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Gap acceptance behaviour and crash risks of mobile phone distracted young drivers at roundabouts: A random parameters survival model

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ABSTRACT

Navigating through complex road geometries, such as roundabouts, poses significant challenges and safety risks for drivers. These challenges may be exacerbated when drivers are distracted by mobile phone conversations. The interplay of road geometry, driving state, and driver characteristics in creating compound risks remains an underexplored area in existing literature. Proper understanding of such compound crash risk is not only crucial to improve road geometric design but also to educate young drivers, who are particularly risk-takers and to devise strict penalties for mobile phone usage whilst driving. To fill this gap, this study examines crash risks associated with gap acceptance manoeuvres at roundabouts in the simulated environment of the CARRS-Q driving simulators, where 32 licenced young drivers were exposed to a gap acceptance scenario in three phone conditions: baseline (no phone conversation), handheld, and hands-free. A parametric random parameters survival modelling approach is adopted to understand safety margins—characterised by gap times—during gap acceptance scenarios at roundabouts, concurrently uncover driver-level heterogeneity with mobile phone distraction and capture repeated measures of experiment design. The model specification includes the handheld phone condition as a random parameter and hands-free phone condition, acceleration noise, gap size, crash history, and gender as non-random parameters. Results suggest that the majority of handheld distracted drivers have smaller safety margins, reflecting the negative consequences of engaging in handheld phone conversations. Interestingly, a group of drivers in the same handheld phone condition have been found to exhibit cautious/safer behaviour, as evidenced by longer gap times, reflecting their risk compensation behaviour. Female distracted drivers are also found to exhibit safer gap acceptance behaviour compared to distracted male drivers. The findings of this study shed light on the compound risk of mobile phone distraction and gap acceptance at roundabouts, requiring policymakers and authorities to devise strict penalties and laws for distracted driving.

1. Introduction

The widespread use of mobile phones whilst driving has become a major safety concern globally, particularly among young drivers. Statistics indicate that mobile phone usage is more prevalent in young drivers than in other age groups. For instance, the proportion of young drivers using mobile phones whilst driving is about 39% in the US (Yellman, 2020), 94% in Australia (Mozo, 2024), and 30% in the UK (RAC, 2024). As a consequence of the tendency towards mobile phone usage, distraction-related collisions are becoming more common (e.g., 3308 fatal crashes in 2022 in the US (NHTSA, 2023) and 16% of road fatalities in Australia in the same year (AAA, 2023)). The current research enhances our understanding of the factors influencing distracted driving in young drivers.

Numerous studies have explored mobile phone distraction (including but not limited to conversation, playing games, reading/sending emails, texting, chatting, checking social media and taking photos), revealing significant consequences for young drivers, including fatal and severe injuries (Phuksuksakul et al., 2021). In general, mobile phone distraction impairs driving behaviour, which ultimately leads to safety issues. As an example, a study found that young drivers who were distracted by mobile phones exhibited longer reaction times when reacting to

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pedestrians walking on the sidewalk (Haque and Washington, 2014). The study reported that mobile phone distraction resulted in delayed detection of pedestrians walking from the sidewalk. This delay could be linked to the increased cognitive load caused by mobile phone usage whilst simultaneously managing driving tasks. Similarly, mobile phone conversations have been reported to increase the cognitive load that directly affects their driving performance, characterised by car-following, lane-changing, and interaction with other road users and infrastructures (Oviedo-Trespalacios et al., 2016). Some notable effects of mobile phone conversations are slower driving (Iio et al., 2021), large speed variation (Emily Parcell et al., 2021), lower vehicle control (Xue et al., 2023), increased spacing (Zhang et al., 2019), harsh braking (Ali and Haque, 2023), indecisiveness in responding to yellow lights (Liao et al., 2015), and many others.

In essence, engaging in mobile phone conservation whilst driving significantly increases workload and makes driving tasks more difficult (Oviedo-Trespalacios et al., 2016). However, it remains unclear how workload increases with a unique road network feature, i.e., roundabout. In other words, whilst mobile phone conservations during driving have been reported to increase crash risk, the correlation and variation of such risk with different road geometry are not well understood, given drivers exhibit adaptive behaviour when they are distracted (Tractinsky et al., 2013, Young and Regan, 2013).

Among different road geometries, roundabouts are an atypical road feature with deflected road geometry, requiring drivers' good navigation skills to control their vehicles. Drivers at roundabouts often require selecting a gap in the circulating traffic stream whilst giving way to traffic on their right or left (depending on driving conditions in a country), whereby the decision-making process of drivers is generally tested. To this end, Montella (2011) found failure to give way at roundabouts is a significant factor in roundabout safety, leading to about 33% of crashes. Another study reported that young drivers are involved in one-third of roundabout crashes, reflecting the sensitivity of young drivers to safely navigate through roundabouts (Burdett et al., 2017). As roundabouts are already a challenging road feature, engaging in mobile phone conversations whilst driving is likely to deteriorate the manoeuvring capabilities of distracted drivers. An earlier study (Cooper and Zheng, 2002) on turning gap acceptance at roundabouts reported that distracted drivers became collision-prone when engaging in mobile phone activities whilst driving on adverse surface conditions. Similarly, Haque et al. (2016) reported no statistically significant differences in gap acceptance at roundabouts of distracted and undistracted drivers, but the safety margin was found to be significant and smaller for distracted drivers. Although these studies, among several others, provide some insights into distracted driving behaviour at roundabouts, our understanding remains elusive about what factors affect distracted driving behaviour at roundabouts and whether the relationship of such factors is homogeneous or heterogeneous, which motivates the present study.

As such, this study investigates the crash risk associated with the gap acceptance behaviour of young, distracted drivers at roundabouts using parametric survival models, allowing us to capture panel nature of data and provide insights into the heterogeneous effects of mobile phone distraction on driving behaviour. To this end, this study aims to answer the following questions.

1. How do safety margins at roundabouts vary across different mobile phone conversations (handheld versus hands-free)?
2. Is the effect of mobile phone distraction on safety margins homogeneous or heterogeneous across drivers?
3. Are driver characteristics (e.g., age and gender) associated with safety margins at roundabouts?

This study makes valuable theoretical and practical contributions to the existing distracted driving literature in three ways. First, by addressing the above three research questions, this study offers detailed insights into the safety determinants for young, distracted drivers at roundabouts—an area that has received limited attention in previous research. Second, from a theoretical perspective, this study develops a random parameters survival model to examine the crash risks associated with the gap acceptance behaviour in roundabouts, representing a unique contribution to the literature capturing unobserved heterogeneity associated with gap acceptance behaviour and uncovering driver-level variations. In the existing literature, most studies analysed data using simple statistical techniques, e.g., Analysis of Variance (ANOVA), paired *t*-tests, and fixed parameters models, which are unable to uncover heterogeneous effects on mobile phone conversations. For instance, most studies on distracted driving found that using mobile phones whilst driving decreases the safety margin; however, these studies failed to note that distracted drivers may also become cautious when using mobile phones whilst driving, leading to higher safety margins. Analysing this heterogeneous behaviour is only possible using the developed random parameters survival model—the application of such a model is scant in distracted driving. Finally, based on study findings, practical recommendations are also elicited, assisting road authorities and stakeholders to devise strict penalties.

The rest of the paper is organised as follows. The next section summarises relevant studies on the topic supporting the research gap addressed in this study, whereas Section 3 begins by explaining the methodology, including the driving simulator description, scenario design, and mobile phone tasks, followed by a description of the data analysis techniques used. Section 4 describes modelling results, whereas these results are discussed and contextualised in Section 5. Finally, Section 6 summarises the major findings and identifies future research directions.

2. Literature review

This section briefly summarises representative distracted driving behaviour studies, forming the background of the current study. Whilst providing an exhaustive review of distracted driving behaviour is beyond the scope of this study, interested readers are referred to Oviedo-Trespalacios et al. (2016) for a detailed review.

