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Investigating work-related distraction's impact on male taxi driver safety: A hazard-based duration model

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ABSTRACT

With the increasing use of phone-based ride-hailing apps, concerns have arisen regarding road safety and driver distraction. Despite the recognized safety risks of driver distraction, limited research has explored how distractions from various ride-hailing systems affect drivers in the taxi industry. To close this gap, the current research utilized a driving simulator experiment involving 51 male taxi drivers in two road environments (urban street and motorway) and three distracted driving conditions (no distraction, auditory distraction via radio dispatching system, and visual-manual distraction via mobile application). A car-following scenario with sudden brake events was incorporated into the experiments because this is a typical safety–critical situation where attention will determine the outcome. The collected performance indicators include brake reaction time, time headway, and car-following distance. The grouped random parameters Weibull accelerated failure time model was applied to model the duration data under different road conditions. The brake reaction time and time headway are dependent variables, while the car-following distance is a covariate in the models. The results indicate that although taxi drivers show longer brake reaction time when distracted by mobile app and radio system, this does not necessarily equate with greater risk or reduced safety since they compensate for the risk of rear-end crashes by maintaining a longer time headway. In general, taxi drivers' brake reaction time and time headway are more profoundly affected by mobile apps when distracted in both urban and motorway scenarios. This highlights the elevated risks associated with such technologies. In addition, significant interaction effects revealed the observed heterogeneity, which suggests that drivers' personal characteristics influence the relationship between distraction type and driving performance. This research provides valuable insights for designing safer ride-hailing operations and systems.

1. Introduction

In recent years, ride-hailing platforms, also known as ride-sharing or on-demand platforms, have become a popular way to match passengers with drivers. Such platforms generally operate with a mobile app where passengers book and request service, and a driver is

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matched based on proximity and availability. Contreras and Paz (2018) reported that by 2018, more than 66 countries were served by ride-sharing platforms such as Uber and DiDi, impacting the traditional taxi industry. In the past, taxi drivers in Hong Kong have relied on radio communication systems to pick up passengers. These services are facilitated by radio dispatch systems (Yang et al., 2000). However, the pressures of ride-hailing services have also led to a digitization of services through pickup apps, which have increased the competitiveness of the taxi industry.

In the taxi industry, mobile app platforms have resulted in notable benefits, including increased revenues for taxi drivers and improved efficiency (Chan et al., 2016). Nevertheless, these mobile phone-based apps increase opportunities for distraction among drivers, as they are required to multitask while driving, using their vision and hands for tasks such as confirming orders, checking routes, conversing with customers, and reading messages (Ansar et al., 2021). Previous radio technology relied heavily on auditory distractions, so it is important to analyze how these technologies could impact road safety. Notwithstanding, by engaging in both radio and app-related distractions while driving, the driver's attention is diverted from the road and primary tasks, thereby increasing the risk of a collision (Oviedo-Trespalacios et al., 2016; Zhang and Kaber, 2016). As a result, radio and mobile app-based taxi services compete for market share and bring unique distractions (auditory and visual-manual) for taxi drivers, which calls for a thorough investigation.

The Hong Kong Transport Department reports that the taxi industry accounts for 7.4 % of the total share of public transportation in the city. In spite of this, taxis have the highest crash rate among different modes of transportation, accounting for 22.2 % of traffic crashes and 24.0 % of road injuries in the year 2020 (Transport Department, 2020, 2021). For transport governance groups, the taxi industry, and platform developers, ensuring safety and minimizing potential hazards, such as distractions from ride-hailing and pick up apps, becomes increasingly imperative.

In light of the above, this study aims to investigate the distraction effects of various ride-hailing systems (radio system and mobile app) on the driving performance of taxi drivers in Hong Kong. Due to their ability to account for the duration dependence, which arises from the relationship between the probability of an event ending soon and its duration, hazard-based duration models have become increasingly popular. In this paper, dynamics of driving performance including brake reaction time and time headway were set as duration variables. Also, unobserved heterogeneity can be address based on random parameter approach (Bhat and Pinjari, 2007; Hojati et al., 2013). In contrast to previous studies on distraction, this research will focus on several key aspects: (1) Comparing the effects of distractions associated with different hailing systems (radio system and mobile app) on taxi drivers' performance, specifically brake reaction time and time headway; (2) Confirming the risk compensatory behavior exhibited by taxi drivers when exposed to different ride-hailing systems. (3) Exploring the safety effects of the interaction between the type of distraction and driver characteristics on their driving performance.

2. Literature review

Driver distraction occurs when the driver's attention is diverted to non-driving-related tasks while in control of a vehicle, reducing their ability to focus on the primary driving task at hand (Klauer et al., 2006). Many studies have investigated driver distraction as a contributing factor to road traffic crashes (Oviedo-Trespalacios et al., 2016; Zhang and Kaber, 2016). In recent years, the emergence of ride-hailing services has introduced new potential distractions for drivers as these platforms involve various multitasking activities alongside driving (Chen et al., 2022; Nguyen et al., 2023, 2024; Xing et al., 2023). However, the comprehensive understanding of the impact of these distractions is still lacking. Additionally, it is crucial to acknowledge that the impact of distraction on drivers is heavily influenced by the type of secondary task involved (Baddeley, 1992; Wickens, 2002). Therefore, a deeper exploration of these new distractions is essential to grasp their implications fully.

Interestingly, in Hong Kong, the hailing systems available to taxi drivers can be classified into two categories according to their multitasking requirements: radio-based dispatch systems and mobile app-based systems. Drivers may face different distraction challenges depending on the system they use. The radio system mainly involves non-visual distractions, impacting auditory and cognitive functions without diverting visual attention. This system operates by connecting taxi drivers and passengers through a radio controller, where the driver receives passenger requests and relevant information for pick-up and drop-off locations via Chen et al. (2022). Yet, previous studies proposed that a driver's performance could be impaired by repetitive auditory distractions from broadcasts or other audio-related tasks which compete for the driver's ability to process visual information (Karthaus et al., 2020; Sonnleitner et al., 2014). The particular impact of work-related broadcasting (pickup orders) on taxi drivers has, however, been relatively unexplored, despite evidence from previous studies that other auditory sources such as phone conversations and music may negatively affect performance (Ali and Haque, 2023b; Haque and Washington, 2014; Saifuzzaman et al., 2015).

On the other hand, the mobile app system primarily introduces visual distractions, as it requires drivers to perform visual tasks on their mobile devices while driving. Distractions of this nature divert a driver's attention from the road, which can result in significant safety hazards (Wickens, 2002). Indeed, previous studies have confirmed that visual distractions affect driving performance more than auditory distractions (Liang and Lee, 2010; Oviedo-Trespalacios et al., 2016; Regan and Oviedo-Trespalacios, 2022). However, there has been little investigation about the impact of taxi drivers using work-related mobile apps (touching the button to confirm an order, checking the route, speaking with the customer, reading the response message, etc.). Only one recent study has examined the effects of work-related distractions on drivers' lateral movements, steering, and speed control when using auditory systems and mobile apps (Chen et al., 2022) but much is still unknown about how drivers using these apps react to emergent safety–critical situations on the road. In this context, a comprehensive investigation is necessary to understand the safety effects of these two hailing systems on taxi drivers' driving behaviour, given the differences in distraction types introduced by them.

As for the driving performance indicators, previous studies identified that distracted drivers' reaction times are affected by sudden hazardous situations that require prompt braking. It is often used to evaluate the impact of various distracting factors, including those induced by mobile devices, on reaction times (Ali and Haque, 2023b; Haque and Washington, 2014; Oviedo-Trespalacios et al., 2016; Oviedo-Trespalacios et al., 2019). Overall, drivers using handheld mobile phones present longer reaction times to sudden events compared to those driving hands-free. Moreover, recent research has suggested that when investigating the relationship between driver distraction and reaction time, the characteristics of the driver should be considered (Ali and Haque, 2023b).

Alongside brake reaction time, another vital measure is the 'time headway,' which describes the safety margins in potentially dangerous situations. A rear-end collision may occur if a distracted driver fails to maintain a safe distance during car-following situations, especially when the leading vehicle suddenly brakes (Li et al., 2019). Previous research has demonstrated that drivers often adopt compensatory strategies to avoid hazards when facing risky situations, such as increasing the car-following distance and adjusting their speed (Chen et al., 2020b; Chen et al., 2022; Li et al., 2019; Oviedo-Trespalacios et al., 2020). Notably, one recent study found that professional drivers are more capable of utilizing risk-compensating strategies than non-professionals (Chen et al., 2021b). Thus, exploring the compensation strategies employed by taxi drivers is of particular interest, as the effectiveness of such strategies may vary in different distraction scenarios. This is an interesting and important topic that remains largely unexplored.

Time-based duration data such as those mentioned above can be analyzed using hazard-based duration models. This model has been extensively used in many transportation studies. For example, there are a variety of forms of time duration formed in traffic incidents, such as highway closure duration (Hojati et al., 2013; Jones et al., 1991; Nam and Mannering, 2000; Chung, 2010), and traffic congestion time (Kang and Fang, 2011; Paselk and Mannering, 1994; Stathopoulos and Karlaftis, 2002). In addition, the duration model has been widely used in travel behavior research to measure departure time preferences and perceptions of waiting times (Frejinger and Bierlaire, 2007; Hamed and Mannering, 1993; Mannering and Hamed, 1990; Sasic and Habib, 2013). In recent years, duration models have gained increasing prominence in modeling driving behavior metrics. Notable examples include the brake reaction time and time headway described above (Ali et al., 2022a; Ali et al., 2020a; Ali and Haque, 2023a; Ali et al., 2022b; Ali et al., 2019; Haque et al., 2021; Haque and Washington, 2014;). It has the advantage of being able to examine the relationship between various exogenous variables (driver characteristics, safety perception, and driving history) and the duration variables, in contrast to the descriptive methods such as Analysis of Variance (ANOVA) (Bellinger et al., 2009; Calvi et al., 2018; Spyropoulou and Linardou, 2019; Yannis et al., 2014). In addition, when compared with linear regression models (Bella and Russo, 2011; Jurecki and Stańczyk, 2014), hazard-based duration models are capable of predicting the length of duration under the influence of various exogenous factors. Furthermore, the probability curve for the duration variable can be plotted to demonstrate its shape and monotonicity, and thus safety critical situations (higher probability of failing to react to the sudden brake) can be identified.

