g., Adell et al. (2011); Saffarian et al. (2013)], and found out that almost all of the car manufacturers opt for providing simple messages to users in the form of auditory (beep sound) and imagery messages. This presentation of the information closely resembles to the heads-up display equipped in some of recent car models. See Figure 3 for an example.

During the connected environment driving conditions, four different types of messages are disseminated to assist during DLC tasks. These messages are fixed, warning, advisory, and lane-changing messages. The first message (i.e., a fixed message) continuously appears on the left corner of the windscreen, representing the speed of and distance to the leading vehicle on the current lane (Figure 3a). The second message (i.e., a dynamic advisory message) displays at the bottom of the windscreen to inform about upcoming driving conditions, such as congestion ahead (Figure 3b). The third message (i.e., a dynamic warning message) flashes up on the heads-up display with a beep sound on the left side of the windscreen. This message notifies critical situations, such as exceeding the posted speed limit (Figure 3a). The last message (i.e., a lane-changing image) appears on the left side of the windscreen with a beep sound whenever a lane-changing opportunity is available on the adjacent lane (Figure 3c). This message provides the information about the subsequent gaps on the adjacent lane. The other driving messages, which are not presented here, include a warning message if a driver drove too close to the leader, and advisory messages about the starting and ending of a lane closure, etc.




(a) Warning and fixed messages

(b) An Advisory message

(c) A lane-changing message

**Fig. 3.** Design of the driving messages presented during a DLC manoeuvre

*Connected environment with communication delay driving condition*

In this driving condition, the vehicular interactions and design of the information are the same as that in the perfect communication driving condition; however, the participants face a 1.5 s delay in receiving all the driving messages. This 1.5 s delay was selected based on a pilot study conducted prior to data collection where different delays in messages were tested (that are, 0.5, 1, 1.5, and 2 s) and the minimum delay was selected when the participants started to react to a delay. This 1.5 s delay also coincides with Talebpour et al. (2016) who reported that a delay of more than 1.5 s has a negative impact on traffic safety.

Before the start of the experiment, the participants have performed a practice drive where they encounter various vehicular interactions and all the driving messages similar to a DLC scenario. Each participant was then allowed to participate in a real experiment once s/he felt confident about driving in the advanced driving simulator and simulated environment.

The simulator experiment has been carefully and innovatively designed in order to avoid any learning effect and sequence bias. Although this paper is limited to analysing DLC behaviour, the experiment consists of car-following events, MLC events, and city interactions. Given the multiple driving events, various driving tasks in each scenario, a break after each drive, and randomised driving sequence, the influence of learning effect is minimal among all the driving conditions.

## 3.4 Data

Seventy-eight participants perform DLCs in three driving conditions, resulting in 234 trajectories. Four participants were unable to perform the third drive because they were feeling uncomfortable, and two participants performed DLCs very close to the exit ramp to the city. These DLCs were excluded. As such, 228 trajectories are used in this study for analysing DLC behaviour. The simulator data consist of basic driving related variables such as speeds, accelerations, positions, and spacings. Driver demographic information is also collected including age, gender, licence type, driving experience, education, etc.

### 3.4.1 Driving behaviour indicators

A wide range of driving behaviour indicators have been used in the past research for analysing DLC behaviour (Ahmed, 1999, Balal et al., 2014, Vechione et al., 2018). A variety of such indicators, listed in Table 2, are used in this study to measure the driving behaviour during DLC manoeuvres.

### 3.4.2 Data processing

To accurately measure the indicators listed in Table 2, a sound methodology is required to pinpoint the start of DLC episode and subsequently, the DLC end point. Note that a DLC episode is the decision-making time period (or a portion of trajectory) in which a driver first recognises that the driving condition on the current lane is less desirable than that on the adjacent (or target) lane, which can give a speed advantage, then the driver starts looking for a DLC gap on the adjacent lane.

**Table 2.** Driving behaviour indicators considered in this study

| Variable | Definition |
|---|---|
| Speed (m/s) | The speed of the driven vehicle (or subject vehicle, SV) during the DLC manoeuvre |
| Spacing (m) | The distance between LV and SV on the current lane between the start of DLC episode and the DLC execution point |
| Acceleration noise (m/s$^2$) | The standard deviation of acceleration/deceleration of a participant between the start of DLC episode and the DLC initiation point; $Acceleration\ noise = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - \bar{a})^2}$; where $a$ is acceleration, $\bar{a}$ is the mean of acceleration, $n$ is the total number of observations, $i$ is index of observation. |
| Lead gap (m) | The distance between the rear bumper of LV on the adjacent lane and the front bumper of SV between the start of DLC episode and the DLC initiation point |
| Lag gap (m) | The distance between the rear bumper of SV and the front bumper of FV on the adjacent lane between the start of DLC episode and the DLC initiation point |
| Time-to-collision (TTC, s) | The time remaining for SV and FV on a collision course (on the adjacent lane) to collide with each other. It is measured as the ratio of the space gap over the relative speed |
| DLC duration (s) | The time taken by the participants to complete the DLC manoeuvre |
| Gap selection (m) | The gap size accepted by the participants during the DLC manoeuvre among 5 possible gap sizes: 15 m, 30 m, 45 m, 60 m, and 90 m |

In the connected environment (with the perfect communication or communication delay) driving conditions, the start of the DLC episode is traced when the driving message (that is, congestion ahead) is provided to the participants. Whilst in the baseline driving condition, the spatial location where the first gap of 60 m is created by the following vehicles on the adjacent lane is considered as the start of DLC episode. Note that the creation of this gap is in fact the criteria for providing the message in the connected environment driving conditions.

To overcome the issue of accurately determining the start of DLC execution point in the past research, this study utilises the lane lateral shift profile of SV, describing a driver's lateral movement corresponding to the lane centre. During car-following, lane lateral shift values remain constant with negligible variations whilst during DLC the lane lateral shift values change drastically. To pinpoint the start of DLC execution point, which is challenging in nature, this study presents a Wavelet Transform (WT)-based approach. Note that the DLC execution point is defined as the starting time of a DLC manoeuvre. WT is a powerful tool and has been successfully used in the literature to detect singularities in traffic and vehicular data (Zheng and Washington, 2012, Zheng et al., 2011a).

Figure 4 shows WT-based approach to detect the DLC execution point (more specifically, the point A in Figure 4), and subsequently DLC duration. Mallat and Hwang (1992) and Zheng and Washington (2012) have demonstrated that wavelet modulus (more specifically, the maxima lines) is a useful way to detect local singularity in a signal (i.e., lane lateral shift profile in this study). Using these maxima lines, the DLC execution point (i.e., A) can be traced back in the time whilst the DLC ending point is obtained from the trajectory data source. The time difference between the start of DLC execution point and the ending point is termed as *DLC duration*.

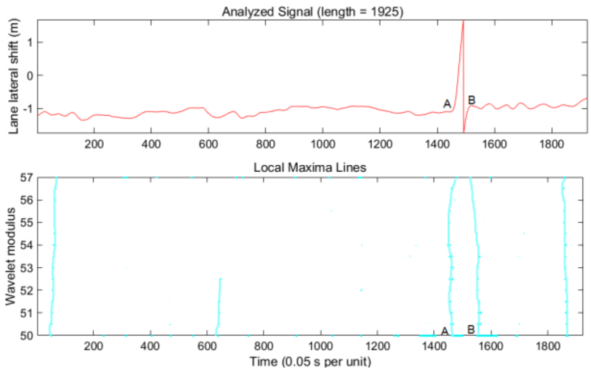



**Fig. 4.** A typical example of DLC duration using lane lateral shift profile (ID = 6)

## 4. Data analysis and statistical models

### 4.1 Descriptive analysis

Driving behaviour indicators are analysed and compared using statistical techniques such as the linear mixed model, the paired *t*-test, and the chi-square test. The linear mixed model is the advanced form of repeated measure ANOVA (Haque et al., 2016), which is capable of capturing the unbalanced nature of dataset. As a few participants in this study were unable to perform the third drive, the linear mixed model is appropriate. The level of significance is assumed to be 5% in this study.

Table 3 summarises the comparison results of average acceleration noise, average spacing, average TTC, average speed, average lead and lag gaps, and average DLC duration across three driving conditions. The linear mixed model reveals that the overall differences in each driving behaviour indicator across three drives are statistically significant.

