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How do the drivers react to different C-V2X-based communication conditions in dilemma zones? A driving simulator study

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A R T I C L E   I N F O

A B S T R A C T

Drivers should react quickly in dilemma zones at signalized intersections, where ill-timed decisions may result in rear-end or angular collisions with other vehicles. Recent advancements in connected vehicle (CV) technologies, particularly cellular vehicle-to-everything (C-V2X), are expected to enhance driver decision-making by providing real-time traffic information. Despite this, most previous studies have not considered the latest C-V2X specifications, leaving critical questions unanswered about how drivers interact with and benefit from this technology in dilemma-zone scenarios. To address this gap, this study builds a co-simulation platform that integrates Unity and VISSIM to simulate four communication conditions: (1) no communication (baseline), (2) perfect communication (green-light countdown), (3) interrupted communication (green-light countdown with loading delays), and (4) communication loss due to the absence of smart infrastructure (out of service information). Sixty-two licensed drivers participated in four randomized trials, each with multiple unpredictable green-to-yellow transitions designed to capture dilemma-zone responses. Driving performance was assessed in terms of stop-or-go decisions and red-light running outcomes. Results of the random parameters binary logit model for stop-or-go decisions indicate that, compared to no communication, drivers are more inclined to proceed through the intersection when communication is lost. In contrast, perfect communication and communication interruption generally reduce this tendency. Furthermore, significant interaction effects revealed the observed heterogeneity, indicating that drivers with specific driving histories respond differently under communication interruption and loss conditions. For the red-light running outcomes, the descriptive analysis shows that under the perfect communication condition, the proportion of red-light running decreases by 3.44% among drivers. Interestingly, even interrupted communication leads to a 2.19% decrease in the proportion of red-light running outcomes. These findings demonstrate the complex ways in which C-V2X-based information can influence driver decisions, emphasizing the need for robust implementation strategies that are context-aware. This study sheds light on how drivers interact with emerging C-V2X systems and provides insights for road authorities and policymakers seeking to enhance safety and reduce crash risks at signalized intersections.

1. Introduction

Due to the high crash rate, signalized-controlled intersections have always been considered a priority for road safety. For instance, the Federal Highway Administration (FHWA, 2021) reported that approximately one-third of all intersection fatalities occur at signalized intersections (Federal Highway Administration report, 2021). Especially in South Korea, it is reported that the number of road traffic crashes attributed to violation behaviors at intersections accounted for 18.23 % of the total crashes in 2019–2022, resulting in 2,551 fatalities and 283,799 injuries (TAAS, 2023). It was also found that drivers' poor or delayed responses to traffic signals contribute to their violation behaviors, such as running yellow lights and red lights, and tailgating the vehicle in front of them (Elmitiny et al., 2010).

One of the most critical challenges at intersections is how drivers respond to traffic lights transitioning from green to yellow, a scenario commonly known as driving in the dilemma zone (Gazis et al. 1960). When driving in a dilemma zone, an aggressive driver may choose to accelerate to cross the intersection (Elhenawy et al., 2015; Hassan et al., 2023), while a conservative driver may hesitate to decide whether to cross or not (Elmitiny et al., 2010). In spite of extensive research on the dilemma zone and its impact on driver behavior (Gazis et al., 1960; Zegeer, 1977; Urbanik and Koonce, 2007), emerging technologies relating to connected vehicle (CV) messages offer drivers additional opportunities to make safer and more efficient decisions.

The Society of Automotive Engineers (SAE) International has established a standard for message broadcasts to CVs. By receiving real-time information about traffic signals, such as the current phase of the signal and how long it is before the signal changes, drivers are able to drive safer and more efficiently (SAE International, 2004). This information transfer relies on wireless communication, which has led to the widespread adoption of the emerging cellular vehicle-to-everything (C-V2X) technology by countries such as China, the United States, and South Korea as a unified standard (Ramohan and Dhinesh Kumar, 2023; Zhao and Wu, 2023). In comparison to dedicated short-range communication (DSRC), C-V2X can significantly enhance the performance of information transmission in both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) contexts (Cook, 2025).

While C-V2X has the potential to deliver low latency and reliable information under ideal (or "perfect") communication conditions, it faces communication challenges during its gradual rollout, including time-varying delays, interruptions, and communication loss. Ali et al. (2020) proposed the importance of examining the effects of communication loss and delay on driving safety. Their findings indicated that DSRC-based communication delays slow the transmission of safety information to drivers, thus negatively affecting their driving decisions. Nonetheless, the gap here is that their experimental design did not consider the most recent capabilities of C-V2X, in which such delay can be reduced to the millisecond range and would be nearly undetectable by drivers (Chen et al., 2020). In this context, such delays would be nearly undetectable by drivers. Besides, the effects of interrupted communication were not considered in Ali et al (2020)'s experiments based on DSRC but would be present in the context of C-V2X. Therefore, although the abovementioned studies have investigated how an impaired connected environment might influence driving safety, the resulting insights into real-world impacts remain unclear. Clarifying these effects is critical not only for evaluating the safety impacts of a C-V2X-based connected environment, especially under non-ideal conditions, but also for helping vehicle manufacturers and road authorities understand the technology's limitations and safety benefits.

Accordingly, this study examines how different C-V2X communication conditions (perfect communication, communication interruption, and communication loss) affect driving behavior and safety in dilemma zones. Specifically, this research aims to (1) characterize both perfect and impaired C-V2X communication conditions and (2) investigate how these communication conditions influence drivers navigating dilemma zones safely, including stop-or-go decisions and red-light running. The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on dilemma zones and C-V2X-based communication conditions. Section 3 describes the development of the co-simulation platform, data collection procedures, and analytical methods. Section 4 presents the results, which are discussed further in Section 5. Finally, Section 6 summarizes the study's key findings, implications, and limitations.

2. Literature review

2.1. Dilemma zone problems

2.1.1. Type I dilemma zone

Dilemma zones have been extensively studied, and they are commonly classified into two types: type I and type II. Gazis et al. (1960) first defined the type I dilemma zone as the distance at which a driver can neither safely decelerate to the stop line nor clear the intersection with a safe acceleration before the light turns red. The presence of a type I dilemma zone is typically assessed using Equation (1) and Equation (2), where X_{msd} means the minimum stop distance, X_{mgd} means the maximum go distance. If X_{msd} is longer than the distance to the stop line (DTSL) and X_{mgd} is shorter than the distance to the stop line (DTSL), the driver will tap into a dilemma zone, as plotted in Fig. 1 (a). The length and boundaries of the type I dilemma zone are typically determined by assuming all relevant parameters remain constant, resulting in a fixed zone for a given road. Traffic engineers often incorporate type I dilemma zone considerations into their designs—such as introducing an all-red phase—to reduce the likelihood of crashes. Although this approach provides useful insights for traffic signal management and road design (Urbanik and Koonce, 2007; Zhang et al., 2014), it overlooks individual variations in driver behavior. In reality, drivers exhibit diverse characteristics and safety perceptions (e.g., aggressive or defensive), and they face differing environments (e.g., varying speed limits, traffic congestion, and other road users) (Pathivada and Perumal, 2017). These factors influence dynamic driving behaviors, such as reaction times and speed control abilities. Consequently, the actual distribution of dilemma zones will differ among drivers, rather than remaining fixed for all.

