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Yield or not to yield? An inquiry into drivers' behaviour when a fully automated vehicle indicates a lane-changing intention

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A R T I C L E I N F O

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A B S T R A C T

Automated vehicles have started to be integrated into the road transportation system and operate in a mixed traffic environment. To ensure a smooth and successful integration, it is vital to have a good understanding of the human factor challenges involved in the process, especially the issues related to other road users who will share roads with automated vehicles. The study focuses on conventional vehicle drivers' acceptance of and interaction with fully automated vehicles (FAV). An online survey with experimental scenarios showing an FAV's lane-changing intention was designed to test the interaction responses of participants. The survey also collected the participants' demographic information (e.g., age, gender, driving experience), self-reported general driving behaviours (e.g., errors, lapses and violations), past benchmark behaviour in the same situation and their acceptance of FAVs. The study recruited 838 participants in total, comprising 465 participants from Australia (216 males vs. 249 females) and 373 participants from China (172 males vs. 201 females). Ordered probit models were developed to predict three types of behavioural responses of drivers in the lane-changing scenario, i.e., positive, disregardful and aggressive responses. The results showed that older drivers, females, and drivers who had less driving experience were more likely to adopt positive interactions with FAVs than their counterparts. Drivers who reported frequent risky driving behaviours (e.g., aggressions, lapses and errors) were less likely to report positive interaction but more likely to report disregardful and aggressive interactions. Drivers reporting more positive/favourable attitudes and a higher trust toward FAVs demonstrated a higher possibility of positive interaction, and those with higher perceived behaviour control were more likely to restrain disregardful interaction. The study helps to form a greater understanding of conventional vehicle drivers' perception of FAVs and the underlying factors that may influence their interaction behavioural tendency.

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1. Introduction

Automated vehicle technologies are developing at a rapid pace globally, aiming to deliver combined benefits to road safety, mobility, and environment by reducing traffic crashes, congestion, and fuel consumption. Automation in vehicles can have different levels, from minimal assistance to a human driver to full control of the vehicle with no human driver behind the wheel – with the whole system referred to as a fully automated vehicle (FAV). The booming of automated vehicle technologies promotes the advances of vehicle-related equipment such as lidar, radar, camera, GPS, and control systems so that the vehicle can recognise road paths, signage, and obstacles correctly and efficiently. While the technological aspect of automated vehicles is moving toward readiness, the public and society should also be prepared for its introduction. Currently, the integration of automated vehicles to the road transport system still faces many challenges and uncertainties, especially when the integration involves various other road users (Mayerhofer et al., 2020). In the past decade, a large amount of studies have investigated the potential users' acceptance toward automated vehicles and their intention to purchase these vehicles (e.g., Buckley et al., 2018; Schrauth et al., 2020; Zhang et al., 2020). However, such acceptance has been less studied for those road users who may not be potential FAV users but still need to share roads with these vehicles. The consequence of not knowing how this group of road users would behave while sharing the roads with FAVs is acute because these vehicles are not on our roads yet, leaving great uncertainty behind the behaviours of road users in the near future.

1.1. Public acceptance of automated vehicles

There has been growing literature that has examined public acceptance and trust of automated vehicles, and the conventional vehicle drivers who are likely to be future AV users have become a main focus (e.g., Buckley et al., 2018; Molnar et al., 2018; Zhang et al., 2019, 2020). For example, Zhang et al. (2019) applied the Technology Acceptance Model (TAM; Davis, 1989) to examine users' acceptance of conditional (SAE Level 3) automated vehicles. Their study also assessed initial trust and perceived risk for the use of automated vehicles. The results showed that perceived usefulness (i.e., the extent to which a person believes that the technology would enhance performance) was a significant positive predictor of initial trust and intentions to use automated vehicles. Further, perceived ease of use (i.e., the extent to which a person believed that the system is easy to use) and initial trust were significant positive predictors of attitudes towards using automated vehicles, with attitudes a significant positive predictor of behavioural intentions. Buckley et al. (2018) applied both the TAM and Theory of Planned Behaviour (TPB; Ajzen, 1991) to assess drivers' acceptance of conditional AVs after participating in a driving simulator task. Consistent with the TAM, perceived usefulness and perceived ease of use accounted for 41 % of the variance in intentions to use automated vehicles. In the TPB model, attitudes (i.e., favourable or unfavourable beliefs), subjective norms (i.e., perception that important others would approve or disapprove of the behaviour), and perceived behavioural control (i.e., PBC- perception of ease or difficulty of use), accounted for 46 % of the variance in intentions. Trust was also shown to explain additional variance in intentions above and beyond the TAM and TPB. Overall, the existing literature has provided some support for using psychosocial models to assess user acceptance of automated vehicles. The current study will expand upon these previous studies by applying the TPB and the construct of trust to assess conventional vehicle drivers' perception toward sharing roads with fully (SAE Level 5) automated vehicles.