*Average lag gap*: The average lag gap for the baseline condition is 37.43 m; the corresponding average lag gaps for the perfect communication and communication delay driving conditions are respectively 47.05 m and 41.97 m. A paired *t*-test reveals an increase of 9.62 m in average lag gaps during the perfect communication driving condition compared to the baseline condition, implying that when drivers are assisted with the information of the subsequent gaps, they maintain larger lag gaps with FVs on the adjacent lane. An increase in a lag gap indicates a higher safety margin during DLC manoeuvres.

*Average lead gap*: The average lead gaps for the baseline, perfect communication, and communication delay driving conditions are respectively 38.60 m, 52.33 m, and 48.28 m. A paired *t*-test suggests an increase of 13.73 m in average lead gaps in the perfect communication driving condition compared to the baseline condition, implying a higher tendency to gain the speed advantage in the perfect communication driving condition when drivers are assisted with the information of gaps.

*Time-to-collision (TTC)*: As a surrogate measure of safety, TTC describes the probability of a collision between two vehicles (SV and FV in this study) on a collision course. The TTCs for the baseline, perfect communication, and communication delay driving conditions are respectively 1.84 s, 2.15 s, and 1.95 s. A higher safety margin (that is, 0.31 s) is obtained in the perfect communication driving condition when drivers are informed about surrounding traffic. Note that a higher TTC implies a higher safety margin.

**Table 3.** Descriptive analyses of driving behaviour indicators considered in this study

| Performance indicators | Driving condition | Mean (SD) | Significance by the linear mixed model | Pairwise comparison (Paired *t*-test) |
|---|---|---|---|---|
| Average speed | Base | 11.23 (2.71) | $F_{2,148}$ = 3.6; *p*-value = 0.029 | Base vs PC = 0.04 |
| | PC | 16.33 (3.02) | | Base vs CD = 0.05 |
| | CD | 13.32 (3.07) | | PC vs CD = 0.40 |
| Average lag gap | Base | 37.43 (15.27) | $F_{2,148}$ = 9.7; *p*-value < 0.001 | Base vs PC = 0.001 |
| | PC | 47.05 (11.02) | | Base vs CD = 0.04 |
| | CD | 41.97 (13.33) | | PC vs CD = 0.70 |
| Average lead gap | Base | 38.60 (19.01) | $F_{2,148}$ = 8.12; *p*-value < 0.001 | Base vs PC < 0.001 |
| | PC | 52.33 (12.22) | | Base vs CD < 0.001 |
| | CD | 48.28 (16.66) | | PC vs CD = 0.98 |
| Average spacing | Base | 35.39 (21) | $F_{2,148}$ = 4.75; *p*-value = 0.009 | Base vs PC = 0.012 |
| | PC | 54.17 (16) | | Base vs CD <0.001 |
| | CD | 52.94 (19) | | PC vs CD = 0.88 |
| Average acceleration noise | Base | 0.952 (0.54) | $F_{2,148}$ = 3.25; *p*-value = 0.041 | Base vs PC = 0.04 |
| | PC | 0.794 (0.41) | | Base vs CD = 0.03 |
| | CD | 0.806 (0.37) | | PC vs CD = 0.90 |
| Average TTC | Base | 1.84 (0.96) | $F_{2,148}$ = 3.1; *p*-value = 0.047 | Base vs PC = 0.002 |
| | PC | 2.15 (0.65) | | Base vs CD = 0.02 |
| | CD | 1.95 (0.8) | | PC vs CD = 0.81 |
| Average DLC duration | Base | 5.11 (3.84) | $F_{2,148}$ = 9.35; *p*-value < 0.001 | Base vs PC < 0.001 |
| | PC | 8.43 (4.48) | | Base vs CD = 0.02 |
| | CD | 6.90 (2.71) | | PC vs CD = 0.35 |

*Base: Baseline; PC: perfect communication; CD: communication delay*

A detailed analysis of TTC across different accepted gap sizes by each driving condition reveals that the TTC increases with the increase in the accepted gap size, and this trend is consistent across each driving condition (Figure 5). Intuitively, a higher TTC is observed when the gap size is 90 m as the distance between the subject vehicle and the following vehicle is relatively large. The differences, across different accepted gap sizes and driving conditions, are tested by paired *t*-tests, and results show a significant difference among all pairs except baseline and communication delay driving conditions for 90 m gap size.

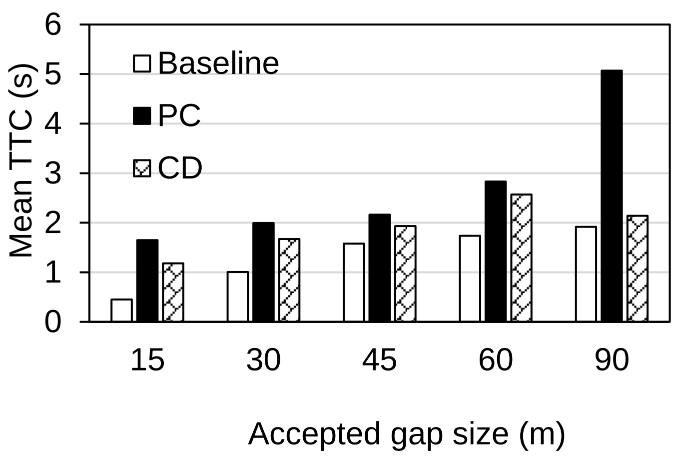



**Fig. 5.** Mean TTC at the DLC point by driving conditions; *PC: perfect communication; CD: communication delay*

To further analyse the differential effect of the connected environment and how TTC risk varies when the information is impaired (that is, delayed by 1.5 s in this study), percentage change in TTC risk is calculated using Equation (1). Change in TTC risk reveals the increase or decrease in the TTC risk by change in the driving condition. Figure 6 shows the change in TTC risk, which implies that compared to the baseline condition, the risk associated with DLC manoeuvres decreases by about 17% and 6% in the perfect communication and communication delay driving conditions, respectively. Whilst the risk has increased in the communication delay driving condition compared to perfect communication driving condition by about 10%.

$$\%\ change\ in\ TTC\ risk = \frac{TTC_i - TTC_j}{TTC_i} \times 100 \quad (1)$$

where, $i$ = baseline and PC; $j$= PC (perfect communication) and CD (communication delay); $i \neq j$.

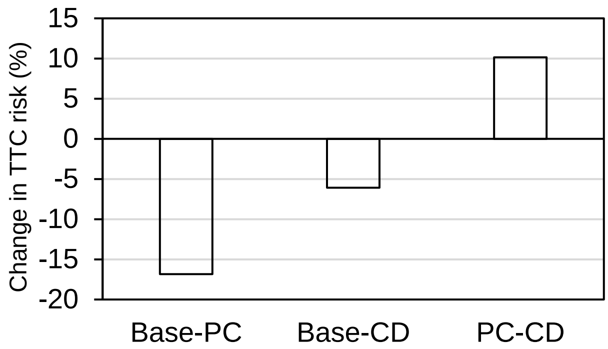



**Fig. 6.** Percent change in TTC risk; *Base: baseline; PC: perfect communication; CD: communication delay; A positive value indicates the risk has increased and vice versa*

*Gap selection*: Figure 7 shows the DLC gap selection behaviour of the participants across three driving conditions. In the baseline condition, the frequencies of selecting 15 m, 30 m, 45 m, 60 m, and 90 m gaps are respectively 24%, 10%, 10%, 14%, and 42%, whilst the corresponding frequencies in the perfect communication driving condition are respectively 2%, 10%, 11%, and 48%. A chi-square test is conducted to test the differences in frequencies of DLC gap selection, and results indicate a significant difference across the driving conditions ($\chi^2_{Baseline-PC} = 14.68; p - value < 0.001; \chi^2_{Baseline-CD} = 8.61; p - value = 0.003;\ \chi^2_{PC-CD} = 5.41; p - value = 0.02$).

