Connectivity's impact on mandatory lane-changing behaviour: evidences from a driving simulator study

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Abstract

The connected environment provides driving aids to help drivers making efficient and safe driving decisions. The literature to date is devoid of conclusive evidences of the connected environment's impact on drivers' mandatory lane-changing (MLC) behaviour. As such, the objective of this study is to examine MLC behaviour through a driving simulator experiment using the CARRS-Q Advanced Driving Simulator. Participants with diverse background performed the experiment in randomised driving conditions: baseline (without the driving aids), connected environment with perfect communication, and connected environment with communication delay. Repeated measure ANOVA in the form of linear mixed model and Generalized Estimation Equation (GEE) are employed to analyse various driving performance indicators during MLC event. We find that drivers in the connected environment tend to wait longer, increase the initial speed, and maintain a larger spacing, compared to when they are driving in the baseline condition. In addition, drivers in the connected environment are likely to reject fewer number of gaps and select relatively bigger gap sizes. Furthermore, post-encroachment time (PET) in the connected environment is higher across different gap sizes, indicating that the connected environment makes MLC safer. The GEE model on gap acceptance suggests that the perfect communication and communication delay has positive and negative impact on the accepted gap size, respectively, and the GEE model on lane-change duration indicates that lane-change duration tends to increase in the connected environment.

Keywords: Connectivity; mandatory lane-changing; gap acceptance; driving behaviour; safety

1. Introduction

The connected environment is promising in mitigating many transportation issues related to safety, mobility, and environmental impact (Kim, 2015). The connected environment provides information that can assist in driving tasks, particularly in lane-changing (LC) that requires information about surrounding traffic. Since LC is a multistage decision making process, it increases driver's workload and stress, thus the chance for the driver to make errors increases which can create safety hazards (Zheng et al., 2010). LC also causes negative impacts on traffic stream. For example, Cassidy and Rudjanakanoknad (2005) reported LC's impact on traffic breakdowns and capacity drops; Ahn and Cassidy (2007) revealed the linkage between LC and stop-and-go oscillations, which was further confirmed by Zheng et al. (2011b).

In traffic flow theory, LC is mainly divided into two types: mandatory and discretionary. Mandatory LC (MLC) is mainly performed to reach a planned lane position,

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while discretionary LC (DLC) is for achieving a desired driving condition, e.g., increasing speed. LC modelling endeavours in the literature can be classified into two categories: modelling LC decision-making (LCD), and modelling LC's impact (LCI) on surrounding traffic (Zheng, 2014). This study focuses on LCD in the context of MLC in a connected environment.

In a connected environment, driving aids e.g., information about gap availability in the target lane, the speeds of surrounding vehicles, and the remaining distance (in case of MLC) can change (in most cases benefit) drivers' MLC decision making. More specifically, connectivity's impact on MLC decision making is expected to be more pronounced at the operational stage that includes gap acceptance and duration of MLC's execution (LC duration hereafter). The former has received significant attention in the LCD modelling (Bham and Goswami, 2007; Bham, 2009; Choudhury et al., 2007; Marczak et al., 2013; Toledo et al., 2005; Toledo et al., 2003) while the latter has been rarely studied in the past (Toledo and Zohar, 2007). Note that the gap in this study is defined as the distance from the rear bumper of the leading vehicle to the front bumper of the following vehicle in the target lane, and LC duration is defined as the time taken by the subject vehicle (SV) to execute the LC manoeuvre.

A sound understanding of connectivity's impact on driver's MLC decision making is important for developing more accurate and more realistic MLC models suitable for operating and controlling connected vehicles, and for designing a safer and more efficient connected driving environment. A survey of recent literature reveals that most of the studies focus on measuring the impact of connectivity on macroscopic behaviour using microsimulation (Guériau et al., 2016; Reina and Ahn, 2015), while some studies proposed algorithms for MLC scenarios (i.e., merging behaviour) for the connected environment and tested using simulation data (Letter and Elefteriadou, 2017; Rios-Torres and Malikopoulos, 2017). However, to accurately analyse drivers' MLC behaviour and to model their MLC decision making mechanism, high-quality vehicle trajectories are required along with detailed human factor information. Primarily because of the novelty of the connected environment (and consequently, the scarce of the data), very few studies in the literature focused on the connected environment's impact on drivers' MLC behaviour. To fill this gap, this research aims to investigate the impact of connectivity (or connected environment; note that these two terms are used interchangeably in the rest of the paper) on drivers' MLC behaviour using a driving simulator experiment in a high-fidelity advanced driving simulator. More specifically, we aim to address the following three questions:

i. Does connectivity impact drivers' driving performance related to MLC, e.g., gap selection, initial speed, waiting time, and spacing?
ii. Does connectivity improve the safety margin associated with MLC manoeuvre?
iii. Does connectivity influence the execution of MLC?

The remainder of this paper is organized as follows. Section 2 presents a literature review on gap acceptance behaviour and LC duration modelling. Section 3 introduces the driving simulator experiment design and data collection. Section 4 explains data processing methodology. Section 5 describes data analysis in detail. Section 6 discusses main findings.

Finally, Section 7 concludes the study by summarizing major findings, limitations, and pointing out some future research topics.

2. Literature Review

This section is divided into two parts: a) gap acceptance behaviour studies, and b) studies related to modelling LC duration.

2.1. Gap acceptance behaviour

Gap acceptance, which is an integral part of LCD models, is an important microscopic parameter in traffic control and management. In most of the existing studies, gap acceptance is modelled based on the gap acceptance theory, which assumes driving behaviour as consistent, and implies that the rejected gaps will not be larger than the accepted gaps (Daamen et al., 2010). According to this theory, if drivers do not find a gap larger than the critical gap in case of merging scenario, they would travel to the end of the acceleration lane without merging to the target lane (Marczak et al., 2013). Usually, the length of lag gap increases with increase in relative speed, and drivers tend to accept a smaller gap size as the remaining distance becomes shorter (Ahmed et al., 1996). Meanwhile, drivers are more likely to select a larger gap size with the increase of the speed (Kondyli and Elefteriadou, 2011).

Table 1 summarizes some representative studies on gap acceptance behaviour in MLC. Almost all studies presented in Table 1 considered relative speed, lead and lag gaps, and remaining distance on the acceleration lane. However, only Marczak et al. (2013) considered the rejected gaps while describing gap acceptance behaviour. Further, drivers' gap acceptance behaviour can also be influenced by personality traits (e.g., aggressiveness, sensation seeking, etc.), and urgency of the LC (Bham and Goswami, 2007), which has rarely been incorporated in the existing models. In addition, most of the existing studies did not consider the connected environment, and ignored human factors (e.g., age, gender, and driving experience). Smith et al. (2016) is an exception, which reported that connected vehicle technology benefits drivers' gap acceptance behaviour, and the anticipated benefits from the connected vehicle technologies are a function of driver's compliance, which is affected by factors related to situation and personality traits. However, no model was developed to capture driver's gap acceptance behaviour in a connected environment.

Table 1 A Summary of Previous Studies Related to Gap Acceptance in MLC

Study	Variables considered in gap acceptance behaviour	Data source	Modelling method
Ahmed et al. (1996)	Gap length, relative speed, remaining distance, delay in completing merging manoeuvre	Field data collected at I-95	Intrinsically linear (exponential)
Hidas (2002)	Relative speed and acceleration of the SV with respect to its potential leader/follower in the target lane	Micro-simulation	Agent based modelling

Sarvi et al. (2002)	Instantaneous speed, position and acceleration of SV, leader and follower in the target lane	Field data collected in Tokyo	Conventional car-following model
Toledo et al. (2003)	Relative speed with respect to the lead and lag vehicles and path plan variables	Field data collected at I-395	Log-linear
Jones et al. (2004)	Maximum deceleration rate, average remaining distance, and minimum gap in the target lane	Micro-simulation	Comparison of available gap with critical gap
Toledo et al. (2005)	Relative speed of the lead and lag vehicles in the direction of LC	Field data collected at I-395	Log-linear
Hwang and Park (2005)	Lead and lag gaps, front gap (spacing), remaining distance, and type of vehicle (heavy vehicle or passenger car)	Field data collected in China	Probit logit model
Choudhury et al. (2006)	Instantaneous speed, position and acceleration of SV, leader and follower in the target lane	NGSIM I-80 dataset	Log-linear
Choudhury et al. (2007)	Remaining distance to the end of the acceleration lane, relative speed of the average speed on the motorway with respect to the SV, relative speeds of the potential leader and the follower in the target lane, and acceleration of the potential follower	NGSIM I-80 dataset	Log-linear
Bham and Goswami (2007)	Personality traits (e.g., aggressiveness, sensation seeking, etc.), and urgency of the LC	NGSIM I-80 dataset	Deterministic and stochastic methods
Wu et al. (2007)	Speed and position of SV, speed, and relative distance to leader and follower	Instrumented vehicle	Empirical analysis
Kim et al. (2008)	Critical lead and lag gaps, and relative speed	Field data collected in Seoul	Comparison of available gap with critical gap
Choudhury et al. (2009)	Effective gap size, relative speed, and presence of lead vehicle	NGSIM I-80 dataset	Log-linear
Bham (2009)	Critical gaps based on accepted and rejected gaps	NGSIM I-80 dataset	No model was developed
Daamen et al. (2010)	Merge location, accepted and offered gaps, and relaxation phenomenon	Field data collected in Netherlands	Empirical analyses
Kondyli and Elefteriadou (2011, 2012)	Speed and position of SV and lead and lag gaps	Field data collected at I-95	Log-linear