$$X_{msd} = V_0 * \delta + V_0{}^2 / 2a_1 \tag{1}$$

$$X_{mgd} = V_0 t_y + a_2 (t_y - \delta)^2 / 2 - L \tag{2}$$

Note:

$V_0 = \text{initial speed at onset of the yellow light}, \delta = \text{reaction time}, a_1 = \text{minimum deceleration}, a_2 = \text{maximum acceleration}, t_y = \text{duration of yellow light}, L = \text{the length of the vehicle}$

2.1.2. Type II dilemma zone & stop-or-go decision

In 1977, Zegeer introduced the type II dilemma zone to account for individual variations in driver decision-making. Type II dilemma zones, also known as "indecisive zones", are areas where drivers determine whether to stop or proceed when they encounter a yellow light. As illustrated in Fig. 1(b), point A represents the beginning of the zone, while point B represents its end, both of which are located before the stop line. These boundaries are set so that 90 % of drivers are likely to proceed at the onset of yellow at point A, while only 10 % are likely to proceed at point B. By estimating drivers' stop-or-go decisions, traffic engineers can plot the distribution and length of the type II dilemma zone for specific driver populations under particular conditions.

A summary of studies regarding drivers' stop-or-go decisions is presented in Table 1, categorized by types of data sources, including video recordings (Chauhan et al., 2022; Pathivada and Perumal, 2017; Pawar et al., 2022), naturalistic driving data (Rahman et al., 2021; Rakha et al., 2008), and driving simulator experiments (Haque et al., 2016; Yan et al., 2015; Zhao et al., 2024). It is important to note that only a few studies have taken into account communication conditions or warning information in a connected vehicle (CV) environment (Ali et al., 2021; Zhang et al., 2022). In spite of the fact that there existed a study that investigated the effects of connected environments on stop-or-go decisions (Ali et al., 2021), the findings did not reflect the latest developments in C-V2X. Therefore, there is a clear need to examine drivers' stop-or-go decisions in dilemma zones under conditions of C-V2X communication.

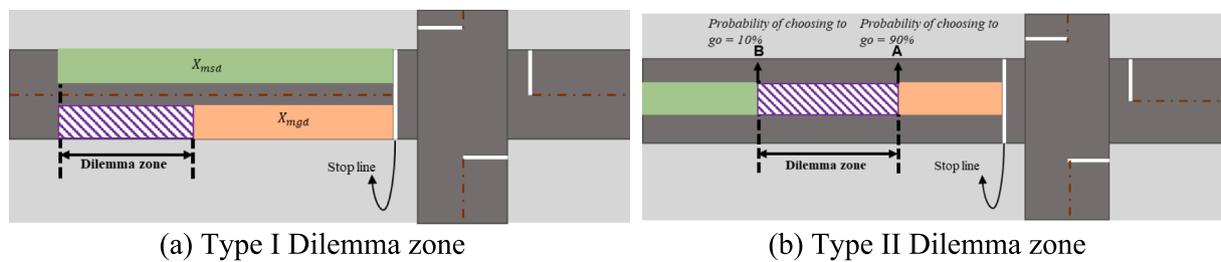In designing dilemma scenarios for driving simulator experiments,

(a) Type I Dilemma zone (b) Type II Dilemma zone

Fig. 1. Two types of dilemma zone.

Table 1
Summary of literature in stop-or-go decision-making.

References	Data collection	Number of observations	Model	Considered factors	Connected environment or not	C-V2X communication condition presence
(Chauhan et al., 2022)	Video recording	389	Binary logit	Initial speed, Distance to stop line, Vehicle type, Lane number	No	No
(Pathivada and Perumal 2017)	Video recording	338	Binary logit	Initial speed, Distance to stop line, Yellow time, Vehicle type	No	No
(Pawar et al., 2022)	Video recording	893	Binary logit	Initial speed, Distance to stop line, Lane number	No	No
(Rahman et al., 2021)	Naturalistic data	1252/1243	Machine learning	Speed, Distance to stop line, Time of day	No	No
(Rakha et al., 2008)	Naturalistic data	1186	Logistic regression	Time to stop line, Driver's characteristics	No	No
(Haque et al., 2016)	Driving simulator	409	Repeated measures logistic regression	Time to stop line, Distraction, Driver's characteristics	No	No
(Yan et al., 2015)	Driving simulator	490	Logistic regression	Time to stop line, Driver's characteristics, Warning condition	Yes	No
(Zhao et al., 2024)	Driving simulator	–	Binary logit	Driver's characteristics, Safety perception, Road condition, Weather, Traffic condition	No	No
(Ali et al., 2021)	Driving simulator	156	Decision tree and panel mixed logit	Initial speed, Distance to stop line, Acceleration noise, Driver's characteristic, Communication conditions	Yes	No
(Zhang et al., 2022)	Driving simulator	540	Logistic regression	Time to stop line, Warning condition	Yes	No
Our study	Driving simulator	1240	Random parameters binary logit model with interaction terms	Initial speed, Distance to stop line, Driving history, C-V2X communication conditions	Yes	Yes

investigations of the type II dilemma zone provide valuable guidance. The type II dilemma zones capture the critical moment when drivers are uncertain as to whether they should stop or proceed at an intersection. To define the boundaries of a type II dilemma zone, many studies utilize the vehicle's distance from the stop line (DTSL) (Bonneson, 1994; Chang et al., 2013; Pawar et al., 2022). It should be noted, however, that due to the fact that DTSL changes with vehicle speed (Rahman et al., 2021), some researchers have chosen to use the time to stop line (TTSL = DTSL / speed) as a more dynamic indicator (Rahman and Kang, 2021; Rakha et al., 2011). Based on previous research, TTSL values vary from 1 to 6 s, thus many simulator studies adopt thresholds within this range to trigger yellow lights and examine driver behavior (Calvi and Petrella, 2022; Hussain et al., 2020). Nevertheless, the distribution of type II dilemma zones may vary widely depending on a variety of explanatory factors, making it difficult to generalize results from one context to another. Since a standardized type II dilemma zone cannot be determined without actual experimental data, a pilot study is key to ensuring that the selected range captures the most critical situations (Kaul and Jipp, 2023). The design of realistic and valid dilemma scenarios should ideally take these considerations into account when conducting simulation-based research.

2.2. Communication conditions & guidance information under C-V2X

As a result of advancements in wireless communication technology, connected vehicles (CVs) can receive real-time information from their surrounding environment in order to support safer, more efficient driving. Cellular vehicle-to-everything (C-V2X) is one of these

technologies that plays a pivotal role in the development of CVs. As illustrated in Fig. 2(a), C-V2X enables both direct transmission (5G-PC5) from vehicle to vehicle (V2V) or vehicle to infrastructure (V2I), and indirect transmission via an LTE-cellular base station. For example, automakers (e.g., Ford and SAIC) have already conducted pilot projects to broadcast real-time traffic signal information such as current signal status and time until change to CVs (Ford, 2023), as shown in Fig. 2(b). If communication conditions are ideal, this safety information can be distributed to drivers in a reliable manner. It is important to note, however, that as C-V2X is gradually rolled out, communication challenges may arise, including interruptions and loss of communication altogether. Despite the recent development of C-V2X technology, these conditions have not been thoroughly examined. In Fig. 2(c), the impaired conditions considered in this study, namely communication interruption and communication loss, are illustrated. Both issues remain unresolved on pilot roads and may pose a safety risk to motorists.