Another critical aspect is the need to address observed and unobserved heterogeneities. Firstly, unobserved heterogeneity results from unobserved factors that cannot be captured by covariate effects on the duration variable, particularly for repeated measurements. Studies have found that ignoring unobserved heterogeneity can result in biased estimates of external covariate effects (Bhat and Pinjari, 2007; Heckman and Singer, 1984; Washington et al., 2020). Therefore, in order to accommodate unobserved heterogeneity, the hazard-based duration approach should be extended to incorporate shared frailty and clustered heterogeneity (Ali et al., 2020b; Ali et al., 2019; Haque and Washington, 2014; Hui, 1990; Nam and Mannering, 2000; Washington et al., 2020), or random parameters approach (Ali and Haque, 2023a; Ali and Haque, 2023b; Ali et al., 2022b; Mannering et al., 2016; Jordan et al., 2019, Washington et al., 2020, Zeng et al., 2023). Within the framework of the random parameter approach, correlated random parameters are employed not only to address unobserved heterogeneity but also to capture potential interactions between the variables in the model. Allowing for correlation in the random parameters accommodates complex relationships among unobservable factors, extending the model's ability to reflect nuanced real-world scenarios (Mannering et al., 2016). Previous studies have shown that incorporating random parameter correlations can reduce estimation bias and provide more insightful results (Balusu et al., 2020; Mannering et al., 2016; Jordan et al., 2019, Washington et al., 2020). Secondly, interaction effects have also been investigated to uncover observed heterogeneity (Calvi et al., 2018). In the context of a statistical model, interaction is a term denoting a non-additive effect of two (or more) variables. Simply put, the combined effect of factor X and factor Y is not equal to the sum of their individual effects. As such, interaction effects pertain to the alteration of the impact of one independent variable on the dependent variable in the presence of a second independent variable. This alteration may manifest as a moderating effect (mitigation) or an intensified effect (magnification). The failure to consider such interactions could result in suboptimal model performance (Chen et al., 2021a; Chen et al., 2020a; Kim and Mokhtarian, 2023). Studies have highlighted the importance of addressing observed individual heterogeneity in order to identify more specific policy implications (Lavieri and Bhat, 2019; Chen et al., 2021b).

Concerned by the gaps evident in the studies mentioned above, our research endeavors to address these critical deficiencies in the current literature. Firstly, taxi drivers have a notably high crash rate, which requires attention and thorough examination. Secondly, using different ride-hailing systems (taxi radio and mobile app), we intend to investigate the work-related distraction effects. Thirdly, as part of our study, we intend to confirm the risk compensatory behavior exhibited by taxi drivers when exposed to different ride-hailing systems. Lastly, the interaction effects between taxi drivers' characteristics and distraction types (the observed heterogeneity) on their driving behavior, will be incorporated in our analysis. It is crucial to remember that taxi drivers differ from typical drivers; they spend extended periods on the road, meticulously honing their understanding of risks. By filling these gaps, our goal is to provide useful insights to improve road safety and understand how ride-hailing systems affect taxi drivers' driving performance.

3. Method

3.1. Experimental design

The present investigation employed the fixed-base driving simulator system (OKTAL's CDS-650) from the Hong Kong Polytechnic University, as depicted in Fig. 1. The simulator system consists of essential components, including a force feedback steering wheel, a dashboard, and three pedals (clutch, brake, and throttle). Moreover, the setup incorporates three 32-inch high-resolution LED screens and a sound system. To enhance the authenticity of the driving environment, a simulation platform (SCANeR studio) was used to create a comprehensive graphical environment, which incorporated elements such as the road network, traffic signs and road markings, road surface conditions, surrounding surroundings, and vehicular traffic, replicating real-world conditions. Throughout the simulator experiment, meticulous records were kept of the driving performance data, which encompassed vehicle position (both lateral and longitudinal), driving speed, and pedal forces relevant to braking events. These data points were recorded at a frequency of 100 Hz, corresponding to a 0.01-second interval.

The experimental protocol, as illustrated in Fig. 1, served as the foundation for the present study. In the pre-experimental phase, every participant was required to fill a questionnaire prior to the formal driving experiment. A variety of information about personal characteristics, safety perception, and driving history was collected. Subsequently participants took a 10-minute driving practice to familiarize themselves with the driving simulator and the ride hailing system (including radio system and mobile application). During the formal experiment, 4 of the 55 taxi drivers who initially were recruited to participate in the experiment suffered from the sickness syndromes of driving simulator. Finally, a total of 51 participants data were utilized for further analysis (Chen et al., 2022).

It is pertinent to mention that a segment of the experimental data was previously utilized to explore the driving performance, encompassing aspects such as lateral control skills and compensatory behavior, among distracted drivers engaged in free-flow driving and car following tasks (Chen et al., 2022). However, it is worth noting that the specific examination of drivers' distracted braking behavior during sudden brake events remains unexplored in the existing literature. As such, the current investigation aims to fill this research gap by focusing exclusively on this aspect.

A series of six driving trials were conducted for each participant in this study, including one sudden brake event under each road environment and distraction type. Driving simulators offer two distinct road environments, including urban streets and motorways, as shown in Fig. 1. Hong Kong-specific road designs, traffic signs, streetlights, vehicle models, and buildings were incorporated into the simulation (Chen et al., 2022; Chen et al., 2019; Chen et al., 2021b). Speed limits on urban streets were 50 kph, and 80 kph on motorways. Three types of distractions were introduced in the present study to examine the impact of ride-hailing distractions: (1) no distraction (baseline condition), (2) distraction by the taxi radio system, and (3) distraction by taxi-hailing mobile app.

At the beginning, the leading vehicle was 50 m ahead of the following vehicle and maintained a constant speed of 50 kph in the urban scenario. On motorways, the leading vehicle cut in 80 m ahead of the following one, and proceeded at 80 kph. Taxi drivers were instructed to follow the leading vehicle. They were advised to adhere to the speed limits on urban streets and motorways, while maintaining their normal driving habits in terms of speed and following distance. After several minutes of following, the driver reaches a straight road segment where a 70-second distraction (via radio or app) is set, during which a sudden brake event is randomly

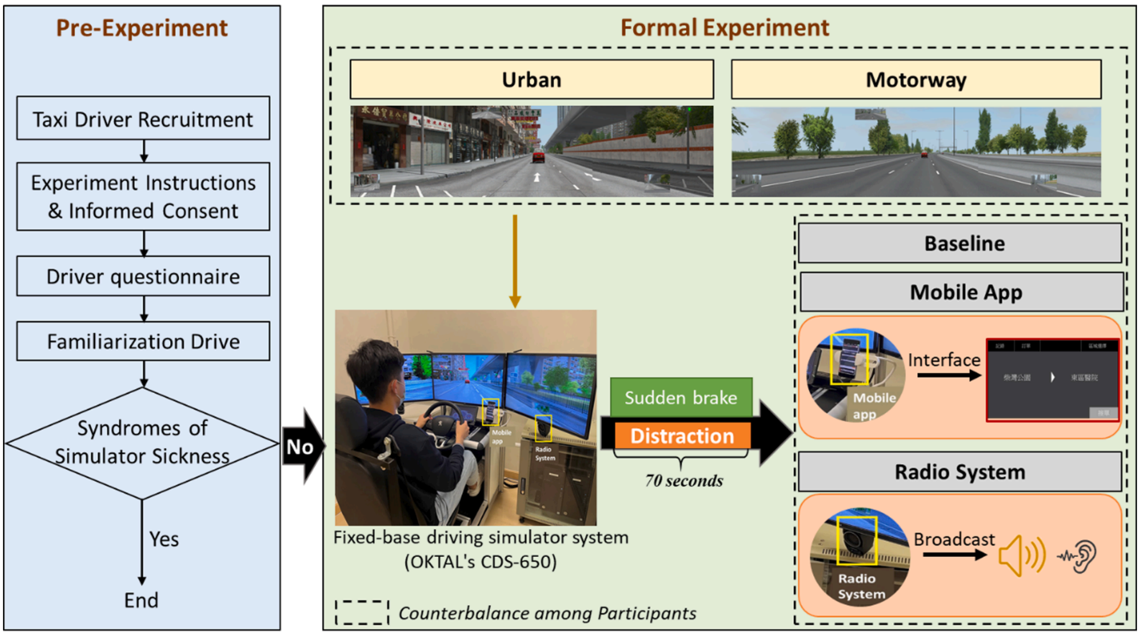


Fig. 1. Simulation Setup and Road Scenarios in the Driving Simulator Experiment.

triggered. Note that sudden brake events were triggered on the road segment with the same geometry design but different locations to avoid introducing additional effects.

Below is a detailed explanation of distraction settings. In order to distract taxi drivers, we created eight ride-hailing requests, such as “Hong Man Tin Station to Queen Elizabeth Hospital”. Locations in those requests are popular spots in Hong Kong, so drivers are familiar with the OD. The drivers were instructed to take requests with origins or destinations in the “Chai Wan” district, such as “Chai Wan Sports Centre to Tung Kwong Hospital”. Requests were randomized to avoid learning effects. For the mobile app distraction, ride-hailing requests were displayed one by one on the phone screen, such as ”Chai Wan Sports Centre to Tung Kwong Hospital“ (see Fig. 1), accompanied by the same decibel beep sound. It appeared for 4 s, then switched to the next request randomly within 4–7 s. The driver would tap the screen when he saw a match ride and take the request. Similar settings were used for the radio system distraction. Radio system distraction differs from mobile app distraction in that ride-hailing requests were broadcast as audio messages with the same decibel level in random order for 4 s. The duration between two consecutive requests is also randomly determined within 4–7 s. In response to the appropriate request, the participants should reply, ”Hey, I’m picking up this passenger“. It mimicked the actual pickup process between the taxi driver and the radio controller.

Due to the difference in speed limits between urban streets and motorways, the leading vehicle travels at 50 kph on urban streets and 80 kph on motorways. A sudden brake event begins when the leading vehicle suddenly brakes at a deceleration rate of 6 m/s^2 on urban roads (10 m/s^2 on motorways). The percentage of speed reduction of the leading vehicle within the same deceleration time was then controlled to be the same in the two road environments. The goal is to control the emergency levels of sudden braking events in two road environments with different speed limits. To assess the drivers’ braking behavior in response to the leading vehicle’s sudden brake, three performance indicators were extracted and calculated as follows: (1) brake reaction time $t_r - t_s(s)$, refers to the time interval from the moment t_s to t_r; t_s refers to the timestamp when the leading vehicle applies the brakes, t_r is the time stamp when the taxi driver reacts to apply the brakes. (2) time headway $THW_{min}(s)$: as a time-based safety measure, it can reflect the potential rear-end conflicts risk between the following vehicle and the leading vehicle on a collision course. Time headway is the time interval between the arrival of the leading vehicle and the following vehicle at a specified test point, tracking the same point on both vehicles (e.g., front bumper to front bumper or rear bumper to rear bumper). During each sudden brake event, the minimum time headway was collected; (3) car-following distance $CFD_s(m)$, this indicator corresponds to the distance gap between the following vehicle’s front bumper and the leading vehicle’s rear bumper at the timestamp when the leading vehicle engages its sudden brake (t_s).

The participants were unaware of the impending sudden brake scenario. A notable limitation of this experiment was that lane-changing maneuvers and overtaking maneuvers were prohibited in car-following tasks. Therefore, the sudden brake event required drivers to react by applying braking action. Importantly, at the moment the leading vehicle suddenly brakes, the taxi driver’s following distance is also captured. This car-following distance would be entered as a covariate.

To minimize potential learning effects, the sequence of the simulated driving trials, distinguished by road environment and

Table 1
Descriptive statistics of the sample.