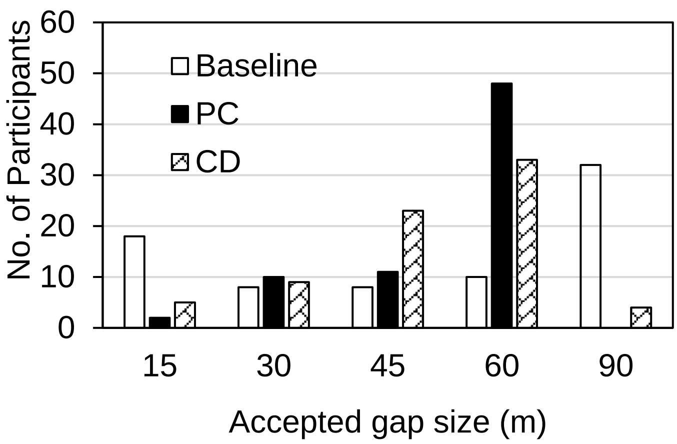



**Fig. 7**. DLC gap selection of the participants across driving conditions; *PC: perfect communication, and CD: communication delay*

As mentioned previously in the design of experiment, the last DLC gap is 90 m whilst the first available DLC gap is 60 m. It is quite evident from Figure 7 that more than 40% of the participants wait for the last DLC gap during the baseline condition, while the corresponding frequency in the perfect communication driving condition is 10%. This result implies that when the participants are assisted with the information of subsequent gaps, they tend to find a gap on the adjacent lane quickly rather than waiting for a long period.

## 4.2 Statistical models

### 4.2.1 Generalized Estimation Equation (GEE) models

To model the gap acceptance behaviour and DLC duration, Generalized Estimation Equation (GEE) is used. GEE, an extension on Generalized Linear Models, has the capability to capture the correlation, an outcome of multiple drives by the same participant. In GEE, various correlation structures exist to capture this correlation, and this study uses an exchangeable correlation structure, which assumes a constant correlation coefficient across three drives for the same participant. For evaluating model fitness, Quasi-likelihood Information Criterion (QIC) and marginal $R^2$ are used.

Table 4 shows descriptive statistics of all the independent variables considered for the statistical models developed in this study. To evaluate the impact of the connected environment on DLC decision-making behaviour, the logarithmic accepted gap size (in meters) is selected as the dependant variable in the first GEE model (i.e., the gap acceptance model). The logarithmic transformation of the accepted gap size ensures that the predicted gap sizes are nonnegative. Whilst for the second GEE model (i.e., the DLC duration model), the DLC duration (in seconds) is selected as the dependant variable to analyse the impact of the connected environment on DLC execution. In case of DLC duration model, using the estimated parameters of DLC duration model, we find that the predicted DLC durations are positive without using the logarithmic transformation. Thus, we did not use the logarithmic transformation for the DLC duration to keep the parsimoniousness of the model and for the easier interpretation of the model results, which is also aligned with previous studies (Toledo and Zohar, 2007, Ali et al., 2018) that have modelled the DLC duration without applying the logarithmic transformation.

The developed models contain three types of explanatory variables: (a) driving condition variables (e.g., perfect communication and communication delay); (b) operational variables (e.g., average speed, average acceleration noise, and accepted gap size[2]); and (c) driver demographics (e.g., age groups and gender). The independent variables were selected based on a thorough literature and by considering each variable's potential impact on behavioural relationship with both the dependant variables (accepted gap size and DLC duration). The parsimonious model in each case is selected based on two criteria: a higher marginal $R^2$ and a lower QIC value.

(a) GEE model for gap acceptance behaviour

Table 5 presents the GEE model estimates for the accepted gap sizes. The parsimonious model shows an exchangeable correlation parameter value of 0.22, implying that there exists a significant correlation among the repeated observations of the same participant. Furthermore,

[2] Only for DLC duration model.

the developed GEE model captures about 20% of the variability in the data, as indicated by the marginal $R^2$.

**Table 4.** A summary of statistics of independent variables included in the models

| Variable | Description of variables | Count | Percentage | Mean (SD) |
|---|---|---|---|---|
| **Driving condition** | | | | |
| Baseline | 1 if a participant drove without driving message, 0 otherwise | 76 | 33.33 | — |
| Perfect communication | 1 if a participant drove with an on-time supply of driving messages, 0 otherwise | 78 | 34.21 | — |
| Communication delay | 1 if a participant drove with delayed driving messages, 0 otherwise | 74 | 32.46 | — |
| **Operational variables** | | | | |
| Average speed | Speed in m/s | - | - | 12.25 (5.60) |
| Average acceleration noise | Acceleration noise measured as standard deviation of acceleration in $m/s^2$ | - | - | 0.85 (0.47) |
| Accepted gap size | Gap size selected by a participant in m | - | - | 57.56 (22.74) |
| **Demographic variables** | | | | |
| *Age groups* | | | | |
| Young drivers (18 – 26 years) | 1 if a participant was a young driver, 0 otherwise | 38 | 48.72 | — |
| Middle-aged drivers (27 – 50 years) | 1 if a participant was a middle-aged driver, 0 otherwise | 32 | 41.02 | — |
| Older drivers (>50 years) | 1 if a participant was an older driver, 0 otherwise | 8 | 10.26 | — |
| *Gender* | | | | |
| Male | 1 if a participant was male, 0 otherwise | 50 | 64.10 | — |
| Female | 1 if a participant was female, 0 otherwise | 28 | 35.90 | — |

The driving condition variables (that are, perfect communication and communication delay) are positive and significant at a 5% significance level in the GEE model for gap acceptance. When the participants are assisted with fully functioning information system (that is, perfect communication), they tend to select relatively bigger gap sizes and a similar behaviour has been observed in the delayed information supply scenario (that is, communication delay). The impact of the perfect communication driving condition on the accepted gap size can be calculated using the estimated GEE model as shown in Equation (2). Note that the same equation can be used to calculate the impact of the communication delay driving condition on the accepted gap size. The GEE model shows an increase of 1.16 m and 1.10 m in the accepted gap size for the perfect communication and communication delay driving conditions, respectively.

$$Accepted\ gap\ size = \exp[2.99 + 0.15 \times PC + 0.10 \times CD + 0.07 \times average\ speed - 0.17 \times average\ acceleration\ noise - 0.16 \times young\ drivers + 0.24 \times older\ drivers + 0.16 \times female] \quad (2)$$

Average speed, which is the speed of the subject vehicle during a DLC episode, is significant and positively associated with gap acceptance behaviour of drivers. A 1 m/s increase in the average speed is likely to increase the accepted gap sizes by 1.07 m, which is also consistent with the findings of the past research (Ali et al., 2018).

**Table 5.** A summary of GEE models

| Model | Variable | Estimate | SE | Wald statistics | *p*-value |
|---|---|---|---|---|---|
| Gap acceptance | Constant | 2.99 | 0.18 | 252.91 | <0.001 |
| | **Driving conditions** | | | | |
| | Perfect communication | 0.15 | 0.06 | 5.87 | 0.015 |
| | Communication delay | 0.10 | 0.06 | 3.96 | 0.046 |
| | **Operational variables** | | | | |
| | Average speed | 0.07 | 0.012 | 27.29 | <0.001 |
| | Average acceleration noise | -0.17 | 0.08 | 4.79 | 0.029 |
| | **Demographics** | | | | |
| | Young drivers | -0.16 | 0.07 | 4.45 | 0.035 |
| | Older drivers | 0.24 | 0.11 | 3.90 | 0.048 |
| | Female | 0.16 | 0.07 | 4.36 | 0.036 |
| | Estimated correlation parameter (alpha) | 0.22 | 0.06 | | |
| | Marginal $R^2$ = 0.20; QIC = 68.51; Quasi-likelihood = -24.81; Number of observations = 228; Number of clusters = 78; Max: cluster size = 3 | | | | |
| DLC duration | Constant | 4.02 | 1.52 | 6.96 | 0.008 |
| | **Driving conditions** | | | | |
| | Perfect communication | 2.22 | 0.09 | 6.32 | 0.012 |
| | Communication delay | 2.11 | 1.05 | 4.01 | 0.045 |
| | **Operational variables** | | | | |
| | Average speed | 0.13 | 0.07 | 3.99 | 0.045 |
| | Accepted gap size | 0.03 | 0.01 | 9.47 | 0.002 |
| | **Demographics** | | | | |
| | Age-group 1 (18-26) | -2.21 | 1.11 | 3.96 | 0.046 |
| | Age-group 3 (>50) | 4.86 | 1.32 | 13.43 | <0.001 |
| | Female | 2.02 | 0.93 | 4.71 | 0.03 |
| | Estimated correlation parameter (alpha) | 0.51 | 0.09 | | |
| | Marginal $R^2$ = 0.21; QIC = 2311; Quasi-likelihood = -1221; Number of observations = 228; Number of clusters = 78; Max: cluster size = 3 | | | | |

Average acceleration noise, which shows recklessness of a driver, is negative and significant in explaining gap acceptance behaviour of drivers, suggesting that a 1 m/s$^2$ increase in acceleration noise tends to decrease the accepted gap size by 1.19 m. A higher value of acceleration noise implies a reckless driver who drives fast and suddenly breaks. A reckless driver is expected to select a lower or risky gap size.