Gurupackiam and Jones Jr (2012)	Traffic density (e.g., congestion)	Field data collected in Alabama	Empirical analysis
Hou et al. (2012)	Speed of SV, relative speed of lead and lag vehicles, distance to lead and lag vehicles in the target lane, and remaining distance	NGSIM US 101 dataset	Genetic fuzzy logic approach
Marczak et al. (2013)	Offered gap, headway, position on acceleration lane, speed difference between potential leader and follower, and speed difference between SV and follower	Field data collected in Netherlands	Empirical analyses
Hou et al. (2014)	Relative speed of lead and lag vehicles, distance to lead and lag vehicles in the target lane and remaining distance	NGSIM US 101 dataset	Bayes classifier and decision trees
Qi et al. (2015)	Lag and lead time gap in the target lane, lead time gap in the current lane	Field data collected in US	Empirical analyses
Cao et al. (2016)	Speed and acceleration, relative speed of lead and lag vehicles	Field data collected in Australia	Probabilistic model
Zhu et al. (2017)	Time headway to lead and lag vehicles in the target lane and relative velocity	NGSIM US 101 and I 80 dataset	Empirical Analyses
Vechione et al. (2018)	Front gap before LC, rear and front gaps after LC	NGSIM I 80 dataset	Empirical analyses

Note that SV refers to Subject Vehicle

2.2. LC Duration Modelling

LC behaviour generally consists of LC decision-making and LC execution. LC duration is an important aspect of LC execution. Though LC duration is considered as one factor or characteristics of LC's impact and has a weak relationship with LCD process, LC execution in general and LC duration in particular often have a significant impact on surrounding vehicles in heavy or congested traffic. To fully capture LC's impact on traffic, it is indispensable to develop models capable of realistically reproducing important characteristics (e.g., LC duration) of LC execution. In the literature, LC decision-making (and its models) has been a topic of research for a long time whereas LC duration is often neglected or simplified as an instantaneous event (Cao et al., 2016; Toledo and Zohar, 2007), which is unrealistic and contradicts with the field observations that LC duration varies from 1 s to 16.5 s (see Table 2 for more information). This ignorance or oversimplification could be because of the difficulty of accurately determining LC duration due to the fact that most of the existing datasets do not contain sufficient information to enable researchers to pinpoint the LC starting time (i.e., LC initiation point). Furthermore, the duration of an LC execution can potentially cause shockwaves in both the initial and the target lanes, capacity drop, and traffic safety hazards (Jin, 2010; Mauch and J. Cassidy, 2002; Sasoh and Ohara, 2002). Moreover, an LC duration model that can satisfactorily explain/estimate how long it would take for an LC to be executed can be a valuable tool for researchers to either develop more realistic models to reproduce LC's impact (an important topic currently under-represented in the LC modelling literature as pointed out in Zheng (2014)) or to evaluate the existing LC impact models that aim to quantify the impact of LC behaviour on surrounding vehicles. Considering LC duration as an instantaneous event can cause biased estimates of traffic flow parameters (Moridpour et al., 2010). Therefore, it is necessary to evaluate the LC duration in addition to LC decision making (e.g., gap acceptance) to completely understand LC behaviour, and subsequently, to improve the accuracy and realism of microscopic traffic simulation.

Table 2 A Summary of LC Duration Studies

Study	Methodology	LC duration
Worrall and Bullen (1970)	Aerial images	1.25 to 1.95 s
Finnegan and Green (1990)	Literature review survey	4.9 to 7.6 s
Wiedemann and Reiter (1992)	-	2.18 to 2.69 s
Chovan (1994)	Intelligent Vehicle Highway System	2 to 16 s
Hetrick (1997)	Field study with an observer	3.4 to 13.6 s
Hanowski (2000)	Field study	1.1 to 16.5 s
Salvucci and Liu (2002)	Simulator study	5.14 s
Lee et al. (2004)	Instrumented vehicle	6.3 s
Tijerina et al. (2005)	Field study with an observer	3.5 to 6.5 s for urban streets 3.5 to 8.5 secs for highways
Toledo and Zohar (2007)	Field study	1 to 13.3 s
Moridpour et al. (2010)	NGSIM dataset	1.1 to 8.9 s for passenger cars

In the literature, researchers have used different approaches to detect the LC initiation point, e.g., using an observer (Hetrick, 1997) and self-reporting (Salvucci and Liu, 2002). However, the presence of an observer can bias the actual driving behaviour, and self-reporting can be error-prone and subject to memory bias. To overcome these issues, Toledo and Zohar (2007) used the lateral movement profile of LC vehicles from NGSIM data to detect LC initiation point. However, they did not consider unsuccessful LC attempts or noise in the data−a well-known problem of NGSIM data (Thiemann et al., 2008).

In addition, the previous studies mainly reported the magnitude of LC duration based on some empirical evidence (Hetrick, 1997; Lee et al., 2004; Tijerina et al., 2005), and modelling LC duration has been largely ignored in the literature with a few exceptions (Toledo and Zohar, 2007). Among these exceptions, Toledo and Zohar (2007) modelled LC duration and reported several factors that affect LC duration, e.g., relative speed in the target lane, spacing to the leader, traffic density, LC direction, and the speed of SV. This model ignored human factors, which can be important in modelling LC duration. Note that this model was mainly developed for the traditional environment and no effort exists for modelling LC duration in a connected environment. Furthermore, the connected environment provides LC driving aids (i.e., availability of gaps in the target lane) that can benefit in LC execution/duration. Connectivity's impact on LC execution/duration is also dependant on human factors such as age, gender, etc. However, connectivity's impact on the LC execution/duration coupled with human factors is still not well known.

3. Experiment Design and Data Collection

As mentioned above, one of the main obstacles of studying connectivity's impact on drivers' LC behaviour is that these vehicles are still not operated at a scale for collecting field data for conducting scientific research. To overcome this challenge, a simulator experiment was carefully designed for the connected environment; and the participants were asked to drive a simulator vehicle in three driving conditions: baseline (without driving aids), driving with perfect communication (PC), and driving with communication delay (CD).

3.1. Driving Simulator

The experiment collects high-quality connected environment data in the form of trajectory and advisory information, using the Centre for Accident Research and Road Safety-Queensland (CARRS-Q) high-fidelity advanced driving simulator. The simulator includes a complete Holden Commodore car with full working controls, instruments, and the three front-view projectors. The projectors provide high resolution 180º field of view to the participants. The simulator is attached to a six-degree-of-freedom rotating base capable of moving and twisting in three directions to mimic the sustained cues for acceleration, deceleration, braking, cornering, and integration with other road features. The simulator uses SCANeR™ studio software attached with eight computers, which connects vehicle dynamics with virtual road environment (Haque and Washington, 2015). The simulator also produces the actual sound, e.g., engine noise, vehicle-road interaction noise, and noise for other traffic interactions, which further enhances the realism of the simulated driving. The simulated road environment and designed traffic interactions are displayed on front projectors, rear mirror, and wing mirrors at a rate of 60 Hz. The data from the driving simulator were collected at a rate of 20 Hz.

3.2. Participants

The participants were recruited by circulating the flyers at public places; social media platforms were also utilized to disseminate the recruitment call for the participants. The participants were selected based on the following conditions: (a) aged between 18 and 65 years old, (b) currently hold a valid driver licence in Australia (either a provisional or open), (c) should not suffer from motion sickness or epilepsy. In total, 78 participants participated in the experiment, and they received AU $75 as a compensation of their time.

Table 3 presents descriptive statistics of the selected participants. 64.1% of the participants are male, and the average age for the male and female participants is 34.1 (SD 12.6) and 24.9 (SD 6.7) years, respectively; the average driving experience is 12.2 (SD 11.5) years. About 79.5% of the participants held an open licence (non-restricted)[1]; 10.3% of the participants were involved in a traffic crash in last one year. When asked "Have you heard of Connected Vehicles or Connected Vehicle Technology PRIOR TO today's experiment",

[1] In Queensland, Australia, newly licensed drivers receive a provisional licence for a period of 3 years before they obtain an open licence.

42.3% of the participants responded “Yes”. Overall, the participants of our experiment have a diverse background.

Table 3 Descriptive Statistics of the Participants

Driver characteristics	**Mean**	**SD**	**Count**	**Percentage**
Driver's age (years)	30.8	11.7	-	-
Gender				
Male	-	-	50	64.1
Female	-	-	28	35.9
Education				
Primary	-	-	2	2.5
Junior (Grade 10)	-	-	1	1.3
Senior (Grade 12)	-	-	18	23.1
TAFE or Apprenticeship	-	-	9	11.5
University	-	-	48	61.6
Licence type				
Open	-	-	62	79.5
Provisional	-	-	16	20.5
Years of driving	12.2	11.5	-	-
Kilometers driven in a typical year				
0-5,000 km	-	-	10	12.8
5,001-10,000 km	-	-	19	24.4
10,000-15,000 km	-	-	15	19.2
15,001-20,000 km	-	-	18	23.1
20,001-25,000 km	-	-	6	7.7
> 25,000 km	-	-	10	12.8
Crash involvement in last one year				
Involved	-	-	8	10.3
Not involved	-	-	70	89.7
Frequency of driving per week				
Less than 2 times	-	-	5	6.4
2-4 times	-	-	28	35.9
5-6 times	-	-	16	20.5
7-8 times	-	-	7	9.0
More than 8 times	-	-	22	28.2
Prior information about Connected Vehicles				
Yes	-	-	33	42.3
No	-	-	45	57.7

3.3. Experiment Design

The total length of the simulated road is about 3.2 km, including a four-lane motorway with two lanes in each direction. The speed limit on the motorway is 100 km/h. The experiment design consists of both MLC and DLC events including failed LC attempts. The scope of this paper is limited to investigating MLC events.