2.1. A review of distracted driving behaviour studies

A thorough literature review is conducted to better understand distracted driving behaviour at different road locations, and some representative studies are summarised in Table 1. Three noteworthy observations from this table are as follows. First, most of the studies used driving simulators with a few exceptions that either used observational studies or in-vehicle videography. Driving simulators provide (i) ease of data collection with minimal risk that is prevalent in the real world, and (ii) a controlled environment to minimise confounding factors in the analysis. For instance, Mutar et al. (2021) evaluated the response time of distracted drivers using a driving simulator and the results revealed a delay in drivers' response, implying an increase in cognitive response time when using a mobile phone compared to driving without it. Choudhary and Velaga (2020) analysed the impact of distracted drivers' decisions at the onset of a yellow light using a driving simulator and reported that compared to normal driving, eating and drinking tasks during driving reduced the stopping time by 6% and 7%, respectively.

Second, past studies analysed distracted driving behaviour in the context of various complex road scenarios, such as navigating curved, hilly roads, intersections, and roundabouts. From the traffic engineering perspective, roundabouts increase safety by streamlining traffic into circulatory movement (Elvik, 2017), but drivers often find roundabouts a difficult and complex road infrastructure (Distefano et al., 2018). In a similar vein, studies have indicated that the demands of driving tasks tend to fluctuate based on factors, such as speed, vehicle attributes, interactions with nearby vehicles, and road infrastructure (Fuller et al., 2008). As such, roundabouts are likely to be task-demanding because

Table 1
Representative studies on distracted driving behaviour on different road types.

Study	Event	Distraction type	Road geometric features	Data	Modelling Technique	Factors	Response variable	Heterogeneity
Ali and Haque (2023)	Responding to hard braking	Mobile phone conversation	Straight urban road	Driving simulator data	Duration model	Age, gender, and vehicle dynamics	Response time	Yes
Al Aufi et al. (2022)	Gap acceptance	Texting whilst driving	Different roadway configurations including roundabout	Driving simulator data	Descriptive analysis	NE	NA	No
Sajid Hasan et al. (2022)	NA	Drinking, eating, smoking, drowsy, grooming, handheld phone, radio, talking to passenger	Signalised and unsignalised intersections	Observational or field data	Descriptive analysis	NE	NA	No
Sheykhfard and Haghighi (2020)	Digital billboards	Looking at digital billboards outside of the car	Urban roads	In-vehicle videography	Structural equation model	Road, environmental, and human factors	Distraction	No
Azimian et al. (2021)	Eye fixation	Cell phone-induced distraction	Roundabout	Driving simulator data	Descriptive analysis	NE	NA	No
Mutar et al. (2021)	Responding to stopping command	Hands-free calling, hand calls, reading text messages, and sending text messages	Straight urban road	Driving simulator data	Descriptive analysis	NE	NA	No
Choudhary and Velaga (2020)	Responding to yellow light	Eating and drinking tasks	Signalised intersection	Driving simulator data	Duration and logistic model	Speed, deceleration and time to stop line	Time lapsed in reducing the speed, crossing the intersection, success rate of stopping encounters and crossing encounters	No
Andrikopoulou and Spyropoulou (2018)	Responding to stop sign	Handheld conversation, hands-free conversation and speaker mode conversation	Unsignalised intersection	Driving simulator data	Descriptive analysis	NE	NA	No
Papantoniou (2018)	Unexpected incidents	Conversation with passengers, cell phone use	Rural and urban road	Driving simulator data	Structural equation model	Driver characteristics, age, gender, and experience	Overall driving performance	No
Ortiz et al. (2018)	NA	Texting with WhatsApp	Roundabout	Driving simulator data	Descriptive analysis	NE	NA	No
Haque et al. (2016)	Gap acceptance	Mobile phone conversation	Roundabout	Driving simulator data	Linear mixed model	NE	NA	No
Yannis et al. (2014)	Animal crossing in front of subject driver	Texting	Circular rural road	Driving simulator data	Lognormal model	Vehicle dynamics	Probability of an accident	No
Leung et al. (2012)	Sudden appearance of truck in front of subject vehicle	Mobile phone usage	Straight and curved roads	Driving simulator data	Descriptive analysis	NE	NA	No

NE: not explored; NA: Not applicable because no model was developed.

drivers need to concurrently perform tasks like decision-making for gap acceptance, interacting and evaluating traffic dynamics of vehicles already in the roundabout, proper lane selection and management for route navigation, and safely traversing through the roundabout with comfortable speed. Complex road environment compounded by mobile phone conversations whilst driving is likely to lead to cautious driving behaviour. Some evidence exists along this direction but on different roadway types, e.g., selecting lower speeds when driving through a tunnel compared to a freeway (Rudin-Brown et al., 2013), winding roads (Tractinsky et al., 2013), and sub-urban roads (Ali and Haque, 2023). In contrast, normal/straight roads are found to negligibly affect driving behaviour (Bamney et al., 2022). The evidence from the literature review suggests that driving behaviour changes depending on task demands, resulting from a combination of distraction and complex road geometry. However, it remains unclear what factors affect driving behaviour at roundabouts, how the safety margin varies with respect to different gap sizes, and whether distraction only decreases the safety margin (i.e., homogeneous effect of mobile phone distraction) or distraction may increase or decrease safety margin (i.e., heterogeneous effects of mobile phone distraction).

Finally, the event in which the effect of distraction is measured varies across studies and some representative examples are (i) responding to leader's hard braking, (ii) gap acceptance behaviour, (iii) looking at billboards outside of the car, (iv) responding to a yellow light, and others. Gap acceptance at roundabouts is of interest herein due to its risky nature. Al Aufi et al. (2022) investigated the effects of texting whilst driving for different roadway configurations (intersections, segments, freeways, and roundabouts; urban, suburban, and rural sections; and straight and curved road cross-sections) and various lighting conditions (nighttime and daytime) using a driving simulator. The findings of this study suggest that the mean lane positions of the young and middle-aged/old age groups significantly differed whilst texting and driving at roundabouts. No further in-depth analysis of gap acceptance behaviour concerning distracted driver safety was conducted. Along the same lines, Haque et al. (2016) evaluated gap acceptance behaviour and quantified safety margins using post encroachment time. This study did not find any statistically significant differences in accepted gap sizes but reported significant differences in safety margins. Whilst this study provided preliminary information that safety margin significantly varies across phone conditions, evidence of which factors affecting the safety margin and whether the safety margin will increase or decrease corresponding to a given determinant are scant. This research gap forms the foundation of the current study.

2.2. A summary of analysis methods in distracted driving behaviour studies

Table 1 summarises notable efforts of analysis methods in distracted driving literature. It can be observed that the majority of the studies have analysed their data using descriptive analyses (e.g., analysis of variance [ANOVA] and paired *t*-tests). Azimian et al. (2021) applied paired *t*-tests to compare between-group differences in fixation durations when the drivers were looking at all the areas of interest, e.g., front mirror, windshield, driver-side mirror, driver-side window, passenger-side mirror, and passenger-side window, and their results showed significant between-group differences. An issue in the application of ANOVA is its inability to handle missing data or imbalanced datasets, which is prevalent in driving simulator studies as some drivers may fall sick during the driving, thereby not completing the entire experiment (e.g., Ali et al. (2020) for imbalanced panel dataset). To overcome this issue, studies have applied linear mixed models—an advanced form of ANOVA that is capable of handling missing data at random. For instance, Haque et al. (2016) analysed imbalanced post encroachment time data from their driving simulator using a linear mixed model. To summarise, although descriptive analyses are useful in examining significant differences between distracted and undistracted driving, they are not capable of providing insights into factors affecting distracted driving, which requires developing statistical models.

To this end, Table 1 indicates that a few studies have developed statistical models, such as a fixed parameters logistic model, a fixed parameters duration model, and a random parameters duration model. In the duration models, the dependent variable varies across studies, e.g., (i) time elapsed in reducing the speed and (ii) time elapsed crossing the intersection. For the logistic models, the dependent variables are accident occurrence, success rate of stopping encounters, and success rate of crossing encounters. A fixed parameters model assumes that the impact of an explanatory variable (e.g., conversation via a handheld phone) will be homogeneous across all drivers. This strong assumption hinders our evaluation of the dual-facet impact of mobile phone distraction on driving behaviour. A recent study found this strong assumption invalid when evaluating distracted drivers' responses to leader's hard braking in car-following (Ali and Haque, 2023). This study reported that most distracted drivers (in the handheld phone condition) reduced their initial speeds more slowly than undistracted drivers, whereas some distracted drivers in the same driving condition (i.e., handheld) exhibited faster braking, reflecting the presence of heterogeneous impact of mobile phone distraction. This study was performed on a straight road with a different stimulus (i.e., leader's hard braking); however, whether the findings are transferrable in the context of roundabouts and heterogeneous behaviour whilst responding to gap acceptance at roundabouts exist are some of the questions that motivate the current study.