Driver's age is divided into three classes, namely, young drivers (18 – 26 years; 38 participants), middle-aged drivers (27 – 50 years; 32 participants), and older drivers (> 50 years; 8 participants). The variable for young drivers is significant and has a negative impact on gap acceptance behaviour of drivers. Compared to middle-aged drivers, young drivers tend to select relatively smaller gap sizes (more specifically, accepted gap size reduces by 1.17 m). The older drivers, on the other hand, tend to select bigger gap sizes compared to middle-aged drivers. Compared to middle-aged drivers, the accepted gap size for older drivers increases by 1.27 m.

The indicator variable for female drivers is positive and significant in explaining gap acceptance behaviour of drivers. Compared to male drivers, female drivers are likely to select a 1.17 m larger gap.

(b) GEE model for DLC duration

Table 5 presents the GEE model estimates for explaining DLC duration as a function of driving conditions (e.g., perfect communication and communication delay), operational variables (e.g., average speed and accepted gap size) and driver demographic (e.g., age and gender). Marginal $R^2$ suggests that the GEE model explains about 21% of the variation in the data.

The driving condition parameters (i.e., perfect communication and communication delay) are positive and significant in explaining drivers' DLC duration. The GEE model for DLC duration: $[4.02 + 2.22 \times PC + 2.11 \times CD + 0.13 \times average\ speed + 0.03 \times accepted\ gap\ size - 2.21 \times young\ drivers + 4.86 \times older\ drivers + 2.02 \times female]$ predicts that DLC durations increase by 2.22 s and 2.11 s respectively for the perfect communication and communication delay driving conditions after controlling for other factors. This increase in DLC duration can be attributed to the fact that the participants are aware of gap sizes on the adjacent lane, thus they may take a longer time to change lanes safely. All other parameters, such as average speed, accepted gap size, age, and gender, can be interpreted similarly as in the case of the gap acceptance model.

4.2.2 Hazard-based duration model

In this study, time-to-collision (TTC)—a surrogate measure of safety that describes the possibility of a lane-changing collision between the subject vehicle and the immediate following vehicle in time domain—is modelled using a hazard-based duration (or survival) model. Note that the time-to-collision (TTC) is calculated at the lane-changing collision point on the adjacent (target) lane. More specifically, TTC is computed when the subject vehicle has changed lanes and moved to the adjacent lane. A Weibull accelerated failure time (AFT) model specification is selected in this study that allows the effects of covariates to rescale (accelerate or decelerate) the duration variable (that is, TTC) directly in the baseline survival function, in which all of the covariates are zero. The AFT model also facilitates an intuitive interpretation of estimated parameters. The mathematical formulation of AFT Weibull model specification can be found in Washington et al. (2011).

To capture the correlation caused by the repeated nature of data, two extensions of the standard Weibull AFT model are tested. The first extension (that is, clustered heterogeneity) fits a standard duration model and the standard errors are adjusted such that all the possible correlation caused by repeated observations of the same participant can be captured. The second extension is shared frailty (that is, gamma frailty) that allows capturing the correlation of the same participant by maintaining the independence across the observations obtained from the different participants. The details about formulation of both these approaches are presented in Washington et al. (2011).

Table 6 shows a summary of statistics for comparison of two Weibull AFT models: clustered heterogeneity and gamma frailty. The likelihood ratio statistics for the clustered heterogeneity and gamma frailty models are respectively 41.61 and 56.18 with the corresponding degrees of freedom (*df*) 9 and 10. The likelihood ratio values for both the models are above the critical value for a 95% confidence level, implying that both the models possess a significant explanatory power in explaining TTC during lane-changing collisions. However, the gamma frailty model indicates a better fit since the likelihood ratio is reasonably higher than that of the clustered heterogeneity model. A likelihood ratio test for comparing two models reveals a chi-square value of 9.26 with one *df* (*p*-value = 0.002), indicating a better fit of the Weibull AFT model with gamma frailty compared to the counterpart. In addition, AIC is also used to compare two models, which takes into account the number of parameters used in the model. Although the gamma frailty model has one extra parameter, the AIC value for this model is 98 while the corresponding AIC value for the clustered heterogeneity model is 125. Thus, the Weibull AFT gamma frailty model is preferred for explaining TTC during lane-changing collisions.

**Table 6.** A summary of the model comparison statistics

| Candidate model | $LL\ (0)$[1] | $LL\ (\hat{\beta})$[2] | Degree of freedom | Likelihood ratio statistic | AIC |
|---|---|---|---|---|---|
| Weibull AFT model with clustered heterogeneity | -59.83 | -39.03 | 9 | 41.61 | 125 |
| Weibull AFT model with gamma frailty | -71.75 | -43.66 | 10 | 56.18 | 98 |

*[1]Log-likelihood function value at zero; [2]Log-likelihood function value at the maximum*

Table 7 presents the significant variables estimated by the Weibull AFT gamma frailty model for TTC during lane-changing collisions. The scale parameter (*P*) estimate is 3.22 and a *t*-test on this parameter reveals that the estimate of *P* is significantly ($t$ = 6.52, *p*-value <0.001) greater than 1, suggesting the positive dependence of duration and monotone hazard function in the Weibull AFT model; this implies that the probability of avoiding a lane-changing collision is decreasing with the elapsed time. For example, the likelihood of not engaging in a lane-changing collision after 4 s is about 4.65 (i.e., $(\frac{4}{2})^{3.22-1}$) times lower than that of 2 s on average. Furthermore, the variance parameter ($\theta$) in the gamma frailty model is found to be statistically significant, as shown by a chi-square test (chi-square = 29.26, *p*-value <0.001), further ensuring the appropriateness of gamma frailty into the Weibull AFT model.

The parsimonious model, as reported in Table 7, contains driving condition variables like perfect communication and communication delay, operational variable such as acceleration noise and accepted gap size, and driver demographic characteristics like driver's age and gender. Note that the vehicle kinematic variables such as speed and positions are not included in the model because of the endogeneity problem with the duration variable. The significant variables in the Weibull AFT model with gamma frailty are described below.

The connected environment with perfect communication is significant at a 95% confidence level and is positively associated with TTC. The TTC in the perfect communication driving condition increases by 21% (i.e., [exp (0.19)]) compared to the baseline condition.

The connected environment with communication delay has a significant and positive impact on TTC. Compared to the baseline condition, the TTC in the communication delay driving condition is about 8% higher. Notably, the model shows that the safety margin is about 2.5 times higher in the perfect communication driving condition than that of the communication delay driving condition.