The details of the scenarios and vehicular interactions are explained in the ensuing paragraphs. Note, the nomenclature used for the design of experiment: subject vehicle (SV) is the simulator vehicle driven by the participants, the leading vehicle in the initial lane is named as LV, and the following vehicles are called as FVs. Leading and following vehicles are collectively termed as programmed vehicles.

Scenario–1: Baseline

In this scenario, each participant is asked to drive the simulator vehicle without any driving aid. The participants face one MLC event (i.e., lane closure due to work zone), where the programmed vehicles are scripted to drive at SV's speed so that all participants experience same vehicular interactions at the same point (the time may vary as per the speed of different participants). It is important to mention here that due to driver heterogeneity, it is very challenging to define a representative speed of the FVs in the experiment. To overcome this problem, a pragmatic and straightforward approach has been adopted: we scripted the FVs to drive at the speed of SV by maintaining a predefined gap, which will not induce the participants to change their driving behaviour due to the influence of the FVs.

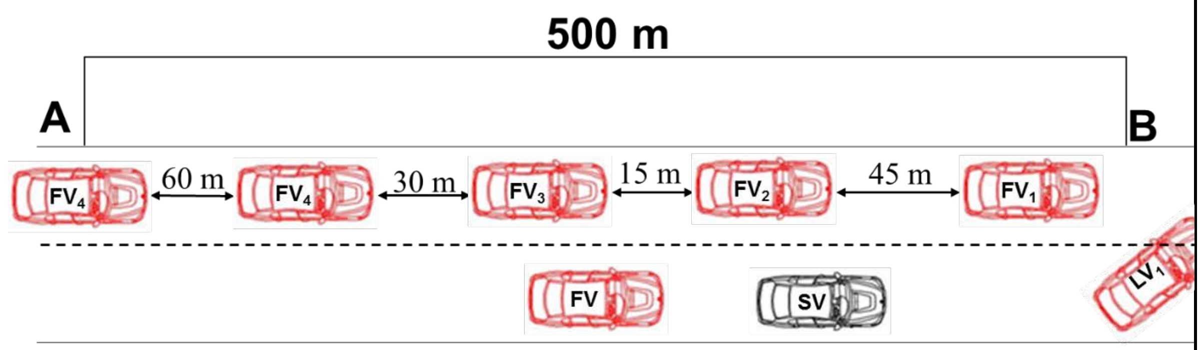
To enable typical types of interactions between SV and the FV, our driving simulator experiment was innovatively designed to ensure that the programmed vehicles were scripted to mimic forced, free, and cooperative LCs. For the first available gap, for example, the FV_1 was scripted to accelerate in order to force SV to abandon the LC attempt, and for the other gaps, FVs either decelerate to show courtesy to SV (i.e., the cooperative LC) or remain unaffected by LC of SV (i.e., the free LC).

At the start of the scenario (point A in Figure 1a), SV starts travelling on the right lane with a leader and a follower in the current lane and maintaining a constant gap of 20 m from SV. Five programmed vehicles start moving in the adjacent lane with respect to the speed of SV.

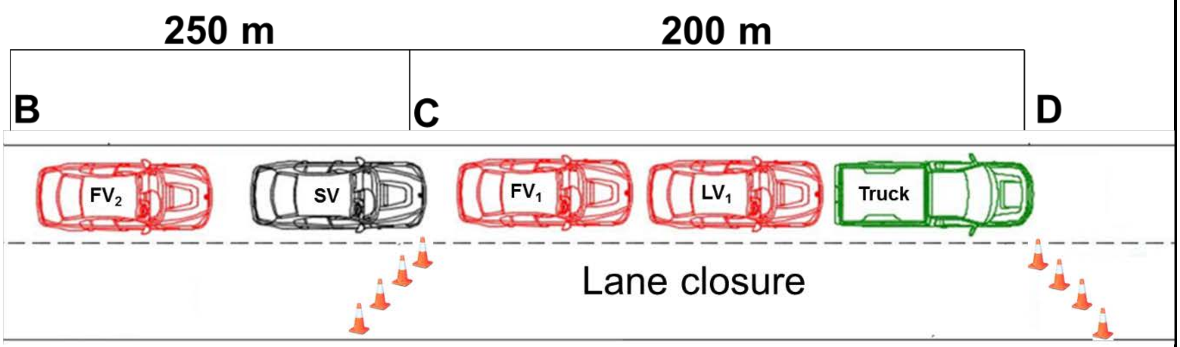
At point B, LV_1 reduces its speed to 40 km/h due to lane closure ahead. FV_1 was programmed to show courtesy to LV_1 to perform the lane change and FV_1 starts moving at a speed of 40 km/h. SV faces a series of five gaps in this MLC event: 45 m, 15 m, 30 m, 60, and 90 m.

In this study, we have intentionally decided to provide identical gap sizes to the participants across different drives because the primary objective of this study is to quantitatively assess and model connectivity's impact on LC decision making and LC duration. Providing randomized gaps to the participants would actually make it very difficult to achieve this goal because we would not be able to distinguish the exact reason for different gap acceptance behaviours: is such difference caused by the connectivity's impact or simply due to different gaps provided? Thus, to minimize confounding factors, we have carefully designed the experiment so that all the participants face the same traffic situation, and the same gaps.

If SV chooses the first gap (i.e., the gap between FV_1 and FV_2), the rest of FVs follow SV with the same gap. Alternatively, SV can take any gap in between FVs. After performing LC, all the vehicles then enter into a single lane work zone (starts from point C, Figure 1b) where they follow a slow-moving truck moving at the speed of 25 km/h. The length of lane closure was about 200 m (point C-D in Figure 1b).



(a) Vehicular interaction before lane closure



(b) Vehicular interaction after lane closure

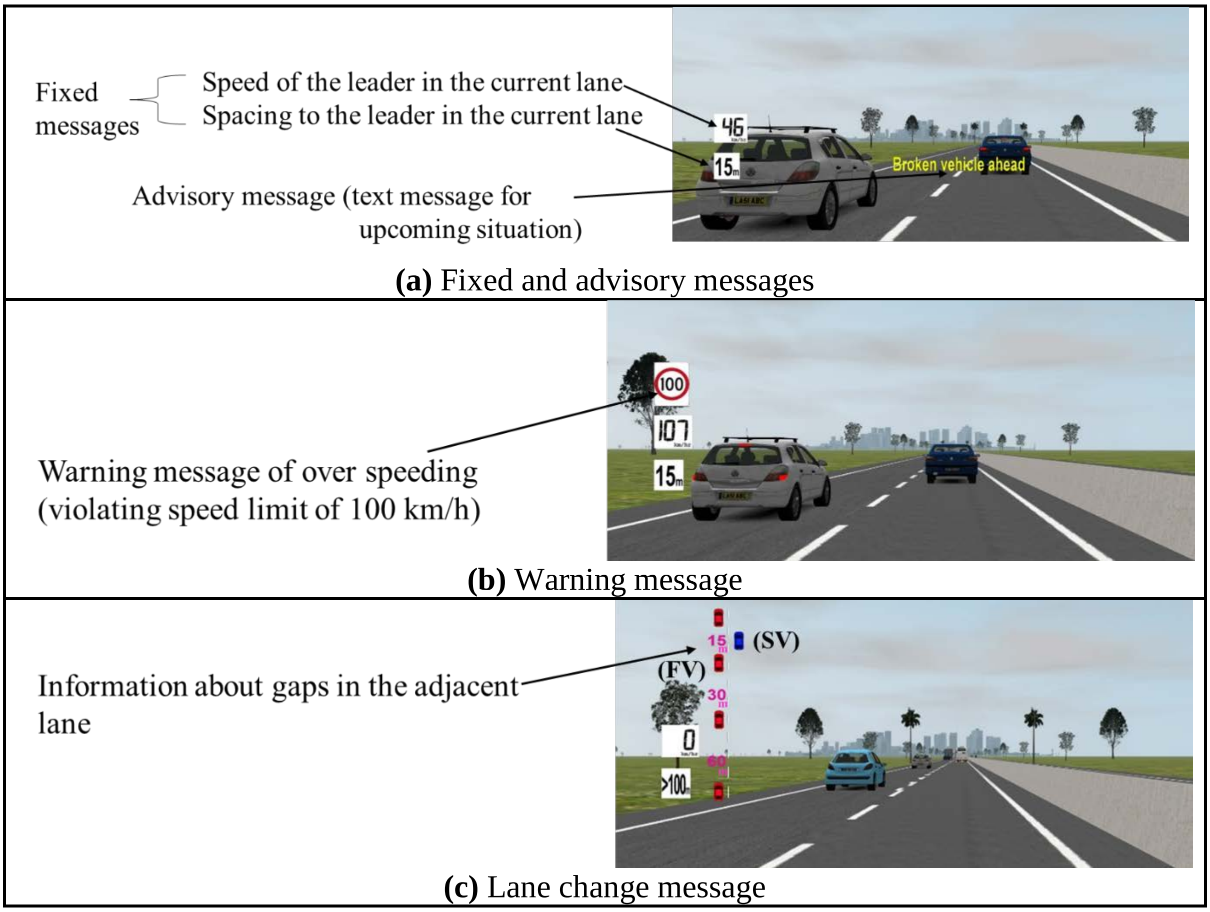
Fig. 1. Design of MLC events (not to scale)

Scenario–2: Perfect Communication (PC)

For driving in a connected environment with PC, drivers were assisted with driving aids without any delay/interruptions. After comprehensively reviewing the literature (Adell et al., 2011; Saffarian et al., 2013) on in-vehicle information systems and how driving aids are currently provided by major car manufacturers, two forms of driving aids are provided in the connected environment, mimicking vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications: auditory (beep sound) messages and imagery messages (displayed on the windscreen, which is similar to the heads-up display equipped in some recent vehicle models; see Figure 2 for an example).