3. Methods

3.1. Advanced driving simulator

A controlled driving simulator experiment was conducted at the Centre for Accident Research and Road Safety–Queensland (CARRS-Q) facility to investigate the driving behaviour of young drivers at roundabouts. The simulator, depicted in Fig. 1(a), featured a fully operational car with an automatic transmission and an integrated audio system that replicated ambient sounds, enhancing the immersive driving experience. The car was mounted on a motion base equipped with six degrees of freedom, which emulated real driving sensations through the steering wheel and enabled the simulation to provide motion cues related to acceleration, braking, cornering, and interactions with diverse road surfaces. A realistic driving experience was curated using three front-view projectors that provided a 180° high-resolution field of view, and LCD monitors were utilised for rear driving information. By utilising the simulator software alongside eight computers, this study successfully integrated vehicle dynamics into the virtual road traffic environment. Essential data, including position and speed, were recorded at intervals of 0.05 s.

3.2. Participants

A sample of 32 participants was selected and recruited through flyers, social networking platforms, and university email addresses. Participants were required to be between 18 and 26 years old and in possession of a valid Australian driver's licence, whether provisional (less than 3 years) or open. Whilst the study participants were evenly divided by gender, the average ages for male and female participants were 21.8 years (with a standard deviation [SD] of 1.80 years) and 21.1 years (SD = 2.19 years), respectively. Participants' driving experience ranged from 1 to 9 years. Approximately 34% of participants reported a history of crash involvement within the past year, whilst the remaining held open driving licenses.

3.3. Experimental plan

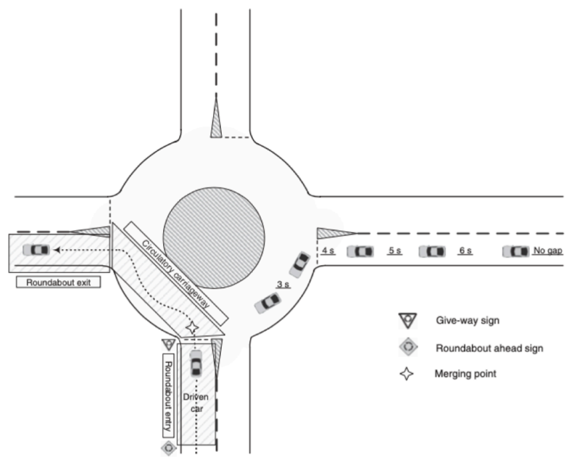
Three driving routes were presented to participants in the simulator. Each of the routes had different starting points on the same road layout to reduce learning effects. Note that the driving condition order was counterbalanced across participants. Participants in the handheld condition were asked to hold a phone to their ear and use the available hand for steering, whilst participants in the hands-free condition conversed using a Bluetooth headset.

3.3.1. Scenario design

In the simulation, this study designed a four-leg roundabout situated in a suburban area with a posted speed limit of 60 km/h. The graphical representation of the roundabout's geometric layout and gap acceptance scenario is presented in Fig. 1(b). The virtual roundabout in the simulation closely resembles standard roundabouts in Australia, whereby driving in Australia adheres to the left-side road rules, and traffic flow at roundabouts follows a clockwise direction around the central island. In the simulation, we incorporated road markings and a "Give Way" sign. Additionally, a "Roundabout Ahead" sign was strategically placed approximately 200 m before reaching the roundabout to alert drivers in advance. These signs and distances adhered to Australian road design standards (Australian Standard, 2001).

The gap acceptance scenario was designed with a sequence of vehicles, each separated by increasing gap sizes ranging from 2 s to 6 s. These

(a) Advanced driving simulator



(b) Roundabout schematic

Fig. 1. Experimental setting.

gaps were maintained whilst the conflicting vehicles moved at a consistent speed of 30 km/h. The gap between the driven vehicle (or participant's car) and the first conflicting vehicle was pre-programmed to be around 2 s, ensuring that the driver would be immediately engaged in the gap acceptance situation. This deliberate design ensured the accuracy and realism of the scenario for studying driving behaviour in gap acceptance scenarios at roundabouts. Note that participants were not asked to select any particular gap or when to enter the roundabout; rather, it was left to their discretion to start navigating through the roundabout.

3.3.2. *Distracted driving task*

A Nokia 500 phone (111.3 mm × 53.8 mm × 14.1 mm) was used for the study. Participants faced a cognitive mobile phone conversation adapted from Burns et al. (2002), which included tasks like solving verbal puzzles and math problems. These questions demanded the processing of information and memorisation, creating cognitive distractions unrelated to driving. A detailed description of mobile activities can be found in Haque et al. (2016).

3.3.3. *Participant testing protocol*

Before the experiment commenced, participants received a concise overview of the study, the distracted driving task, and instructions on operating the mobile phone device. They then engaged with a facilitator who sought consent and subsequently facilitated the mobile phone discussions. Driver demographics, such as age, gender, self-reported experience, and information about mobile phone use, were collected using a pre-driving questionnaire. For instance, the frequency of mobile phone usage was asked in three categories, namely frequent, moderately frequent, and less frequent. These variables were treated as categorical variables in the model like gender and crash involvement. Participants familiarised themselves with the simulator and performed a practice drive (shorter and significantly different than the actual drive) to ensure they were comfortable and acquainted themselves with simulator controls and navigation procedures, such as overtaking and gap acceptance scenarios and adhering to speed limits and directional signs. Participants were instructed to drive as they normally do like obeying speed limits. During the experimental drives in the hands-free and handheld conditions, participants engaged in continuous phone conversations with an experimenter that were initiated before and maintained throughout the drive. Breaks were provided after each of the three experimental drives. Note that to minimise confounding factors during the analysis, cognitive mobile phone conversations, adapted from Burns et al. (2002), remained the same during handheld and hands-free driving conditions.

3.4. *Data collection and model development*

3.4.1. *Data*

Thirty-two participants completed three drives, yielding 96 trajectories for analysis. Specifically, in the roundabout scenario after a vehicle enters, participants remain in the collision course with the following vehicle, and their safety can be analysed using gap time, which is found to be an appropriate traffic conflict measure for angle collisions (Li et al., 2024). Gap time can be defined as the remaining time between the crossing of the rear of the leader and the front of the subject vehicle in a roundabout. Longer gap time values indicate safer conditions (or higher safety margin), offering more time for the conflicting vehicle to react and avoid collisions. Fig. 2 shows visual summaries of