**Table 7.** Model results of the Weibull AFT with gamma frailty[3]

| Parameter | Coefficient | SE | $z$-statistics | $p$-value | exp($\beta$) | 95 % CI [exp($\beta$)] | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower | Upper |
| Constant | 0.28 | 0.13 | 2.15 | 0.03 | | | |
| **Driving conditions** | | | | | | | |
| Perfect communication | 0.19 | 0.09 | 1.99 | 0.046 | 1.21 | 1.851 | 2.069 |
| Communication delay | 0.08 | 0.039 | 2.04 | 0.04 | 1.08 | 1.918 | 2.002 |
| **Operational variables** | | | | | | | |
| Acceleration noise | -0.33 | 0.137 | -2.46 | -0.33 | 0.72 | 1.861 | 2.059 |
| Accepted gap size | 0.004 | 0.001 | 4.17 | 0.004 | 1.01 | 1.959 | 1.961 |
| **Demographics** | | | | | | | |
| Young drivers | -0.219 | 0.100 | 2.18 | 0.029 | 0.80 | 1.800 | 2.040 |
| Older drivers | 0.316 | 0.139 | 2.26 | 0.024 | 1.37 | 1.769 | 2.150 |
| Male | -0.20 | 0.09 | -2.22 | 0.026 | 0.82 | 1.882 | 2.034 |
| $P$ | 3.22 | 0.34 | | | | 0.865 | 3.055 |
| Variance of gamma frailty, $\theta$ | 0.76 | 0.15 | | | | 1.846 | 2.074 |

$LL$ ($\hat{\beta}$) = -43.46; $LL$ ($0$) = -71.75; Likelihood ratio statistics = 56.18; $p$-value <0.001; AIC = 95; No. of observations = 228; No. of groups = 78

Acceleration noise—measured as standard deviation of acceleration during a DLC manoeuvre—is significant and negatively associated with the likelihood of avoiding a lane-changing collision. A 1 m/s$^2$ increase in the acceleration noise decreases the TTC by 28%, implying that a driver with a higher acceleration noise has a lower safety margin during a DLC manoeuvre.

The TTC of drivers is significant and positively influenced by the accepted gap size. A one meter increase in the accepted gap size is likely to lead to 1% increase in the TTC. However, this relationship is not linear. Instead, the accepted gap size has a linear relation with the logarithmic of TTC as shown in model equation. Note that a higher gap size on the adjacent lane indicates a higher safety.

Similar to the GEE models, driver's age is divided into three groups. The variable for young drivers is negative and significant in explaining the TTC during DLC manoeuvres. Compared to middle-aged drivers, young drivers appear to be associated with a lower TTC, with a TTC approximately 20% lower than that of middle-aged drivers.

The variable for older drivers is positive and has a significant impact on TTC. Compared to middle-aged drivers, older drivers have a 33% higher TTC.

The indicator for male drivers is significant and negatively associated with TTC. Results suggest that male drivers have 18% lower TTC than that of female drivers, implying that male drivers have a lower safety margin.

[3] $\ln(TTC) = constant + b_1 \times perfect\ communication + b_2 \times communication\ delay - b_3 \times acceleration\ noise + b_4 \times accepted\ gap\ size + b_5 \times young\ drivers + b_6 \times older\ drivers + b_7 \times male$

## 5. Discussion: the connected environment's impact on safety

### 5.1 DLC driving behaviour in the connected environment

The Weibull AFT gamma frailty is used to provide insights into the effects of the connected environment on the DLC driving behaviour, more specifically, on the safety associated with it. Moreover, the fitted AFT model is used to evaluate the impact of the connected environment on safety across driver demographic characteristics. The developed AFT model is used to plot survival curves that depict the DLC associated risk in different environments. The probability of avoiding a lane-changing collision is calculated using the survival function (shown in Equations 3 and 4) and the corresponding parameter estimates (Table 7). For instance, the probabilities of avoiding a lane-changing collision for a driver in the perfect communication driving condition after 2 s and 3 s are calculated as

$$S(t=2)_{Perfect\ communication} = EXP\left[-\left(EXP\left(-3.22(0.28-0.33\times 0.85+0.004\times 57.56+0.19\times 1)\right)\right)\times 2^{3.22}\right] = 0.67 = 67\% \quad (3)$$

$$S(t=3)_{Perfect\ communication} = EXP\left[-\left(EXP\left(-3.22(0.28-0.33\times 0.85+0.004\times 54.56+0.19\times 1)\right)\right)\times 3^{3.22}\right] = 0.23 = 23\% \quad (4)$$

Figure 8 shows the predicted probabilities of 'avoiding a lane-changing collision' using the survival function and the model estimates. Intuitively, the probability of avoiding a lane-changing collision decreases with the elapsed time. Thus, the likelihood that a driver does not engage in a lane-changing collision decreases over the time. Note that a higher probability of avoiding a lane-changing collision implies a higher safety margin. For instance, the probability of avoiding a lane-changing collision is about 67% when the time into lane-changing collision course is 2 s during the perfect communication driving condition, and the corresponding probability at 3 s is about 23%.

Clearly, the probabilities of avoiding a lane-changing collision in the perfect communication driving condition are higher compared to those in the baseline condition. The likelihood of avoiding a lane-changing collision when the time into lane-changing collision course is 3 s during the baseline condition is 6%, whilst the corresponding the probability for the perfect communication driving condition is 23%, suggesting that the likelihood of not engaging in a lane-changing collision is 17% higher when drivers are assisted with the subsequent gap information. The average time to avoid a lane-changing collision in the perfect communication condition is approximately 5 s (when the probability is almost zero, Figure 8), while the corresponding time in the baseline condition is approximately 3.7 s, indicating that the safety margin in the perfect communication driving condition, on average, is about 1.3 s longer than that of the baseline condition. These findings imply that the connected environment with perfect communication driving condition increases the safety margin during DLC manoeuvres. This agrees with Guériau et al. (2016) who reported safety benefits during lane-changing when drivers are assisted with vehicle-to-vehicle communication.

The impact of connected environment on driving behaviour, more specifically, on traffic safety is hypothesised in the literature (Kim, 2015, Gandhi et al., 2014). However, there is no concrete evidence of such impact mainly because of the novelty of the connected environment. With the help of survival curves presented in Figure 8, it can be deduced that the safety margin in the perfect communication driving condition is increased during DLC manoeuvres. This is intuitive because the information provided by the connected environment decreases the workload and mental stress exerted by gathering the surrounding traffic information and simultaneously focussing on the DLC driving tasks. The connected environment also helps drivers to be aware of the situation, make more informed, efficient, and safer DLC decisions, and thereby enhancing the safety associated with DLC manoeuvres.

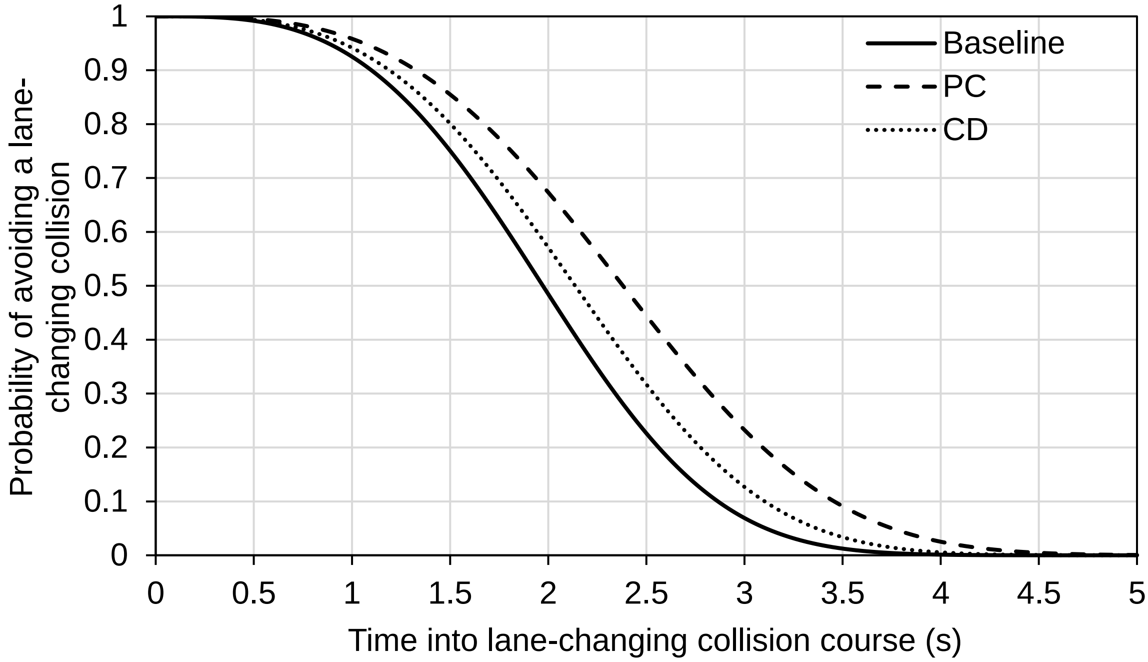



**Fig. 8**. Survival curves across driving conditions in a DLC manoeuvre; *PC: Perfect communication; CD: Communication delay*