Explanatory variable			Mean (Standard deviation)	Count (%)
Personal Characteristics	Number of years holding a taxi driving license		13.3 (5.8)	–-
	Weekly working days		5.7 (0.9)	–-
	Frequent user of mobile app	Yes	–-	32 (62.7)
	(Over 50 % of successful pickups)	No	–-	19 (37.3)
	Frequent user of radio system	Yes	–-	5 (9.8)
	(Over 10 % of successful pickups)	No	–-	46 (90.2)
Safety Perception and Driving History	Strong resistance to both ride-hailing systems	High	–-	11 (21.6)
		Neutral	–-	8 (15.37)
		Low	–-	32 (62.7)
	Perceived that use of mobile apps while driving is a crash contributory factor	High	–-	34 (66.7)
		Neutral	–-	9 (17.6)
		Low	–-	8 (15.7)
	Involved in a traffic accident in previous 12 months	Yes	–-	12 (23.5)
		No	–-	39 (76.5)
	Received traffic violation tickets in previous 12 months	Yes	–-	23 (45.1)
		No	–-	28 (54.9)
	Number of points incurred for traffic violations		3.6 (4.1)	–-
Performance Indicators				
Covariate		**Environment**	**Mean (Standard deviation)**	–-
Car following distance (m)		Urban street	34.23 (9.11)	–-
		Motorway	98.42 (5.03)	–-
Dependent variable				
Brake reaction time (s)		Urban street	1.49 (0.52)	–-
		Motorway	1.53 (0.53)	–-
Time headway (s)		Urban street	2.71 (0.76)	–-
		Motorway	4.35 (0.25)	–-

distraction type, was randomized for each participant. This randomization/counterbalance process served to enhance the robustness and impartiality of the study's outcomes by mitigating any systematic biases that might arise from a fixed trial sequence.

3.2. Sample

A total of 51 male taxi drivers were recruited to participate in the driving simulator experiment, facilitated through the collaboration with taxi driver associations in Hong Kong. Rigorous selection criteria were implemented to ensure the qualification of participants, including being engaged as full-time taxi drivers, possessing a valid taxi driving license, falling within the age range of 25 to 45 years, and demonstrating good physical fitness.

It is worth noting that the proportion of female taxi drivers in Hong Kong stands at approximately 15 % (approximately 6000 out of 40,000 valid taxi driver licenses), as reported by the Hong Kong Transport Department. However, due to their limited exposure to full-time taxi driving (mostly engaged in part-time work (Meng et al., 2019)) and a relatively low accident rate (in 2016, only 1.67 % of taxi crashes involved female drivers, corresponding to 75 out of 4493 accidents), only male taxi drivers were considered eligible for inclusion in this study.

The research protocol received ethical approval from the Human Research Ethics Committee of the Hong Kong Polytechnic University, confirming its compliance with ethical guidelines. A full explanation of the nature and purpose of the experiment was provided to each participant before they agreed to take part in the experiment. A US$50 reward was given to each participant in appreciation of their participation.

Table 1 presents the characteristics of the participants involved in the study. On average, the participants possessed 13.3 years of professional driving experience (with a standard deviation of 5.8 years), and their average working day spanned 5.7 h (with a standard deviation of 0.9 h. In terms of safety perceptions, 21.6 % of the participants expressed Strong resistance to both ride-hailing systems, while 66.7 % of the participants acknowledged that using mobile apps while driving poses a potential safety hazard. Notably, 23.5 % of the participants had a record of traffic accidents within the preceding 12 months. Interestingly, 62.7 % of the pickups were carried out using mobile apps, with a smaller proportion (9.8 %) utilizing the radio system. It is worth noting that despite the relatively low percentage of pickups made through the radio system, many participants reported frequently listening to taxi radio while driving to locate potential customers.

During the experiments, each participant engaged in driving simulations encompassing 3 distraction scenarios and 2 road environments, resulting in a total observation of 306 trials (51 participants × 6 experimental conditions). Three performance indicators were extracted, including brake reaction time, time headway, car following distance. It is important to note that brake reaction time and time headway are the dependent variables in our subsequent analysis, while the car-following distance would be included as a covariate in our analysis.

3.3. Model specification

In this study, the hazard-based duration model is applied to model brake reaction time and time headway of the taxi drivers. Based on the extensive literature on this method, the hazard-based duration model stands out as a well-recognized and efficient method for studying duration data in transportation. The duration data that will be modeled in this study are time headway and brake reaction time, which are defined in Section 3.2. The cumulative distribution function $F(t)$ and the probability density function $f(t)$ of a hazard-based duration approach are presented in Equation (1), where T is continuous duration variable, t represents a specified time stamp before an event occurs, $f(t)$ can be derived from taking the first derivative of $F(t)$.

$$F(t) = P(T < t) = \int_0^t f(t)dt \tag{1}$$

Correspondingly, the survival function is obtained in Equation (2), providing the probability that a certain duration will be greater than or equals to time t. In other words, $S(t)$ is defined as the probability that the duration of brake reaction time or time headway takes no shorter than the time t:

$$S(t) = 1 - F(t) \tag{2}$$

Moreover, the conditional probability of hazard function can be mathematically expressed in Equation (3). Specifically, hazard rate can be interpreted as the probability of an event occurring within a certain time between t and $t + \Delta t$, given that the time elapses up to time t (Washington et al., 2020).

$$h(t) = \frac{f(t)}{S(t)} \tag{3}$$

As part of the hazard-based duration approach, parametric survival models (proportional hazards model and accelerated failure time model) are commonly used to explore the factors that influence duration dependence. In this study, the accelerated failure time model is preferred as it assumes that all explanatory covariates directly reduce or accelerate the duration time in a baseline survival function where all variables are zero, as shown in Equation (4).

$$S(t|X) = S_0(t^*T) \tag{4}$$

Based on the accelerated failure time model, we obtain the following Equation (5) by taking the logarithm of survival time T. X represents a vector of independent variables, β denotes a vector of estimated coefficients, and ε is an error term.

$$\ln(T) = \beta X + \varepsilon \tag{5}$$

Additional assumption on the distribution of the duration variable T is required once the accelerated failure time model is determined. In this study, the Weibull distribution was selected for the duration variable for several reasons. First, it has been noted by Bhat and Pinjari (2007) that this distribution can be used to identify unobserved heterogeneity. Second, this distribution works well with data with monotonic hazard rate. Third, a large body of literature supports the use of Weibull distributions for reaction time, time to collision, time headway, etc., based on the model fit and intuitiveness. (Ali and Haque, 2023b; Ali et al., 2020b; Haque and Washington, 2014). Furthermore, the plotted Weibull distribution of fitted curve in Fig. 2 **(a)** and **(b)** shows close fit to the observed duration data, as confirmed by a Kolmogorov-Smirnov test (at 95 % significant level). For urban street: (i) Brake reaction time: Statistic = 0.149; P-value > 0.1; (ii)Time headway: Statistic = 0.112; P-value > 0.1; For motorway: (iii) Brake reaction time: Statistic = 0.162; P-value > 0.1; (iv) Time headway: Statistic = 0.122; P-value > 0.1.

The hazard function and survival function of the Weibull duration model can then be expressed in Equations (6), and (7):

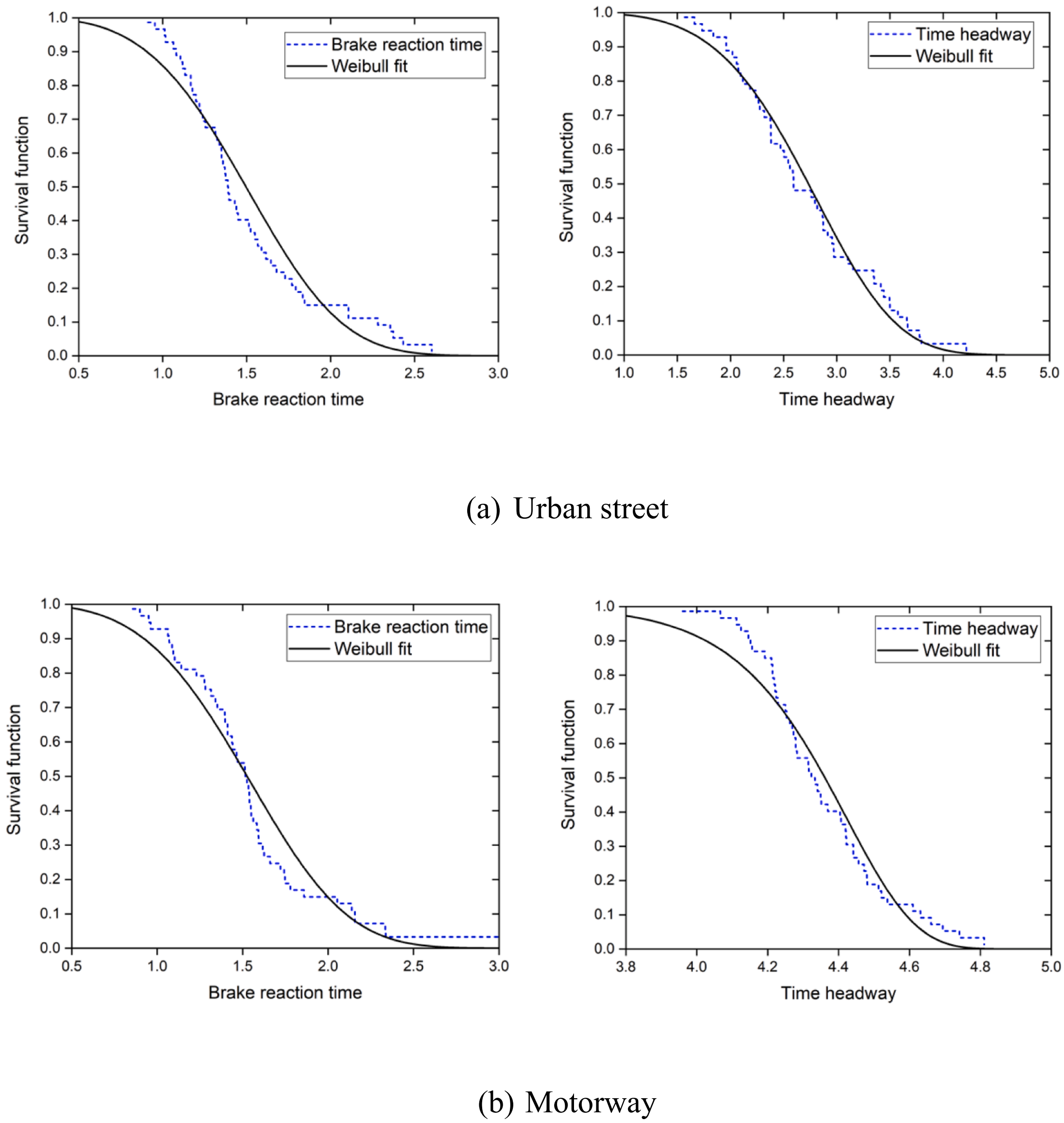


Fig. 2. Fitted Weibull distribution of brake reaction time and time headway.

$$h(t) = (\lambda P)(\lambda t)^{P-1} \tag{6}$$

$$S(t) = EXP\left(-\lambda t^{P}\right) \tag{7}$$

The P and λ in equations (6) and (7) denote a shape parameter and a location parameter, respectively. To be more specific, the hazard rate is monotonically increasing if the P value is greater than 1 (or decreasing if the P value is less than 1), otherwise the hazard rate is constant when the P value equals to zero. The distribution of λ is related to the duration dependence as shown in Equation (8). Then, the survival function can be transformed into Equation (9) in order to prepare for further investigation in subsequent sections.

$$\lambda = EXP[-P(\beta X)] = EXP[-P(\beta_0 + \beta_1 X_1 + \cdots \beta_n X_n)] \tag{8}$$

$$S(t) = EXP\left[-EXP[-P(\beta_0 + \beta_1 X_1 + \cdots \beta_n X_n)]\left(t^{P}\right)\right] \tag{9}$$

In a simulator experiment setting, repeated measurements from the same driver produce groups of behavior data. Also, Ali et al. (2020a, 2023b) emphasized that the response of drivers to safety critical events while driving is heterogeneous. Based on this knowledge, we hypothesize that ride-hailing systems can have a heterogeneous effect on distraction. To achieve this, several potential extensions were introduced to the Weibull model in order to capture unobserved heterogeneity at the individual level. Specifically, three approaches have been commonly used to accommodate heterogeneity in Weibull models. They are the clustered heterogeneity (Cleves, 2008; Ali and Haque, 2023a), the gamma frailty (Balusu et al., 2020; Hui, 1990; Nam and Mannering, 2000; Washington et al., 2020), and random parameters approaches (Mannering et al., 2016).

