Effects of collision warning characteristics on driving behaviors and safety in connected vehicle environments

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Abstract: With the emerging connected vehicle (CV) technologies, a novel in-vehicle omni-direction collision warning system (OCWS) is developed. For example, vehicles approaching from different directions can be detected, and advanced collision warnings caused by vehicles approaching from different directions can be provided. Effectiveness of OCWS in reducing crash and injury related to forward, rear-end and lateral collision is recognized. However, it is rare that the effects of collision warning characteristics including collision types and warning types on micro-level driver behaviors and safety performance is assessed. In this study, variations in drivers' responses among different collision types and between visual only and visual plus auditory warnings are examined. In addition, moderating effects by driver characteristics including drivers' demographics, years of driving experience, and annual driving distance are also considered. An in-vehicle human-machine interface (HMI) that can provide both visual and auditory warnings for forward, rear-end, and lateral collisions is installed on an instrumented vehicle. 51 drivers participate in the field tests. Performance indicators including relative speed change, time taken to accelerate/decelerate, and maximum lateral displacement are adopted to reflect drivers' responses to collision warnings. Then, generalized estimation equation (GEE) approach is applied to examine the effects of drivers' characteristics, collision type, warning type and their interaction on the driving performance. Results indicate that age, year of driving experience, collision type, and warning type can affect the driving performance. Findings should be indicative to the optimal design of in-vehicle HMI and thresholds for the activation of collision warnings that can increase the drivers' awareness to collision warnings from different directions. Also, implementation of HMI can be customized with respect to individual driver characteristics.

Keywords: Connected vehicles; Collision warning system; Human-machine interfaces; Instrumented vehicles; Field tests; Driving performance

1. Introduction

Road safety has been a major global public health issue. In 2016, 1.35 million people have died on the roads (World Health Organization, 2018). Over 90% of road crashes are attributed to human error. For example, 41% of road crashes are related to recognition errors because of driver distraction and inattentiveness, and 33% are related to decision errors (NHTSA, 2015). To this end, the emerging connected vehicle (CV) technologies including vehicle imaging, vehicle sensing, vehicle-to-vehicle (V2V) communication, and vehicle-to-infrastructure (V2I) communication technologies have been developed and implemented (Lan et al., 2021, 2022; Yang et al., 2022). They have demonstrated to be effective in reducing the risk of road crashes (Li et al., 2017a; Yang et al., 2020).

One of the innovations that can increase the drivers' awareness and reduce the crash risk is collision warning system (CWS). CWS can provide instantaneous warnings to the drivers for potential hazards associated with approaching traffic from different directions. With respect to the point of vehicles' contact, collision warnings can be stratified into three categories namely forward collision warnings (FCW), rear collision warnings (RCW) and lateral collision warnings (LCW). Results indicate that FCW is effective in reducing the crashes attributed to the acceleration of subject vehicle (Mozaffari and Nahvi, 2020), sudden brake of a leading vehicle (Cicchino, 2017; Xiong et al., 2019; Fu et al., 2019; Zhao et al., 2019b; Zhang et al., 2021), and merging traffic at the work zones (Qiao et al., 2017; Hang et al., 2022). Effectiveness of FCW is more remarkable under the adverse weather condition, compared to clear weather condition (Wu et al., 2018). RCW can avoid the crash attributed to an accelerating or fast-moving vehicle from behind (Hang et al., 2012). Jenkins et al (2007) and Sayer et al. (2010) found that LCW can help avoid lane departure and crash attributed to improper lane changing.

However, existing studies mainly focus on one among FCW, RCW and LCW only. It is rare that differences in drivers' responses among FCW, RCW and LCW are investigated because of the operational domain of them is not explicit. Indeed, different thresholds for hazard detection and activation of warnings could be established for different collision warning types. Therefore, missing rate of drivers can be reduced, and recognition accuracy for collision warnings can be improved. To this end, differences in the effects of FCW, RCW, and LCW of an in-vehicle omni-direction collision warning system (OCWS) on the drivers' awareness, behaviors and safety performance would be evaluated.

To allow a driver to interact with a vehicle, human-machine interface (HMI) is commonly used to display the vehicle performance and driving-related information, with a built-in display screen, monitor, or tablet. Just, layout, format, and content of HMI can affect the interaction between drivers and vehicles (Cummig et al., 2007; Fitch et al., 2014; Jakus et al., 2015; Francois et al., 2017; Li et al., 2017b; Winkler et al., 2018; Biondi et al., 2018), and therefore the drivers' awareness, cognition, and driving performance (Cumming et al., 2007). More specifically, detailed information can improve drivers' driving performance (Zhang and Ioannou, 2016; Sayer et al., 2010) while too much information may result in drivers' misjudgment and excessive distraction (Vaezipour et al., 2018). Additionally, Jakus et al., (2015) and Biondi et al. (2017) indicated that combined visual and auditory warnings can significantly reduce drivers' response time, as compared to either visual display or auditory warning. Furthermore, Meng and Spence (2015) found that tactile warnings can enhance drivers' awareness, compared to visual and auditory warnings. Last but not least, effectiveness of collision warnings on drivers' awareness may vary with the format of visual display (Campbell et al., 2007).

On the other hand, driver characteristics including socio-demographics, driving experience and annual driving distance can affect the interactions between drivers and vehicles (Cumming et al., 2007; Konstantopoulos et al., 2010; Dobres et al., 2016; Pitt and Sarter, 2018). This can be attributed to the effects of driver characteristics on drivers' acceptance, recognition and trustfulness to the information displayed through HMI (Shin et al., 2015; Ekman et al., 2019). For example, Pitt and Sarter (2018) found that older drivers may have longer reaction time, and missing of tactile information may be prevalent for them when amount of information increases. Furthermore, Konstantopoulos et al. (2010) found that reaction time of experienced drivers to visual information may be shorter than that of novice drivers. To this end, it is necessary to consider individual heterogeneity for the association between the design of HMI for collision warnings and driving performance.

The remainder of this paper is structured as follows. Section 2 and 3 describe the objective and the design of OCWS and HMI of the instrumented vehicles. Experimental design and methodology of analysis are given in Section 4 and 5. Section 6 and 7 presents the results and discussion of analysis. Finally, concluding remarks are given in Section 8.

2. Objective

In this study, two types of OCWS are presented through the designated HMI: i) visual warning only, and (ii) visual plus auditory warnings. Then, effects of the characteristics of collision warning on the driving behaviors and driving safety would be assessed in the field tests. There are two main objectives for this study.

i) To examine the differences in drivers' responses to collision warnings among different collision types and warning types;

ii) To examine the intervention effects by drivers' characteristics on the association between collision type, warning type, and drivers' performance.

Contribution of this study is twofold. First, optimal design of in-vehicle HMI for OCWS can be proposed to increase drivers' awareness and improve driving performance. Second, thresholds for the activation of collision warnings for different collision directions can be customized with respect to driver characteristics for in-vehicle driver assistance systems of future CV.

3. In-vehicle omni-direction collision warning system

In this study, effects of in-vehicle OCWS on the driver behaviors and driving performance are evaluated. With respect to the point of vehicles' contact, warnings for forward, rear-end, and lateral collision will be presented. As shown in Figure 1, collision warnings will be activated when the time-to-collision (TTC) is lower than a prescribed threshold value (TTC_s). For instance, TTC and point of vehicles' contact depend on relative position and relative speed of the two instrumented vehicles, which are equipped with communication devices.