In the connected environment, four different types of messages (or driving aids) are displayed to assist in driving tasks, namely fixed messages, advisory messages, warning messages, and an LC message. The fixed messages appear on the bottom left corner of the screen and provide information about the speed of the leading vehicle and the distance to the leading vehicle in the current lane (Figure 2a). An advisory message, in form of text message, such as “Broken Vehicle Ahead” is presented at the bottom of the screen (Figure 2a) to inform about the upcoming situations. Warning messages (Figure 2b) flash up only during critical situations. For example, if a participant crosses the speed limit, the speed limit sign will flash up with a beep sound. A lane change message appears whenever a lane change opportunity is available (Figure 2c). A blue colour car represents SV in Figure 1c, while all FVs are presented in red colour; Figure 2c also indicates three subsequent gaps in the target lane. The details of driving aids disseminated in the connected environment are provided in Table 4. The suitability of these messages had been tested and confirmed during the pilot study.

In this study, we did not give any suggestion to the participants regarding the suitability of any gap size. In fact, one of the principles we adopted in designing the experiment is to only provide facts and avoid providing any recommendations to the participants. There are two main reasons for using this strategy: first, we want to avoid introducing any bias into the process of a driver's LC decision making; the objective of this research is to investigate the participants' LC decision making when they are given descriptive information related to their driving tasks, and the LC decision itself was totally left for each participant to make. Any suggestive information would make it impossible to reveal the real impact of the connectivity itself because whatever observations we collect would very much depend on how the information is provided rather than what information is provided. Furthermore, we found out that almost all the car manufacturers do not provide any recommendations to users, perhaps to avoid any legal and liability issues (if anything goes wrong). For example, it is totally up to the driver whether he/she uses automatic cruise control or not. To closely resemble a participant's real life experience, we have decided to adopt the same strategy.



(a) Fixed and advisory messages

(b) Warning message

(c) Lane change message

Fig. 2. Driving aids presented on the windscreen

Scenario-3: Communication Delay (CD)

In the driving scenario with CD, a delay of 1.5 s was imposed in providing information from the connected environment to drivers. We tested the communication delay in the pilot testing with a series of different delays in the driving aids (i.e., 0.5, 1, 1.5, 2 s) and observed that the participants were unaffected or did not feel any delay in the information when the delay was less than 1.5 s. They started to notice and react to the delay when the delay was 1.5 s in the driving aids. Meanwhile, delays longer than 2 s were not tested since some of the driving aids only lasted for 3 s.

Talebpour et al. (2016) also tested the effect of communication delay in a simulation setup and reported that a delay of about 1.5 s could have a significant impact on traffic safety. Hence, based on the pilot testing results and the previous study, we adopted a delay of 1.5 s. This simulated delay can be attributed to technical difficulties caused in sending and receiving messages.

Table 4 Description of Driving Aids

Type of event	**Information presentation**		**Any other way of presentation**
	Text/Image	**Audio**	
Following too close to leader	Spacing with red border	Continuous beep for 3 s	Image of available gaps in the adjacent lane
Start of lane closure	Broken vehicle ahead	Beep for 1 s	
End of lane closure	Lane closure ends in 200 m	Beep for 1 s	
Speed limit crossed	Speeding and speed limit image	Beep for 1 s	
Current speed of the leader and the distance of SV to the leader was available to the driver			

In our study, the experiment has been meticulously designed and effective strategies have been carefully implemented to minimize any potential learning effect. More specifically, for each participant, the order of the scenarios was randomized with one exception that communication delay only came after a participant has experienced the perfect communication. Moreover, although this paper only explains the MLC design, the design of the experiment consists of car-following events, several MLC and DLC events, and city events, which are not explained herein because the scope of this study is limited to MLC only. These multiple events make it more unlikely for a participant to remember details for a particular event. Note that a drive (in each scenario) in the experiment took a participant about 10–12 mins to complete and the total time for a participant to complete the whole experiment is less than one hour. Thus, the workload of the participants is reasonable and comparable to that in many existing studies using a driving simulator (Cantin et al., 2009; Ma and Kaber, 2005; Palinko et al., 2010; Törnros and Bolling, 2006). Meanwhile, to further minimize/avoid the learning effect caused by multiple drives, the surrounding environment (e.g., colour of FVs, vehicle type, and type of the road blockage) has been changed completely for each drive. In addition, after each drive, the participants were required to take a short break.

In summary, given the randomized sequence of the drives, the number of events that take place in each drive, a break between the drives, and different driving environment and surrounding traffic in each drive, it is highly unlikely that the participants' knowledge and driving ability regarding the LC condition could be influenced by the learning effect in our experiment. Furthermore, the statistical model for gap acceptance developed using Generalized Estimation Equation (GEE) captures the correlation among the observations of the same driver. If any learning effect still persists, the modelling technique has the capability to accommodate the correlation caused by the leaning effect to a certain extent. More discussion on GEE is provided later.

To collect information on driving behaviour and their experience on driving in a connected environment, each participant was asked to participate in a pre-drive and a post-drive questionnaire surveys. The pre-drive survey collected information about each participant's socio-demographic background, driving experience, and driving behaviour (based on driving anger expression inventory (Deffenbacher et al., 2002)). After each driving scenario, each participant completed NASA Task Load Index (NASA-TLX (Hart and Staveland, 1988)). Finally, the post-drive survey captured information about user acceptance, trust in the technology, and sensation-seeking behaviour. The participant testing protocol is presented in Appendix A.

4. Data Processing

4.1. Driving performance indicators for gap acceptance behaviour

A variety of driving performance indicators, as reported in Table 5, are analysed and compared to examine the gap acceptance behaviour of drivers in the connected environment. Some of the selected performance indicators are presented in Figure 3.

The selected performance indicators are significantly influenced by LC initiation and response point. Ambiguity in LC initiation and response points in many previous studies makes their findings less reliable. To accurately measure these performance indicators, it is critical to develop a sound methodology to identify LC initiation and response points. The methods used in this study for identifying LC initiation and response points are presented below.

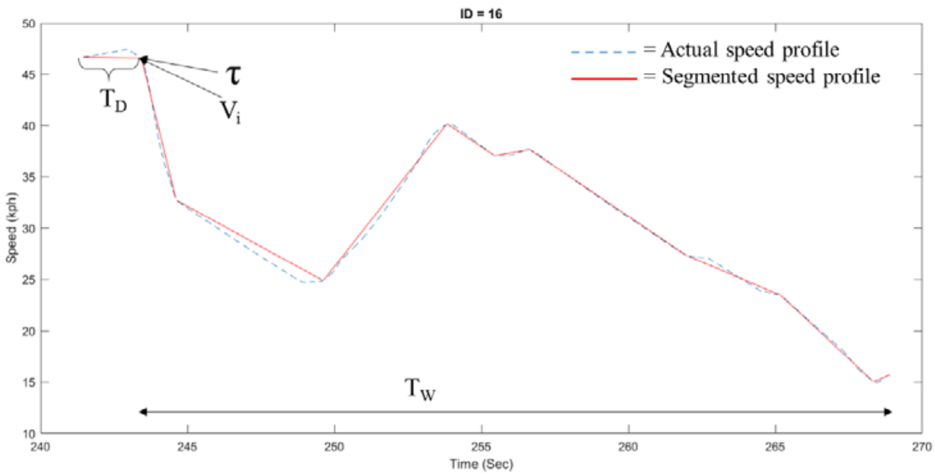


Fig. 3. Illustration of some performance indicators used in this study

Table 5 Driving Performance Indicators Considered for this Study

Parameter	Definition
Initial speed (V_i)	The instantaneous speed of the participants at the response point when they responded to the MLC event either by accelerating or decelerating
Waiting time (T_W)	The time taken by the participants to find an appropriate gap for MLC
Decision initiation time (T_D)	The time taken by the participants to respond to the MLC event once it has been triggered
Acceleration noise	The standard deviation of acceleration/deceleration of a participant between response and LC initiation points
Spacing	Distance between the leading vehicle and the SV in the current lane between response and LC initiation points
Post-encroachment time (PET)	The time lapse between the end of the encroachment of the SV on the LC point in the target lane and the time taken by the immediate follower in the target lane to arrive at the same point
LC duration	The time taken by the participants to complete the LC manoeuvre
Gap selection	The gap size accepted by the participants during the MLC event among 5 possible gap sizes: 15 m, 30 m, 45 m, 60 m, and 90 m
Number of rejected gaps	Once a gap is selected then the number of rejected gaps are determined prior to selecting a particular gap

4.1.1. LC initiation point

The LC initiation point in this study is defined as the point in time where LC manoeuvre starts. Correctly identifying the LC initiation point can be challenging. To pinpoint the actual LC initiation point, this study uses the vehicle's lane lateral shift, which is measured as the lateral distance of the vehicle's center relative to the lane center. Lane lateral shift values remain fairly constant in car-following mode but change abruptly during LC. More specifically, once a lane-changer initiates an LC manoeuvre, the lane lateral shift value increases drastically, and when the same lane-changer reaches to the target lane, the lane lateral shift value becomes stable again.