Mathematically, the clustered heterogeneity can be expressed in Equation (10) – multivariate density corresponding to the survival function. The marginal hazard functions at a time t for q members of a given cluster, denoted by $[\lambda_1(t), \cdots, \lambda_q(t)]$, are given by (Cleves, 2008; Ali and Haque, 2023a) in Equation (11).

$$f(t_1, \cdots t_q) = -\frac{\partial^q S(t_1, \cdots t_q)}{\partial_{t_1} \cdots \partial_{t_q}} \tag{10}$$

$$\lambda_1(t) = -\frac{\partial S(t_1, \cdots t_q)/\partial_{t_1}}{S(t_1, \cdots t_q)}\Bigg|_{t_1 = \cdots t_q = t}, \cdots \lambda_q(t) = -\frac{\partial S(t_1, \cdots t_q)/\partial_{t_1}}{S(t_1, \cdots t_q)}\Bigg|_{t_1 = \cdots t_q = t} \tag{11}$$

Then, the hazard function addressing heterogeneity with shared gamma frailty is shown in Equation (12), where α_i has a gamma distribution with mean one and variance θ, h_{ij} is the hazard function for participant i in the j^{th} driving session, β is a vector coefficient of estimated variables, and X_{ij} is a vector of explanatory variables (Balusu et al., 2020; Hui, 1990; Nam and Mannering, 2000; Washington et al., 2020).

$$h_{ij}(t|\alpha_i) = \alpha_i h_{ij}(t) = \alpha_i h_0\left[t\mathrm{EXP}(\beta X_{ij})\right] EXP(\beta X_{ij}) \tag{12}$$

The random parameter approach allows the coefficients for explanatory variables to vary across individuals, accounting for individual level heterogeneity (Mannering et al., 2016). As shown in Equations (13) and (14), β_i denotes normally distributed random parameter with a mean vector of β. ω_i refers to an independent normally distributed random error term.

$$\beta_i = \beta + \omega_i \tag{13}$$

Sometimes, it is also necessary to account for correlation in the random parameters to avoid biased estimations (Mannering et al., 2016). In the current study, correlated random parameters were also used to account for interdependencies within unobserved heterogeneity. The random parameters were defined with regard to their correlation in accordance with the methodologies described in previous studies (Greene, 2016; Balusu et al., 2020; Jordan et al., 2019; Washington et al., 2020).

This study used a simulated maximum likelihood estimation method to estimate the parameters in Equation (14). 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 adopted to examine the statistical difference between the correlated and uncorrelated random parameters models. Specifically, $LL(\beta_{urp})$ and $LL(\beta_{crp})$ denote the log-likelihood at convergence of the uncorrelated and correlated group random parameter models, respectively.

$$\chi^2 = -2[LL(\beta_{urp}) - LL(\beta_{crp})] \tag{14}$$

Moreover, the Voung test proposed by Vuong (1989) was used to determine if there were statistical differences between non-nested candidate models (clustered heterogeneity approach, gamma frailty approach, and random parameter approach) that could not be directly compared using likelihood ratio tests. As shown in Equation (15), each observation obtains the statistic m_i by consider the densities $f_1(y_i)$, $f_2(y_i)$ for the competing models. Vuong statistics can be calculated and used to determine which model is best for a given set of data. As follow Equation (16) where $\overline{m}$ is mean of the sample n, and s_m is the standard deviation of the sample n. V follows a standard normal distribution, thus comparisons can be made with its critical value (1.96 with 95 % confidence level). If $|V|$ is less than 1.96, then the two competing models are not significantly different; if V is less than -1.96, then model 2 performs a better role;

otherwise, model 1 is preferred (Balusu et al., 2020).

$$m_i = \log[f_1(y_i)/f_2(y_i)] \tag{15}$$

$$V = \frac{\sqrt{n}[1/n]\sum_{i=1}^{n} m_i}{\sqrt{1/n\sum_{i=1}^{n}(m_i - \overline{m})^2}} = \frac{\sqrt{n}\overline{m}}{s_m} \tag{16}$$

Furthermore, the observed heterogeneity was also captured by considering all possible interactions effect among explanatory variables. The interaction effect represents the moderating effects of one independent variable on the relationship between the dependent variable and independent variable (Chen et al., 2021b). Consequently, our study can shed more light on the mitigating or magnifying effects of interaction between driver characteristics and distraction types, thereby providing some indication of management policies for enhancing taxi driver safety.

4. Results

4.1. Weibull duration model for brake reaction time

The hazard-based duration model with Weibull distribution was used to analyze brake reaction time for urban and motorway scenarios. To identify the most appropriate model, a comparison of the models accounting for heterogeneity was conducted as shown in Table 2. In both urban and motorway scenarios, the Vuong statistics indicate that the uncorrelated grouped random parameters models outperformed clustered heterogeneity or gamma frailty models ($V < -1.96$). As a result, the Weibull accelerated failure time model with uncorrelated grouped random parameters was selected for modelling brake reaction time in the event of sudden brake events initiated by a leading vehicle. In addition, potential interaction effects were examined in order to identify the observed heterogeneity.

We also applied a likelihood ratio test to compare the statistical fit of uncorrelated and correlated grouped random parameters models. The test results affirmed no notable distinction between the two models based on the Chi-square statistics (please refer to the Appendix Table A1). In this regard, the uncorrelated grouped random parameter model was selected for further discussion.

Several assumptions including normal, triangular, uniform, lognormal distributions were tested for the random parameters, and the results of model fit are described in Table A2. Some limitations of other assumptions should be mentioned here. For example, triangular distribution is more suitable for situations with a lack of precise data but known possible maximum and minimum values. It can only be applied when data are roughly concentrated around a single region. On the other hand, there is no peak in the uniform distribution, meaning it does not represent the concentration of data around a particular point. In addition, parameter specified is constrained to be positive in lognormal distribution, which can cause problems in estimation. Therefore, considering the model fit, intuitiveness, universality, and flexibility, a normal distribution (result of many natural and social processes) was finally selected.

Results of the uncorrelated grouped random parameters Weibull accelerated failure time model for brake reaction time are presented in Table 3 for urban streets and motorways. The scale parameter (P) for urban street scenarios is 8.53 and for motorway scenarios is 8.33, both of which are significantly greater than one at a 95 % confidence level. This indicates that the hazard is monotonically increasing in duration, implying an increase in the likelihood of a driver initiating a braking action as time progresses. For example, on urban streets, the probability of the driver applying the brakes after 3 s is 21.18 times ($\frac{h(3)}{h(2)} = \left(\frac{3}{2}\right)^{8.53-1}$) higher than that after 2 s. Similarly, on motorways, the probability of the driver applying the brakes after 3 s is 19.53 times ($\frac{h(3)}{h(2)} = \left(\frac{3}{2}\right)^{8.33-1}$) higher compared to that after 2 s. As predicted, the probability of a driver taking the brake reaction increases over time, which is consistent with real-life scenarios in which drivers respond to braking events, thereby demonstrating the theoretical validity of a Weibull duration model.

4.1.1. Impacts of random parameters on brake reaction time

As shown in Table 3, car following distance and mobile app distraction coefficients are random in the model for urban streets, while the weekly working days and mobile app distraction in the motorway model have random coefficients. Indeed, the relationship between some random parameters and brake reaction time are not necessarily monotonic, which is more realistic since not all drivers

Table 2
Comparison of Weibull accelerated failure time model for brake reaction time.

Candidate model 1 versus Candidate model 2	Vuong test	
	Urban street	Motorway
clustered heterogeneity versus gamma frailty	−2.72	−1.08
clustered heterogeneity versus uncorrelated grouped random parameters	−4.52	−4.20
gamma frailty *versus* uncorrelated grouped random parameters	−2.48	−3.63

Table 3
Results of the uncorrelated grouped random parameters Weibull accelerated failure time model of brake reaction time.

Parameters	Urban street			Motorway		
	Coefficient	z-stat	$exp(\beta)$	Coefficient	z-stat	$exp(\beta)$
Constant	−0.208***	−2.82	0.81	−0.133**	−2.03	0.88
Car following condition						
Initial car following distance (Mean)	0.008***	6.95	1.01	–	–	–
Initial car following distance (Standard deviation)	0.006***	21.28	–	–	–	–
Distraction type (Base: No distraction)						
Mobile app (Mean)	0.299***	8.30	1.35	0.422***	15.87	1.53
Mobile app (Standard deviation)	0.134***	7.10	–	0.120***	6.74	–
Radio system	0.105***	4.15	1.11	0.138***	4.83	1.15
Personal characteristics						
Number of years holding a taxi driving license	−0.007***	−4.05	0.99	–	–	–
Weekly working days (Mean)	0.070***	6.48	1.07	0.078***	6.84	1.08
Weekly working days (Standard deviation)	–	–	–	0.037***	20.67	–
Frequent user of mobile app	−0.118***	−5.54	0.89	−0.116***	−5.65	0.89
Safety perception and Driving History						
Strong resistance to both ride-hailing systems	0.067***	2.69	1.07	0.207***	8.45	1.23
Involved in traffic accident in the past 12 months	–	–	–	−0.050**	−2.09	0.95
Number of points incurred for traffic violations	−0.015***	−5.78	0.99	–	–	–
Interaction effect						
Mobile app * Strong perception that using mobile apps while driving contributes to crashes	−0.078**	−2.07	0.92	–	–	–
Mobile app * Received traffic violation tickets in past 12 months	–	–	–	−0.160***	−4.48	0.85
Radio system * Received traffic violation tickets in past 12 months	–	–	–	−0.070**	−1.94	0.93
Model fit						
Number of observations	153			153		
Log-likelihood of constant only	−62.74			−61.54		
Log-likelihood at convergence	15.91			15.17		
Number of estimated parameters	13			12		
Akaike Information Criterion (AIC)	−5.8			−6.3		

Note:
* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

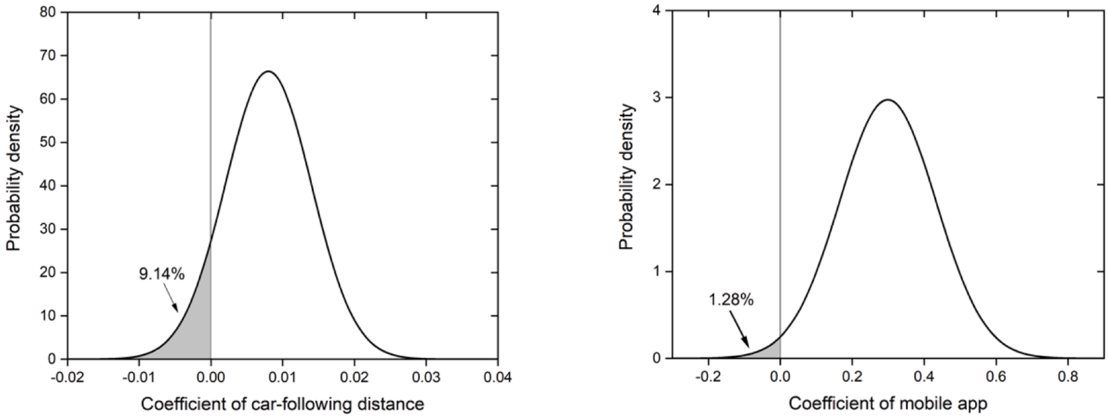
behave in the same way in reality. Specifically, if the coefficients of the random parameters only contains the mean part as the estimation of fixed parameters, it will provide one stable and uniform impact (either positive or negative) on the duration variable. It is important to note that, if the standard deviation of the random parameters follows a normal distribution, it will result in a distribution with a total coefficient on either side of 0.