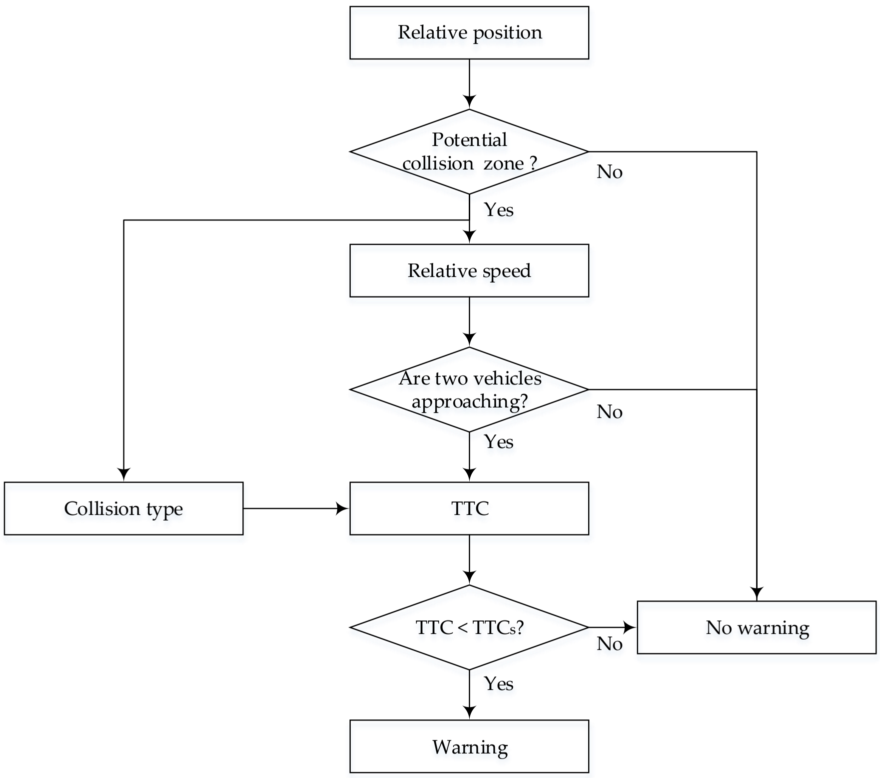


Figure 1 Flowchart for the calculation of time-to-collision (TTC) and activation of collision warnings

Figure 2 illustrates the relationship between relative position and movement of subject and control vehicles, and the occurrence and type of potential collisions. As shown in Figure 2, *O* denotes the geometric center and *A*, *B*, *C*, and *D* denote the four corners of the subject vehicle. Similarly, *O′* denotes the geometric center and *A′*, *B′*, *C′*, and *D′* denote the four corners of the control vehicle respectively. *O′* is set as the origin of the local coordinate system, as shown in Figure 2. Moving direction of the subject vehicle is parallel to *y*-axis and regarded as the positive y-axis direction. Also, the normal of y-axis is x-axis, and the direction of the control vehicle approaching to the subject vehicle is regarded as the positive x-axis direction. In addition, v_n, w_n and l_n denote the velocity, width and length of the subject vehicle, and v_i, w_i and l_i denote the velocity, width and length of the control vehicle, respectively. α is the interacting angle between the moving directions of the two vehicles. h and d denote the horizontal projection distance and the vertical projection distance from vehicle i to vehicle n, respectively. $k_{B'C}$, $k_{B'D}$ and $k_{D'C}$ denote the slopes of $B'D$, $B'C$ and $D'C$, respectively. d_1 and h_1 denote the horizontal projection distance and the vertical projection distance from vehicle i to vehicle n, respectively, when D is located on the extended line of B' and C'.

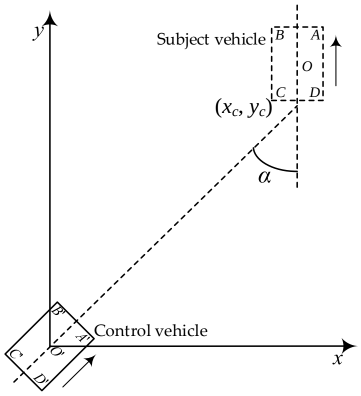
Rear-end, lateral and forward collisions are defined according to the collision point at the subject vehicle. Rear-end collision would occur (for the subject vehicle) when any point on the edge CD (except C and D) is hit by the control vehicle. Lateral collision would occur when any point on the edge BC and AD is hit. Forward collision would occur when any point on the edge AB (except A and B) is hit. Collision warning would be activated only when the subject vehicle is located in the potential collision zone as illustrated in Figure 2. The potential collision zone is determined based on the relative position between corner C of subject vehicle and four corners of control vehicle. Then, TTC is estimated, and activation of collision warnings is determined as follows.

Firstly, relative position of the subject vehicle from the control vehicle is determined. Also, the calculation should be continued only when the subject vehicle is located at potential collision zone as shown in Figure 2.

Then, relative speed of the subject vehicle with respect to the control vehicle is estimated. For example, whether the two vehicles are approaching each other would be determined. Also, collisions may happen to the subject vehicle only when the two vehicles are approaching.

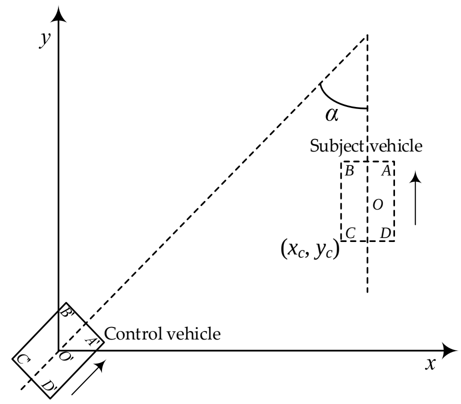
Furthermore, point of contact and collision type would be determined, and TTC would be estimated. For example, if $\alpha \neq 0$ & $\cot\alpha < k_{B'C} \leq \frac{2d_1 - 2y_{B'} - l_n}{2h_1 - 2x_{B'} - w_n}$ is satisfied, there is potential for rear-end collision. Corner B' of the control vehicle would be in contact with the edge CD of the subject vehicle, as shown in Figure 2(a), and the scenarios of this collision can be found in Figure 3(b). Then, TTC is estimated using the ratio of relative distance to relative speed of control and subject vehicles, with due consideration of vehicles' dimensions (Schwarz, 2014; Jasper et al., 2017).

Lastly, whether the collision warnings would be activated can be determined by comparing between estimated TTC and TTC_s. In particular, values of TTCs for forward, lateral and rear-end collisions are set at 5 second (Scott and Gay, 2008; Yan et al., 2015; Tawfeek and El-Basyouny, 2018). Warnings would be activated when $\mathrm{TTC} \leq TTC_s$.