To pinpoint LC initiation time using the vehicle's lane lateral shift profile, we develop a simple algorithm that first traces the peak of lane lateral shift (marked by 'circle') and moves in the reverse direction of lane lateral shift until the lowest point is obtained–marked as LC initiation point (indicated by 'diamond' sign). From the vehicle trajectory dataset, the lane numbering is used for identifying the ending point of LC event (shown by 'cross' sign in Figure 4). The developed algorithm automatically stops when an LC initiation point satisfies a condition: 20 consecutive points (i.e., 1 point is equal to 0.05 s), in the reverse direction of lane lateral shift, should be greater than the current point. Note that this condition is placed because practically LC duration cannot be less than 1 s and to avoid any error in the data. A typical example of obtaining LC initiation point is shown in Figure 4.

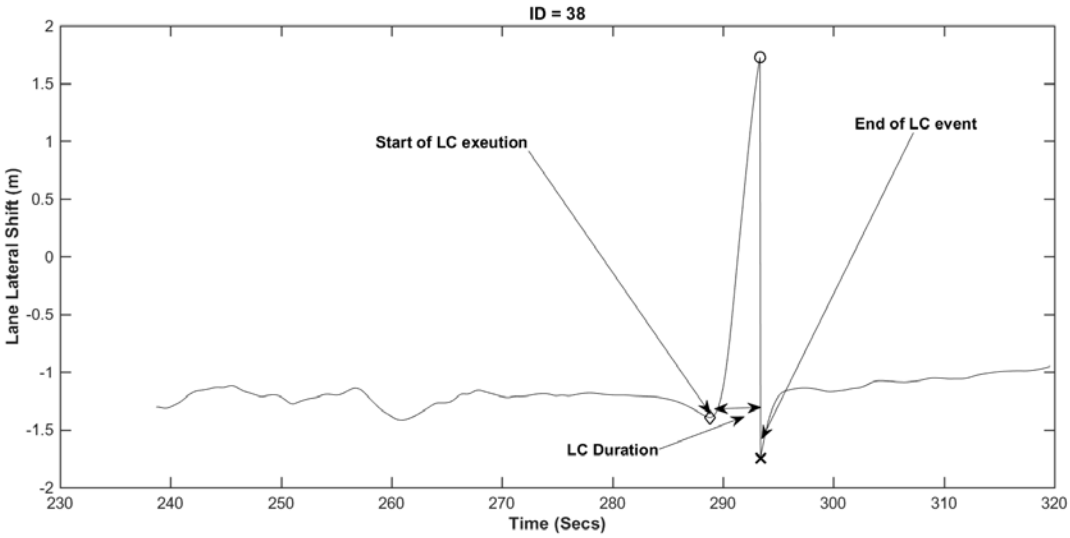


Fig. 4. An example of the lane lateral shift profile

To verify the accuracy of the LC initiation point obtained from the developed algorithm, the wavelet transform (WT) based approach developed in Zheng et al. (2011a) and Zheng and Washington (2012) for detecting singularities in the traffic data is used. Consistent results (i.e., LC initiation points) are obtained from these two approaches, which suggests that LC initiation points used in our study are reliable and can be used to determine LC duration.

4.1.2. Response point (τ)

The response point in this study is defined as the point where a participant responds to the lane closure in the MLC event. Previous studies use an average value for this important variable, i.e., the average reaction time. The average value, however, does not account for driver heterogeneity and makes results less reliable. To overcome this issue, we use the driver's speed profile to determine the response point of each driver separately. Note that, the speed profile before the start of the MLC event and after the LC initiation point is excluded because they are irrelevant. Using the Bottom-Up algorithm (Keogh and Pazzani, 1998), speed profiles are segmented to identify the response of the participants to the MLC event. Briefly, the Bottom-Up algorithm first creates finest possible segments of the speed profile and then merges neighbouring segments until the error of the corresponding segment is lower than the tolerance limit. From the Bottom-Up algorithm, we obtain the segmented speed profile. Then for each segment, its slope (e.g., the average acceleration or deceleration during the corresponding segment) is calculated to determine the response of a participant to the MLC event. More specifically, we use the empirical definition given by Ozaki (1993): if the acceleration or deceleration is within 0.05g (where 'g' is acceleration due to gravity), it can be regarded as a steady-state regime (in our case, it means a participant's behaviour is not influenced by the MLC event); and if the absolute value of the slope is greater than 0.05g, it is in the acceleration state, which indicates the participant's response to the MLC event.

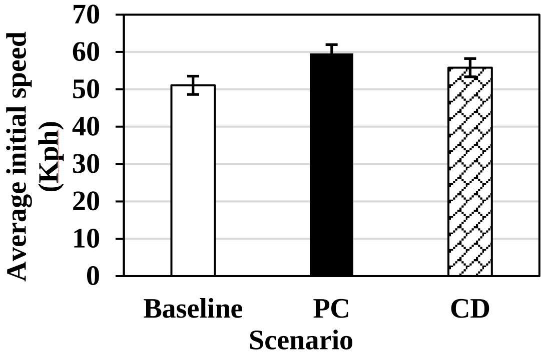
In the connected environment, it is straightforward to find the starting point of the MLC event by tracing the point in time when the first driving aid (i.e., lane closure ahead) is transferred to the driver. However, in case of the baseline condition, the spatial location where the programmed vehicles in the target lane create the first gap of 45 m is taken as starting point of the MLC event. After the start of the MLC event, the point where the first acceleration or deceleration segment starts (obtained from the Bottom-Up algorithm), is taken as the response point. It is reasonable to assume this point as the response point because as soon as drivers recognize the MLC event, they either slow down to look for an appropriate gap or accelerate to attain a gap in the target lane. The response point is further used to calculate other variables in both the baseline and the connected environment scenarios.

5. Results

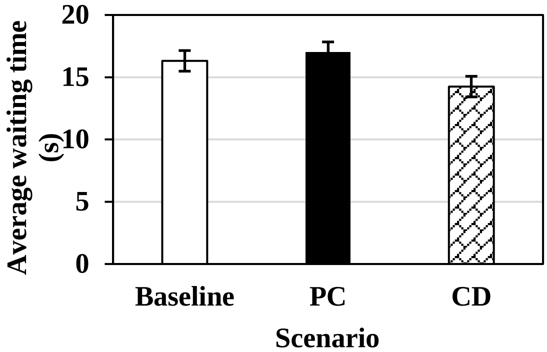
5.1. Descriptive analysis of driving performance indicators

The driving performance indicators across the driving conditions are compared by repeated measures ANOVA technique in the form of a Linear Mixed model (Haque et al., 2016; Raudenbush and Bryk, 2002), as the dataset was not balanced due to exclusion of driving data from four drives by four participants experiencing simulator sickness in their third drive. Figure 5 shows a comparison of initial speed, waiting time, decision initiation time, acceleration noise, spacing, PET, and LC duration across three driving conditions along with statistical significance tested by the linear mixed model. Among them, the differences in initial speed, waiting time, acceleration noise, spacing, and PET are found to be statistically significant.

Decision initiation time (DIT): As reported in Figure 5, the average DIT in the baseline is 1.75 s; the corresponding DITs are 1.53 s and 1.77 s, for PC and CD, respectively. It suggests that drivers are aware of the MLC event due to driving aids in the connected environment and consequently respond earlier to the situation. Further, communication impairment (i.e., CD) increases the DIT. DITs, measured across three drives, are not statistically different ($F^{1}_{2,\,150}$ = 1.901, p-value = 0.153). No significant difference is observed between the drives as well. The possible reason could be that as it is an MLC event and all the participants respond in almost similar time, hence no statistically significant difference is observed.