An insight into the detailed information transmission process can deepen the understanding of various communication conditions. As shown in Fig. 2 (c), under perfect communication, data packets from traffic signals (the initiator) to CVs (the receiver) are transmitted normally, then translated into guidance information for drivers (Forouzan, 2007). In communication interruption, by contrast, the signal transmission process experiences repeated failures, as shown in Fig. 2 (c). Specifically, based on the Transmission Control Protocol, there exist several retransmission mechanisms to confront signal interference situations (Postel, 1981). The typical one for C-V2X is to retransmit the loss or damaged data package when the timeout period expires (millisecond level) (Soto et al., 2022). After repeated retransmissions and failures, information such as traffic signals requiring high real-time performance will automatically be discarded and will not be updated to the driver later. Therefore, if drivers fail to receive continuous information in a few seconds then it is possible to infer that they encountered a communications interruption (Rayamajhi et al., 2020). In reality, several situations may cause communication interruption, including signal interference, and network congestion (Chen et al., 2020; Zhao and Wu, 2023). From the view of drivers, they may fail to receive the complete signal information in time while driving, then their driving behavior may be affected to some extent.

As shown in Fig. 2 (c), in communication loss, no transmission protocol is in place between the vehicle and the traffic signal, and the transmission channel is always closed. Peculiarly, communication loss indicates that information changes are not accessible on some road sections. In reality, this typically happens in regions where smart infrastructure coverage is incomplete. However, achieving full coverage of the 5G Network and updated intelligent traffic management system is not an immediate process. To be specific, the American Association of State Highway and Transportation Officials (AASHTO) estimates that by 2025, only 20 % of signalized intersections will be capable of V2I communication, and by 2040, 80 % of signalized intersections will be V2I capable (Mashayekh et al., 2014). Thus, drivers will experience a total loss of real-time signal information in some locations owing to outdated traffic signals for a long-term period. In general, drivers will inevitably encounter impaired communication conditions in C-V2X based connected environments. It is therefore necessary to evaluate how drivers react to various communication conditions to ensure safe driving.

In summary, the C-V2X technology is rapidly gaining traction as a global standard for broadcasting CV messages, yet its influence on driving safety is not fully understood. Meanwhile, high crash involvement at intersections-especially in dilemma zones-remains a critical safety issue in South Korea, which calls for a more focused investigation. To fill this gap, this study examines the impact of different C-V2X communication conditions (perfect, interrupted, and lost) on stop-or-go decisions. The red-light running outcomes were further compared under these communication conditions. The findings of this research are expected to clarify how the evolving C-V2X ecosystem can enhance driver decision-making, decrease crash risks, and equip road authorities and policymakers to leverage its capabilities for safer, future-ready transportation systems by examining these conditions.
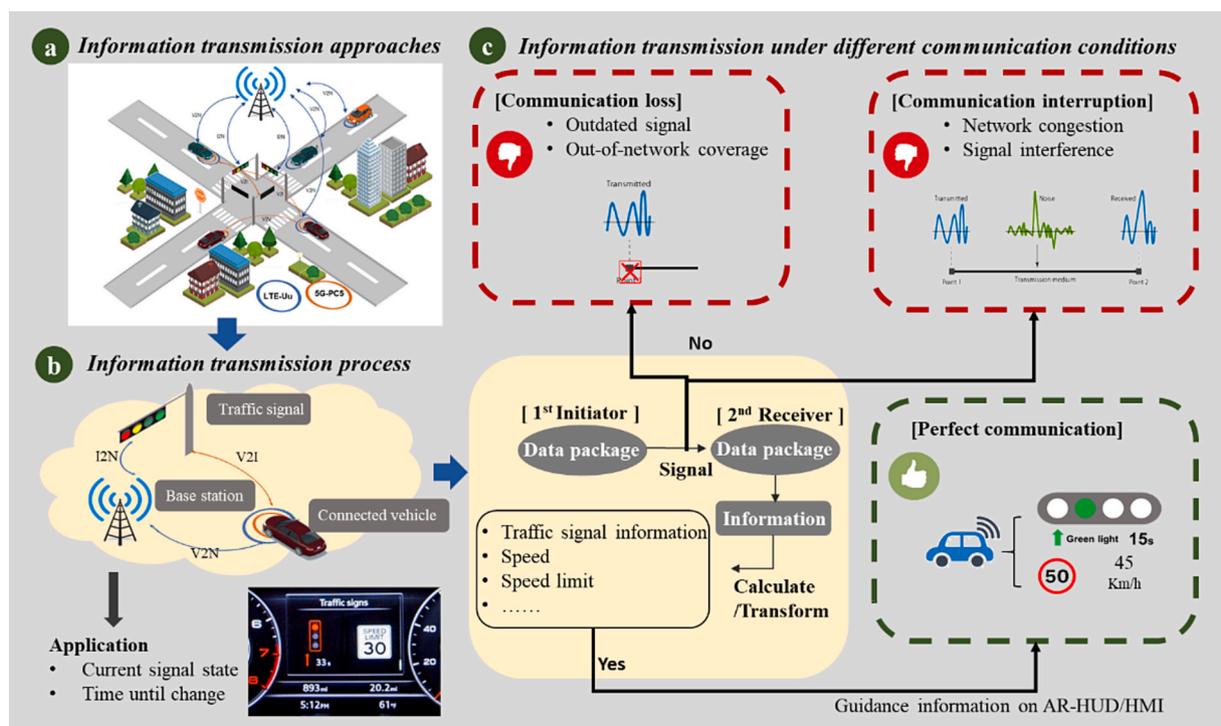

Fig. 2. The information transmission and communication conditions based on C-V2X.

3. Experimental design and data analysis

3.1. Co-simulation platform development

Fig. 3 depicts the process of developing our co-simulation platform. In this study, a 4–5 km long road in Daejeon, South Korea was simulated. Firstly, the high-quality base map of the road and models of surrounding buildings need to be captured. Then, the base map and models were imported to Unity to create virtual reality scenes. Next, the road network was created in PTV VISSIM, and then the traffic flow, pedestrians, and cyclists can be generated on the road network. Afterward, VISSIM and Unity were linked via VISSIM API to implement the two platforms' co-simulation, enabling mutual data exchange. Finally, the built scenario can be used for further simulator experiments.

3.2. Experiment design

Fig. 4 presents the experiment protocol. A pilot study was conducted to ensure the proper setting of the dilemma zones in the experiment. After the pilot study, participants were invited for the formal experiment, whereby each participant driver was required to fill out a pre-driving questionnaire. Then they were given a 10-minute instruction about C-V2X communication conditions, and relevant safety information along with a 10-minute practice drive to familiarize themselves with the driving simulator and driving scenarios. A total of 75 participants were recruited, from which 13 failed to complete the experiment due to simulator sickness syndromes or other reasons, and 62 participants finalized the experiment.

As shown in Fig. 4, each participant needs to drive under four different C-V2X communication conditions, namely (1) baseline with no information, (2) perfect communication with green-light countdown information, (3) communication interruption with green-light countdown and loading information, and (4) communication loss with out of service information. To enhance comprehension, the driving scenarios under different communication conditions from a driver's view are presented in Fig. 5 (a) to (d). The information is projected onto the windshield of the CV, representing an advanced display technology – augmented reality heads-up display (AR-HUD). All information showed up dynamically in several seconds with a beep sound at certain moments or positions on the basis of their role and the setting of the dilemma zone.