In Fig. 3, the mean and standard deviation of random parameters are used to plot the coefficient distributions to provide further insight (Sharma et al., 2020). Fig. 3 **(a)** indicates that 90.86 % of the taxi drivers show longer brake reaction time when a larger distance is maintained between following and leading vehicles on urban streets. However, there are approximately 9.14 % of taxi drivers who demonstrate shorter brake reaction time with a wider car following gap. In addition, the heterogeneous effect of mobile apps shows that the majority of taxi drivers (98.72 %) react slower under mobile app distractions, while about 1.28 % react faster. Fig. 3 **(b)** indicates that 98.25 % of drivers who work more days per week have longer reaction time on motorways, while 1.75 % have shorter brake reaction time. Likewise, the variation in the magnitude of mobile app distraction coefficients on motorways captured the heterogeneity among participants (0.02 % have shorter brake reaction time).

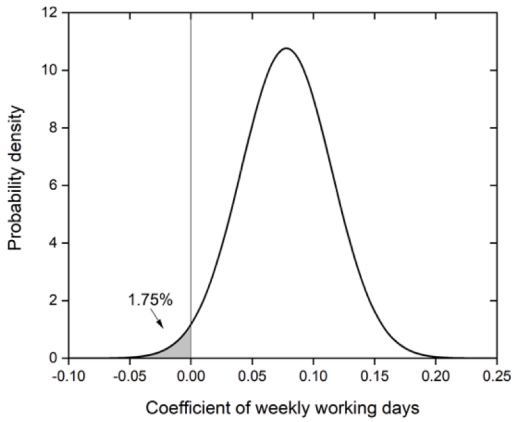
4.1.2. Impact of fixed parameters on brake reaction time

Based on the exponential function for each coefficient $exp(\beta)$, more additional insight can be explored from parameter estimates in Table 3. In particular, the exponential effects capture the percentage change in the value of the duration variable resulting from a one-unit increase in the continuous variable. Additionally, they demonstrate the impact of changing the value of a dummy variable from 0 to 1 on duration. As such, it is imperative to consider the exponential effect when analyzing duration data in order to better understand how different explanatory variables affect the dependent variables.

Fixed parameters for the variables in the model include (1) Urban: the distraction by radio system, the number of years holding a



(a) Urban street



(b) Motorway

Fig. 3. Random parameters distribution in brake reaction time model.

taxi driving license, the number of weekly working days, being a frequent user of ride-hailing mobile app, strong resistance to both ride-hailing systems, and the driving offense points incurred currently; (2) Motorway: the distraction by radio system, being a frequent user of ride-hailing mobile app, strong resistance to both ride-hailing systems, and involved in traffic accident in previous 12 months.

Regarding the identified fixed parameters, radio system distraction significantly affects the driver's brake reaction time. For urban streets and motorways, drivers distracted by radio systems have a longer braking reaction time than drivers who are not distracted by 11 % and 15 %, respectively. Also, brake reaction time is negatively associated with years of holding a taxi driving license. Moreover, the model results indicate that along with the increase in taxi driving experience, the brake reaction time decreases by 1 % on urban streets. As one would expect, a driver with more extensive driving experience will respond more quickly, although this effect does not appear to be substantial in our study. There is a positive relationship between the weekly working days of drivers and brake reaction time. The model suggests that one additional working day leads to an increase of 7 % in brake reaction time on urban streets. The frequency with which taxi drivers use ride-hailing apps to find passengers has a significant impact on brake reaction time. In particular, drivers who frequently use ride-hailing mobile apps are able to reduce their brake reaction time by 11 % and 11 %, respectively, on urban streets and motorways. Thus, drivers who have mastered the use of the ride-hailing mobile app are more likely to react quickly to sudden brake events. Considering the driver's safety perception, the model indicates that the brake reaction times for drivers who have strong resistance to both ride-hailing systems are approximately 7 % and 23 % longer on urban streets and motorways, indicating that the drivers may feel nervous and uncomfortable when using the ride-hailing systems. As for the violation records, a driver's total number of driving offense points incurred is also significant in the model and negatively associated with brake reaction time on urban streets. Interestingly, brake reaction time decreases by 1 % with each additional point. Perhaps taxi drivers with higher driving offense points are more aware of other road users' behavior because they are more sensitive to accumulating more points. Furthermore, drivers who have been involved in a traffic accident within the past 12 months have a 5 % shorter brake reaction time on motorway than those who have not.

4.1.3. Impacts of interaction terms on brake reaction time

Importantly, we incorporated potential interaction effects into our model in order to capture the observed heterogeneity. The interaction terms that were significant at 95 % confidence level were included in the final model specification. It was found that the interaction between mobile app distraction and risk perception factor (a strong perception that using mobile apps while driving contributes to crashes) has a statistically significant negative effect on the driver's brake reaction time in the urban scenario. Indeed, it is possible that drivers' higher risk perceptions may mitigate the distraction caused by mobile apps, thereby shortening the brake reaction time. In the context of a motorway, the interaction between distraction caused by the mobile app and the driver's history of traffic penalties (received tickets for traffic violations in the past 12 months), as well as the interaction between radio system distraction and the driver's history of traffic penalties, are negatively associated with brake reaction time. Perhaps the penalties imposed on taxi drivers may have a deterrent effect, which may result in them driving more attentively when distracted.

4.2. Weibull duration model for time headway

In this study, time headway as a time-based safety measure, describes the probability of a rear-end collision between the two vehicles on a collision course. For the analysis of time headway across two road environments, a hazard-based duration model with a Weibull distribution was employed. The Vuong test statistics are presented to compare the various models estimated for time headway in Table 4. With regards to motorway scenarios, models with uncorrelated grouped random parameters performed better than models with clustered heterogeneity or gamma fragility (V<-1.96). However, there was no statistical difference between these models when it came to urban street scenario ($|V| < 1.96$). Since the explanatory variables are the same for the three candidate models, here we only presented and discussed the estimation results of the uncorrelated grouped random parameters model with their counterparts due to space limitations. For the results of clustered heterogeneity and gamma frailty, please refer to the Appendix Table A3. In this regard, the Weibull accelerated failure time model with uncorrelated grouped random parameters was chosen to estimate both urban and motorway time headways. The observed heterogeneity was further examined in light of potential interaction effects.

In addition, the likelihood ratio test was used to assess the statistical differences between the models with correlated and uncorrelated random parameters. The likelihood ratio statistics indicated that there is no statistically significant difference between the two models in terms of the statistical fit (as shown in Table A1). Therefore, the uncorrelated grouped random parameter model was selected for further discussion.

Table 5 present the estimation results of the uncorrelated grouped random parameters Weibull accelerated failure time model for time headways on urban street and motorway. The scale parameter (P) for urban street scenarios is 12.98 and for motorway scenarios is 40.13, both of which are significantly greater than one at a 95 % confidence level. This indicates a positive duration dependence in the hazard function, suggesting a decrease in the survival probability of time headway. In other words, the probability of driver avoiding a rear-end collision decreases with the elapsed time. An example would be that after 5 s, the probability of being involved in a rear-end collision increased 14.49 times compared to after 4 s in urban scenario. Likewise, on motorways, the probability of a rear-end collision after 10 s is more than 61.73 times greater than after 9 s. Accordingly, the Weibull duration model is intuitively valid.

4.2.1. Impacts of random parameters on time headway

Mobile app distraction and car-following distance are found to be random on urban streets and motorways. Table 5 indicates that there is a positive association between mobile app distraction and time headway, as illustrated by the mean effects of the coefficients. However, the standard deviation of the distribution lends support to the idea that different drivers adjust their time headway differently when distracted by mobile apps. As shown in Fig. 4**(a) and 4(b)**, the majority of taxi drivers (88.55 % on urban streets and 86.07 % on motorways) would maintain a greater safety margin. Yet, the heterogeneous effects of mobile app distraction on taxi drivers' time headway suggests that 11.45 % and 13.93 % show shorter time headways respectively on urban streets and motorways.

4.2.2. Impacts of fixed parameters on time headway

In Table 5, fixed parameters for the variables in the model include (1) Urban: the distraction by radio system, the number of years holding a taxi driving license, the number of weekly working days, received traffic violation tickets in previous 12 months, and involved in traffic accident in previous 12 months; (2) Motorway: the distraction by radio system, the number of years holding a taxi driving license, being a frequent user of ride-hailing mobile app, involved in traffic accident in previous 12 months, and the driving offense points incurred currently.

Table 4
Comparison of Weibull accelerated failure time model for time headway.

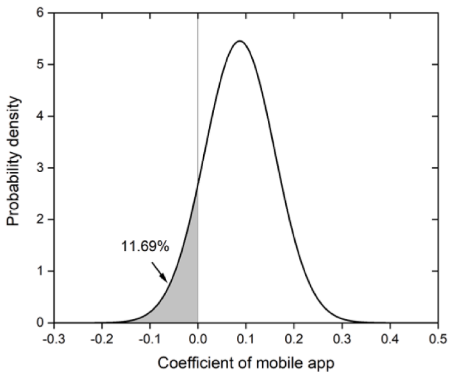
Candidate model 1 versus Candidate model 2	Vuong test	
	Urban street	Motorway
clustered heterogeneity versus gamma frailty	−1.23	−1.61
clustered heterogeneity versus uncorrelated grouped random parameters	−1.36	−2.09
gamma frailty *versus* uncorrelated grouped random parameters	−0.68	−2.11

Table 5
Results of the uncorrelated grouped random parameters Weibull accelerated failure time model of time headway.