## 5.2 Perfect communication versus Communication delay driving condition

The impact of the communication impairment or differential effect of the connected environment can also be analysed using the survival curves presented in Figure 8, and a difference in safety margin can be observed. Notably, drivers in the perfect communication driving condition have about 10% higher probability of not engaging in a lane-changing collision than that of communication delay driving condition (when the probability curve touches the zero probability, Figure 8), suggesting that driving with perfect communication (on-time supply of information) is safer compared to driving with communication delay (that is, the delayed supply of information). The differences in the probabilities to avoid a lane-changing collision between the perfect communication and communication delay driving conditions at the time into lane-changing collision course of 1, 2, and 3 s are respectively 2%, 10%, and 11%, implying that the safety margin is consistently higher in the perfect communication driving condition compared to the communication delay driving condition. Thus, it is reasonable to conclude that any impairment in the communication, such as delayed information supply (delayed by 1.5 s in the case of this study), is likely to deteriorate the driving performance during DLC manoeuvres, which agrees with the past research. For instance, Talebpour et al. (2016) reported that a delay of more than 1.5 s has a significant impact on the traffic safety. Ali et al. (2019a) found that a 1.5 s delay has a profound impact on MLC manoeuvres. Although this study opts for a delay of 1.5 s, a wide of range of delays should be tested to understand the impact of different delays on DLC behaviour. Such work is left for future research.

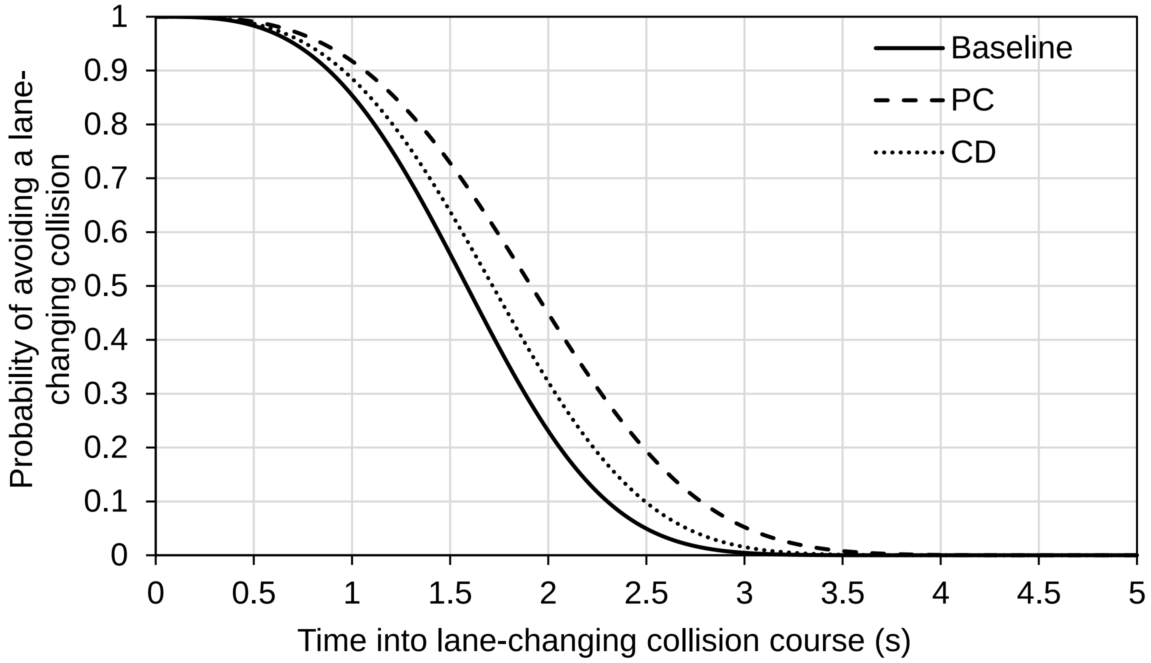
### 5.3 Effects of the connected environment on the safety for different driver demographics

It is hypothesised that the effect of connected environment on safety could vary across different driver demographics, such as age and gender. To examine such effects, survival probability curves for different driver demographics are plotted, and discussed in this section.

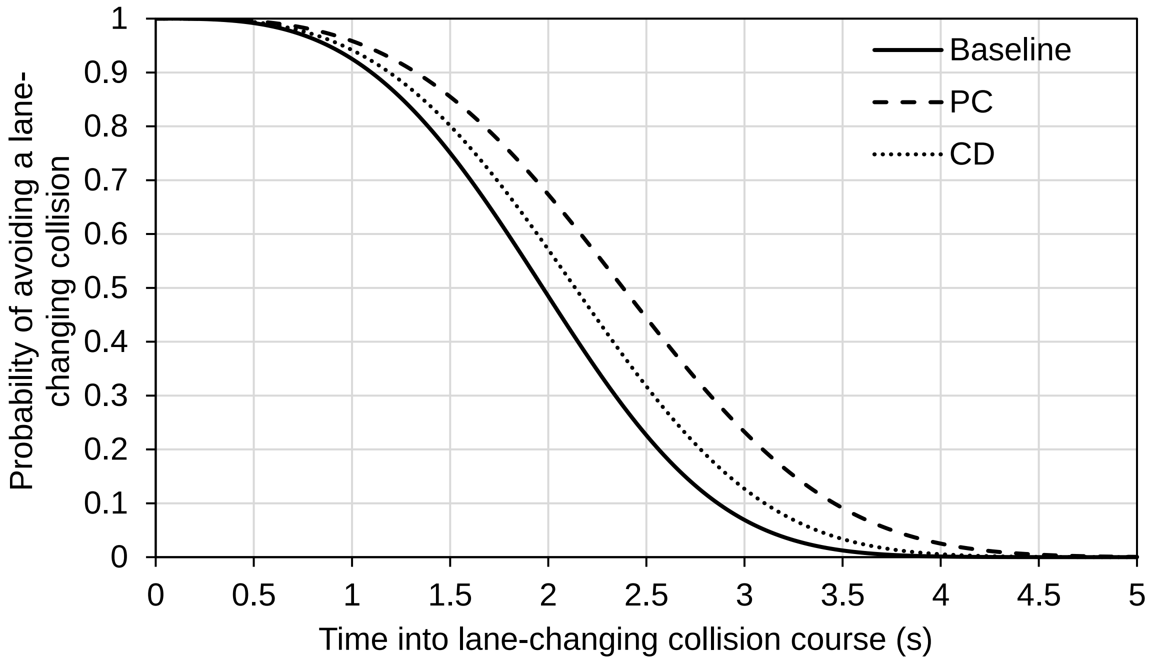
#### 5.3.1 Driver age

Figure 9 indicates the survival curves for different age groups, reported in Table 4. For the time into lane-changing collision course of 1, 2, and 3 s, the survival probabilities of avoiding a lane-changing collision for young drivers during the perfect communication driving condition are respectively 85%, 23%, and 0.4% (Figure 9a). The corresponding survival probabilities for middle-aged drivers are 92%, 48%, and 6% (Figure 9b). For older drivers, the corresponding survival probabilities are 97%, 77%, and 38% (Figure 9c).