In perfect communication, the green-light countdown information was shown for 3 s at a selected signal triggering moment, which is identical to the information display in the case of communication interruption. In the event of a communication interruption, the countdown was displayed briefly for a randomly selected duration (0.1, 0.3, 0.5, 0.7, or 0.9 s) before switching to a "loading" GIF animation, which lasted for a total of 3 s. This sequence of information display simulates the realistic information prompt in the case of communication interruption following signal interference. In communication loss, the "out-of-service" information was sent to the driver 200 m before the following stop line of the intersection, reflecting the realistic application of CVs confronting communication loss. In reality, the CV driver should be informed if the following traffic signal is not capable of communicating with the connected vehicle after crossing the last intersection.

For each trial, five traffic signals were randomly selected from all intersections in the route and then activated to the green light (3 s left) with subsequent yellow light (last 3 s) at varying times to stop line (5–9 s). The driving vehicle's time to stop line is calculated in real-time as the ratio of distance to the stop line to its speed, simulating various critical levels of dilemma zones. The setting is aligned with previous studies, indicating that the type II dilemma zone is roughly spread over a time distance of 1–6 s between the vehicle and the stop line when the yellow light turns on (Calvi and Petrella, 2022; Hussain et al., 2020).

In general, all other traffic signals in the experiment were constant green lights and the speed limit of the road was 50 km/h. The participants completed the trials in Category 1 scenarios before Category 2 scenarios to avoid potential bias due to psychological tricks. The orders for the first 2 trials and the last 2 trials were randomized to avoid learning effects among participants. Each trial lasted approximately 15 min, with a 5-minute break between consecutive trials, resulting in a total experiment time of about 1.5 h per participant. As each driver encountered 5 dilemma zone events per trial, the total number of observations for analysis was 62 participants × 4 trials × 5 events, yielding 1,240 observations.

3.3. Sample

Sixty-two participants (aged 19 to 45, with a mean age of 30.48 years) completed the experiment, and their demographic and driving characteristics are summarized in Table 2. The sample included 40 males and 22 females, reflecting a gender ratio similar to that of licensed drivers in South Korea (Korean National Police Agency, 2023). In terms of driving history, all participants had held a driver's license for an
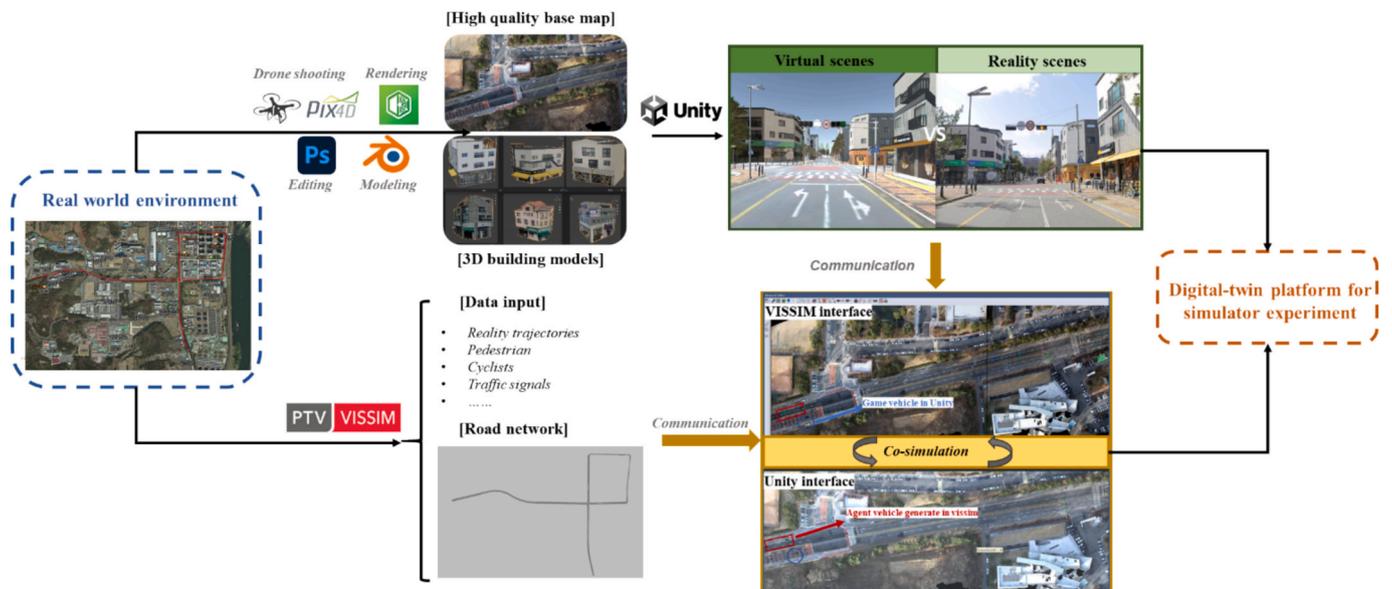
Fig. 3. The framework of the co-simulation platform.
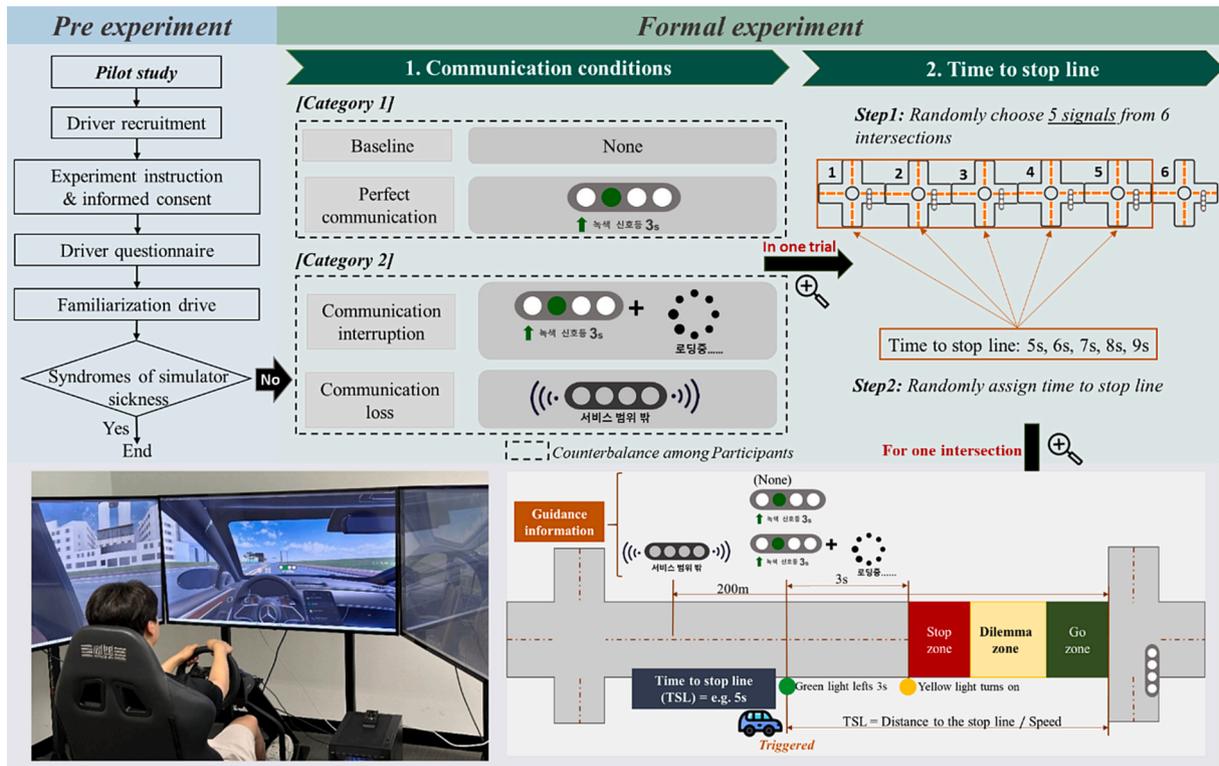
Fig. 4. The design and protocol of the experiment.