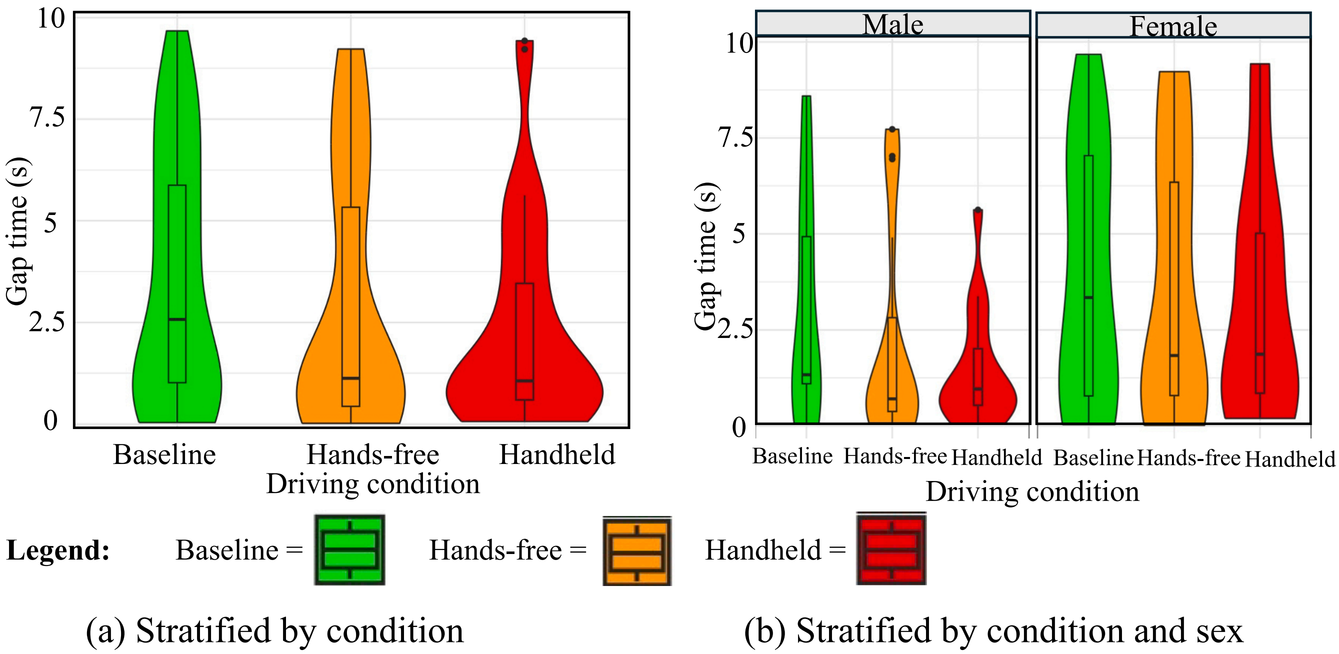


Fig. 2. Visual summaries of the gap times.

the gap times, stratified by condition and sex, which already shows a difference in gap times distribution within these subgroups.

Individual trajectories were used to calculate gap times and other driving behaviour variables like acceleration noise in the roundabout entry zone (see Fig. 1(b)), initial speed at the onset of entering the roundabout, and deceleration before accepting a gap. These driving behaviour variables were merged with driver demographics for model development to understand safety during gap acceptance, which is described in the ensuing paragraph.

3.4.2. Parametric survival model

This study applies hazard-based duration (or survival) models for modelling gap times at roundabouts, defined as the remaining time in an angle collision between the participant (or driven) car and the conflicting vehicle. Hazard-based duration models are frequently applied for various transport applications where the time until an event occurs is under consideration (Washington et al., 2020). In the context of our study, these models provide time-varying probabilities of angle collisions, reflecting the riskiness of manoeuvring at roundabouts. Ensuing paragraphs describe the formulation of the hazard-based duration modelling approaches considered in this study.

3.4.2.1. Weibull model with gamma heterogeneity. Let $F(t)$ denote the cumulative distribution function, providing the probability of avoiding an angle collision before the time t, leading to

$$F(T) = P(T < t), \tag{1}$$

where, $P(\bullet)$ corresponds to the probability, and T is a positive and continuous random variable representing the time to event of interest. The probability density function ($f(t)$) can be obtained as the first derivative of $F(t)$ as

$$f(t) = \frac{dF(t)}{dt}. \tag{2}$$

From the probability density function, the corresponding hazard function ($h(t)$) can be obtained. Intuitively, the hazard function represents the instantaneous risk of the event occurring. It is obtained as the limit of the conditional probability of avoiding an angle collision between t and $t + dt$, given that the collision has not occurred up to time t, as $dt \rightarrow 0$. Mathematically, it can be written as

$$h(t) = \frac{f(t)}{1 - F(t)}. \tag{3}$$

The corresponding survival function ($S(t)$) provides the probability of avoiding an angle collision being greater than or equal to some specified time t, which can be obtained as

$$S(t) = P(T \geq t) = \frac{f(t)}{h(t)}. \tag{4}$$

Several hazard-based duration models have been developed to incorporate the effect of covariates on the hazard function (see Rubio et al. (2019) for a general overview). The most common models in practical applications are the "proportional hazards" and "accelerated failure time". The former models consider hazard ratios to be constant over time, whereas the latter models allow covariates to rescale the baseline survival function (where all covariates are zero) (Washington et al., 2020). This study applies an accelerated failure time approach, whereby an intrinsically linear function is used to express the relationship of gap times with its explanatory variables as

$$log(T) = \boldsymbol{\beta}'\boldsymbol{X} + \varepsilon, \tag{5}$$

where, $\boldsymbol{\beta}$ denotes a vector of regression parameters, $\boldsymbol{\beta}'$ denotes the transposed of $\boldsymbol{\beta}$, $\boldsymbol{X}$ indicates the vector of covariates (see Table 2), and ε is an error term. The conditional survival and hazard functions for the accelerated failure model can be obtained (Washington et al., 2020) as

$$S(t|\boldsymbol{X}) = S_0[t\exp(\boldsymbol{\beta}'\boldsymbol{X})], \tag{6}$$

$$h(t|\boldsymbol{X}) = h_0[t\exp(\boldsymbol{\beta}'\boldsymbol{X})]\exp(\boldsymbol{\beta}'\boldsymbol{X}), \tag{7}$$

where, S_0 and h_0 denote the baseline survival function and the baseline hazard function, respectively.

Estimating survival and hazard functions in a fully parametric setting requires specifying a distribution. Some commonly used distributions in the literature are Weibull, lognormal, gamma, Gompertz, log-logistic, and exponential (Washington et al., 2020). Empirically, the Weibull distribution has been found to provide a good fit for modelling gap times. For instance, Ali et al. (2019) found the Weibull distribution to be

Table 2
Summary statistics for variables considered in the survival model.

Variable type in the model	Variable	Description	Count (%)	Mean (SD)
	Phone condition			
Independent variables (X)	Baseline	If a participant drove without any phone conversation = 1, otherwise = 0 (reference category)	32 (32.33)	—
	Handheld	If a participant drove with handheld phone conversation = 1, otherwise = 0	32 (32.33)	—
	Hands-free	If a participant drove with hands-free phone conversation = 1, otherwise = 0	32 (32.34)	—
	Driver demographic			
	Gender			
	Male	If a participant was male = 1, otherwise = 0 (reference category)	16 (50)	—
	Female	If a participant was female = 1, otherwise = 0	16 (50)	—
	Crash involvement history in the last three years			
	Involved	If a participant was involved in a crash = 1, otherwise = 0	11 (34.28)	—
	Not involved	If a participant was not involved in a crash = 1, otherwise = 0 (reference category)	21 (65.62)	—
	Driver behaviour variables			
	Acceleration noise	The standard deviation of acceleration/ deceleration of a driver in the roundabout entry zone (m/s^2)	—	1.48 (0.67)
	Gap size	The available gap size (m) between two consecutive vehicles already in the roundabout	—	6.2 (1.4)
Dependent variable (Y)	Gap time	The remaining time (s) in an angle collision between the driven car and the conflicting vehicle	—	2.92 (1.91)

SD: standard deviation

statistically superior to other distributions, as confirmed by an Anderson-Darling test. Following this earlier study, an Anderson-Darling test was applied and the null hypothesis for this test was that the duration variable followed a Weibull distribution, and the test statistic confirmed a failure to reject the null hypothesis at a 95% confidence level (*test statistic* = 0.33; *p*-value = 0.44). As such, the Weibull distribution is selected in this study, and its probability density function can be written as

$$f(t) = \lambda\kappa(\lambda t)^{\kappa-1}\exp[-(\lambda t)^{\kappa}], \tag{8}$$

leading to the hazard function

$$h(t) = \lambda\kappa(\lambda t)^{\kappa-1}, \tag{9}$$

where $\lambda > 0$ and $\kappa > 0$ denote the rate and shape parameters of the Weibull distribution, respectively.