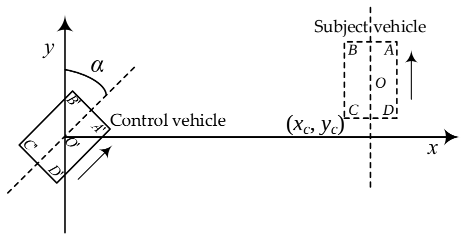
Precondition: $\alpha \neq 0$ & $\cot\alpha < k_{B'C} \leq \frac{2d_1-2y_{B'}-l_n}{2h_1-2x_{B'}-w_n}$

(a) Rear-end collision (B'-CD)



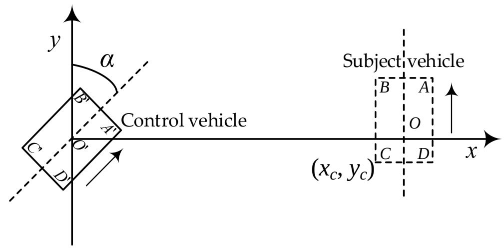
Precondition: $\alpha \neq 0$ & $0 < k_{B'C} \leq \cot\alpha$

(b) Rear-end collision (B'-CD) or lateral collision (C- $A'B'$)



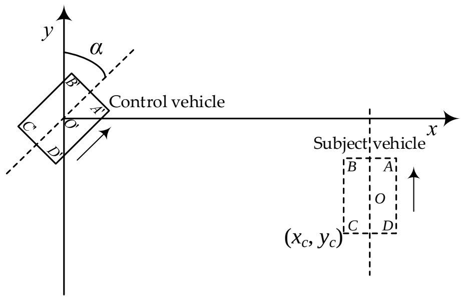
Precondition: $\alpha \neq 0$ & $y_{A'} \leq y_C \leq y_{B'}$ & $x_{B'} \leq x_C$

(c) Lateral collision (C- $A'B'$)



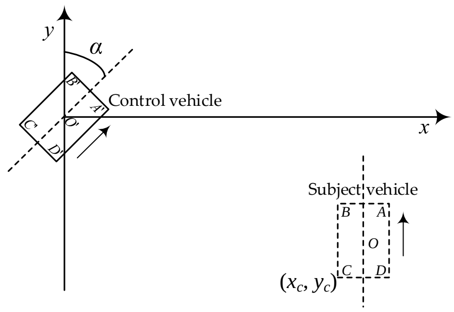
Precondition: $\alpha \neq 0$ & $y_{D'} \leq y_C < y_{A'}$ & $x_{D'} \leq x_C$

(d) Lateral collision (A'- BC)



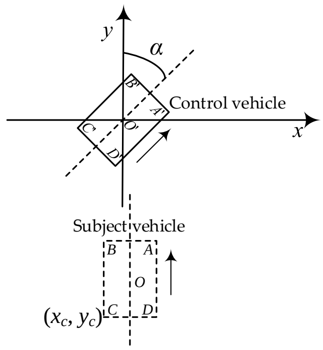
Precondition: $\alpha \neq 0$ & $-\frac{2l_n}{2h-2x_{D'}-w_n} < k_{D'C} < 0$

(e) Lateral collision (B-$A'D'$)



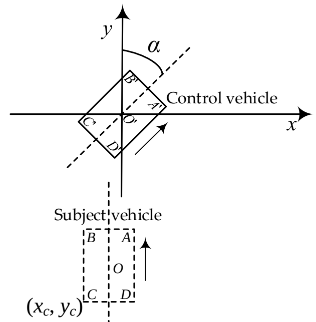
Precondition: $\alpha \neq 0$ & $k_{D'C} \leq -\frac{2l_n}{2h-2x_{D'}-w_n}$

(f) Lateral collision (B-$A'D'$) or forward collision (D' -AB)



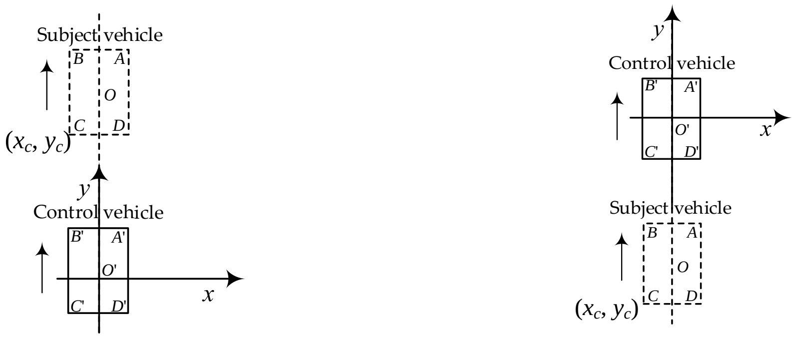
Precondition: $\alpha \neq 0$ & $y_C \leq y_{C'} - \frac{l_n}{2}$ & $-\frac{w_n}{2} \leq x_C \leq x_{D'}$

(g) Forward collision (D' –AB and A –$C'D'$)



Precondition: $\alpha \neq 0$ & $y_C \leq y_{C'} - \frac{l_n}{2}$ & $x_{C'} - w_n \leq x_C < -\frac{w_n}{2}$

(h) Forward collision (D' –AB and A –$C'D'$)



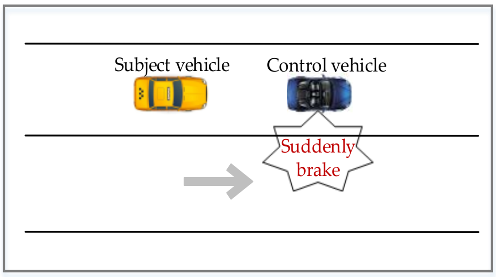
Precondition: $\alpha = 0$ & $-\frac{3w_n}{2} \leq x_c \leq \frac{w_n}{2}$ & $y_c > \frac{l_i}{2}$

(i) Rear-end collision

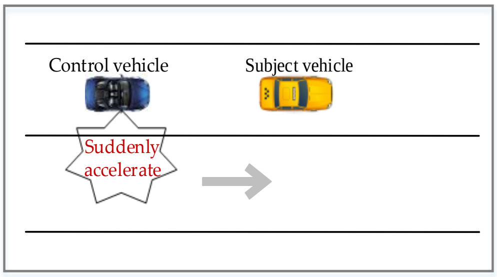
Precondition: $\alpha = 0$ & $-\frac{3w_n}{2} \leq x_c \leq \frac{w_n}{2}$ & $y_c < -\frac{l_i}{2} - l_n$

(j) Forward collision

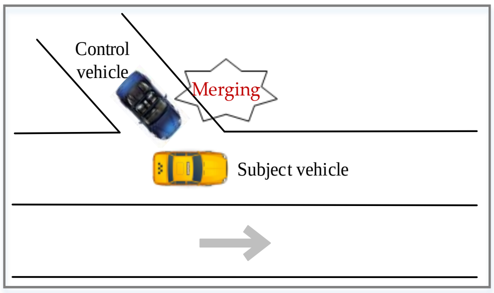
Figure 2 Illustrations of the position relationship of the two instrumented vehicles and collision types