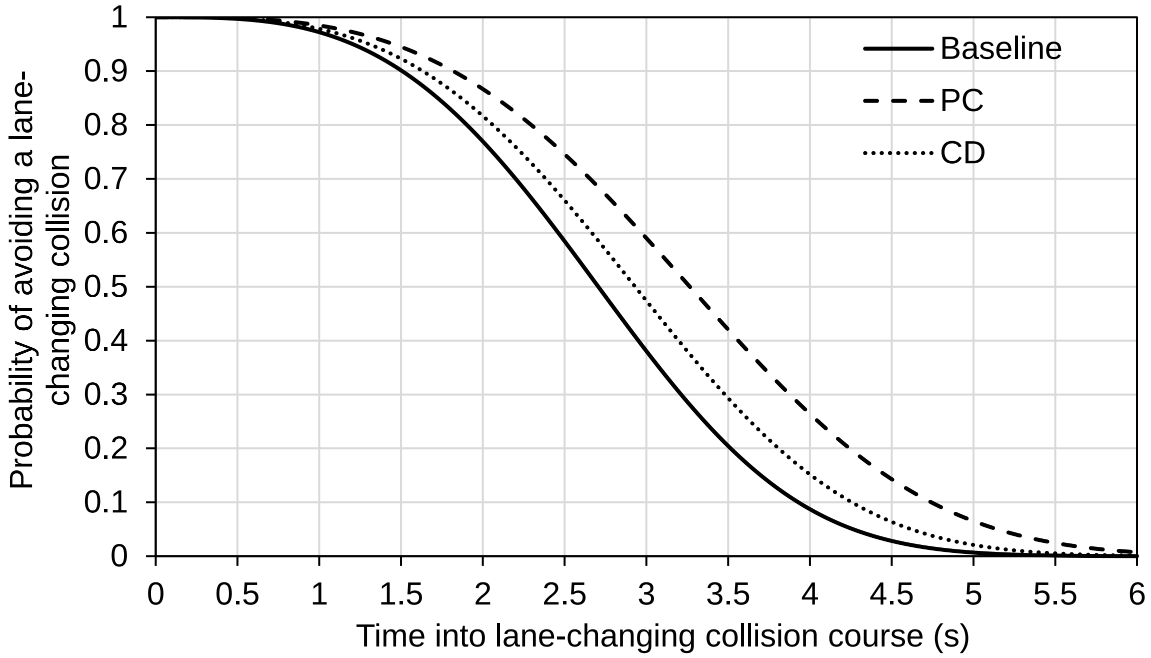
The likelihood of not engaging in a lane-changing collision for middle-aged drivers during the perfect communication driving condition at the time into lane-changing collision of 2 s is found to be twice to than that of young drivers. This implies that under the same driving conditions (that are, on-time/uninterrupted supply of driving messages), the safety margin for middle-aged drivers is higher than that of young drivers. Young drivers, who are reported to be riskier and at risk of colliding with other drivers, are found to maintain a shorter TTC when driving without surrounding traffic information (Montgomery et al., 2014). Middle-aged drivers, on the other hand, in the literature are found to be at lower risk of collision compared to young drivers (Khatoon et al., 2013). It can be concluded that the connected environment makes DLC manoeuvres safer for both young and middle-aged driver compared to when driving without the connected environment. Similar findings have been reported by Son et al. (2015), who analysed the effectiveness of in-vehicle information on young drivers. Young drivers seem to take less advantage of available information compared to that of the middle-aged drivers; however, their collision risk appears to be lower in the connected environment driving conditions. Research shows that young drivers are less likely to accept vehicle technologies like advanced driving assistance system, collision warning system (Young et al., 2004, Lee, 2007, Twisk and Stacey, 2007). Lee (2007) concluded that vehicle technology may not provide intended safety improvements because young drivers do not totally accept the system. Young et al. (2004) observed less acceptability of young drivers toward intelligent speed adaption and lane departure warning systems. Hence, it can be concluded that user acceptability of the connected environment could be one of the reasons that young drivers take less advantage of the available driving aids. For example, young drivers may be over-confident about their driving skills and think driving aids are unnecessary; or another possible reason is young drivers may not want their peers to look down at them because they are using driving assistance systems to help their driving. But, in order to get a definitive answer to this question, an independent study will be needed.




(a) Young drivers




(b) Middle-aged drivers




(c) Older drivers

**Fig. 9.** Effect of the connected environment on different age cohorts during a DLC manoeuvre; *PC: Perfect communication; CD: Communication delay*

The probability of avoiding a lane-changing collision during the perfect communication driving condition at the time into lane-changing collision course of 2 s is 29% higher for older drivers compared to middle-aged drivers, implying that older drivers have a higher safety margin compared to middle-aged drivers when driving in the perfect communication driving condition. The collision risk for older drivers in the literature is reported to be higher compared to the middle-aged drivers (McGwin Jr and Brown, 1999). In contrast, older drivers, who have a higher processing time in implementing safe actions to avoid potential crashes, appear to utilise the surrounding traffic information during the perfect communication driving condition and thus, make more informed and safer DLC decisions, resulting in a lower collision risk. This agrees with the past research. For instance, Donmez et al. (2006) reported that older drivers accept in-vehicle information system more than that of middle-aged drivers and take more advantage of the system as in the case of this study. Similar findings are reported in Gish et al. (2017).

The likelihood of not engaging in a lane-changing collision for older drivers at the time into lane-changing collision course of 2 s during the perfect communication driving condition is approximately 44% higher than that of young drivers, suggesting that the safety margin of young drivers is three times lower than that of older drivers. Finn and Bragg (1986) compared the driving behaviour of older and young drivers and reported that older drivers are highly experienced, more skilful, risk-averse, and well aware of safety critical situations compared to their young counterparts. McGwin Jr and Brown (1999) reported the higher likelihood of young drivers in engaging crashes compared to older drivers, which complements the findings from survival curves reported in Figure 9. Furthermore, in the literature, older drivers are reported to benefit more from in-vehicle information systems, such as collision avoidance warning system (Kramer et al., 2007) and intersection approach system (Caird et al., 2008). In line with past research (Caird et al., 2008, Kramer et al., 2007, McGwin Jr and Brown, 1999), this study also finds that older drivers utilise the surrounding traffic information provided by the connected environment compared to young drivers, implying a higher safety margin for older drivers in the connected environment driving conditions. This also agrees with a study on effectiveness of in-vehicle information on driving behaviour (Son et al., 2015).

To summarise, this study confirms that safety margin in the connected environment driving condition is different across different age groups, which agrees with previous research findings on the effects of advanced driver assistance systems on driving behaviour of different age cohorts. More specifically, older drivers show a higher acceptance to lane departure warning system compared to young drivers (Son et al., 2011).

#### 5.3.2 Gender

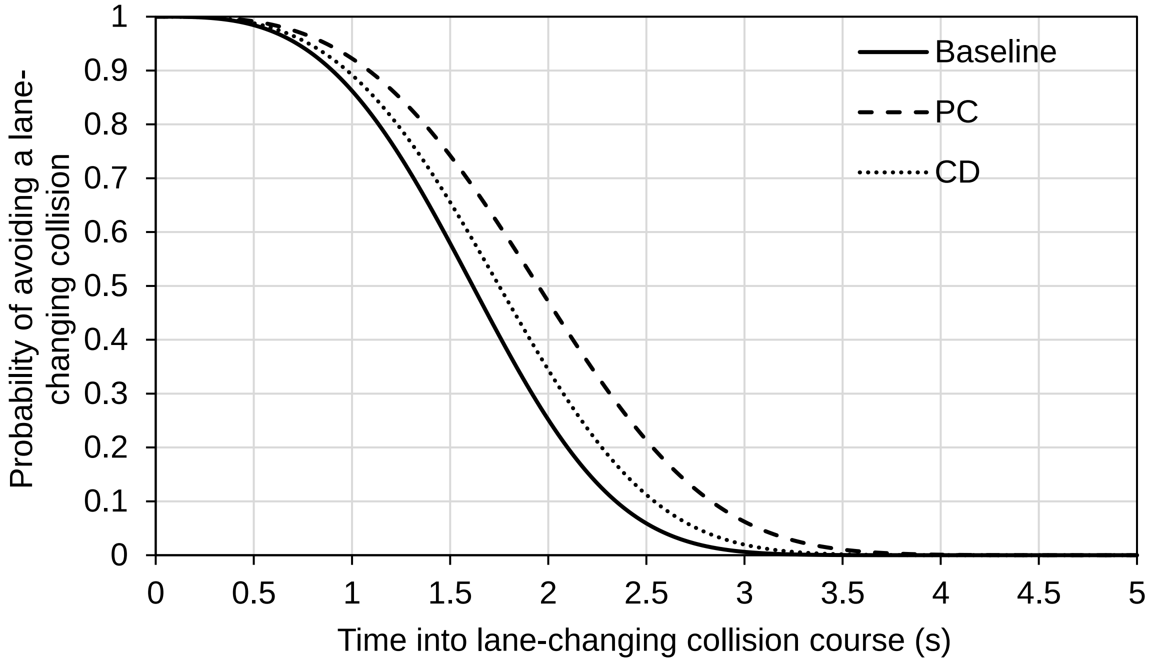
Figure 10 indicates the survival curves for likelihood of not engaging in a lane-changing collision for male and female drivers across different driving conditions. For male drivers, the probability of avoiding a lane-changing collision in the baseline condition at the time into lane-changing collision course of 2 s is 25% while the corresponding probability for female drivers in the baseline condition is 48%. In line with the past research (Montgomery et al., 2014, Kim et al., 2013, Iversen and Rundmo, 2004), this study also finds that the male drivers are more risk-takers than the counterpart, and are more likely to engage in safety critical events. The probabilities of avoiding a lane-changing collision for female drivers in the perfect communication (and baseline) driving condition at the time intervals of 1, 2, and 3 s are respectively 95% (93%), 67% (48%), and 23% (7%), whilst the corresponding probabilities for male drivers are 92% (86%), 47% (25%), and 6% (0.6%). These findings imply that the connected environment has significant and positive effects on both male and female drivers' DLC behaviours. Meanwhile, the safety margin for female drivers in the perfect communication driving condition is about 22% higher than that of male drivers (when the probability is close to zero, Figure 10), suggesting that female drivers are likely to take more advantage of surrounding traffic information provided by the connected environment, and perform DLC manoeuvres more safely compared to the male drivers. Lyu et al. (2019) also reported higher safety benefits for advanced driving system for female drivers compared to male drivers.