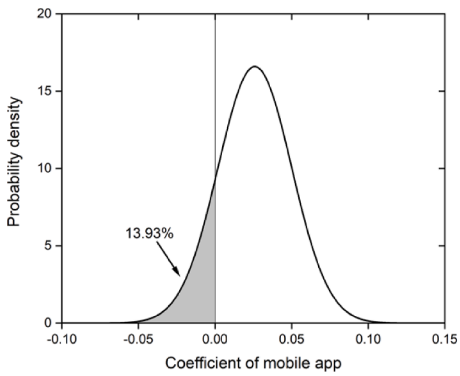
Parameter	Urban street			Motorway		
	Coefficient	z-stat	*exp*(*β*)	Coefficient	z-stat	*exp*(*β*)
Constant	0.074*	1.46	1.08	1.05***	27.05	2.86
Car following condition						
Initial car following distance (Mean)	0.024***	31.05	1.02	0.004***	10.85	1.00
Initial car following distance (Standard deviation)	0.002***	14.27	–	0.0003***	12.35	–
Distraction type (Base: No distraction)						
Mobile app (Mean)	0.089***	5.72	1.09	0.026***	4.30	1.03
Mobile app (Standard deviation)	0.074***	7.98	–	0.024***	7.22	–
Radio system	0.068***	4.18	1.07	0.024***	4.18	1.02
Personal characteristic						
Number of years holding taxi driving license	−0.005***	−4.15	0.995	−0.001**	−2.04	1.00
Weekly working days	0.016**	2.13	1.02	–	–	–
Frequent user of mobile app	–	–	–	−0.015***	−3.23	0.99
Driving History						
Received traffic violation tickets in previous 12 months	0.087***	6.57	1.09	–	–	–
Involved in traffic accident in previous 12 months	−0.067***	−4.52	0.94	−0.031***	−5.82	0.97
Number of points incurred for traffic violations	–	–	–	0.001*	1.58	1.00
Interaction effect						
Radio system * Frequent user of radio system	−0.115**	−2.45	0.89	−0.044**	−2.40	0.96
Model fit						
Number of observations	153			153		
Log-likelihood of constant only	−30.86			192.87		
Log-likelihood at convergence	103.86			277.69		
Number of estimated parameters	12			12		
Akaike Information Criterion (AIC)	−183.7			−531.4		

Note:
* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

In terms of the fixed parameters, driver distraction by radio system significantly increases the time headway by about 7 % and 2 % over the baseline condition in urban streets and on motorways, respectively. For the effects of driver characteristics, number of years holding taxi driving license is negatively associated with time headway. Specifically, the time headway of these drivers is 0.5 % shorter



(a) Urban street



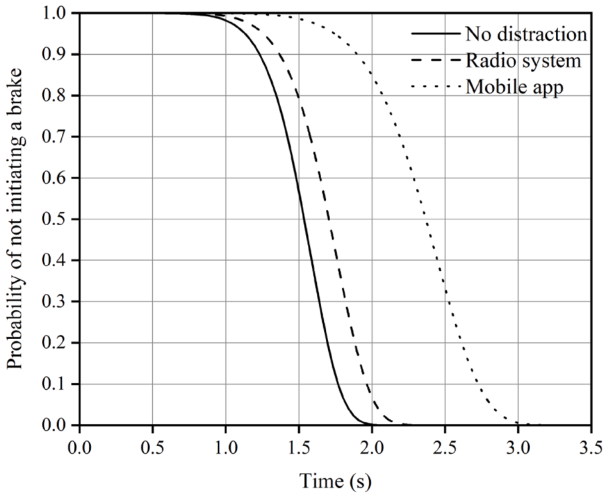
(b) Motorway

Fig. 4. Random parameters distribution in time headway model.

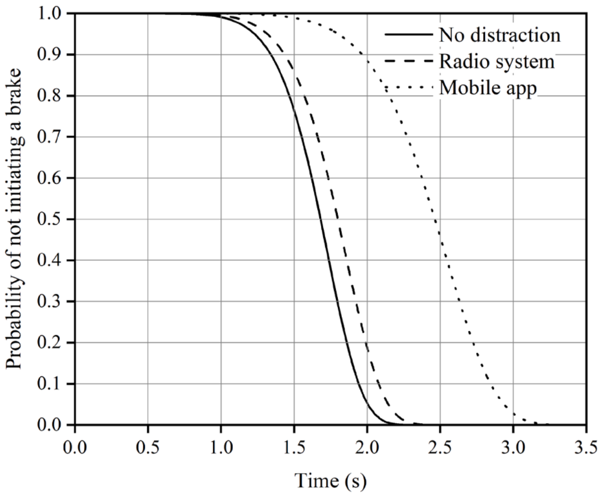
than their counterparts on urban streets. In addition, a positive relationship is found between the weekly working days and the time headway. On urban streets, taxi drivers' time headway increases by 2 % for every additional day of work. In terms of phone use habits, the time headway of frequent users of mobile ride-hailing app is 1 % shorter than their counterparts on motorways. Time headway is also significantly affected by driving history at the 1 % level. For example, receiving traffic violation tickets in the past 12 months was identified as a significant factor affecting time headway. On urban streets, the time headway of drivers with violation records is up to 9 % higher than their counterparts. In contrast, the time headway of drivers involved in traffic accidents in the previous 12 months is significantly shorter than their counterparts. Compared to drivers without accident records, drivers with accident records tend to decrease their time headway by 6 % on urban roads and by 3 % on motorways.

4.2.3. Impacts of interaction terms on time headway

To better account for the heterogeneity observed in the data, we also included potential interaction effects in our time headway models. In both urban streets and motorways, the interaction between the radio system distraction and frequent users of the radio system is significantly and negatively associated with the time headway. Certainly, it is possible that the driver's proficiency with the radio system can mitigate the effect of the radio system on driver distraction, resulting in a longer safety distance.



(a) Urban street



(b) Motorway

Fig. 5. Survival function of brake reaction time across different distraction types.

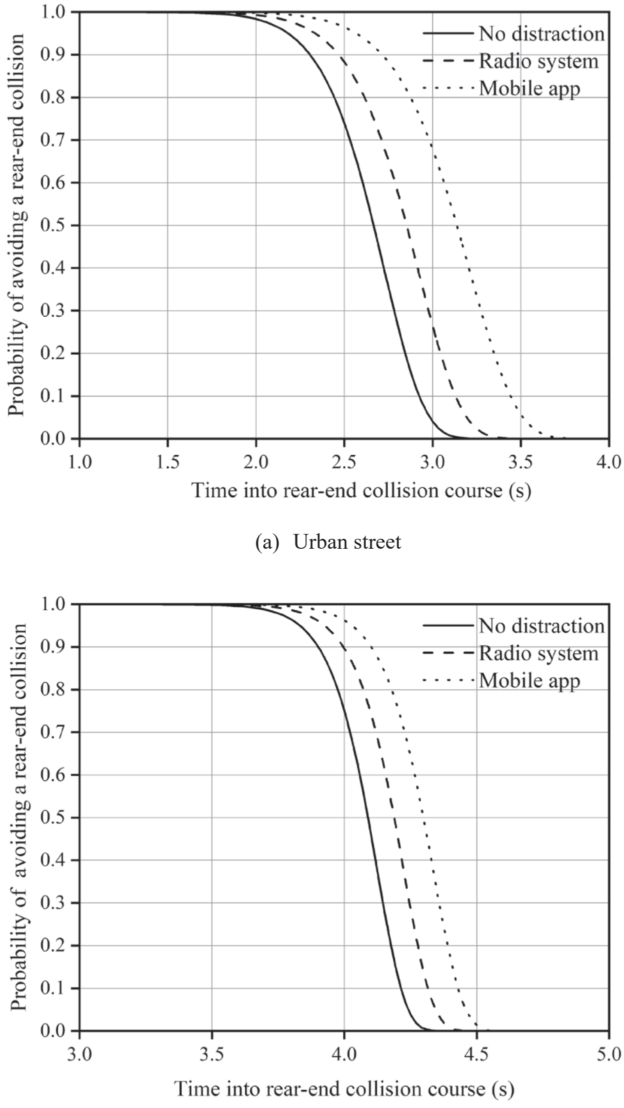
5. Discussion

The present study examined how ride-hailing systems affect taxi drivers' reactions and car-following behavior, two key indicators of driver performance in safety–critical situations, using a driving simulator approach. Uncorrelated grouped random parameters Weibull accelerated failure time models were fitted to evaluate the impacts of different ride-hailing systems on taxi driver's safety performance in terms of brake reaction time and time headway. Several personal characteristics, safety perception and driving history variables also influence taxi drivers' driving performance. We will discuss our findings in the sections that follow.

5.1. Driving performance under different distractions

5.1.1. Effects of ride-hailing systems on brake reaction time

Results from the study indicate that radio systems and mobile apps distract taxi drivers and increase their brake reaction times on urban streets and motorways. Earlier studies have indicated that both auditory and visual distractions negatively affect drivers' vehicle control performance and mental workload (He et al., 2014; Horrey and Wickens, 2006; Lee et al., 2002; Liang and Lee, 2010). However, the estimated random parameters also suggest that for about 1.28 % of the taxi drivers, distraction by the mobile app is associated with shorter brake reaction time on urban street. The fact that, for most drivers, mobile apps are consistently associated with



(a) Urban street

(b) Motorway

Fig. 6. Survival function of time headway across different distraction types.

longer brake reaction time, highlights the general impact of distractions. However, in this case, only 1.28 % self-regulate, which contrasts with previous research that linked extensive experience, such as taxi drivers' experience, to better self-regulation (Oviedo-Trespalacios et al., 2020). A potential explanation is that the risks assessed in the present paper are generally derived from the unexpected event (sudden brake). In this regard, self-regulation may not be applicable since awareness of the risk is required by its definition.

The parameter estimates of the models can be used to calculate survival probabilities and to plot them as survival curves, as shown in Fig. 5. By utilizing the mean of the continuous explanatory variables as well as the dummy explanatory variable's reference category, a survival probability for the brake reaction time of a driver experiencing radio system distraction at t s is calculated. Similarly, it is possible to plot the survival curves for the brake reaction times under the baseline condition (no distraction) and mobile app distraction in both urban and highway settings. The results show that the probability of failing to react to a sudden brake event decreases as time passes. It is important to note that in the distracted driving condition, the probability of not initiating a braking reaction was higher than in the baseline condition (no distractions) throughout the entire event.

Specifically, at $t = 1.5$ s, the survival probabilities of brake reaction time were 56.8 %, 79.4 %, and 98.6 % for no distraction condition, the radio distraction and mobile app distraction respectively in urban-street driving environment (see Fig. 5 **(a)**) The corresponding survival probabilities in motorway scenario were 76.5 %, 85.9 %, and 98.9 % respectively (see Fig. 5 **(b)**). In urban scenarios, drivers take 2.1 s to react to sudden brake events without being distracted by any in-vehicle ride-hailing system. On the other hand, when driving while distracted by radio broadcasts and text messages displayed on the app screen, brake reaction times are estimated to be 2.3 s and 3.1 s, respectively. On the motorway, it can also be concluded that drivers are expected to spend 2.2 s, 2.4 s, and 3.3 s, respectively, to respond to the front vehicle's unexpected braking on the baseline, radio, and mobile app conditions. In both scenarios, it takes 1.5 times longer to initiate braking reaction when distracted by mobile app compared to the baseline condition. As expected, and in line with previous evidence, distraction impairs driving and, in this case, reaction time (Oviedo-Trespalacios et al., 2016). In spite of the fact that this finding is not entirely new, it still provides confirmation that distraction's impact is evident even among groups of the population who have extensive experience such as taxi drivers.