(a) Forward collision scenario

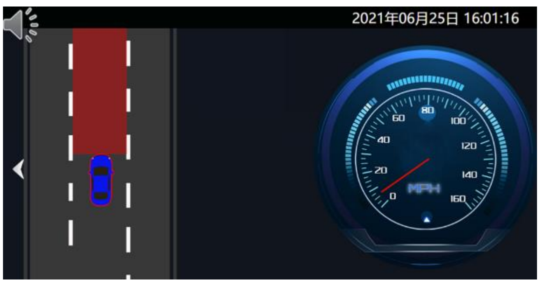


(b) Rear-end collision scenario



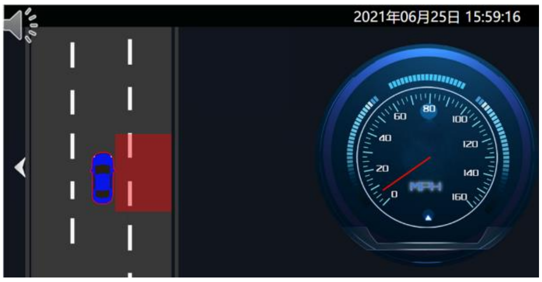
(c) Lateral collision scenario

Figure 3 Triggering events (of control vehicle) for the collision warnings



(a) Forward collision warning

(b) Rear-end collision warning



(c) Lateral collision warning

(d) Position of in-vehicle human machine interface

Figure 4 Layout and position of the in-vehicle human machine interface

Figure 4 illustrates the HMI of in-vehicle OCWS and the position of HMI. As shown in Figure 4(a), 4(b) and 4(c), collision warnings are shown on the left-hand side of the display screen. On the other hand, the speedometer is shown on the right-hand side. As shown in Figure 4(d), the HMI is located in the middle of the windscreen, i.e., on the right-hand side of the driver (left-hand driving rule is adopted in China Mainland). This is consistent with that of preceding study (Jeong et al., 2013). Results of a preliminary test indicated that drivers' view would be blocked when the HMI is located in the front of the drivers (Zhao et al., 2019c). In this study, drivers' responses to two warning types: (i) visual only (speaker switched off), and (ii) visual plus auditory (speaker switched on), are investigated (Peter et al., 2014; Zhao et al., 2019c). For the visual only warning, a red rectangle is displayed in the screen, indicating the position of collision point, either forward, rear, and lateral (left and right), with a conflict vehicle (i.e., the control vehicle that is connected with the subject vehicle). For the visual plus auditory warning, in addition to the screen display, a beeping sound at a frequency of 50Hz is disseminated.

(a) Global Navigation Satellite System

(b) Dedicated Short Range Communication

(c) Ford Focus

Figure 5 Illustration of equipment and instrumented vehicles

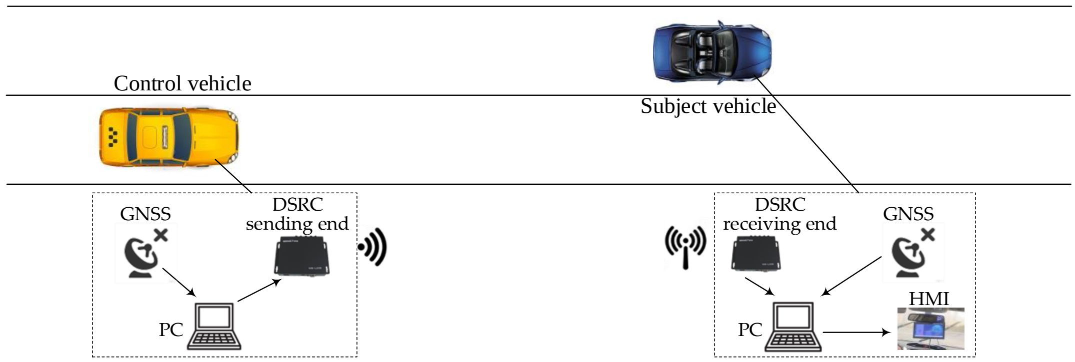


Figure 6 Data transmission of OCWS and HMI

Figure 5 illustrates the equipment to be fit on the subject and control vehicles that are "connected". In particular, the two instrumented vehicles are equipped with Global Navigation Satellite System (GNSS), Dedicated Short Range Communication (DSRC) devices, and personal computers (PCs) (see Figure 5(a) and 5(b)). The DGNSS mode of the CHCNAV P3 GNSS is used in this study. Accuracy of positioning is 0.4 m + 1 ppm and that of speed measurement is 0.1 km/h, respectively. Figure 5(c) shows the two instrumented vehicles. In particular, car model - Ford Focus is used. As shown in Figure 6, for the control vehicle, the PC processes the data collected from GNSS, and transmit the information on the position, speed, and acceleration and heading angle of the control vehicle, to the subject vehicle through the DSRC devices. Together with the data gathered from GNSS of the subject vehicle, relative position, velocity, and acceleration of two vehicles and interacting angle between two vehicles in their moving direction are determined by the PC of the subject vehicle. Then, collision warnings will be activated and shown on the in-vehicle HMI depending on TTC, TTC_s, and points of contact of the two "connected" vehicles.

4. Experimental Design

4.1 Test track

In this study, field tests were carried out at the test bed for connected and autonomous vehicles of Ministry of Transport National Closed Field Test Base of Autonomous Driving at Chang'an University, Xi'an, China. Figure 7 illustrates the test track for the experiment. The test track is an undivided two-way two-lane roadway. Total length is 1.6 km and road width is 7.5 m. There are three horizontal curves, two of which have a radius of 50 m and length ranging from 140 m to 160 m. Length of the remaining curve ranges from 70 m to 80 m, and the radius is 30 m. Speed limit of the test track is set at 60 km/h.

Figure 7 Test track for the experiment

4.2 Driving scenarios and experimental design

Figure 8 presents six schemes of experiments developed for this study using the aforementioned test track. In each scheme, the driving distance is about 3.2 km (i.e., driving through the track circuit twice). Also, three collision warnings are presented in each scheme. Six collision warning scenarios (i.e., 3 collision types X 2 warning types) are investigated, and each participant is asked to complete two schemes. For example, the speaker is switched off when the first scheme is used (i.e., visual only), and switched on when using the second scheme (i.e., visual plus auditory). Each participant consumes around 20 minutes to complete the experiment. It includes the briefing and introduction of HMI, familiarization of the operation of test vehicle, and the main driving tests. To avoid learning effect, within-subject design is adopted and two out of six experiment schemes are randomly assigned for each participant.

In each trial, the participant would be asked to complete two schemes and drive the subject vehicle along the right lane at a speed no more than 60 km/h. For the subject vehicle, rear-end collision warnings would occur when the control vehicle quickly approaches from the rear of subject vehicle. Lateral collision warnings would occur when the control vehicle approaches from the side. Forward collision warnings would occur when the control vehicle suddenly decelerates in the front.

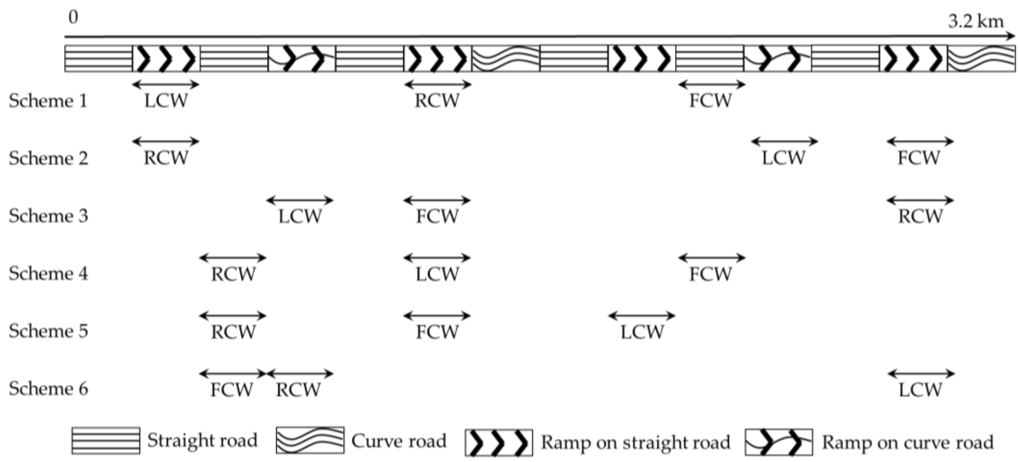


Figure 8 Six schemes of experiments

4.3 Participants

51 participants have completed the trials. Inclusion criteria of the participants are: (1) holding a valid driving license; (2) have experience of driving on the freeway; and (3) have good physical health. In addition, written consent is obtained and an honorarium of RMB 80 is given for the participation. Table 1 illustrates the distributions of the participants. Majority of the participants are male (86.3%) and half of participants hold a valid driving license more than 6 years. Average age is 34.3 years. In addition, 45.1% of participants drive more than 10 thousand km per year.