Equation (5) represents a fixed parameters model, assuming the influence of explanatory variables on gap times is the same for each observation (or driver). As such, parameters are fixed and remain constant across observations/drivers. This strong assumption may become problematic when unobserved factors associated with the determinants of gap times are not accounted for. As such, capturing unobserved heterogeneity becomes paramount (Mannering et al., 2016) and is considered in this study because substantial unobserved heterogeneity may exist in gap times as drivers may respond to mobile phone distraction differently. To this end, unobserved heterogeneity can be captured by introducing a heterogeneity (frailty) term in the conditional survival function (Nam and Mannering, 2000). Assume that the heterogeneity term is denoted as $w \geq 0$, which is distributed over the population as $g(w)$, with a conditional survival function $S(t|w)$, leading to an unconditional (marginal) survival function as

$$S(t) = \int_0^{\infty} S(t|w)g(w)dw. \tag{10}$$

In the context of the Weibull distribution, w is assumed to follow a gamma distribution (Mannering et al., 2016, Washington et al., 2020) with mean = 1 and variance $(\theta) = 1/\eta$, such that

$$g(w) = \frac{\eta^{\eta}}{\Gamma(\eta)}EXP[-\eta w]w^{\eta-1}. \tag{11}$$

The survival function for Weibull distribution can now be obtained as

$$S(t|w) = \exp[-(w\lambda t)^{\kappa}]. \tag{12}$$

The unconditional survival function can now be expressed as

$$S(t) = \int_0^{\infty} S(t|w)g(w)dw = [1 + \theta(\lambda t)^{\kappa}]^{-\frac{1}{\theta}}, \tag{13}$$

leading to the hazard function

$$h(t) = \lambda\kappa(\lambda t)^{\kappa-1}[S(t)]^{\theta}. \tag{14}$$

Note that when $\theta \rightarrow 0$, such a case reflects that heterogeneity is not present and the hazard reduces to Eq. (9), and the variance of the heterogeneity term (w) becomes zero.

3.4.2.2. Weibull model with random parameters. Contrasting to gamma heterogeneity, another common approach to capturing unobserved heterogeneity consists of using random parameters models (Mannering et al., 2016) that allow model parameters to vary across the observations. The gamma heterogeneity model presented in the previous section can be viewed as a restrictive form of a random parameters model whereby a single gamma distributed heterogeneity term captures variation across observations. The random parameters can be specified as (Washington et al., 2020)

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \Gamma\gamma_i, \tag{15}$$

where, $\boldsymbol{\beta}$ indicates the vector of mean values of the random parameter, γ is the user-specified term (e.g., gamma distributed, a normally distributed term, etc.), and Γ is a symmetric matrix (Washington et al., 2020). The unrestricted form of this matrix allows for capturing the correlation between random parameters and helps calculate the standard deviation of random parameters. In a conventional setting, the mean of the random parameters model is fixed, whereas, in the current study, it is parameterised as a function of gender, allowing us to capture heterogeneity-in-mean of the random parameter.

The random parameters model is estimated using a simulated maximum likelihood approach with 1,000 Halton draws (Bhat, 2003), ensuring the stability of model parameter estimates. To capture the panel nature of experiment design during model estimation, the same draw for all phone conditions for a given participant was taken. In safety literature, this modelling approach is known as a grouped random parameter with heterogeneity-in-mean approach.

To intuitively interpret model output, [1-exp(β) × 100)] is calculated, allowing us to quantify the effect of each model parameter on gap time. This measure suggests a *per cent* change in gap time, that is, a unit increase in continuous explanatory variables and a change from zero to one for dummy variables.

4. Results

Three parametric accelerated failure time survival models are estimated, capturing the panel nature of the experiment design. These models are: (i) a fixed parameters Weibull model with clustered heterogeneity, (ii) a fixed parameters Weibull model with gamma heterogeneity, and (iii) a grouped random parameters Weibull model. Note that a clustered heterogeneity model captures the potential correlation of panel data. Table 3 provides a comparative summary of these three models, and some noteworthy observations are as follows. First, the likelihood ratio test statistics or deviance for the clustered heterogeneity model, gamma heterogeneity model, and grouped random parameters model are respectively 31.4, 43.2, and 58.2, which are greater than the critical value for a 95% confidence level, suggesting that all models can sufficiently explain gap times. Second, to determine a statistically superior modelling approach, the random parameter and clustered heterogeneity models cannot be directly compared with the gamma heterogeneity model via a likelihood ratio test because they are not nested. To this end, the Vuong test statistic (Vuong, 1989) is applied for model comparison. An absolute value of Vuong statistic less than the critical value (1.96) at a 95% confidence level implies that the test does not support preferring one model over another (Washington et al., 2020). In contrast, a positive value of Vuong statistic greater than 1.96 favours model 1 over model 2 and similarly, a negative value of Vuong statistic less than −1.96 favours model 2 over model 1. As an illustration, this study considers model 1 as the random parameter model, whereas model 2 is the gamma heterogeneity model. The comparison yields a positive value of Vuong statistic (2.05), which is greater than 1.96 (the 95 % confidence level); therefore, model 1 (the random parameters model) is preferred over model 2. The Vuong statistic for comparing clustered heterogeneity and gamma heterogeneity models is 1.25, suggesting these models are not statistically different.

Further complementing these results, the Akaike Information Criterion (AIC) is calculated for all models, which concurrently accounts for model deviance and the number of parameters. Results indicate that although the random parameter model has one (two) extra parameter(s) compared to the gamma (and clustered) heterogeneity models, its AIC is 326.9, which is lower than the other two models, implying an improved fit of the random parameter model. Finally, McFadden Pseudo R-square (ρ^2) is also calculated for all models, suggesting more explanatory power of the random parameter model as evidenced by its relatively higher McFadden Pseudo R-square value, further ensuring our selection of the grouped random parameter model for understanding safety margins at roundabouts. Further, the selection of this model also highlights its statistical superiority over the fixed parameters model variants that do not uncover driver-level heterogeneity, thereby assisting in answering our research questions.

Table 4 presents the model estimation summary, whereby the Weibull parameter (κ) of the distribution is 2.71. A t-test on this parameter suggests that it is significantly greater than one, implying a monotone function for the angle collision event. Further, Table 4 indicates statistically significant non-random and random parameters in the model.

Table 3
Comparison of different duration model variants considered in this study.

Model	LL (0)	LL (β)	n	AIC	McFadden ρ^2
Clustered heterogeneity	−183.3	−167.6	7	349.2	0.086
Gamma heterogeneity	−183.3	−161.7	8	339.4	0.118
Grouped random parameter	−183.3	−154.2	9	326.4	0.159

n: no of model parameters; AIC: Akaike Information Criterion.

The non-random parameters include the dummy variables for the hands-free driving condition and crash involvement history, acceleration noise, and gap size. The random parameter in the model is the dummy variable for the handheld phone condition. Whilst several distributions are tested for this random parameter, a normal distribution is found to be statistically superior compared to other competing distributions, which is consistent with safety literature (Mannering et al., 2016). Note that several other variables are tested for random parameters, but no model provides a relatively better fit than the model presented in Table 4.

Acceleration noise is significant in the model and positively associated with gap times. Specifically, one m/s^2 increase in acceleration noise tends to decrease gap times by 25.6% ([1-exp(β)*100)]). Herman et al. (1959) pointed out that drivers with higher acceleration noise often exhibit risky driving behaviour, and our model also affirms this behaviour as drivers with higher acceleration noise are found to possess a lower safety margin during the gap acceptance scenario at roundabouts.

The gap size is found to be significant in the model and positively associated with the likelihood of avoiding a collision. A one meter increase in the gap size leads to a 43.9% increase in gap time, reflecting a higher safety margin associated with large gap sizes.

The model reveals a negative and statistically significant relationship between drivers' prior involvement in a traffic crash in the past three years and gap times. Compared to drivers who were not involved in a crash, drivers with a crash history possess a small safety margin. Specifically, the gap times of drivers with a crash history are approximately 43.4% lower than that of drivers without a crash history.

The dummy variable for the hands-free phone condition is significant in the model and negatively associated with gap times, with hands-free conversations appearing to reduce safety margins by 54.1% relative to the baseline or no phone condition.

The model indicates that the dummy variable for the handheld phone condition is random and significantly associated with the probability of avoiding a collision. The mean parameter estimate is negative, implying that most drivers possess shorter gap times. However, a small proportion of drivers have longer gap times (see Fig. 3(a)), reflecting the heterogeneous effects of handheld phone conservations. Whilst drivers with shorter gap times indicate a negative impact of a handheld phone conversation (risky behaviour), drivers with longer gap times exhibit cautious behaviour, reflecting their risk compensation behaviour.