$F_{2,\,150} = 5.09$, $p = 0.007$



$F_{2,\,150} = 2.35$, $p = 0.099$

[1] *For the repeated measure ANOVA in the form of a Linear Mixed model, the F-test compares two variances, and the first subscript of F (i.e., 2) represents between-groups degrees of freedom, while the second number (i.e., 150) reports the within-groups degrees of freedom.*

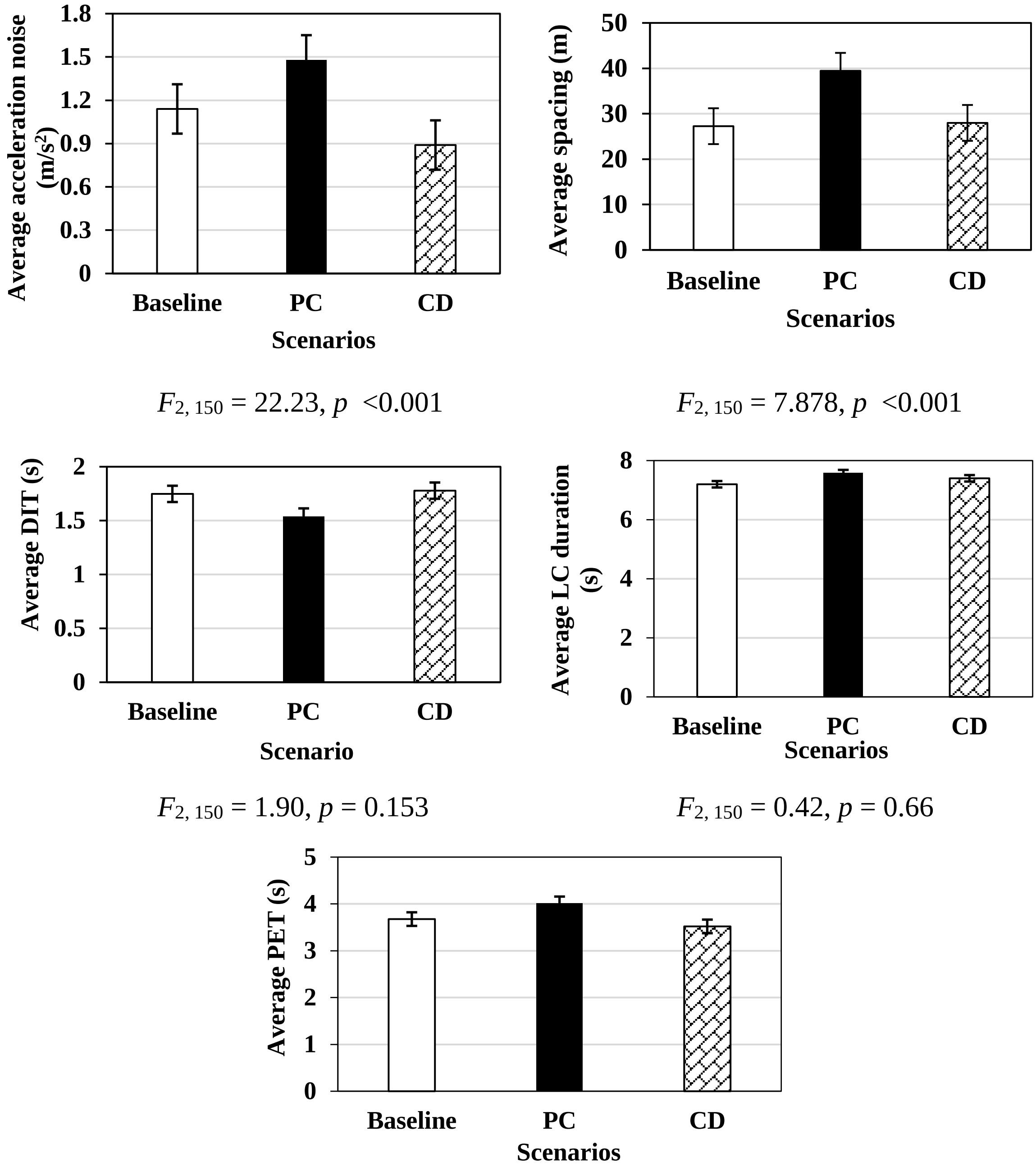


Fig. 5. Impact of connectivity on driving performance indicators (error bar shows SE)

Post-encroachment time: The difference in post-encroachment time (PET) is found to be significantly different across the three drives ($F_{2,150} = 2.34$, p-value = 0.098). For the 15 m gap size, PETs in the baseline, PC, and CD are respectively 4.03 s, 4.75 s, and 4.03 s (see Table 6). A similar trend of PETs has been found across all the gap sizes. Further, the differences in PETs are not significantly different between drives in any gap size, measured by post hoc paired t-tests.

Percentage change in PET risk is calculated using Equation (1) that determines the increase or decrease in the risk with respect to change in scenario. Figure 6 indicates the percentage change in PET risk. Results suggest that the risk associated with MLC reduces by 9% in the PC scenario compared to the baseline and increases by approximately similar magnitude in the CD scenario compared to the baseline. The differential effect of the connected environment suggests that the risk also increases from the PC to CD by more than 16%.

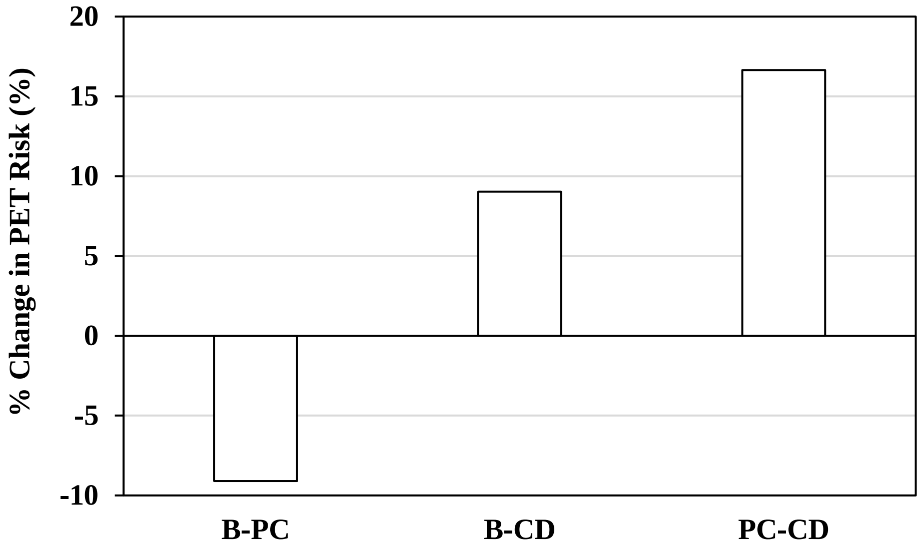
$$\%\ change\ in\ PET\ risk = \frac{PET_i - PET_j}{PET_j} \times 100 \qquad (1)$$

Where, i = PC and CD; j = baseline and PC; $i \neq j$

Table 6 PET at LC Point by Driving Scenarios

Gap Size (m)	**Driving Scenario**		
	Baseline	**PC**	**CD**
Mean PET for 15 m gap (SD)	4.0 (1.1)	4.8 (0.7)	4.0 (0.7)
Mean PET for 30 m gap (SD)	3.7 (0.8)	3.6 (0.9)	3.4 (0.6)
Mean PET for 45 m gap (SD)	4.1 (1.2)	4.8 (1.6)	4.1 (1.8)
Mean PET for 60 m gap (SD)	2.6 (1.4)	2.8 (1.6)	2.1 (1.7)

Note: Overall significance by linear mixed model for PET $F_{2,150} = 2.34$, *p-value = 0.098*



Note: B = Baseline; A positive value indicates the risk has increased and vice versa.

Fig. 6. Percent change in PET risk

Gap selection: Table 7 summarizes the frequencies of accepted gap sizes across all the driving scenarios. In the baseline scenario, the frequencies of selecting 15 m, 30 m, 45 m, and 60 m, are 9%, 32%, 29%, and 21%, respectively. A chi-square test is employed to test the differences in the frequencies of accepted gap sizes between scenarios and results indicate a significant difference between the baseline and PC (χ^2 = *7.3; p-value = 0.06*) as well as the PC and CD (χ^2 = *6.3; p-value = 0.09*), while the corresponding difference is not statistically significant between the baseline and CD (χ^2 = *1.2; p-value = 0.7*). It can be inferred from results that the risky gap selection of the participants is reduced by 50% in the PC scenario (i.e., 15 m gap) and the participants prefer to take a relatively bigger gap size (indicated by the higher frequency for 45 m to be the accepted gap size in the PC scenario).

Table 7 Gap Selection of Drivers across Driving Scenarios

Scenario	Accepted Gap Size									
	15 m		30 m		45 m		60 m		90 m	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Baseline	7	9	25	32	29	37	16	21	1	1
PC	3	4	22	28	37	47	16	21		
CD	6	8	27	36	28	38	13	18		

Rejected gaps: In the PC scenario, about 47% of drivers did not reject any gap (and accepted the first gap of 45 m); about 28% rejected the first two gaps before accepting a gap; around 20% rejected the first three gaps, while no one waited for the last gap (Figure 7). A chi-square test shows a significant difference in frequencies of rejected gaps across the driving conditions ($\chi^2_{baseline-PC}$ = *86.1*; *p-value <0.001*, $\chi^2_{baseline-CD}$ = *37.5; p-value <0.001*. χ^2_{PC-CD} = *21.7; p-value <0.001*).