Table 1 Description of 51 participants

Variable	Attribute	Number	Percentage
Gender	Male	44	86.3%
	Female	7	13.7%
Age	18-29 years	24	47.1%
	30 years or above	27	52.9%
Occupation	Professional drivers	7	13.7%
	General driver	44	86.3%
Education level	Secondary education or below	22	43.1%
	Tertiary education	29	56.9%
Years of driving experience	6 years below	26	51.0%
	6 years or above	25	49.0%
Annual driving distance	10 thousand km below	28	54.9%
	10 thousand km or above	24	45.1%

51 participants have participated in the test and each participant has completed one trial. As shown in Table 2, 258 valid observations are captured.

Table 2 Number of warning scenarios

	Forward collision	Rear collision	Lateral collision	Total
Visual only	43	41	45	129
Visual plus auditory	43	41	45	129
Total	86	82	90	258

5. Methodology

In this study, effects of collision types and warning types including (i) visual warnings only, and (ii) visual plus auditory warnings on driving performance are investigated. In addition, intervention effects by drivers' characteristics on the association between collision types, warning types, and drivers' performance are considered. Driver performance indicators considered are relative speed change, time taken to accelerate/decelerate, and maximum lateral displacement. Generalized estimation equation (GEE) approach is adopted to examine the effects of drivers' characteristics, collision type, warning type and their interactions on driving performance. It is hypothesized that variations in driver performance among collision types and warning types are considerable. Also, driver characteristics including socio-demographics, driving experience and annual driving distance can intervene with the association.

5.1 Driving performance indicators

To assess the drivers' responses to collision warnings, driving performance indicators including relative speed change, time taken to accelerate/decelerate, and maximum lateral displacement are considered. Also, as the perception-reaction time of drivers to any collision warnings is about 1.5 seconds (Bella and Sivestri, 2017). Information on the (longitudinal and lateral) position, speed, and acceleration of the subject vehicle within 2.5 seconds after the activation of OCWS is used for the calculation.

In conventional road safety studies, mean and standard deviation of speed were used to indicate driving safety (e.g., Wang and Wang, 2018; Chen et al., 2022). However, they are not capable of indicating the strength of drivers' responses. To this end, relative speed change is adopted to infer the drivers' perception for the anticipated collision risk and strength of drivers' response (Zhao et al., 2019c; 2021b). Also, strength of response is positively correlated to drivers' perception (Zhao et al., 2019c). Relative speed change given as follows is estimated,

$$P_s = \begin{cases} \frac{v_0 - v'}{v_0} \times 100\%, v' = v_{min} \\ \frac{v' - v_0}{v_0} \times 100\%, v' = v_{max} \end{cases} \quad (1)$$

where v_0 denotes the speed of the subject vehicle when OCSW is activated; v' is the maximum speed of the subject vehicle within 2.5 seconds after the activation of OCWS for rear-end and lateral collision (control vehicle not visible), or the minimum speed within 2.5 seconds for forward and lateral collision (control vehicle visible). Negative value of P_S implies unanticipated responses of the drivers.

Time taken to accelerate/decelerate can infer the perception-response time of drivers (Wu et al., 2018; Wang et al., 2021; Hang et al., 2022). For instance, it refers to the time between the activation of collision warnings and the attainment of deceleration rate reduced by 25% (when control vehicle is visible) or acceleration rate increased by 25% (when control vehicle is not visible). A smaller value of time taken to accelerate/decelerate infers a quicker response. If a driver does not respond, a maximum value of 2.5 seconds is assigned.

Maximum lateral displacement can infer the lateral stability of locomotor function of drivers (Rosey et al., 2008; Pitt and Sarter, 2018; Pawar et al., 2022). Maximum lateral displacement is negatively correlated to the capability of drivers' control. Note that lane changing is not considered as lateral displacement. When displacement is greater than half width of road (1.875 m), the drivers are considered to have changed the lane.

5.2 Statistical analysis

In this study, Generalized Estimation Equation (GEE) approach is used to measure the relationship between driving performance indicators and possible factors. As an extension of the generalized linear (GLM) approach, GEE approach relaxes the assumption of dependent variables (Liang and Zeger, 1986). For example, GEE approach is capable of unbalance panel data. GLM approach requires the dependent variables to be independent and exponentially distributed. For the GEE model, Quasi-likelihood Estimation Method is used to estimate the parameters and the working correlation matrix is used to capture the correlation attributed to multiple observations. The GEE model is given by,

$$u_i = E(Y_i) = g(X_i\beta) \quad (2)$$

where Y_i denotes the continuous dependent variables following a Gaussian distribution of driver i; u_i is the expected value of Y_i; X_i is the matrix of covariates of driver i; β is a vector of estimated coefficients; g is a function which reflect the relationship between Y_i and X_i.

Coefficients β are calculated using a set of k differential equations with quasi-likelihood estimator. It is given by,

$$U_k(\beta) = \sum_{i=1}^{N} \frac{\partial u_i}{\partial \beta_k} V_i^{-1}(Y_i - u_i) = 0 \quad (3)$$

where V_i represents a covariance matrix for a given Y_i. It can be expressed by

$$V_i = \sigma^2[(1-\rho)I + \rho J) \quad (4)$$

where σ is the standard deviation; I is a $N \times N$ identify matrix for the working correlation. J is a $N \times N$ matrix with all elements that equal to 1. ρ is the correlation coefficient for repeated measurements of dependent variables.

GEE model can accommodate different types of correlation structure, including independent, exchangeable, k-dependent, autoregressive, Toeplitz and unstructured. To select an appropriate matrix, the quasi-likelihood information criterion (QIC) proposed by Pan (2001) is used. Such approach has been applied both in theory and practice (Chiou et al., 2020; Hang et al., 2022). In this study, an exchangeable correlation structure is assumed based on the smallest QIC values. In this study, the geeglm function in R 4.0.2 is used.

6. Results

6.1 Relative speed change

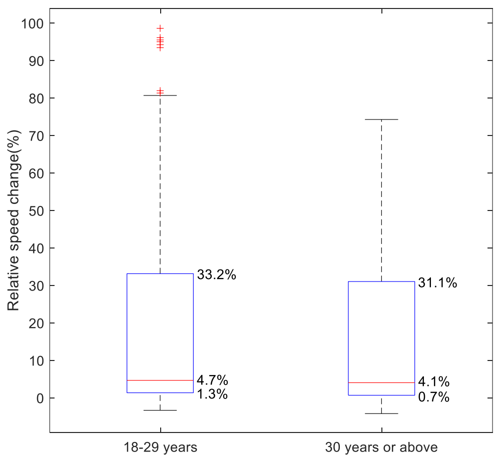
Based on 258 observations, the GEE model is developed to explore the effects of drivers' characteristics, collision type, warning type and their interaction on their relative speed change. Table 3 shows the results of parameter estimates for relative speed change.