From Table 4, it is also clear that the heterogeneity in the handheld phone condition is a function of driver gender. Using a simulation approach, gap times for males and females are calculated and their distributions are presented in Fig. 3(b). A comparative analysis indicates that female drivers in the handheld phone condition possess a higher safety margin than male drivers, with the gap time of females being 1.14 times longer than that of males.

Note that this study aims to further understand the heterogeneous impact of hands-free or handheld driving as a function of factors such as crash involvement, age, licence type and so on, but these parameters were either statistically insignificant in the model or did not improve the model goodness-of-fit. A plausible reason could be a small sample size, which is discussed later in the paper.

5. Discussion

5.1. Safety at roundabouts in distracted driving conditions

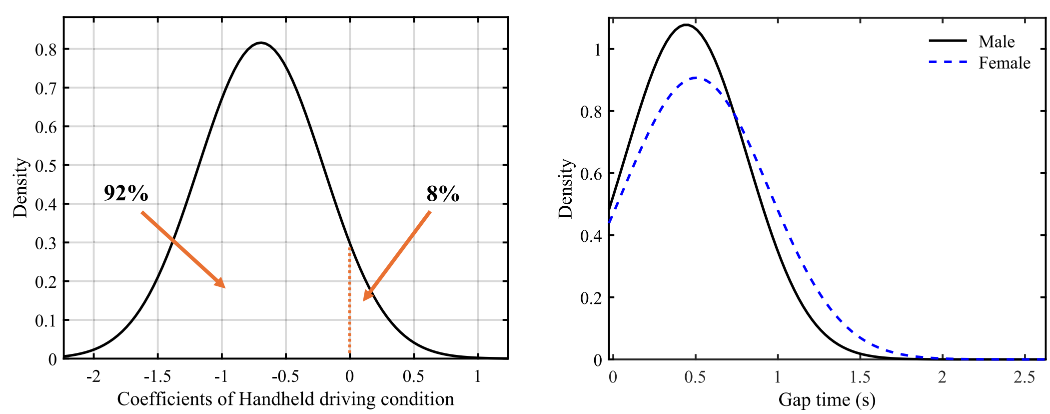
To understand young, distracted drivers' safety at roundabouts, survival curves are developed using the grouped random parameters survival model. More specifically, using the Weibull survival function and parameter estimates reported in Table 4, the probabilities for drivers avoiding an angle collision are calculated, whereby the mean value and reference category of continuous and dummy variables are used, respectively.

Fig. 4 presents collision avoidance probabilities under different driving conditions, and a decreasing trend with time is noted, implying

Table 4
Model estimation results for the grouped random parameters Weibull accelerated failure time model with heterogeneity-in-mean.

Parameter	Coefficient	*s.e*	z- statistics	*p*-value	exp(β)	95 % CI of [exp(β)]	
						Lower	Upper
Constant	−1.348	0.626	−2.15	0.0315	–	–	–
Phone condition							
Hands-free	−0.779	0.284	−2.74	0.006	0.459	0.100	1.017
Handheld (mean)	−1.507	0.324	−4.65	< 0.001	0.221	0.414	0.857
Handheld (S.D)	0.487	0.193	2.52	0.0117	–	–	–
Heterogeneity in the mean of handheld phone condition							
Female	0.746	0.371	2.01	0.0442	2.109	1.382	2.835
Vehicle dynamics							
Acceleration noise	−0.296	0.124	−2.38	0.0173	0.744	0.087	1.575
Gap size	0.364	0.105	3.47	0.0005	1.439	1.233	1.645
Driver-specific variables							
Crash involvement history							
Involved	−0.569	0.239	−2.38	0.0173	0.566	0.098	1.035

LL(β) = -154.2; LL (0) = -183.3; χ^2 = 58.2; *p*-value < 0.001; AIC=326.4; Number of observations = 96; ρ^2 = 0.159, Number of clusters = 32; Max: cluster size = 3; Weibull parameter (κ): 2.71 (*p*-value < 0.001).



(a) Distribution of the random parameter for the handheld driving condition

(b) Gap time distribution of male and female drivers distracted by handheld phone conversations

Fig. 3. Distributional effect and differential gap time for gender.

that distracted drivers are more likely to engage in an angle collision at roundabouts compared to non-distracted drivers, reflecting smaller safety margins in distracted driving conditions. For instance, the probability of avoiding an angle collision in the baseline condition at 1 s is 78 %, whereas the corresponding probabilities for the handheld and hands-free driving conditions are < 1 % and 12.89 %, respectively. Fig. 4 indicates that the average time to avoid an angle collision in the baseline condition is 3.5 s, whereas the corresponding times for the handheld and hands-free conditions are respectively 0.8 s and 1.6 s. A comparative analysis suggests that the safety margin in the distracted driving condition is twice as small as that of the baseline driving condition. This finding indicates that engaging in mobile phone conversations whilst driving significantly increases collision risk as drivers may accept a smaller gap or do not properly manoeuvre at roundabouts, thereby making distracted drivers risk-prone. Li et al. (2020) found that mobile phone distraction increases intersection crossing completion time by about 10%, leading to an increased propensity for angle collisions at intersections.

Engaging in mobile phone conversations whilst driving can lead to deteriorated driving performance, measured commonly through metrics like reducing speed, loss of situational awareness, less control over manoeuvrability, delay in response, not following traffic rules and many others (Ali and Haque, 2023). Vehicle manoeuvring and control could explain distracted drivers' angle collision behaviour as these drivers are often found to have less control over their manoeuvring and exhibit large longitudinal and lateral fluctuations in their movement (Xue et al., 2023). Another factor could be accepting a smaller gap size, which has repeatedly been reported as risky behaviour. Distracted drivers are reported to wait longer before accepting a gap, which may enforce selecting a smaller gap thereby increasing safety concerns (Haque et al., 2016). These findings corroborate with wider distraction literature where distracted drivers are found to wait longer or accept smaller gap sizes, e.g., signalised intersections (Li et al., 2020) and unsignalised intersections (Choudhary and Velaga, 2019). It is worth noting that some past studies reported no statistically significant difference among gap selection of distracted drivers (e.g., Haque et al. (2016)), which can be attributed to the adaptive driving behaviour of distracted drivers and/or risk compensation behaviour by prioritising the driving task in complex situations like roundabouts. However, our study finds a statistically significant relationship of gap size with collision avoidance

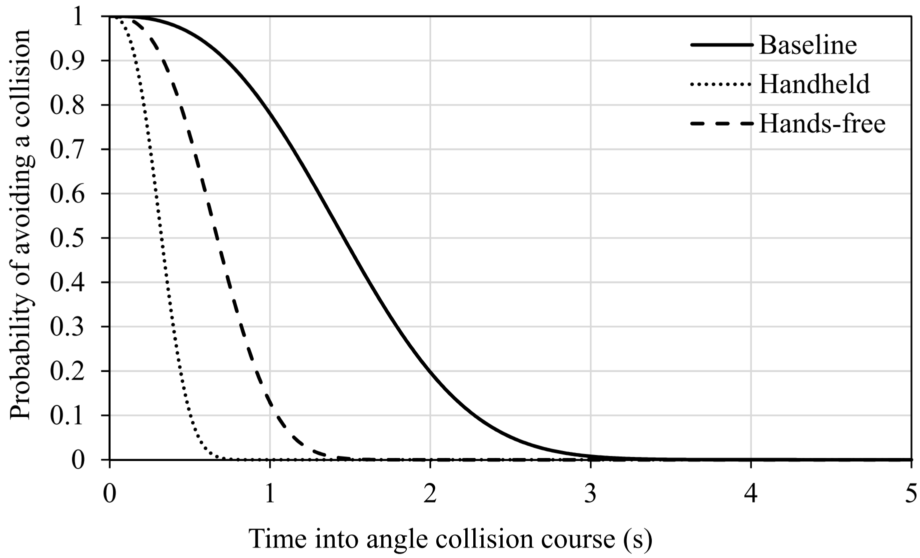


Fig. 4. Angle collision survival probability for different driving conditions.

probabilities, implying that drivers' gap acceptance behaviour significantly impacts their collision probability, which corroborates Haque et al. (2016)'s finding that safety margins of distracted drivers are lower despite insignificant gap selection.