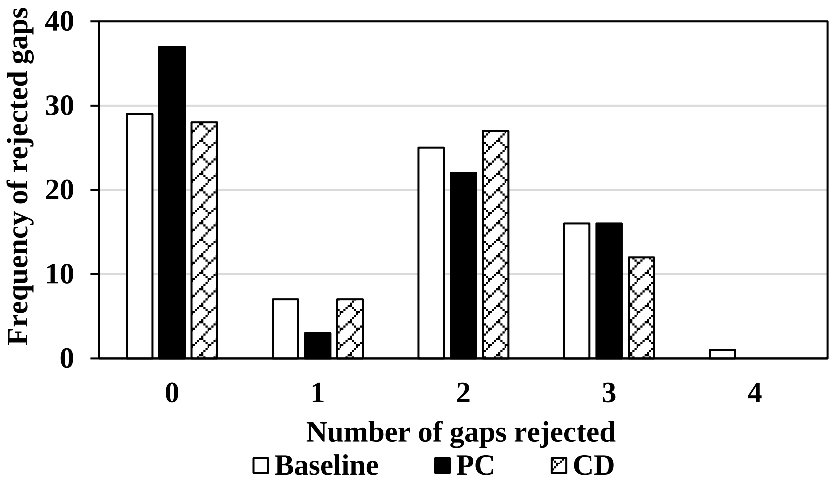


Fig. 7. Number of rejected gaps across all driving conditions

5.2. Generalized Estimation Equation (GEE) Models

This study develops Generalized Estimation Equation (GEE) models for modelling gap acceptance and LC duration using R package ‘geepack’ (Yan et al., 2008). GEE is an extended version of the Generalized Linear Models (Nelder and Baker, 1972) that can capture the correlated data where the correlation is an outcome of multiple observations of the same participant. While the GEE approach is capable of accommodating various correlation structures, this study uses an exchangeable correlation structure−a correlation structure with the constant correlation coefficient for all observations of the same participant. Since GEE models are especially used for panel data where linear regression and many other techniques fail due to correlated residuals, common model fitness measures, e.g., R^2 and likelihood measures, are not appropriate. Instead, Quasi-likelihood Information Criterion (QIC) (Pan, 2001) can be used to select the most appropriate correlation structure in GEE models. Further, marginal R^2 (Zheng, 2000) is used as a measure of fitness for GEE models.

The GEE models in this study reveal potential factors that can affect the gap acceptance behaviour and LC duration. In the first model, the accepted gap size (in meters) is the dependent variable for detecting the impact of the connectivity's on the participants' gap acceptance behaviour. To ensure that predicted gap sizes are nonnegative, logarithmic transformation is applied to accepted gap size. LC duration is the dependent variable in the second model for investigating the factors affecting the LC duration under the connected environment. There were two types of explanatory variables: a) driving performance variables summarised in Table 5 (e.g., initial speed, remaining distance, average spacing, and etc.) and b) driver demographics summarized in Table 3. The potential explanatory variables were selected based on the literature and each variable's potential behavioural or physical relationship with gap acceptance and LC duration, and the most parsimonious model in each case was selected based on marginal R^2 and QIC criteria. Data from all 78 participants are available in the first two drives while four observations are missing from the third drive, thus an unbalanced panel is used.

5.2.1. Gap acceptance model

The GEE model estimates of accepted gap sizes are presented in Table 8. The developed model estimates a value 0.22 for the exchangeable correlation parameter (Table 8), suggesting a significant correlation among the repeated observations of each participant. The marginal R^2 indicates that model captures about 15% of the variability in the data.

The driving scenario variable (i.e., PC) has been positive in the GEE model and indicates that when the communication is perfect (i.e. without any interruption in information supply), the participants tend to select bigger gap sizes while the communication impairment (i.e., CD) has a negative impact on the gap acceptance behaviour; the participants tend to accept smaller gap sizes when there is impairment in communication. The impact of the PC on the accepted gap size can be calculated using Equation 2 (note that the same equation can be used for the CD). In the PC and CD scenarios, the accepted gap size increase and decrease by 0.09 m and 0.10 m, respectively.

$$Accepted\ gap\ size = exp[3.88 + 0.09 \times PC - 0.1 \times CD - 0.0005 \times Remaining\ distance + 0.0096 \times Average\ spacing + 0.006 \times Average\ speed + 0.003 \times (CD \times Average\ speed) - 0.0002 \times (Average\ speed \times Average\ spacing)] \quad (2)$$

Consistent with previous studies, the remaining distance (RD) variable−measured as the distance between the points where the participants start LC execution and the end point of the current lane− is also found to be significant and positive in the gap acceptance model. A 1 m increase in RD tends to increase the accepted gap size by 0.0005 m, suggesting that when RD is higher, the participants are more likely to select a higher gap size because of no urgency of LC while a lower RD implies a higher urgency of LC, in which the participants are more likely to become impatient and opt for a lower gap size (Ahmed et al., 1996).

Average spacing has been found to be positive and significant in the GEE model. A 1 m increase in spacing leads to about 0.009 m increase in the accepted gap size. The model also suggests that the participants tend to accept a bigger gap size when spacing is larger (Table 8), which is reasonable because a larger spacing indicates a less urgency of LC, thus the participants can wait longer for a relatively larger gap size (Toledo et al., 2003).

Table 8 Summary of GEE Models

Model	Variable	Estimate	SE	Wald statistics	*p*-value
Gap acceptance[1]	Constant	3.88	0.05	7071	<0.001
	PC*	0.09	0.04	4.02	0.04
	CD**	-0.10	0.05	3.15	0.07
	Remaining distance	0.0005	0.0001	13.43	<0.001
	Average spacing	0.0096	0.0016	30.42	<0.001
	Average speed	0.006	0.002	8.71	<0.001
	CD: Average speed	0.003	0.0007	18.56	<0.001
	Average speed: Average spacing	-0.0002	0.00004	28.79	<0.001
Model Statistics	Estimated correlation parameters (alpha)	0.18	0.06		
	Marginal R^2	0.15			
	QIC	42.6			
	Quasi-Likelihood	-18.02			
	Number of observations	230			
	Number of clusters	78			
	Maximum cluster size	3			
LC duration[2]	Constant	11.90	0.88	184.6	<0.001
	PC*	1.38	0.51	7.43	0.006
	Accepted gap size	0.00002	0.0001	5.60	0.018
	Average speed	-0.05	0.011	22.12	<0.001
	Remaining distance	-0.006	0.002	8.30	0.004
	Experience	0.05	0.03	4.30	0.04
Model Statistics	Estimated correlation parameters (alpha)	0.06	0.07		
	Marginal R^2	0.15			
	QIC	2589.0			
	Quasi-Likelihood	-1288.1			
	Number of observations	230			
	Number of clusters	78			
	Maximum cluster size	3			

** PC = 1, driving scenario is perfect communication, otherwise = 0; ** CD = 1, driving scenario is communication delay, otherwise = 0*

[1] Model equation: $ln(accepted\ gap\ size) = \beta_0 + \beta_1 \times PC + \beta_2 \times CD + \beta_3 \times Remaining\ distance + \beta_4 \times Average\ spacing + \beta_5 \times Average\ speed + \beta_6 \times (CD \times Average\ speed) + \beta_7 \times (Average\ speed \times Average\ spacing)$

[2] Model equation: $LC\ duration = \beta_0 + \beta_1 \times driving\ scenario + \beta_2 \times Accepted\ gap\ size + \beta_3 \times Average\ speed + \beta_4 \times Remaining\ distance + \beta_5 \times Experience$

Average speed, which indicates the mean speed of the participants between response and LC initiation points, has found to be significant and positive in the GEE model. A 1 km/h increase in the average speed tends to increase the accepted gap size by 0.006 m. Intuitively, drivers with the lower speed require bigger gap sizes to change lanes safely (Kondyli and Elefteriadou, 2011).

The GEE model contains an interaction term, i.e., a dummy variable for the CD and average speed. The effect of the interaction term on the accepted gap size can be determined using Equation (3). For the interaction term, the median value of each independent variable is used instead of the mean because the median value becomes reliable than the mean when the standard deviation is high. Using Equation (3), the model predicts that when there is impairment in communication (i.e., CD = 1), with an increase in average speed from 41 km/h (the 1st quartile) to 56 km/h (the 3rd quartile), the accepted gap size tends to reduce by 1.5 m. Furthermore, this interaction term suggests that if a participant is driving at a slower speed, then s/he wants a bigger gap to merge into the target lane when the communication is impaired.

$$Accepted\ gap\ size = exp[3.88 + 0.09 \times PC\ - 0.10 \times CD - 0.005 \times median\ RD + 0.0096 \times median\ average\ spacing + 0.006\ median\ average\ speed + 0.0033 \times (1 \times first/third\ quartile\ average\ speed) - 0.00022 \times (median\ average\ speed \times median\ average\ spacing)] \quad (3)$$

Similarly, the GEE model has another interaction term, i.e., average spacing and average speed. Since this interaction term consists of two continuous variables, one variable is fixed at the median value and other variable is changed from the 1st quartile to the 3rd quartile to determine the effect of interaction term on the accepted gap size. By keeping average spacing at the median value (using Equation 3), the model predicts that the increase in average speed from the 1st quartile to the 3rd quartile is likely to reduce the gap size by 3 m, while the accepted gap size is reduced by 9 m when spacing is increased from the 1st quartile to the 3rd quartile, keeping average speed constant at the median value. The relation indicates that if a participant is driving too close, then the urgency of the LC increases, and in such situations, the participant is likely to require a bigger gap to change lanes safely.

Interestingly, no demographic factor was found to be significant in the gap acceptance model. This could be due to two reasons: (i) the impact of demographic factors may be captured by the existing parameters such as average spacing, average speed, and remaining distance; (ii) limited sample size. Additional studies with more participants are required to investigate the impact of demographic factors on gap acceptance behaviour.

5.2.2. LC duration model

Table 8 also reports the GEE model estimates of LC duration as a function of driving condition, accepted gap size, average speed, remaining distance, and driving experience. Marginal R^2 suggests that the estimated GEE model captures about 15% of the variation in the data.

In this model, the driving condition parameter (i.e., PC) has been found to be significant and positive (Table 8). The GEE model for LC duration: $[11.90 + 1.38 \times PC - 0.00002 \times Gap\ size - 0.054 \times Average\ speed - 0.006 \times RD - 0.05 \times Experience]$ predicts that LC duration increases by about 1.38 s in the PC scenario after controlling for all other/exogenous factors. The increase in LC duration could be due to the availability of information about gaps to the participants, thus they can take a longer time to change lanes more safely. Other significant parameters, i.e., accepted gap size, average speed, remaining distance, and driving experience, can be interpreted similarly.