Table 3. Results of parameter estimation for relative speed change

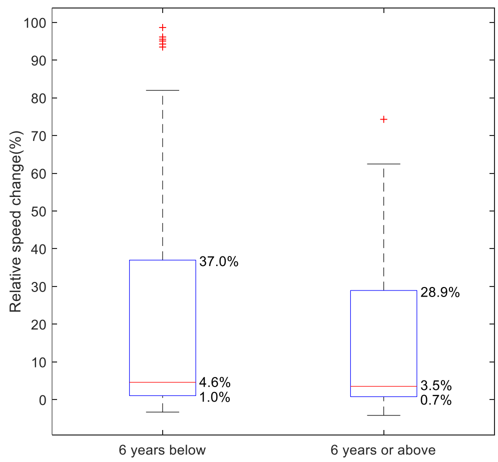
Variable	Coefficient	S.D.	Wald
Constant	0.50	0.05	105.15**
Age 30 or above	-0.05	0.02	4.60*
6 years or more driving experience	-0.12	0.05	6.25*
Visual plus auditory warning	0.01	0.01	0.61
Rear-end collision	-0.48	0.05	112.15**
Lateral collision	-0.42	0.05	83.45**
Years of driving experience * Rear-end collision	0.16	0.06	7.19*
Years of driving experience * Lateral collision	0.15	0.06	5.76*
QIC	22.33		

** at the 1% level of significance; * at the 5% level of significance

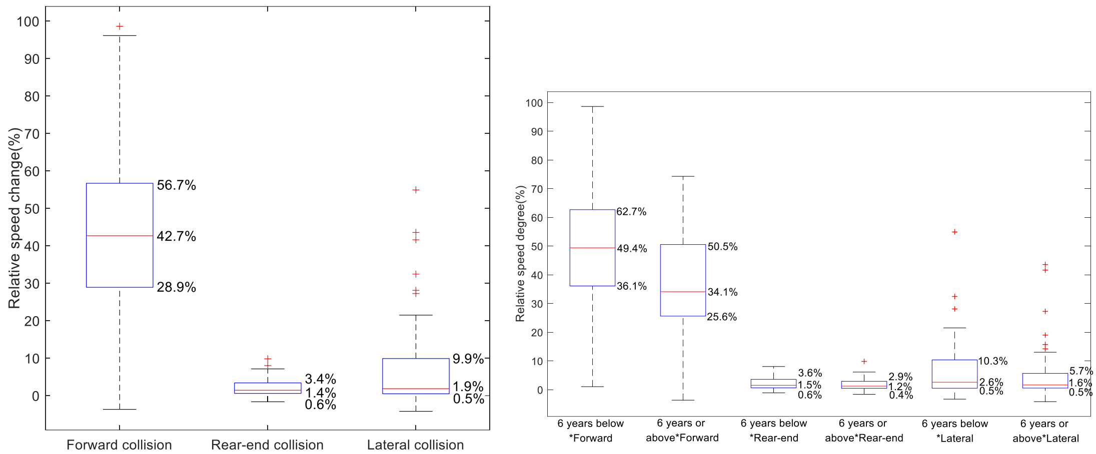
As shown in Table 3, relative speed change is negatively associated with age and driving experience, at the 5% level of significance. Also, relative speed change for rear-end collision and lateral collision are lower than that for forward collision, at the 1% level of significance. Furthermore, driving experience can modify the association between relative speed change and collision type, at the 5% level of significance. Figure 9 illustrates the box plots for relative speed change with respect to different factors. As shown in Figure 9(c), difference in relative speed change among different collision type is remarkable. Furthermore, as shown in Figure 9(d), modifications by years of driving experience on the relationship between relative speed change and collision type are remarkable.



(a) Age



(b) Years of driving experience



(c) Collision type (d) Years of driving experience X collision type

Figure 9 Box plots for relative speed change

6.2 Time taken to accelerate/decelerate

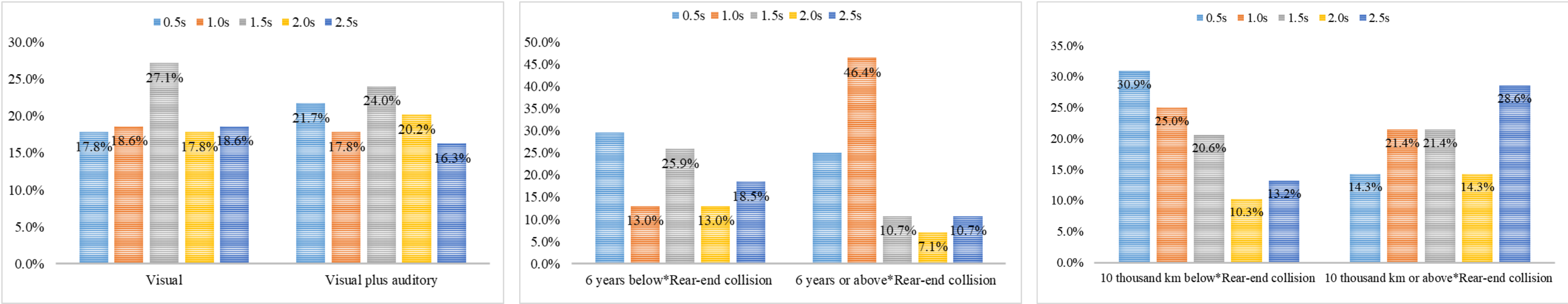
258 observations are used to analyze the effects of drivers' characteristics, collision type, warning type and their interaction on their time taken time to accelerate/decelerate using the GEE model. Table 4 shows the results of parameter estimation for time taken to accelerate/decelerate.

As shown in Table 4, time taken to accelerate/decelerate is affected by warning type, at the 5% level. Just, no significant effect can be found for driving experience, annual driving distance, and collision type. Furthermore, collision type can modify the association between time taken to accelerate/decelerate and driving experience, annual driving distance, and warning type, at the 5% level of significance. Figure 10 illustrates the distribution of time taken to accelerate/decelerate with respect to warning type and possible interaction effects.