The results suggest that visual-manual interactions for ride-hailing requests impose a greater distraction than auditory interactions, as drivers who are distracted by mobile apps have a longer reaction time. Indeed, previous research has also demonstrated that visual distractions are more likely to affect vehicle control than auditory-cognitive distractions (Liang and Lee, 2010; Oviedo-Trespalacios et al., 2016). Accordingly, compared to auditory distraction, visual distraction involves shifting the eyes from the road to the mobile phone, and thus impairs the driver's capability to react to hazards and driving performance to a greater extent (Ali and Haque, 2023b; Haque and Washington, 2014; Saifuzzaman et al., 2015).

The findings presented in this paper have significant policy implications for the realm of road safety and technology regulation. The observed differences in distraction levels between visual-manual and auditory interactions for ride-hailing requests highlight the pressing need for industry stakeholders and regulators to critically evaluate the integration of technology into vehicles. There is a clear imperative to prioritize "safe-by-design" principles when developing and implementing new technologies, ensuring that they do not compromise driver attention and road safety. Furthermore, the evidence that visual distractions are more detrimental to vehicle control and reaction times than auditory distractions underscore the importance of regulations aimed at mitigating visual distractions within the vehicle environment. This points to the necessity of stringent guidelines governing in-vehicle displays, mobile apps, and other technology interfaces to minimize potential risks to drivers.

5.1.2. Effects of ride-hailing systems on time headway

The model results revealed that taxi drivers' time headway increases when using the radio system and mobile app in both urban and motorway environments. The findings are consistent with the previous research on risk compensation theory (Mannering and Bhat, 2014), suggesting that drivers might be more cautious and alert in order to mitigate the increased risk of accidents when they use electronic devices while driving. However, the estimated random parameters also suggest that for about 1.28 % of the taxi drivers, distraction by the mobile app is associated with shorter brake reaction time on urban street. The fact that, for most drivers, mobile apps are consistently associated with longer brake reaction time, highlights the general impact of distractions. Indeed, drivers would try to minimize their crash risk by adopting compensatory behaviors, including reducing speed and increasing following distances (Chen et al., 2021b; Li et al., 2019; Muhrer and Vollrath, 2011; Saifuzzaman et al., 2015; Yan et al., 2022).

The probability of avoiding a rear-end collision and the survival curves can be calculated and plotted based on the parameter estimates and the survival function specification. Fig. 6 illustrates the survival probability of time headway, indicating a decreasing probability of avoiding rear-end accidents over time across different types of distraction. It is noteworthy that in the distracted driving condition, the probability of a driver avoiding a rear-end collision is higher than in the baseline condition. This behavior can be interpreted as a safety-conscious response, in which drivers become more cautious when distracted by ride-hailing systems and tend to maintain greater safety margins between vehicles.

We also estimated that the average time to avoid a rear-end collision in the baseline condition is about 3.3 s (when survival probability is almost zero) on urban street. The corresponding time estimates for radio and mobile app distractions are 3.5 and 3.8 s, respectively. This indicates that the safety margins in distracted conditions are about 1.1 and 1.2 times longer than in the baseline condition. Similarly, the average time to avoid a rear-end collision on a motorway is estimated at 4.5, 4.6, and 4.7 s under the baseline condition, radio distraction, and mobile app distraction, respectively. Interestingly, the average time to avoid a rear-end collision under mobile app distraction is the longest of the three distraction types, suggesting a stronger risk compensation due to stronger distraction effects. There is evidence from previous studies that auditory distractions can overload working memory, which can interfere with visual information processing for the primary driving task (Sonnleitner et al., 2014; Strayer et al., 2016; Watson and

Strayer, 2010;). On the other hand, there is a more significant overlap between using mobile apps and monitoring the road traffic environment (reading text messages on the phone screen versus noticing the sudden braking of the leading vehicle in this study). As such, based on Wickens' multiple resource theory, visual inputs can have a more significant distraction impact than auditory inputs (Karthaus et al., 2020; Wickens, 2002, 2008).

The effectiveness of drivers' strategy to compensate for mobile app distraction are higher on urban streets than on motorways. For instance, at $t = 3$ s, the probability of avoiding a rear-end collision in the absence of distractions decreases to 4.0 %, while the corresponding probabilities are 26.5 % and 67.9 % under radio and mobile app distractions respectively (see Fig. 6 **(a)**). On motorways, the probability of avoiding a rear-end collision in the absence of distractions decreases to 4.0 % at $t = 4.2$ s, while the corresponding probabilities are 46.2 % and 76.2 % under radio and mobile app distractions respectively (see Fig. 6 **(b)**). On the other hand, the effectiveness of drivers' strategy to compensate for radio distraction is higher on motorways than on urban streets. These findings are very interesting as they highlight that the impact of compensatory strategies is context-dependent, which has been a largely unexplored dimension of self-regulation.

A potential explanation for the effectiveness differences between urban streets and motorways is the higher visual load in urban environments (Horberry et al., 2006; Oviedo-Trespalacios et al., 2018) and the monotonous/predictable environment of motorways (McCartt et al., 1996). On one hand, the driver can experience a richer out-of-vehicle experience on urban streets (more traffic lights and colorful street stores) than in the motorway environment in this simulator experiment. As a result, taxi drivers should exhibit enhanced compensatory behaviors since they distribute most of their visual attention outside of the vehicle and can only devote a limited amount of attention to processing information from a mobile app. On the other hand, compared to urban streets, the road environment on motorways is quite monotonous, leading to driver drowsiness or fatigued over time. Prior studies have also demonstrated that drivers' attention declines during long highway drives (Adanu et al., 2021; Higgins et al., 2017; Sussman et al., 1985). Upon being stimulated by the radio broadcast, it takes them longer to regain consciousness and remember the information. To compensate for this, they tend to maintain a longer headway. Interestingly, drivers are more susceptible to being distracted by visual-based information on urban street, while they are sensitive to auditory distractions while driving on motorways. Based on these results, we recommend introducing multi-choice ride-hailing platforms (audio or visual) tailored to the driving environments (urban or motorway). Naturally, it is also important to ensure that drivers have a good understanding of the risks and their own capabilities, as some of them could overestimate their performance when using a particular modality of phone use.

5.2. *Effects of drivers' characteristics on driving performance*

5.2.1. *Personal characteristics*

Taxi driver experience (number of years holding a taxi driving license) appears to be correlated with safety performance. Brake reaction time and time headway values tend to be lower among the taxi drivers who have more driving experience. Several studies have found that more experienced drivers tend to maintain shorter headways and react faster to brake events than their counterparts, suggesting a higher level of self-confidence and a more aggressive driving (Oviedo-Trespalacios et al., 2018; Ohlhauser et al., 2011; Yang et al., 2021).

Job demands of individuals were also a significant variable in the present study. Specifically, we considered weekly working days reflects the working demands of these full-time taxi drivers. Due to long work hours in a week, it is not uncommon for taxi drivers to suffer from certain levels of chronic fatigue, resulting in reduced alertness and impaired driving performance. Overall, drivers who spend more time behind the wheel have longer brake reaction times (slower reaction to hazardous events). Also, they prefer to maintain greater safety margins when engaging in driving distracted, which is consistent with the previous research on risk compensation theory (Oviedo-Trespalacios et al., 2020).

Moreover, although existing research has revealed changes in driver fatigue levels during a daily shift (Meng et al., 2019), the current findings suggest that taxi drivers may develop chronic fatigue as a result of continuous work schedules. Thus, when exploring driving fatigue, it is important to consider the driver's weekly work schedule. Also, it is observed that frequent users of mobile apps have faster braking action, as well as maintaining a greater safety margin. This is in line with the results of previous studies suggesting that task familiarity contributes to a reduction in crash risk (Chen et al., 2019; Chen et al., 2022; Chen et al., 2021b; Hansma et al., 2020).

5.2.2. *Safety perception and driving history*

Drivers who show a strong resistance (have more concerns) to both the radio and app-based ride-hailing systems (higher risk perception) tend to react slower (especially on motorway) when presented with an unexpected hazard. This can be because of the negative emotions about using ride-hailing apps (fear of being involved in crashes) and the tension/nervousness that comes with them. In this context, these drivers would feel a higher level of mental workload when they are required to use the ride-hailing systems, thus leading to a longer reaction time. The inevitable use of ride-hailing systems demands future research to explore drivers' concerns and perceived challenges when using these platforms. This will support their adaptation to these in-vehicle systems and allow them to drive safely. In this context, a fundamental question arises regarding the equity implications of mandating drivers to use either of these systems, particularly when they perceive the system as inherently dangerous. The evaluation of our ability to cope with distraction is a highly individual matter. Therefore, if a scenario unfolds in which a company universally implements a standard system, and a subset of drivers perceives the system as unsuitable or lacks confidence in its proper use, there is a potential risk. These drivers may find themselves in a situation where they are unable to exercise self-regulation and have the autonomy to decide which risks to undertake. This situation is particularly concerning as their employment may be essential, leaving them with limited choices.

Driver's accident record was found negatively associated with time headway. In other words, taxi driver who has been involved in a traffic accident in the past 12 months tends to adopt a smaller safety margin. On motorways, they also display a shorter brake reaction time. The reason for this might be that drivers with accident records tend to drive aggressively, especially professional drivers (Anusha and Nagendra, 2021). An aggressive driving behavior can involve closely following a leading vehicle, which can increase the risk of rear-end collisions (Kovaceva et al., 2020; Adavikottu and Velaga, 2023; Chen et al., 2019).

On the other hand, taxi drivers who received traffic tickets in the past 12 months showed shorter brake reaction times and longer time headways (a safer margin). Drivers previously penalized are more likely to adopt more cautious driving behaviors due to the sanctions' deterrent effects, thus reducing unsafe driving behavior (Gibbs, 1985; Hössinger et al., 2012; Lawpoolsri et al., 2007; Sze et al., 2012). In light of this understanding, it is reasonable to propose that the threat of penalties discourages drivers from engaging in risky behaviors. It is important to note that taxi drivers are particularly sensitive to the accumulation of driving offense points associated with tickets, because these may result in their licenses being suspended – a critical concern given their dependence on driving for income (Wong et al., 2008; Chen et al., 2020a). Furthermore, drivers compensated per-trip are likely to be further discouraged by monetary fines, commonly imposed through violation tickets (Chen et al., 2020a). Due to this, taxi drivers with trip-based earnings are more vigilant and responsive, especially if they have previously been fined.

5.3. Interactions effects

Drivers' safety perception and driving history influence the effects of ride-hailing systems on brake reaction time (see Table 3). In particular, the increasing effect of mobile app distraction on brake reaction time on urban streets is mitigated among taxi drivers with higher safety perception. The results suggest that, for the drivers who consider using ride-hailing mobile apps to be a significant crash contributory factor, an 8 % decrease in the brake reaction time would be observed compared with their counterparts. It is possible that this is due to the high motivation of these drivers to respond to the dangerous situation of using mobile apps while driving, as described in the protection motivation theory (PMT) proposed by Rogers (1975). According to this theory, individuals determine their responses to threats through two cognitive processes: threat appraisal and coping appraisal. A taxi driver who perceives a high crash risk and vulnerability is less likely to experience a significant physical threat from a distraction by a mobile app, since they are more motivated to protect themselves (be more cautious and thereby react quickly). According to Taubman-Ben-Ari et al (2004), a high level of threat appraisal contributes a lower frequency of reckless driving. In light of the possibility that drivers' perception of crash risks could influence their driving behavior, more emphasis could be placed on safety education for new technologies such as ride-hailing services. We recommend that taxi drivers receive comprehensive and regular safety training based on our current findings.