6. Discussion

Many studies hypothesized that the connected environment can improve traffic mobility (Buisson et al., 2018; Jin et al., 2014; Kim, 2015; Zeng et al., 2012). In this research, we have evaluated the influence of the connectivity on a number of traffic stream parameters such as speed and spacing. This study finds that initial speed and spacing increase in the connected environment. It is interesting to note here that increased spacing in the connected environment may reduce road capacity. Results also suggest that drivers utilise the driving aids of the connected environment by becoming more cautious and reacting early to the situation (as demonstrated by DIT, when drivers are informed about lane closure and consequently they take shorter time to react compared to the baseline).

Since the connected environment provides critical information about surrounding traffic related to MLC, we hypothesize that the connectivity influences drivers to take larger (or safer) gaps. Results indicate that about 3% of the participants accepts a smaller gap size (i.e., 15 m) in the PC scenario while the corresponding gap selection is about 9% in the baseline. Furthermore, the information of subsequent gaps (more than two in this study) provides valuable information to drivers for selecting an appropriate gap; thus they know and can wait longer to get a larger gap. In addition, a gap acceptance model is developed that incorporates driver's impatience behaviour using the remaining distance. The number of rejected gaps (an indicator of drivers' impatience behaviour) was found to be highly correlated with the remaining distance and thus, was dropped from the final model to avoid multicollinearity. Our preference of keeping the remaining distance over the number of rejected gaps was largely caused by the fact that the correlation between the number of rejected gaps and the accepted gap size is partially caused by our design. Furthermore, in this study, the relative speed is insignificant because the programmed vehicles (LV and FV) were scripted to take the speed of SV.

Studies have also reported the safety benefits of the connected environment (Buisson et al., 2018; Kim, 2015; Zeng et al., 2012). Therefore, we hypothesize that the connectivity would reduce the safety hazards associated with MLC. To test this hypothesis, post-encroachment time (PET) is used as a surrogate safety measure. Results show that PET is about 0.34 s higher in the PC scenario compared to the baseline. The increase in the PET suggests that the safety margin associated with MLC has increased. Percent change in PET risk further confirms that risk is decreased by about 9% in the PC scenario when compared to the baseline while this risk is increased in the CD scenario, suggesting that communication impairment has a negative impact on traffic safety.

The connected environment provides a variety of information about surrounding traffic such as spacing and availability of gaps in the target lane. Therefore, we hypothesize that the connectivity would increase the LC duration because drivers are aware of the availability of several gap sizes and no need for them to rush to change lanes. To determine LC duration, previous studies use inadequate techniques to pinpoint LC initiation point, thus their results are less reliable. Hence, in this study, the lane lateral shift profile is used to determine LC duration, and LC initiation point is rigorously determined (for details, refer to section 3.4). Furthermore, the GEE model suggests that a typical driver increases the LC duration by 1.38 s in the connected environment. Thus, our hypothesis that LC duration increases in the connected environment is confirmed. Moreover, an LC duration model is developed using the accepted gap size, average speed, remaining distance, and driving experience. Similar findings are also reported in Toledo and Zohar (2007).

Driving simulators are commonly used to study road traffic-related issues. Its validity has been generally accepted in the science community (road safety community and human factors community in particular), when the driving simulator experiment is carefully designed. This is particularly true for experiments using high-fidelity driving simulators, which provide high resemblance to the real life driving environment and traffic conditions, as the case in our study. In the recent past, using a different driving simulator experiment with the same driving simulator, Saifuzzaman et al. (2015) have modelled the car-following behaviour with the task-capability interface model using the driving simulator data, and later Saifuzzaman et al. (2017) have demonstrated that the model is able to provide valuable insights to puzzling traffic problems observed in NGSIM data such as traffic hysteresis.

In the current experiment, we have put great effort in: (i) providing realistic driving environment, and designing driving scenarios; (ii) controlling participants' workload; (iii) minimizing learning effect. Of course, it would be impossible to totally eradicate the discrepancy between driving behaviour in a driving simulator environment and that in real life. However, this will not have any significant consequence on the validity of the findings reported in our study because our focus is the relative change of MLC behaviour in a connected environment compared with MLC behaviour in an environment without driving aids, and the absolute change of MLC behaviour is not important. Since all the driving scenarios were completed using a driving simulator, it is a reasonable expectation that the relative change can be replicated in the real world, even if the absolute change in the real life is far away from that in the driving simulator environment.

7. Conclusion, Limitations, and Future Work

This paper investigates the impact of the connectivity (or connected environment) on driver's MLC behaviour, particularly on gap acceptance behaviour and LC duration in an MLC event. An innovative driving simulator experiment was designed to mimic the real-time information transfer using V2V and V2I communication. We recruited 78 participants with an age cohort between 18 and 65, and asked them to drive in three different driving conditions with different levels of connectivity. Using the linear mixed model, the data obtained from the driving simulator experiment are used to analyse the connectivity's impact on driving performance indicators related to MLC. This study finds that the connected environment has a significant impact on initial speed, waiting time, and spacing. Overall, drivers tend to have a higher initial speed, wait longer, and maintain a larger spacing to the leading vehicle in the connected environment. Results also indicate that drivers tend to select relatively a bigger gap size in the connected environment compared to the baseline. The connected environment also improves safety as indicated by PET. In general, safety margins are increased and the risk associated with MLC is decreased in the connected environment. Furthermore, the GEE model indicates that MLC duration increases by 1.38 s in the connected environment.

The in-depth investigation of driver's lane changing behaviour in a connected environment is long overdue because of scarce of the data. Hence, the high-quality vehicle trajectory and advisory information data collected in this study can be valuable and inspire future studies on this important topic. In addition, as one of the first studies that focus on MLC in a connected environment, findings from this study can be helpful in understanding driving behaviour in the connected environment. More specifically, as a critical component of most of LC models, the gap acceptance model developed in this study can be integrated into MLC models for connected vehicles.

This study is limited to MLC only. Further studies are required to investigate the impact of the connectivity on the DLC behaviour where the urgency of LC is reduced. The present study does not consider the reaction time, which is an important parameter in driving behaviour modelling. This study considers five gap sizes as the dependent variable in the gap acceptance model. To increase the prediction power, a larger number of gap sizes are recommended in future LCD modelling endeavours. A follow-up study at micro-level focusing on different age cohort and gender can provide useful and valuable insights to the connectivity's impact on driving behaviours of different age groups and gender. This would also reveal a group of road-users, which are less likely to be affected by the connectivity. Such information could help in designing a more effective connected driving environment. Given the limited sample size, we were unable to observe any effect of the drivers' demographics on the gap acceptance behaviour. Understanding on such driver heterogeneity could make the gap acceptance model (and subsequently LC models) more realistic. Lastly, field experiments are needed to validate the results obtained from our experiments using the advanced driving simulator. In addition, Sharma et al. (2017) highlight the importance of human factors in traffic flow models. Unfortunately, existing efforts in incorporating human factors in LCD to better understand driver's behaviour in a connected environment are limited. Such work is ongoing.

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Appendix A: Participant Testing Protocol

After arriving at the CARRS-Q facility, the research officer (RO) welcomed each participant and gave a brief introduction about the objective of the experiment and its procedure. Participants were then asked to read the informed consent form and sign if they agreed to participate. Participants were asked to complete a pre-driving questionnaire survey that required about 10-15 mins. The pre-drive questionnaire survey included demographics, driving history, and driving behaviour information.

Participants were asked to drive in three driving conditions: a baseline condition (without any driving aid), connected environment with perfect communication, and communication delay. The driving conditions were randomised for each participant to reduce the learning effects. The simulated route consists of a motorway and urban driving conditions. The route/road network information was conveyed with the help of map showing the layout of the scenario.

In the following, the RO described the type of driving aids available to participants in the connected environment by using images presented in Figure 2. Each type of message was explained in great detail. Participants were asked to pay special attention and ask the questions, if any. The RO told participants to obey speed limit signs and emphasized that driving aids are presented for assistance only and decision to comply with driving aids is still at discretion of participant. Once the instructions were finished, participants were taken to the simulator room where a brief summary was given about the driving simulator controls and instruments before they stepped into the simulator vehicle. During the experiment briefing, participants were advised not to consume any food item or beverage during the experimental drives to avoid nausea. Before the actual research drive, each participant performed a familiarisation drive of 7-10 mins to become familiar with the simulator vehicle, driving in connected environment with driving aids. During the practice drive, participants encountered various MLC and DLC opportunities. Participants were encouraged to change lane to become familiar with longitudinal and lateral controls of simulator vehicle. Upon completing the practice drive, the RO asked each participant that whether he/she was confident enough to proceed for the actual research drive or want a repeat of practice drive. A majority of participants were comfortable with one practice drive and proceeded for actual research drives. At the end of each research drive, participants completed a driving workload questionnaire survey while remained in the simulator. After each research drive, participants took a break either seated in the simulator vehicle or by coming out of the vehicle; in the meantime, scenarios were loaded on the projectors for the next research drive. Before concluding the session, participants completed a post-drive questionnaire including user acceptance, trust in the system, and sensation seeking. The RO thanked the participants for their volunteer participation and reimbursed them as a compensation for their participation time.