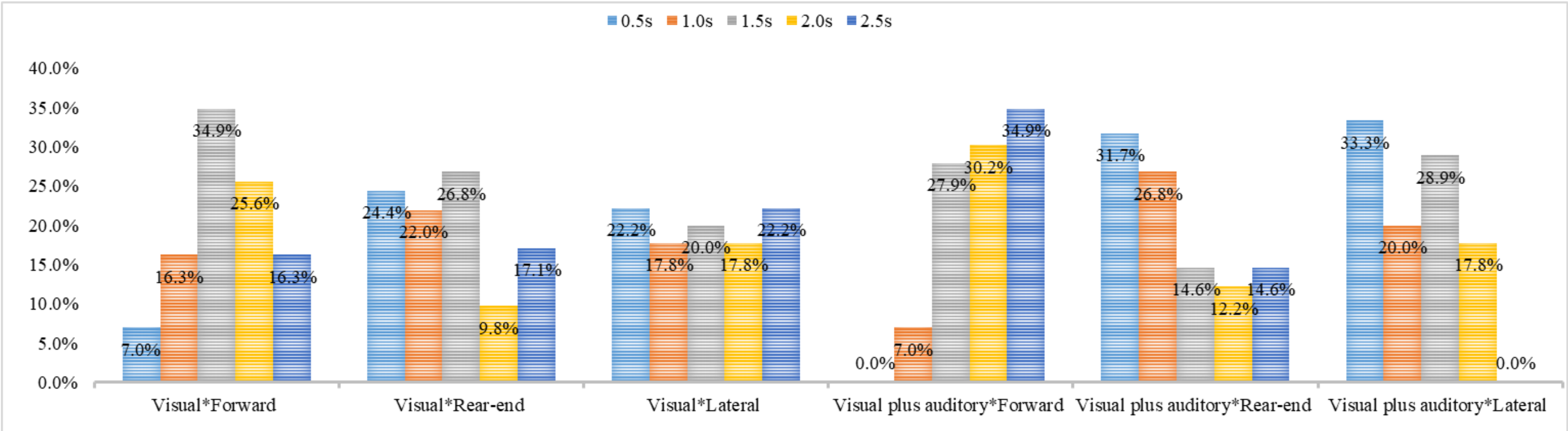
Table 4 Results of parameter estimation for time taken to accelerate/decelerate

Variable	Coefficient	S.D.	Wald
Constant	1.67	0.10	310.36**
6 years or more driving experience	-0.05	0.08	0.44
Annual driving distance (10 thousand km or above)	-0.06	0.13	0.21
Rear-end collision	-0.28	0.16	2.94
Lateral collision	-0.14	0.14	1.01
Visual plus auditory warning	0.33	0.11	8.73*
Years of driving experience * Rear-end collision	-0.24	0.11	4.69*
Annual driving distance * Rear-end collision	0.49	0.12	16.89**
Warning type * Rear-end collision	-0.44	0.20	4.90*
Warning type * Lateral collision	-0.67	0.17	15.34**
QIC	115.57		

** 1% level of significance; * 5% level of significance



(a) Warning type (b) Years of driving experience x rear-end collision (c) Annual driving distance x rear-end collision



(c) Warning type x collision type

Figure 10 Distribution of time taken to accelerate/ decelerate

6.3 Maximum lateral displacement

11 observations are excluded because of lane changing. These include 10 observations in lateral collision scenarios and 1 observation in forward collision scenarios. 247 observations were used in the GEE model to explore the effects of drivers' characteristics, collision type, warning type, and their interaction on the maximum lateral displacement. Table 5 presents the results of parameter estimation for maximum lateral displacement.

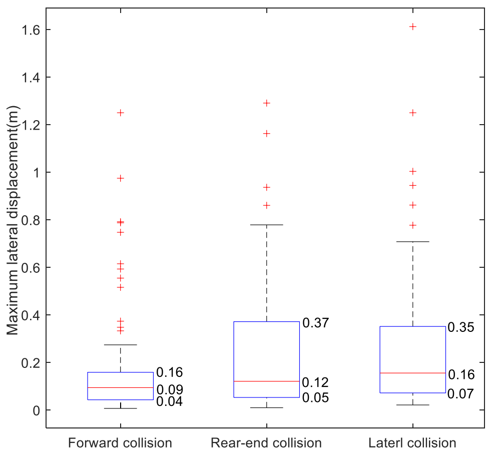
Table 5 Results of parameter estimation for maximum lateral displacement

Variable	Coefficient	S.D.	Wald
Constant	0.38	0.14	8.07*
6 years or more driving experience	0.10	0.06	3.04
General drivers	-0.22	0.14	2.85
Rear-end collision	0.12	0.05	7.23*
Lateral collision	0.10	0.04	5.58*
Visual plus auditory warning	-0.29	0.11	6.72*
Years of driving experience * Rear-end collision	-0.12	0.06	4.12*
Years of driving experience * Warning type	-0.14	0.06	5.58*
Driver occupation * Warning type	0.26	0.11	5.47**
QIC	37.32		

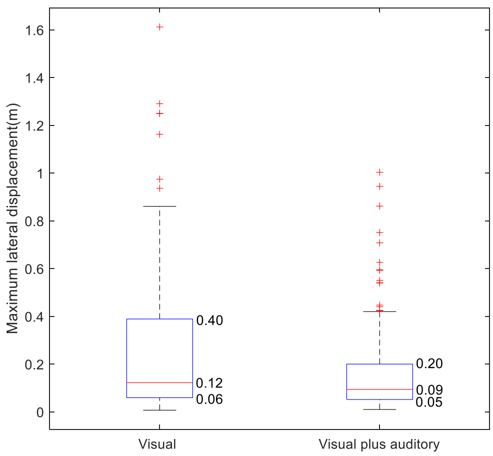
** 1% level of significance; * 5% level of significance

As shown in Table 5, maximum lateral displacement for rear-end collision and lateral collision are higher than that for forward collision, at the 5% level. In contrast, maximum lateral displacement for visual plus auditory warning is lower than that for visual only warning, at the 5% level. Furthermore, driving experience can modify the relationship between maximum lateral displacement and collision type and warning type. Last but not least, driver occupation can modify the relationship between maximum lateral displacement and warning type.

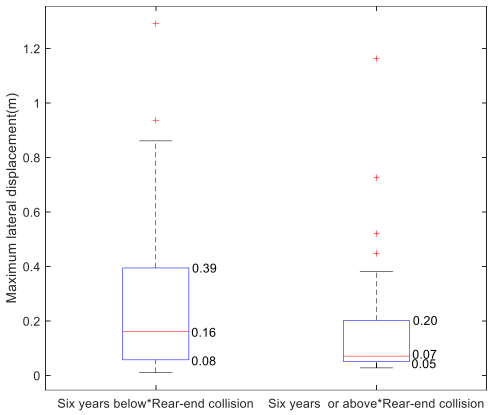
Figure 11 illustrates the box plots for maximum lateral displacement. As shown in Figure 11, variations in the range of maximum lateral displacement are remarkable among different collision types (Figure 11(a)), warning types (Figure 11(b)), driving experience x rear-end collision (Figure 11(c)), driving experience x warning type (Figure 11(d)), and driver occupation x warning type (Figure 11(e)).