(a) Baseline (no communication)

(b) Perfect communication

(c) Communication interruption

(d) Communication loss
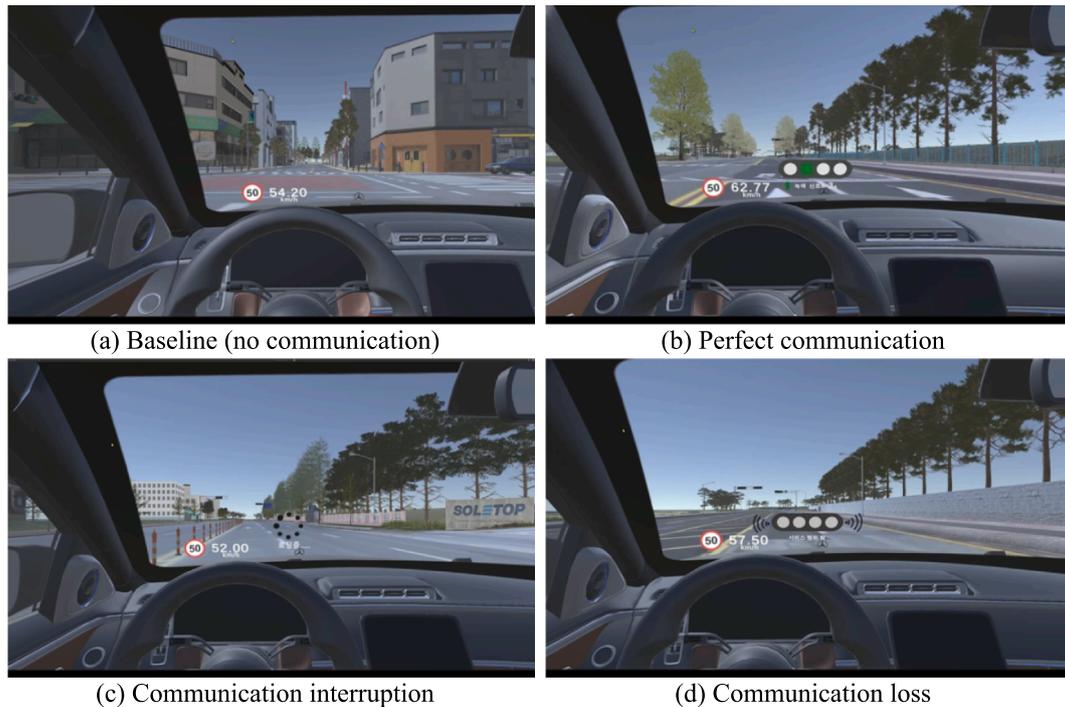
Fig. 5. Driving scenario from a driver's view.

average of 9.41 years. Approximately 24 % of participants reported being involved in a traffic crash within the past 12 months. Additionally, 43.55 % indicated frequent encounters with dilemma zones, and up to 38.71 % reported feeling hesitant when deciding whether to stop or proceed in such situations. Participants also self-rated their aggressiveness in yellow-light running decisions, with a mean score of 4.85 out of 10, based on their self-reported frequency of such behavior every 10

experiences of yellow light.

3.4. Data analysis

A binary logit model was developed to understand the likelihood of the driver's stop-or-go decision. To this end, assume y_{ij} denotes a categorical for the decision of driver i in scenario j, whereby 1 represents the

Table 2

Descriptive analysis of the sample.

Explanatory variables			Count (%)	Mean (standard deviation)
Driver Characteristics	Gender	Male	40 (64.52)	
		Female	22 (35.48)	
	Age			30.48 (5.80)
Driving history	Years of holding a driving license			9.41 (5.26)
	Involved in a traffic crash in the past 12 months	Yes	15 (24.19)	
		No	47 (75.81)	
	Frequently encounter dilemma zones	Yes	27 (43.55)	
		No	35 (56.45)	
	Often hesitate to stop-or-go	Yes	24 (38.71)	
		No	38 (61.29)	
	Aggressiveness of driving style			4.85 (2.22)

driver has proceeded through the dilemma zone and is 0 otherwise. Under the framework of the binary logit model, the linear function for the discrete outcome of y_{ij} is shown in Equation (1):

$$U_{ij} = \beta x_{ij} + \in_{ij} \tag{1}$$

where, x_{ij} is a vector of explanatory variables for each driver; the systematic utility, $U_{ij} > 0 (y_{ij} = 1)$, indicates that driver i proceeds to the dilemma zone in scenario j, relative to stopping; Also, $\in_{ij}$ is a normally distributed error term.

The probability of observing $y_{ij} = 1$ in the data is given by the Equation (2):

$$P_{ij} = \Pr\left(y_{ij} = 1\right) = 1/1 + e^{(-U_{ij})} \tag{2}$$

Under the framework of the binary logit model, the random parameter approach was incorporated to account for within-individual correlation and heterogeneity across individuals by allowing the coefficients for explanatory variables to vary across individuals (Mannering et al., 2016). As shown in Equation (3),

$$\beta_i = \beta + \omega_i \tag{3}$$

where β_i denotes normally distributed random parameters with a mean vector of β. ω_i refers to an independent normally distributed random error term.

The simulated maximum likelihood estimation method was applied to estimate the parameters. To ensure the stability of the model estimates, 1000 Halton draws were employed (Sharma et al., 2020; Ali and Haque, 2023a; Bhat, 2003). The likelihood ratio test was given by Equation 4,

$$\chi^2 = -2[LL(\beta_f) - LL(\beta_{rp})] \tag{4}$$

which is utilized to evaluate the statistical difference between the fixed and random parameters binary logit models. Specifically, the $LL(\beta_f)$ and $LL(\beta_{rp})$ denote the log-likelihood at the convergence of the fixed and random parameter models, respectively.

Furthermore, to understand the effect of the explanatory variable of probability, marginal effects were calculated, implying the effect of a one-unit change in an independent variable on the probability. Further, all possible interaction effects among explanatory variables were considered in estimated models to capture observed heterogeneity. More specifically, interactions between driver characteristics and communication conditions provide a more accurate impact on a driver's stop-or-go decision, thereby indicating management policies for enhancing drivers' safety in connected vehicles.

4. Results

4.1. Stop-or-go decisions

Table 3 presents a descriptive analysis of participants' stop-or-go decisions across different communication conditions. The proportion of stop-or-go decisions varied depending on the communication condition. Out of 310 stop-or-go decision samples for each condition, the proportion of drivers choosing to stop was highest under perfect communication (92.58 %) and interrupted communication (88.71 %). Under communication loss, however, a greater percentage of drivers chose to proceed when encountering a yellow light (35.81 %) compared with the baseline condition (29.35 %).