## 6. Conclusions

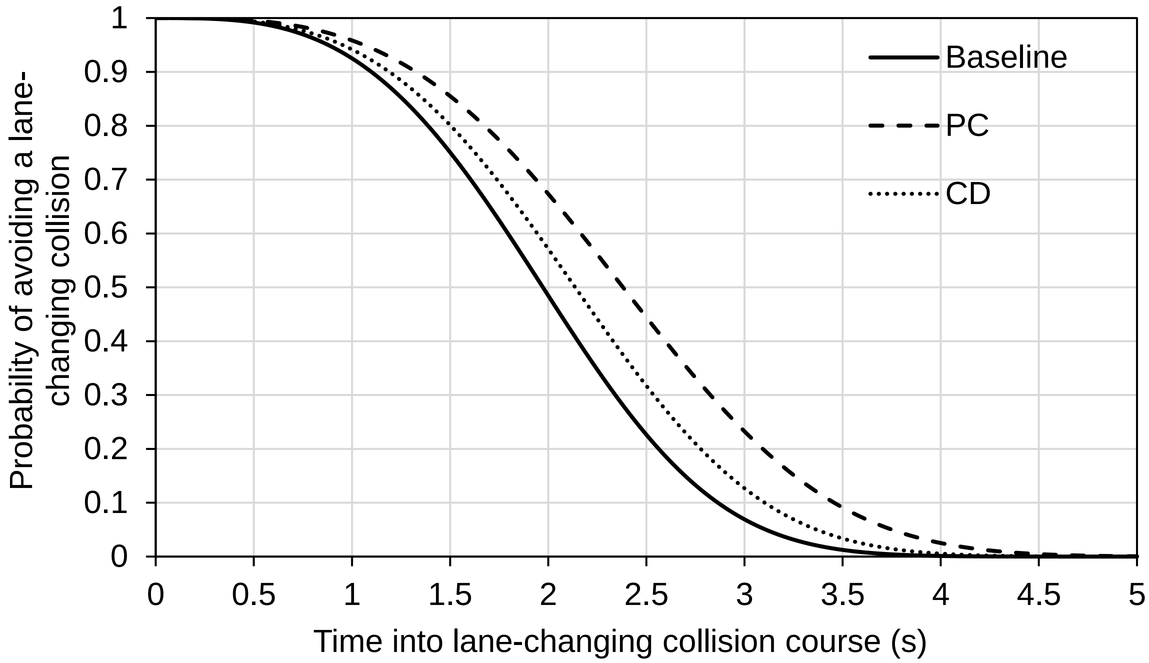
This paper investigates the driving behaviour in the connected environment during DLC manoeuvres. Seventy-eight participants from a diverse background, aged between 18 to 65 years, performed DLC manoeuvres simulated in the CARRS-Q high-fidelity driving simulator, mimicking vehicle-to-vehicle and vehicle-to-infrastructure communications. Various key driving behaviour indicators are analysed using the linear mixed model to determine the effects of the connected environment, and results suggest that the connected environment has a significant impact on spacing, speed, acceleration noise, and others. Drivers in the connected environment tend to perform DLC with bigger gap sizes. The safety margin associated with DLC manoeuvre, measured by TTC, also increases in the connected environment.

The GEE model of gap acceptance reveals a positive effect of the connected environment on DLC gap selection as drivers tend to select bigger and safer gap sizes. Similarly, the GEE model of DLC duration shows that the connected environment increases

DLC duration. Both the GEE models include driver demographics that describe the impact of driver characteristics on driving behaviour.




(a) Male




(b) Female

**Fig. 10.** Effects of the connected environment on the probability of avoiding a lane-changing collision during a DLC manoeuvre: difference between gender; *PC: Perfect communication; CD: Communication delay*

To gain more insights about how the connected environment influences safety and driver demographics, a hazard-based duration model (i.e., the Weibull AFT gamma frailty model) is developed. This model identifies three classes of variables affecting TTC including driving conditions (perfect communication and communication delay), operational variables (acceleration noise and accepted gap size) and driver demographic factors (age and gender). Overall, the model suggests that the connected environment enhances the safety associated with DLC manoeuvres. Moreover, the safety margin is higher in the perfect communication driving condition than that of the communication delay and baseline driving conditions. However, the communication delay driving condition has a higher safety margin compared to the baseline condition. It is also found that young drivers benefit the least from the connected environment, while old drivers benefit the most. Male drivers compared to female drivers have lower safety margins when driving without the information assistance system. Female drivers tend to take the maximum advantage from the connected environment compared to male drivers.

The findings from this study shed light on the impact of the connected environment on DLC manoeuvres. Driving behaviour, as reported in the literature, varies across different driver demographics and the anticipated benefits of the connected environment can be significantly influenced by driver demographics (Sharma et al., 2017). As such, this study provides insights into the impact of the connected environment for different age groups and gender. Such information can not only help in designing a more effective connected driving environment, in particular driving messages, but can also be used to develop suitable countermeasures for risky drivers to avoid engaging in safety critical events. In addition, the findings also highlight the importance of including human factors into lane-changing decision models and subsequent traffic simulations to better mimic the lane-changing decision-making process when the surrounding traffic information is available.

Driving in the simulated environment and acceleration of the simulator car could be different from that in the real-world car. Thus, a comparison between the acceleration of the simulator car and real-world car has been carried out by calculating a scale ratio—a ratio of the acceleration of the simulator car to the acceleration of the real-car car. For accelerations of the simulator car, the accelerations of all 78 participants driving in the simulator were extracted when they started driving from the stop line and reached a speed of 50 kph. Their average acceleration was 3.20 m/s$^2$. The corresponding average acceleration of a real Holden Commodore car is 2.30 m/s$^2$ (Zal, 2019). Thus, the scale factor is 1.39, which suggests that the acceleration in the simulator car is about 1.4 times faster than the real-world car. Similar scale factors have been reported in the previous studies (Blana and Golias, 2002, Gemou, 2013), comparing the speed of the real car with the simulator car. Although the acceleration in the driving simulation environment is higher, this difference should not impact the findings of this study as it is focussed on the relative change in discretionary lane-changing behaviour between driving in the traditional environment and in a connected environment. Since all the driving scenarios were completed using the advanced driving simulator, it is a reasonable to assume that the relative change can be replicated in the real world. Such relative comparison and its applicability have been well acknowledged in the literature (Knapper et al., 2015, Jamson and Jamson, 2010, Hurwitz et al., 2005).

Due to scarcity of the connected environment data, this study used the advanced driving simulator to collect high quality vehicle trajectory data. It would be interesting to further validate the findings of this study with the data from field experiments. In addition, this study utilised only one driving simulator and observed driving behaviour of one participant while other traffic in the simulator was programmed. A more realistic approach could be the use of connected driving simulators that enable capturing vehicular interactions of more than one driver in a more realistic manner. Such effort is ongoing. Furthermore, this study is limited to providing identical gap sizes in each drive. A possible research direction could be randomising the gap sizes across various drives and then determine the impact of the connected environment on gap selection behaviour. This future research can also help in understanding the inter-driver heterogeneity during gap selection.

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