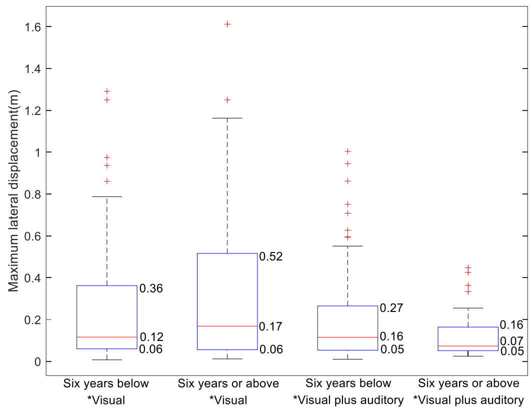
(a) Collision type



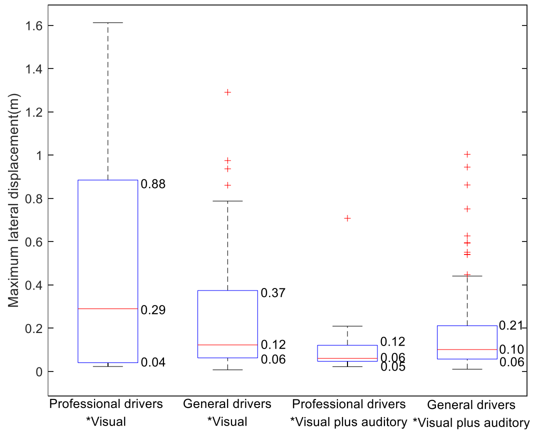
(b) Warning type



(c) Years of driving experience x rear collision



(d) Years of driving experience x warning type



(e) Driver occupation x warning type

Figure 11 Box plots for maximum lateral displacement

7. Discussions

7.1 Effects of warning type and collision type

Warning type significantly affects driving performance. Such finding is consistent with that of previous studies (Ali et al., 2020; Zhang et al., 2022). Although aided auditory warnings may induce distraction, proportion of drivers who could reach the anticipated deacceleration/deceleration rate within 2 seconds increases when auditory warnings are applied (in addition to visual warnings only). This may be because auditory signals are more effective in drawing the attention of drivers, especially in emergency, as compared to visual stimulus (Engström et al., 2005). This aligns with the results of previous studies (e.g., Liu and Jhuang, 2012; Biondi et al., 2017) for the reduction of brake reaction time with the use of auditory warnings. Indeed, drivers in general prefer combined mean of information dissemination (Liu and Jhuang, 2012; Biondi et al., 2017). Hence, driving performance can be improved. In addition, maximum lateral displacement reduces when visual plus auditory warning is adopted. This may be because drivers in general take longer time to perceive the information presented in visual form (Gray et al., 2013; Haas and van Erp, 2014). Furthermore, auditory message is more effective for drawing the attention of the drivers, especially in emergency (Spence and Ho., 2008; Haas and van Erp, 2014; Wang et al., 2020).

On the other hand, collision type also significantly affects the driving performance. For example, drivers' responses tend to be more rigorous for forward collision but weaker for rear-end collision. One possible reason is that it is easier for the drivers to notice forward collision (Cummings et al., 2007; Zhao et al., 2021a). On the other hand, according to the driving regulations in China, drivers are liable when they hit the rear part of a moving vehicle in the front on the public roads. Furthermore, warning type can modify the association between drivers' time taken to decelerate/accelerate and collision type. For example, time taken to respond for rear-end and lateral collision reduce while that for forward collision increase, when visual plus auditory warning is adopted. One explanation is that it is easier to observe forward collision (Cummings et al., 2007). Another explanation is that the sound excels in grabbing drivers' attention when they are involved in potential hazards (Wang et al., 2020), especially when there is an approaching vehicle in the blind zone (Chang et al, 2009; Chen et al, 2011). Furthermore, the results support that the consistency of information content and display in HMI design should be considered (Pitts and Sarter, 2018). For example, forward collision warnings should be presented by symbols on HMI while lateral and rear-end collision warnings should be shown by symbols plus beep warnings. Additionally, among the 258 observations, drivers might have misunderstood or ignore the warnings and have unanticipated responses for about 12% of the time (1.6% for $P_s \leq -0.03$ and 10.1% for $-0.03 < P_s \leq 0$) (Zhao et al., 2021b).

7.2 Effects of driver characteristics

Drivers' age and driving experiences significantly affect the strength of drivers' responses for collision warnings. Such finding is consistent with that of previous studies (Pitt and Sarter, 2018; Yang et al., 2020; Kramer et al., 2007; Eriksson, 2019). In particular, young drivers may have stronger responses than the older drivers to the collision warnings. It could be because young drivers tend to be more sensitive to any information presented (Mahoney et al., 2011; Zhao et al., 2019a). On the other hand, experienced drivers tend to have weaker responses, in term of relative speed change and maximum lateral displacement, to the collision warnings, compared with the inexperienced drivers. This aligns with the findings of previous studies (Kramer et al., 2007; Cummings et al, 2007; Ali et al., 2020; Hang et al., 2022). This could be attributed to the higher competence of hazard detection and defensive driving skill of experienced drivers, as compared to novice drivers (Zhao et al., 2020).

Nevertheless, there is significant interaction between warning type, years of driving experience, and driving performance. For experienced drivers, driving performance is better when visual plus auditory warnings are adopted, compared to visual only warnings. This could be because the eye-off-road time can be reduced when visual plus auditory warnings are adopted (Wang et al., 2020). This is particularly true for experienced drivers since they tend to be more sensitive to auditory information disseminated through in-vehicle systems (Biondi et al., 2014). Furthermore, the result is supported by Large et al. (2019) who found that besides symbols, HMI should also provide beep warnings to experienced drivers so as to help them understand the potential dangers.

There are some limitations for this study. First, information on the perception and attitude toward collision warnings and HMI is not collected. In the future study, it is worth exploring drivers' acceptance for collision warning system and preference of information content and layout shown on HMI using attitudinal survey. Second, the distraction effects by visual and auditory warnings of HMI as well as the location of HMI are not measured. It is worth exploring drivers' distraction by the collision warnings and location of HMI using advanced technologies like eye tracking. Third, effects of environmental and traffic conditions such as adverse weather conditions and presence of other road users on the driving performance should be considered (Yang et al., 2023). For example, it is worth investigating the influences of low visibility as well as involvements of pedestrians and other vehicles on the driving performance using the driving simulator approach (Wu et al., 2018; Zhao et al., 2019c). Finally, it is not possible to distinguish among different collision types with the auditory warnings and different thresholds in the current system. In the extended study, the consistency of collision type, warning type and amount of information considering drivers' differences would be investigated (Seaman et al., 2022).

8. Conclusions

In this study, effects of collision type (forward, rear-end, and lateral collision) and warning type (visual only and visual plus auditory warnings) of in-vehicle OCWS on the driving performance in the CV environment are explored using field tests. In addition, confounding and interaction effects by driver characteristics including age, years of driving experience, and annual driving distance on the association between driving performance, collision type, and warning type are also considered. Three driving performance indicators including relative speed change, time taken to accelerate/decelerate, and maximum lateral displacement are adopted. Two instrumented vehicles equipped with GNSS and DSRC system are used to replicate the CV environment. The GEE approach is applied to model the association between driving performance and possible influencing factors.

Results show that collision type, warning type, driver age, and years of driving experience significantly affect the driving performance. Also, there are significant interactions between years of driving experience, warning type and collision type. For example, experienced drivers tend to have faster but weaker responses to the warnings, compared to inexperienced drivers. Time taken to accelerate/decelerate can be reduced when visual plus auditory warning is used, compared to visual only warning. In addition, the association between time taken to accelerate/decelerate and warning type is modified by collision type. For example, reduction in the response time taken is more profound for rear-end and lateral collision warnings than forward collision warnings when visual plus auditory warning is adopted.

Results are indicative to the future design of in-vehicle collision warning system, such as the time and threshold value of activation for different collision types (Ali et al., 2020), and optimal graphical user interface design with and without auditory messages for future CV (Kramer et al., 2007). For example, if visual only warnings are given, compared to forward collision, the 'larger' threshold value of activation should be set for lateral and rear-end collision. Also, HMI should provide only visual warnings for forward collisions but provide visual plus auditory warnings for lateral and rear-end collisions. Furthermore, optimal information content and user interface design could be implemented with respect to the personal characteristics including age and driving experience of drivers. For example, auditory warnings such as beep warnings should be given to experienced drivers (Adell et al., 2008; Chen et al., 2021).

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