Table 4 presents the estimation results of the random parameters binary logit model with interaction effects for stop-or-go decisions. During the model estimation process, the variables expected to vary across individuals were assessed to determine whether they were significantly random. This approach allows us to appropriately address the heterogeneity across individuals and the correlation within individuals, considering the structure of the repeated measures data. In this regard, the current random parameter binary logit model was selected for result interpretation. As reported in Table 4, several model goodness-of-fit measures, including AIC and *McFaddenPseudoR*^{2}, indicate that the current model is well-fitted and demonstrates good predictive performance. Besides, all parameters for the variables in the estimated model, including random parameters, fixed parameters, and interaction terms, are statistically significant at a level of 10 %.

The analysis highlights that drivers' stop-or-go decisions vary significantly depending on the type of guidance information provided under different communication conditions. Moreover, coefficients for perfect communication and communication interruption are estimated to be random, indicating non-monotonic relationships between these conditions and drivers' decisions. For perfect communication, it shows a decreasing effect on decisions to proceed for 95.93 % of drivers, while approximately 4.07 % of drivers demonstrate a higher propensity to proceed under the same condition. Similarly, for communication interruption, most drivers (94.68 %) are more likely to stop, but 5.32 % show a greater tendency to proceed. Marginal effects indicate that compared to the no-communication condition, perfect and interrupted

Table 3

Descriptive analysis of driving stop-or-go decisions.

Count (%)	Communication conditions			
	Baseline	Perfect communication	Communication interruption	Communication loss
Stop	219 (70.65)	287 (92.58)	275 (88.71)	199 (64.19)
Go	91 (29.35)	23 (7.42)	35 (11.29)	111 (35.81)
Total	310 (100)	310 (100)	310 (100)	310 (100)

Table 4

Estimation results of random parameter binary logit model with interaction effects for stop-or-go decision.

Variables	Random parameters binary logit model		
	Estimated parameters	$z-value$	Marginal effects
Constant	−0.287	−0.56	–
Dilemma setting			
Initial speed	0.521***	11.14	0.041
Initial distance to stop line	−0.077***	−15.88	−0.006
Communication conditions (Baseline: no communication)			
Perfect communication (Mean)	−3.949***	−6.36	−0.308
Perfect communication (SD)	2.266***	5.59	–
Communication interruption (Mean)	−3.266***	−7.20	−0.255
Communication interruption (SD)	2.023***	6.12	–
Communication loss	0.411**	2.35	0.032
Driving history			
Years of holding a driving license	−0.049**	−3.34	−0.004
Involved in a traffic crash in the past 12 months	−0.315*	−1.68	−0.025
Often hesitate to stop-or-go	−0.501**	−3.05	−0.039
Interaction effects			
Perfect communication * Frequently encounter dilemma zones	1.424**	3.14	0.111
Communication interruption * Frequently encounter dilemma zones	1.301***	3.41	0.102
Perfect communication * Aggressive driving style	1.103**	2.32	0.086
Communication interruption * Aggressive driving style	1.216**	3.05	0.095
Number of observations	1240		
Number of estimated parameters	15		
Log-likelihood at zero,LL(0)	−362.151		
Log-likelihood at convergence,LL(β)	−636.776		
McFaddenPseudoR^2	0.431		
AIC	754.3		

Note:

*** Statistical significance at the 1% level.

** Statistical significance at the 5% level.

* Statistical significance at the 10% level.

communication reduce the probability of proceeding by 30.8 % and 25.5 %, respectively.

The model includes fixed parameters categorized into three groups: dilemma setting, communication conditions, and driving history. The dilemma zones (or in other words – activation of the yellow light) in this experiment is set by the time to reach the stop line, randomly assigned between 5 and 9 s at five intersections. This was calculated in real-time by dividing the distance from the vehicle to the stop line by its speed. However, for improved interpretability and model fit, the explanatory variables for the dilemma setting used in the model are the vehicle's initial speed and distance to the stop line rather than the time to stop line indicator.

As seen in Table 4, a driver's speed at the onset of the green-light countdown shows increasing effects on his or her decision to proceed. Marginal effect reveals that every 1 m/second increase in speed increases the probability of choosing to proceed by approximately 4 %. Conversely, the distance to the stop line shows a decreasing effect on the decision to proceed, with a 1-meter increase in distance reducing the probability of choosing to proceed by about 1 %. Among the communication conditions, communication loss accompanied by an "out of service" prompt increases the probability of choosing to proceed by 3.2 % compared to no communication.

Regarding driving history, driving experience reduces the

probability of choosing to proceed, with each additional year of experience decreasing the probability by 1 %. Similarly, prior crash involvement within the past 12 months reduces the probability of choosing to proceed by 2.5 % compared to drivers without crash records. Besides, drivers who frequently hesitate in stop-or-go situations are also less likely to choose to proceed, with a 3.9 % decrease in such probability.

Significant interaction effects reveal observed heterogeneity among drivers. Interactions between perfect communication and frequent engagement in dilemma zones, as well as between communication interruption and frequent dilemma zone engagement, show increasing effects on decisions to proceed, with probabilities rising by 11.1 % and 10.2 %, respectively. Additionally, interactions between perfect communication and aggressive driving style, and between communication interruption and aggressive driving style, are also positively associated with the decision to proceed, increasing such probability by 8.6 % and 9.5 %, respectively. These findings underscore the importance of understanding the nuanced effects of dilemma zone situations, communication conditions, and driving history on drivers' decisions. The results also highlight the role of communication technology and driver-specific factors in shaping decision-making processes.

4.2. Red-light running behavior

Out of 1240 observations of stop-or-go decisions, 240 observations indicate that drivers choose to proceed at the onset of the yellow light. The driver who chooses to proceed faces the risk of running a red light if he or she fails to cross the stop line during the yellow signal. Table 5 presents a descriptive analysis of drivers' red-light running outcomes across different communication conditions. The results indicate that the proportion of red-light running varied depending on the communication condition. The results show that the red-light running rate increased under communication loss (22.52 %), but decreased under perfect (13.04 %) and interrupted (14.29 %) communications compared with the baseline condition (16.48 %).

5. Discussion

5.1. The effects of communication conditions

5.1.1. Stop-or-go decision

The estimated random parameters from the drivers' stop-or-go decision model indicate that both perfect communication and communication interruption are negatively associated with the likelihood of proceeding among the majority of drivers. This effect is likely due to green-light countdown information, which warns that the green light is about to end, encouraging drivers to stop for safety reasons. Under perfect communication, drivers receive clear and continuous information about the signal change, encouraging more of them to prioritize safety by stopping. Even under communication interruption, the partial warning effect still reduces the probability of drivers choosing to proceed. Green-light countdown systems have been implemented to effectively reduce the likelihood of drivers proceeding or running red lights, as validated by various studies (Paul et al., 2022; Huang et al., 2014; Lum and Halim, 2006; Islam et al., 2017). However, these systems

Table 5

Descriptive analysis of red-light running behavior.