5.2. Comparing collision probability in handheld and hands-free phone conditions

It is evident from Fig. 4 that collision patterns vary between the two phone conditions. Results suggest that the likelihood of handheld distracted drivers avoiding an angle collision is twice as small as that of hands-free distracted drivers. Collision avoidance probabilities are also calculated for drivers engaged in these two distracted driving conditions and the probability differences (hands-free minus handheld) at 1 and 1.5 s are 12.88% and 0.21%, respectively. These results imply that handheld distracted drivers are more likely to collide with vehicles in roundabouts. Existing distraction literature suggests that drivers distracted by handheld phone conversations are riskier because of higher cognitive workload, resulting in drivers exhibiting either compensatory or cautious behaviour or risky behaviour (Fitch et al., 2015, Ishigami and Klein, 2009). A meta-analysis comparing the safety of handheld and hands-free phone conditions reported that regardless of phone type, driving behaviour deteriorates when using phone mobiles; however, the magnitude of deterioration is greater in the handheld phone condition (Ishigami and Klein, 2009). Similarly, when responding to the hard braking of the leader, a study found that handheld distracted drivers responded slowly and took a long time to reduce their speed, which is likely to lead to abrupt braking to avoid a collision (Ali and Haque, 2023). In another study, Prat et al. (2017) conducted 426 semi-structured interviews and found that hands-free conversations are perceived to be less risky than handheld conversations. Finally, some studies found no significant difference or similar risky behaviour between these two mobile phone conditions (e.g., Haque and Washington (2014)), which could be attributed to complex interactions/manoeuvres, requiring drivers to prioritise their driving tasks, thereby nullifying the effect of different mobile phone usage. However, in our study, we find significant differences in collision avoiding probabilities and drivers distracted by handheld phones possess smaller safety margins than hands-free distracted drivers.

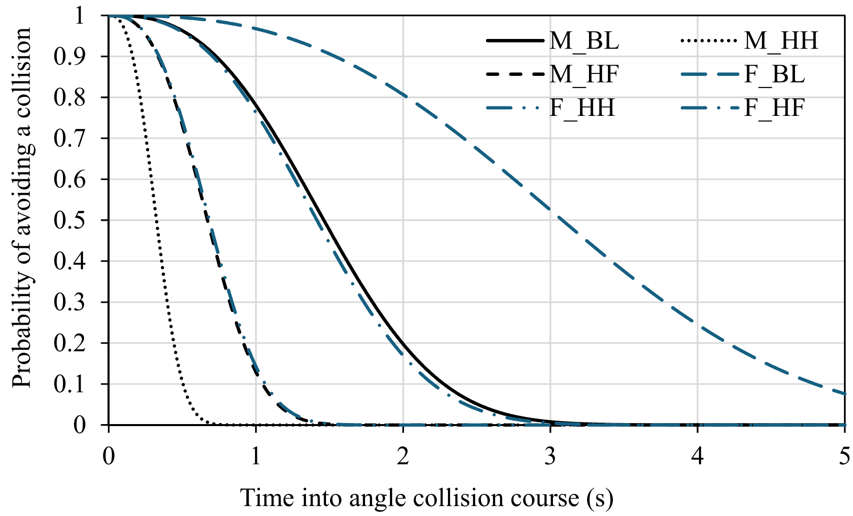
5.3. Effects of driver characteristics on collision avoidance probability of distracted drivers

5.3.1. Gender

Collision probabilities of different genders under different driving conditions are presented in Fig. 5. The collision survival probabilities of female drivers at 1 s for the baseline, handheld, and hands-free phone conditions are 96.77%, 14.21%, and 76.24%, respectively, whereas the corresponding probabilities for male drivers at the same time are 78.03%, <1%, and 12.88%, respectively. This comparison reveals irrespective of driving condition, female drivers have a relatively lower likelihood of an angle collision compared to their male counterparts. It is often reported that females exhibit very cautious behaviour because of their high risk perception of distracted driving and its consequences, thereby exhibiting risk compensatory behaviour. Gershon et al. (2018) compared crash and near-crash events of young drivers and found a smaller frequency of these events for females, which was attributed to females' risk compensation behaviour. Similarly, female drivers were reported to drive slowly, maintained a large distance from the leader and had longer time headways in a car-following task (Saifuzzaman et al., 2015). Similarly, Choudhary and Velaga (2017) found that female drivers on rural roads tended to drive slower relative to male drivers. This slower driving by females could be attributed to their risk compensation behaviour when engaging in a mobile phone conversation. A recent survey of 424 Italian young drivers found that females perceive a higher risk of using mobile phones than males, which was found to be correlated with their personal attributes and driving habits (Fraschetti et al., 2021). Beyond distracted literature, females are also found to be safer and more proactive in their driving, e.g., responding to hard braking of the leader in a connected environment (Sharma et al., 2020), sensitive to traffic conditions (Atombo and Wu, 2022), and deliberate traffic violations (Useche et al., 2021). Male drivers are generally found to be aggressive (Gaymard et al., 2019), and consequently, their collision probability is higher in this study than that of female drivers.

5.3.2. Crash involvement history

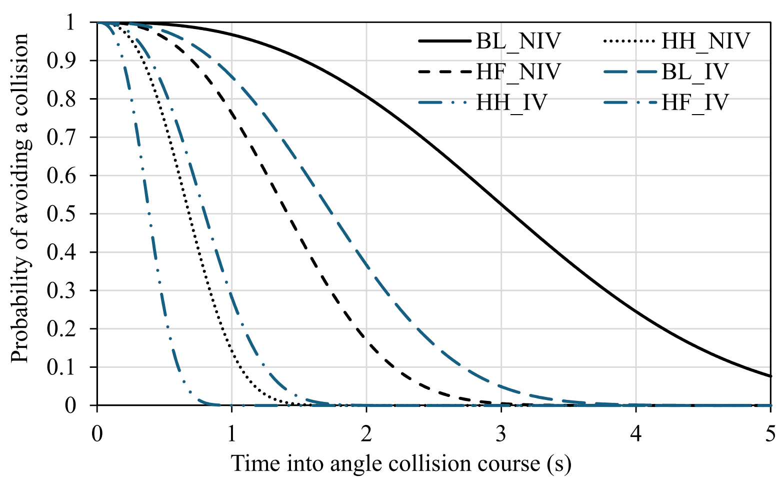
Leveraging the grouped random parameter survival model, the survival collision probability of drivers who self-reported their involvement in a crash is also calculated and displayed in Fig. 6. Since this information was collected through a pre-driving questionnaire survey, this study expects some bias in participants' responses as they may not want to reveal their prior crash involvement. Results, therefore, should be



M and F denote male and female drivers, respectively.

BL, HH, and HF respectively indicate baseline, handheld, and hands-free driving conditions.

Fig. 5. Gender effect on collision survival probability under different driving conditions. *M and F denote male and female drivers, respectively. BL, HH, and HF respectively indicate baseline, handheld, and hands-free driving conditions.*



NIV and IV denote drivers with no prior history of involving in a crash and with a prior history of involving in a crash, respectively.

BL, HH, and HF respectively indicate baseline, handheld, and hands-free driving conditions.

Fig. 6. Collision survival probability for crash history drivers under different driving conditions. *NIV and IV denote drivers with no prior history of involving in a crash and with a prior history of involving in a crash, respectively. BL, HH, and HF respectively indicate baseline, handheld, and hands-free driving conditions.*

viewed with caution. Results indicate that drivers with prior crash history are more at risk than their counterparts, suggesting persistent risky driving behaviour despite these drivers being engaged in a crash in the past. Although a past study suggests that drivers experiencing a crash in the past are likely to exhibit safer behaviour (Yue et al., 2020), our study observes contrasting findings, which could be attributed to age group as our study focusses on young drivers, who are repeatedly found to underestimate the crash risk and engage in risky manoeuvres, which could be attributed to their sensation seeking and risk taking behaviour (Scott-Parker et al., 2013).