On motorways, the increasing effects of radio system and mobile app distractions on brake reaction time are alleviated among taxi drivers with a previous record of traffic violations. In particular, these drivers show a 13 % decrease in brake reaction time when distracted by a mobile app compared to their counterparts, and a 6 % decrease when distracted by a radio system. This is reasonable since taxi drivers may be deterred from violating the law by the penalties (Gibbs, 1985). Essentially, drivers would avoid committing a crime for fear of punishment if confronted with dangerous situations. Earlier studies have found that drivers with traffic violations tickets tend to reduce their risk-taking behaviors (Chen et al., 2020a; Ngueutsa and Kouabenan, 2017; Chung et al., 2021). Specifically, under the current Hong Kong Driving-offence Points (DOP) system, a driver will be issued DOPs or a monetary fine. In this context, using ride-hailing systems would therefore present a risky situation that contributes to increased crash risks or chances of being published for dangerous driving. This could result in these taxi drivers being more aware of distracted driving conditions. In a way, our study supports the effectiveness of Hong Kong's current sanctions system for combating traffic violations.

On the other hand, Table 5 suggest that the association between distractions caused by radio system and preferred safety margins may be moderated by driver characteristics. Specifically, the increasing effect of radio distraction on time headway would be reduced by the frequent user of radio system. In particular, the time headway of frequent radio users decreased by 10 % on urban streets when distracted by a radio system compared to their counterparts, and by 4 % on motorways. Clearly, the effective training of the use of the auditory system increases driver's self-efficacy, thereby reducing the distractions effects. For instance, it was found that novice drivers' self-efficacy for driving competence and hazard identification skills improve after training and self-practice (Marksaityte et al., 2017; Seibokaite et al., 2022). This suggests that more attention should be paid to designing training programs for taxi drivers who are not familiar with the use of ride-hailing systems, such as the new licenses and older drivers.

6. Implications of the research

Our study yields several key policy implications aimed at enhancing road safety and the well-being of taxi drivers when utilizing ride-hailing systems. Firstly, since we found that the safety impact of mobile app is more profound than the radio system, promoting voice-based or hands-free interactions within ride-hailing platforms can mitigate the increased risk derived from the longer reaction time. Despite their distracting effects, voice recognition systems reduce the visual demands when drivers use smartphones or other in-vehicle systems (Simmons et al., 2017). For companies developing ride-hailing apps, the interface should be flexible enough to allow drivers to use voice commands for tasks such as verifying orders and communicating with passengers. Additionally, an auditory feature could be included in the mobile app that passengers use to book and request services. Thus, text-based requests could be replaced with speech-based broadcasts.

Secondly, our findings indicate that taxi drivers who frequently use ride-hailing apps tend to react more quickly during sudden brake events. This suggests that their extensive experience with these platforms may mitigate their risk when it comes to safety–critical situations. A comprehensive safety training program that is tailored specifically to ride-hailing systems is essential in light of the expected increase in use of these systems in the future. The focus of such programs should be on managing distractions and improving attention with simulator studies based on real-world situations. Through collaboration between taxi companies and training centers, drivers could gain hands-on experience, enabling them to navigate the challenges associated with ride-hailing systems and minimize distraction risks.

Thirdly, our results indicated that although taxi drivers show longer brake reaction times when distracted by mobile apps and radio systems, this does not necessarily lead to reduced safety. They mitigate this risk by maintaining a greater safety margin from the vehicle ahead. Nevertheless, if many drivers improperly compensate by adopting longer time headways when using apps on the road, it could adversely impact overall travel efficiency. In light of this, the compensatory behaviors observed under distraction in this study could be incorporated into advanced driver assistance systems (ADAS). These systems could then calibrate a safer margin of headway that optimizes safety without compromising mobility.

Fourthly, taxi drivers who have received traffic tickets in the past 12 months demonstrated improved safety behaviors, as evidenced by their shorter brake reaction times and longer headway distances. Therefore, traffic enforcement may enhance driving safety due to its deterrent effect. To reinforce this positive trend, regulatory bodies must establish clear, specific penalties tailored to the use of ride-hailing services. Drivers in Hong Kong are prohibited from using hand-held telecommunications equipment, including mobile phones, while driving. Offenders can be fined up to HK$2,000 on conviction. Hands-free kits are recommended for drivers who need to use hand-held mobile phones while driving. Nevertheless, the penalties and safety tips for using mobile phones should be updated to reflect current safety standards. For example, it is possible to implement a graduated fine system where penalties increase with repeated offenses. Also, the assignment of driving offense points can result in the suspension or revocation of taxi driving privileges if certain thresholds are exceeded. We can also require drivers to complete safety courses addressing the risks associated with using mobile apps while driving. Additionally, encouraging drivers to take periodic breaks is essential to combat the potential for chronic fatigue and reduced attention resulting from long work hours, which could increase crash risk. Taxi companies can promote driver alertness by incorporating short breaks into drivers' schedules. To maintain high safety standards and discourage risky behaviors associated with mobile app distractions, these measures should be clearly communicated and consistently enforced.

7. Conclusion

In recent years, ride-hailing services have transformed passenger-driver communication, providing passengers with a convenient means of requesting rides and improving the mobility of the city. These services have also been instrumental in increasing taxi drivers' income. However, there's a growing concern regarding the potential distractions associated with ride-hailing systems, which can impair driving performance and increase the risk of accidents. This is particularly significant considering the higher accident rate among taxi drivers, highlighting the need for a comprehensive investigation.

This present simulator study aimed to investigate the impact of different ride-hailing systems (radio and mobile apps) on taxi drivers' safety performance. Two key performance indicators, brake reaction time and time headway, were utilized to assess the risk of rear-end collisions during car-following tasks with sudden brake events. The grouped random parameters Weibull accelerated failure time models with interaction terms are adopted, accounting for repeated measurements, unobserved heterogeneity, and observed heterogeneity. The findings indicate that distracted taxi drivers, whether by radio or mobile app, exhibited longer brake reaction times. However, they also maintained greater safety margins, as evidenced by longer time headways under distraction conditions. This suggests that taxi drivers tend to adopt compensatory strategies when distracted, possibly due to their superior driving skills and experience. It's important to note that these findings do not promote distractions but highlight the importance of understanding how drivers adapt in different conditions, with the ultimate goal of reducing distractions and enhancing road safety.

The study also revealed that various driver characteristics play a role in safety performance. Drivers resistant to ride-hailing systems exhibited longer reaction times when distracted, possibly due to increased cognitive load. In urban environments, experienced drivers had shorter brake reaction times and time headways, while those working more days demonstrated the opposite pattern, possibly due to fatigue. On motorways, frequent users of ride-hailing mobile apps exhibited smaller safety margins, indicating higher confidence. Additionally, drivers with traffic tickets or points tended to have greater safety margins, possibly due to increased caution. Interaction effects were observed, with safety perception and driving history mitigating the effects of ride-hailing distractions on brake reaction time, and frequent radio users moderating the impact of taxi radio distractions on time headway. These findings highlight the intricacies and individual differences in driver behavior, emphasizing the need to consider these factors in safety studies.

Several limitations in this study warrant consideration for future research endeavors. To begin, there is room for refinement in the characterization of urban street environments, as city roads typically present a higher degree of complexity, featuring numerous intersections, traffic signals, and pedestrian crossings. Additionally, our study did not account for the combined distractions that drivers may face, such as simultaneously using the radio and mobile apps. Investigating the outcomes of these combined distractions in real-world scenarios could provide valuable insights. Also, a limited number of 51 participants participated in our simulator study. There's no doubt that more complex models call for a greater number of participants, which helps yield superior results. It is recommended that a larger sample size be used in a future extended study based on the power analysis. Addressing these limitations in future studies is essential to gain a more comprehensive understanding of the impact of in-vehicle distractions on driving behavior and safety risk. By doing so, we aim to contribute to the development of a safer ride-hailing system that takes into account the intricacies of real-world driving conditions and helps mitigate potential hazards for both drivers and passengers.

CRediT authorship contribution statement

Shi Ye: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Tiantian Chen:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Oscar Oviedo-Trespalacios:** Writing – review & editing, Conceptualization. **N.N. Sze:** Funding acquisition, Conceptualization. **Sikai Chen:** 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.

Data availability

The authors do not have permission to share data.

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Appendix A

Table A1
Results of likelihood ratio tests.

Log-likelihood of	Brake Reaction Time		Time Headway	
	Urban	Motorway	Urban	Motorway
Fixed Parameters Model	−21.02	−16.55	93.86	260.88
Uncorrelated Random Parameters Model	15.91	15.17	103.86	277.69
χ^2 (df)	73.86 (2)	63.44 (2)	20.00 (2)	33.62 (2)
Correlated Random Parameters Model	15.85	15.21	104.70	279.08
χ^2 (df)	0.06 (1)	0.04 (1)	0.84 (1)	1.39 (1)

Table A2
Model fit under different assumptions for random parameters distributions.

Brake reaction time	Urban street				Motorway			
	(n)	(t)	(u)	(l)	(n)	(t)	(u)	(l)
Log-likelihood at convergence	**[15.91]**	<u>16.09</u>	14.89	15.17	**[15.17]**	<u>15.75</u>	13.17	13.18
Time headway	**Urban street**				**Motorway**			
	(n)	(t)	(u)	(l)	(n)	(t)	(u)	(l)
Log-likelihood at convergence	**[103.86]**	100.90	100.38	<u>105.07</u>	**[277.69]**	278.14	278.49	<u>279.07</u>

Note: (n) − standard normal distribution, (t) − triangular distribution, (u) − uniform distribution, (l) − log-normal distribution

Table A3
Results of the clustered heterogeneity and gamma frailty Weibull accelerated failure time model of time headway in urban street.

Parameter	Clustered heterogeneity			Gamma frailty		
	Coefficient	z-statistic	exp(β)	Coefficient	z-statistic	exp(β)
Constant	0.066	0.70	1.07	0.066	0.70	1.07
Car following condition						
Initial car following distance	0.024	18.87	1.02	0.025	19.03	1.03
Distraction type (Base: No distraction)						

(continued on next page)

Table A3 (*continued*)

Parameter	Clustered heterogeneity			Gamma frailty		
	Coefficient	z-statistic	exp(β)	Coefficient	z-statistic	exp(β)
Mobile app	0.109	4.50	1.12	0.092	3.58	1.10
Radio system	0.067	2.40	1.07	0.075	2.82	1.08
Personal characteristic						
Number of years holding taxi driving license	−0.004	−2.47	1.00	−0.003	−1.70	1.00
Weekly working days	0.017	1.37	1.02	0.001	0.13	1.00
Driving History						
Received traffic violation tickets in previous 12 months	0.079	3.62	1.08	0.067	3.05	1.07
Involved in traffic accident in previous 12 months	−0.038	−1.56	0.96	−0.042	−1.61	0.96
Interaction effect						
Radio system * Frequent user of radio system	−0.076	−0.94	0.93	−0.072	−1.00	0.93
Model fit						
Number of observations	153			153		
Log-likelihood of constant only model	−30.86			−27.81		
Log-likelihood at convergence	93.86			98.09		

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