Count (%)	Communication conditions			
	Baseline	Perfect communication	Communication interruption	Communication loss
Yes	15 (16.48)	3 (13.04)	5 (14.29)	25 (22.52)
No	76 (83.52)	20 (86.96)	30 (85.71)	86 (77.48)
Total	91(100)	23(100)	35(100)	111(100)

typically integrated into physical traffic signals rather than being displayed through connected vehicles in a C-V2X environment. Notably, for participants in this study from Daejeon City, South Korea, green-light countdowns are not part of the current traffic system. Therefore, it is vital to explore how such systems may influence drivers' decision-making and improve intersection safety.

Further, the estimation results indicate that drivers are more likely to choose to proceed under communication loss conditions. It can be explained by heightened tension caused by the absence of information about the approaching traffic signal, which motivates aggressive behavior. In accordance with the frustration-aggression hypothesis (Dollard et al., 1939), frustration from unmet expectations can lead to aggressive behavior as individuals try to regain control. During a communication loss, drivers receive an "out of service" notification about 200 m from the stop line, indicating no further updates on the signal status. This disruption undermines their reliance on real-time guidance, forcing them to depend solely on their judgment. Consequently, the uncertainty can create cognitive conflict, prompting drivers to adopt riskier strategies, such as rushing through intersections, in an effort to regain control. In this case, change in behavior shows how losing communication affects decision-making. Without real-time guidance, drivers may experience distorted perceptions of risk, leading them to overcompensate by driving aggressively rather than exercising caution.

5.1.2. Calculation of type II dilemma zone

As shown in Fig. 6, the probability of a driver choosing to proceed was calculated and plotted based on the model estimation results. By using the mean values of continuous explanatory variables and the reference category for dummy variables, a probability for choosing to proceed of a driver experiencing perfect communication at a distance of X meters from the stop line was calculated utilizing a cumulative distribution function. Additionally, probability curves were plotted for baseline (no communication), communication interruption, and communication loss conditions. Fig. 6 clearly illustrates that the probability of choosing to proceed decreases as the distance to the stop line increases under all communication conditions. Furthermore, the probability of choosing to proceed is higher under communication loss

compared to the baseline condition, while it is lower under perfect and interrupted communication.

Additionally, Fig. 6 indicates that the type II dilemma zone distributions vary across communication conditions. For instance, under baseline conditions, the dilemma zone spans from 45.13 m to 102.20 m. Under communication loss, however, the distribution is shifted 5.34 m farther from the stop line compared to the baseline. This shift indicates that when the dilemma zone is located closer to the stop line, it is less critical for drivers to proceed at the same speed of 50 km/h. Conversely, the distribution of the dilemma zone under communication loss suggests a more challenging situation for drivers, whereas it appears less critical under perfect and interrupted communication compared to the baseline condition. These findings underscore how communication conditions significantly influence driver behavior and the spatial characteristics of the dilemma zone, which has important implications for traffic signal design and safety interventions.

5.2. The effects of dilemma setting

The results of this study reveal that the probability of drivers choosing to proceed increases with higher initial speeds and shorter distances to the stop line. These findings align with evidence from prior observational (Pathivada and Perumal, 2017; Chauhan et al., 2022; Pawar et al., 2022), naturalistic (Rahman et al., 2021), and driving simulator studies (Haque et al., 2016), which consistently document the influence of these factors on stop-or-go decisions. Intuitively, drivers are more inclined to cross the intersection when they are closer to the stop line or traveling at higher speeds. Moreover, a longer distance to the stop line combined with lower initial speeds presents a greater challenge for drivers to clear the intersection within the yellow-light phase. This increased difficulty may increase the likelihood of running a red light due to time and distance constraints (Elmitiny et al., 2010; Hussain et al., 2020).

5.3. The effects of driver characteristic

The estimation results from the stop-or-go decision model revealed several significant associations between driving history-related factors
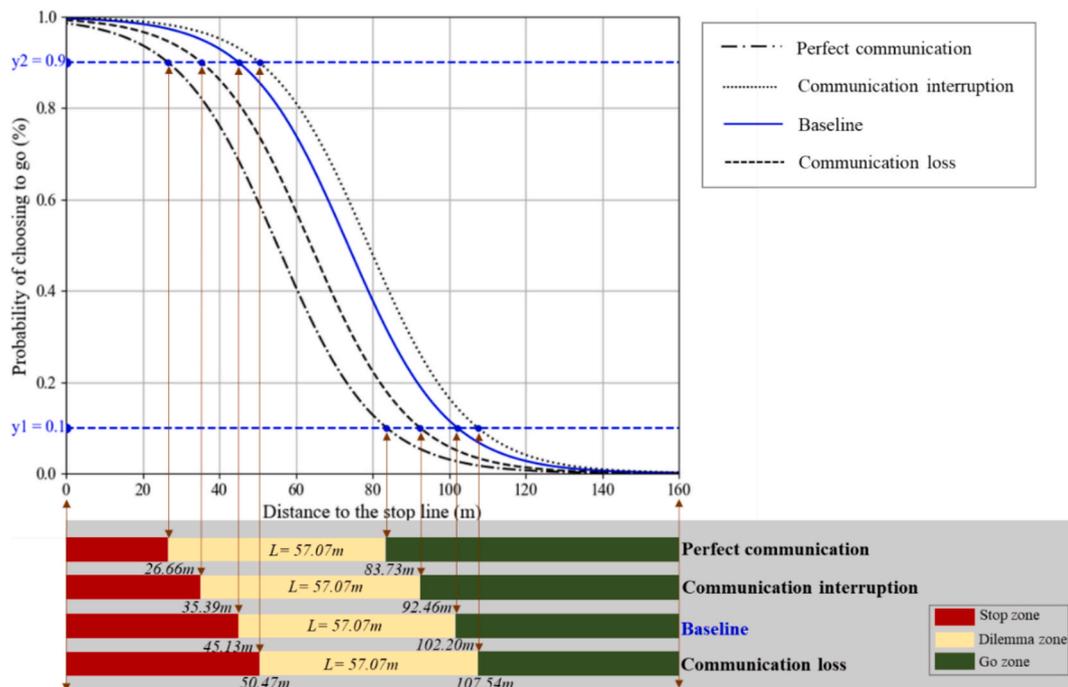

Fig. 6. The probability of a driver choosing to go under different communication conditions.

and decision-making behavior. One notable finding is that drivers with more years of driving experience are less likely to proceed, possibly due to their heightened risk awareness and safer driving habits. This aligns with previous research, which has shown that a driver's safety perception tends to improve with increased driving experience (Brown and Groeger, 1988; Chen et al., 2021; Sayed et al., 2022). Experienced drivers are generally more cautious than novice drivers (Borowsky and Oron-Gilad, 2013; Chen et al., 2022), which explains their lower likelihood of taking risks in dilemma zones.

Drivers' crash involvement records also had a significant impact, with prior crash involvement reducing the likelihood of choosing to proceed. The reason for this is likely to be that drivers become more risk-averse after experiencing crashes, and adapt their behavior by choosing safer options, such as stopping when approaching a dilemma zone. There is support for this relationship in Wilde's (1998) Risk Homeostasis Theory (RHT), which suggests that individuals adjust their behavior to maintain a consistent level of perceived risk. It has been documented in several studies that drivers' increased risk perception leads them to behave more cautiously (Ba et al., 2016; Schmidt-Daffy, 2014; Chen et al., 2020).