5.4. Effect of gap size on collision avoidance probability in different distracted conditions

As mentioned in Section 4, gap size affects collision avoidance probability, this study explores the effects of two gap sizes (3 s and 6 s) using the estimated model, see Fig. 7. Note that this type of comparison can be performed for different gap sizes, but we are demonstrating the comparison of two gap sizes for illustrations. The increasing gap size indicates a positive effect on collision avoidance probability as survival curves for 6 s gap size tend to shift left, suggesting that a relatively large gap size decreases the collision probability. The collision survival probabilities at 0.5 s for 6 s gap size in the baseline, handheld, and hands-free phone conditions are 99.31%, 66.44%, and 94.47%, respectively, whereas the corresponding probabilities at the same time for 3 s gap size are respectively 87.57%, <1%, and 33.41%. A notable finding is that the difference between the 6 s and 3 s gaps in terms of survival probability for the baseline condition is small, but the corresponding difference is high for distracted driving conditions, highlighting the high crash risk probability of distracted drivers. In general, a large gap size provides sufficient space in the adjacent lane (circulatory way in the context of roundabouts), whereby drivers can easily

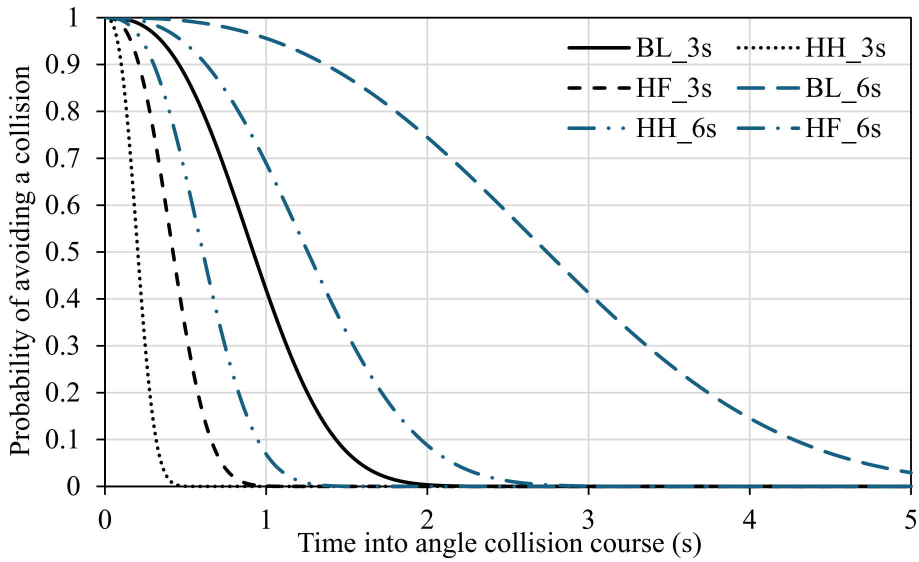


Fig. 7. Collision survival probability for two gap sizes under different driving conditions.

manoeuvre and adjust their behaviour without the pressure of the following vehicle. However, in terms of large gap sizes, distracted drivers are in fact more risk-prone, which could be attributed to risk underestimation when distracted by mobile phone conversations. Choudhary et al. (2022) compared perceived risk and actual driving performance and found that distracted drivers significantly underestimated the crash associated with a given driving task. From a gap acceptance perspective, existing literature indicates that drivers are likely to select large gap sizes because of less risk of sideswipes or rear-end (Nobukawa et al., 2015), and our empirical analysis of gap acceptance supports this finding. Whilst analysing drivers' merging behaviour in work zone areas, Weng et al. (2015) found that drivers' can quickly accept a gap or the merging vehicle has a bigger probability of completing a merging manoeuvre quickly when (a) the speed of merging vehicle is faster than mainline traffic, (b) the lead vehicle in the adjacent lane is a heavy vehicle, and (c) a sizeable gap in the adjacent lane. This finding corroborates with several past studies (not in distraction literature), e.g., Ali et al. (2018) reported that in a connected environment, drivers select relatively bigger gap sizes during mandatory lane-changing compared to the traditional driving environment, indicating safer merging behaviour of drivers in a connected environment.

5.5. Study implications

The use of mobile phones (i.e., handheld and resting on any part of the body) whilst driving on Queensland roads is illegal and this restriction always applies to all drivers if the phone is on or in use. A driver caught using a mobile phone whilst driving receives a fine (AUD 1161) and four demerit points (DTMR, 2024). To enforce mobile phone laws, artificial intelligence (AI)-operated cameras are installed throughout Queensland. Fixed and portable cameras are used for continuous and short-term monitoring, respectively.

Our findings have practical implications, which could be useful in devising strict penalties and designing educational programmes for young drivers. For instance, as found in this study, despite having been involved in a prior crash, drivers tended to exhibit risky driving behaviour at roundabouts. To this end, coupled with regular monitoring of roundabouts, AI-based video analytics for extreme conflict detection could be applied to identify risky behaviours, which would form the basis for focussed educational programmes during licensing to nurture safer driving habits. From a penalty perspective, although Queensland laws are fairly strict (12 or more demerit points within 3 years), more stringent penalties may include: (i) greater demerit points, (ii) licence suspended if caught just once, and (iii) mandatory education-based rehabilitation programmes before resuming driving.

6. Conclusions

This study examined distracted drivers' behaviour at roundabouts when they faced a gap acceptance scenario. To this end, a group of 32 licenced drivers, aged between 18 and 26 years and equally distributed in gender, participated in a simulator experiment using the CARRS-Q Advanced Driving Simulator. The collected data served as the basis for developing several Weibull accelerated failure time models, which allowed for the identification of driver-level variations. Among these models, the grouped random parameters model with heterogeneity-in-mean emerged as the most effective approach for modelling gap times.

The modelling results revealed that distracted drivers are more at risk when they are merging into roundabouts, whereby collision probability was the largest for the handheld driving condition followed by the hands-free and baseline driving conditions—this finding addresses the first research question. The model also unravelled the heterogeneous effects of mobile phone usage on collision probability (i.e., gap times may increase or decrease), which addresses the second research question. The random parameter for the handheld driving condition indicated that although the majority of drivers possessed higher collision probabilities compared to the baseline condition, a small proportion of drivers were found to possess smaller collision probabilities, which could be attributed to risk perception and subsequently risk compensation behaviour of distracted drivers. Further, the model contained non-random parameters, including driver gender and prior crash involvement. Specifically, females are found to be risk-averse with crash risk being lesser than males at roundabouts, and drivers with prior history of crash involvement are more likely to collide at roundabouts than their counterparts—addressing the third research question. Although this study tested driver age and other driver demographic variables in the model, they were not retained in the parsimonious model either because they did not improve the overall model fit or they were not statistically significant in the model—more research with a large sample size is warranted along this line.

This study can be extended in several directions. First, due to the small sample size (32 participants that are relatively smaller compared to other driving simulator studies), this study could not investigate the effects of several variables, such as waiting time before merging, initial speed, and deceleration. Since these variables have been shown to affect safety, future studies can further explore this topic with a larger sample size to fully understand the relationship of these factors through advanced modelling methodologies like correlated random parameters. Second, this study only tested the main effects, whereas higher-order interaction effects could also be tested. Third, this study only found a statistically significant random parameter in the model, whereas more random parameters would assist in developing a correlated random parameters model that can uncover unobserved heterogeneity due to the interaction of two random parameters. Finally, although this study only tested distraction caused by a mobile phone conversation, it is worth investigating and comparing other distractions at roundabouts, e.g., conservation with a passenger, grooming, operating a music player, and eating/drinking whilst driving. Such comprehensive analysis will identify and inform which types of distraction are relatively more dangerous and prevalent at roundabouts so that tailored interventions can be devised.

CRediT authorship contribution statement

Esther Memeh: Writing – review & editing, Writing – original draft, Software, Investigation, Formal analysis, Data curation. **Yasir Ali:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Francisco Javier Rubio:** Writing – review & editing, Visualization, Validation, Methodology, Investigation. **Craig Hancock:** Writing – review & editing, Validation, Supervision, Software. **Md Mazharul Haque:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition, Data curation, Conceptualization.

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 data that has been used is confidential.

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