It was found that previous experience with hesitation in stop-or-go decisions had a decreasing effect on the likelihood of choosing to proceed. There are two ways in which this relationship can be interpreted. In the first instance, hesitation prolongs the reaction time of the driver, which reduces the opportunity for the driver to accelerate through the intersection, thus making stopping the more practical option. Furthermore, hesitation can be attributed to drivers' uncertainty as to whether proceeding will result in a successful crossing or a failed attempt, such as running a red light. As a result of this uncertainty, individuals evaluate potential gains and losses in accordance with the Prospect Theory (Kahneman and Tversky, 1979). In order to avoid the potential losses associated with unsuccessful crossings, drivers tend to prioritize safety and mitigate risks by choosing to stop. There have been previous studies that have validated the application of Prospect Theory to explain drivers' decision-making in similar situations (Schmidt-Daffy, 2014; Koh and Chin, 2022). It is evident from these findings that driving history, risk perception, and personality traits significantly influence drivers' decisions in dilemma zones. An understanding of these behavioral dynamics is essential in order to develop tailored interventions that can improve intersection safety and mitigate risky driving behavior.

5.4. The interaction effects

The estimated results from the stop-or-go decision model indicate that drivers who have extensive experience handling dilemma zones are less affected by communication conditions, such as perfect communication and communication interruptions. This can be explained through the concept of self-efficacy, introduced by Bandura (1977). As it pertains to driving, self-efficacy refers to a driver's belief that they will be able to effectively handle critical events, such as navigating dilemma zones, which in turn affects their decisions and reactions. A major source of self-efficacy is mastery performance, which is strengthened through practice and experience. According to previous studies, well-designed training programs for novice drivers are consistently shown to improve self-efficacy, resulting in safer driving behaviors (Marksaityte et al., 2017; Seibokaite et al., 2022; Ye et al., 2024). This study suggests that frequent engagement with dilemma zones promotes drivers' self-efficacy, enabling them to demonstrate safer behaviors, such as a reduced tendency to proceed.

Our analysis revealed that aggressive driving style tends to reduce the positive impact of both perfect and interrupted communication conditions on drivers' stop-or-go decisions. Specifically, aggressive drivers exhibited higher risk tolerance, making them less responsive to signals designed to encourage safer behavior. These findings align well with previous international studies that have explored similar driver behaviors and responses to risk (Ulleberg and Rundmo, 2003; Dahlen,

2012; Richer and Bergeron, 2012). Additionally, according to Wilde's (1998) Risk Homeostasis Theory, aggressive drivers often interpret countdown information as an opportunity to accelerate rather than a safety warning, further supporting our observations.

6. Implications for practice and policy

There are several important implications arising from the findings. To begin with, the co-simulation platform developed in this study provides a valuable testbed for exploring various applications of connected vehicles. Based on this, it's recommended to collaborate with industries involved in connected vehicles and wireless technology development alongside academic institutions. This collaboration will enable comprehensive testing of connected vehicle applications by updating wireless technology within the platform before deploying these applications on real roads. Such proactive measures can help prevent unnecessary investments and enhance road safety.

Secondly, driver behavior appears to be riskier under conditions of communication loss, underscoring the need to consider such vulnerabilities before deploying C-V2X at scale on real roads. The communication loss condition examined in this study is a scenario where updated signal information is not available, emphasizing the importance of expanding smart infrastructure coverage. To mitigate the risks associated with communication loss, governments and relevant authorities should prioritize investments in comprehensive smart infrastructure networks that facilitate seamless and reliable communication between vehicles and traffic management systems. Additionally, as achieving complete smart infrastructure coverage takes time, it is essential to design and apply communication systems that reduce drivers' stress and uncertainty, promoting safer driving even in the absence of information.

Last but not least, the interaction effects observed in this study highlight the need for personalized information systems in future connected vehicles and related safety interventions. For the personalized information systems, while forceful warnings may influence aggressive drivers' behavior, these interventions may not be necessary for defensive drivers. An adaptive warning system that considers diverse driving styles could enhance communication technologies' effectiveness and overall safety in connected environments. Further, a tailored training program that addresses the varying experiences and history of drivers may strengthen their ability to adapt to different communication situations. A program of this nature should incorporate real-time simulations of dynamic communication transitions, which will assist drivers in managing safety in the face of continuously changing circumstances.

7. Conclusion

With the emergence of wireless communication technology, particularly C-V2X, it has been recognized as a promising solution to enhancing driving safety by connecting vehicles to traffic signals and providing drivers with real-time guidance. However, C-V2X technology is still in its infancy, communication conditions may not always function optimally and may be impaired by interruptions or complete loss of communication. It is therefore imperative that we understand the safety implications of these varying communication conditions. This study examined the effects of different C-V2X communication conditions on drivers' performance in dilemma zones. In particular, the effects of perfect communication, interrupted communication, and communication loss on stop-or-go decisions were evaluated using random parameters binary logit models with interaction terms. Additionally, the outcomes related to the red-light running rates for drivers who chose to proceed were compared under different communication conditions.

Our findings suggest that drivers are more likely to stop under both perfect and interrupted communication conditions. Contrary to that, drivers tend to proceed if communication is lost. Furthermore, the study highlights the importance of driving history when making decisions. More experienced drivers, those involved in previous accidents, or those

who often hesitate in dilemma zones are less likely to proceed. The interaction effects suggest that individual driving history moderates the relationship between communication conditions and decision-making. For instance, the positive association between perfect and interrupted communication and drivers' decisions to drive is reduced by aggressive driving styles and frequent dilemma zone experiences. In addition to the stop-or-go decisions, the rates of red-light running among drivers who choose to go decrease in both perfect and interrupted communications compared to the baseline communication condition.

Future research should address several limitations of this study. First, guidance information could be further refined to meet the needs of different communication conditions. As an example, strategies to mitigate drivers' increased tendency to proceed when communication is lost should be explored in order to enhance safety outcomes. Secondly, the current experimental design did not take into account continuous transitions between communication conditions that occur in real-world scenarios. There is a potential for future studies to investigate how drivers adapt to transitions between perfect, impaired, and restored communication, which would provide insight into their behavior under more dynamic and complex conditions. Thirdly, this study focused primarily on younger to middle-aged drivers, in line with the objectives of the initial design and evaluation of the proposed system. Nevertheless, we recognize the importance of ensuring that connected vehicle technologies are accessible and effective for older drivers, who have distinct cognitive, perceptual, and physical requirements. It is therefore imperative that future research adapts and rigorously assesses the system specifically for older drivers. By targeting such efforts, connected vehicle technologies will be more accessible, inclusive, and effective for individuals of all ages (Chen et al., 2019, 2021, Xu et al., 2025). Lastly, while our results provide insights into the relationship between aggressive driving style and risky decision, it's important to note that the definition of aggressive driving style and the explored driving behavior may vary across studies conducted in different regions. Therefore, the applicability of our quantitative results to other regions warrants further cross-cultural validation. In addressing these limitations and building upon this study's findings, future research can advance our understanding of C-V2X communication conditions and their implications for driving safety, paving the way for safer and more reliable connected vehicle systems.

CRediT authorship contribution statement

Shi Ye: Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Tiantian Chen:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization. **Oscar Oviedo-Trespalacios:** Writing – review & editing, Methodology, Conceptualization. **Yasir Ali:** Writing – review & editing, Methodology, Formal analysis. **Taeho Oh:** Software, Project administration, Methodology. **Inhi Kim:** Supervision, Project administration, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

Data availability

The data that has been used is confidential.

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