Previous research has shown that perceptions towards automated vehicles may differ across countries and cultures (e.g., Kaye et al., 2020; Kyriakidis et al., 2015; Schoettle & Sivak, 2014; Schrauth et al., 2020). For example, Kaye et al. (2020) found that when compared to drivers from Australia and Sweden, drivers from France reported significantly higher intentions to use highly (SAE Level 4) automated vehicles in the future. Schrauth et al. (2020) examined acceptance and trust of conditional automated vehicles across seven countries in Europe (France, Germany, Slovenia, Spain, and Sweden), Australia, and the US. The findings revealed that participants from Spain reported the highest average ratings of general acceptance and initial trust of automated vehicles, while participants from Slovenia reported the lowest average ratings of general acceptance, and participants from Germany reported the lowest scores on initial trust. Furthermore, Schoettle and Sivak (2014) examined perceptions towards conditional automated vehicles across six countries which are India, the US, Australia, Japan, the UK, and China. They found that a higher proportion of participants from India (42 % of $n = 527$) rated being very concerned about automated vehicles compared to participants from the US (26 % of $n = 501$), Australia (16 % of $n = 505$), Japan (15 % of $n = 585$), the UK (15 % of $n = 527$), and China (9 % of $n = 610$). Collectively, this research supports the view that perception of and intention to use automated vehicles may differ across countries, and therefore it builds upon the prior research by applying a theoretical model of acceptance (TPB) to examine drivers' acceptance of automated vehicles with participants from different countries (i.e., Australia and China).

1.2. Road users' interaction with automated vehicles

With the rapid update of vehicle automation technology, humans interacting with automated vehicles has received much research focus (e.g., Gerber and Schroeter, 2020; Li et al., 2020). However, in contrast to the interaction between the vehicle and the user, limited attention has been paid to the interaction between the automated vehicles and the external road users (e.g., pedestrians, cyclists, and conventional vehicle drivers) (Dey et al., 2017; Madigan et al., 2019). As higher levels of automated vehicles have not been widely in use, naturalistic observations on road users' interaction with real automated vehicles are still scarce. Madigan et al. (2019) collected video data from the CityMobil2 automated shuttle demonstration trial in France and Greece and investigated the interaction patterns between automated vehicles and other road users. Their study demonstrated that in situations where traffic flow was not separated by road infrastructures, the road users, especially cyclists, were more likely to engage in risky behaviours by travelling closely to automated vehicles.

As a compromise of real automated vehicles, the Wizard of Oz technique is adopted in several studies, which creates a seemingly driverless car by disguising the vehicle controller as a car seat or hiding them behind the seat (Faas & Baumann, 2019; Faas, Mathis, & Baumann, 2020; Dey et al., 2017; Fuest et al., 2019; Fuest et al., 2018; Rothenbücher et al., 2016). This technique allows for an on-site observation and naturalistic recording of the road users' interaction behaviours with automated vehicles in which the driver is not observable to them. For example, Rothenbücher et al. (2016) employed a Wizard of Oz study to observe the interactions between pedestrians and "driverless" vehicles. Sixty-seven participants' interactions with the vehicle were captured in the study and the results showed that pedestrians had a generally positive response to the car. The study also reported that the erratic behaviour of the "driverless" car could lead to a hesitancy of pedestrians' crossing behaviour. Similarly, Dey et al. (2017) used Wizard of Oz setup to investigate pedestrians' crossing behaviour in front of automated vehicles. Their study showed that the distance and speed of the vehicle were dominant factors that influenced pedestrians' decision to cross the road. Similar findings were also reported by Fuest et al. (2018) who found that driving behaviour also influenced participants' decision to cross the road. Another Wizard of Oz experiment conducted by Rodríguez et al. (2018) showed that the critical gap for a pedestrian to cross and the self-reported stress level did not change significantly between vehicle conditions (i.e., a car with self-driving sign vs. a driver reading a newspaper). Overall, these naturalistic observation studies deploying Wizard of Oz technique have mostly focused on the interactions between automated vehicles and pedestrians.

Compared to the on-site observations, questionnaires are more widely used to measure participants' attitudes and behavioural intentions toward automated vehicles. They allow for data to be collected from a large sample of respondents, with responses on various specific conditions or scenarios. However, the validity of the questionnaire results greatly relies on the participants' honesty in responding and the ability of them to recall or imagine a particular situation. Merat et al. (2018) conducted a questionnaire-based study with 664 pedestrians and cyclists who took part in the CityMobil2 automated vehicle trial demonstration to investigate their perception of safety and priority while interacting with automated vehicles. The study suggested that participants' perception of safety declined when interacting with automated vehicles compared to the conventional vehicles. Moreover, the study reported that participants had lower perception of safety but higher expectation on priority when interacting with automated vehicles in shared space without dedicated lanes. Pyrialakou et al. (2020) used a stated preference survey to identify public's perceived safety of driving, cycling, and walking near automated vehicles, and the results indicated that cycling near an AV was perceived least safe, followed by walking, and then driving.

Driver and road user communication cues, such as eye contact and hand gesture, have played an important role in communicating each other's intention (Kitazaki and Myhre, 2015; Rasouli et al., 2017). Without the presence of a driver, conjecture of the vehicle's intention becomes more challenging for the interacting road users and this may influence their movement decisions and safety perception during the interaction. It is well known that automated vehicles are designed to deliver greater safety benefits by eliminating driver errors and strictly following safety rules. Due to such features, some automotive manufacturers and researchers are concerned that there might be aggressive road users taking advantage of the identifiable automated vehicles that are operating autonomously by for instance, stepping into the automated vehicles' path on purpose or failing to yield right of way to them (Connor, 2016; Rasouli and Tsotsos, 2019; Kaye et al., 2022). Liu et al. (2020) conducted a cross-national survey in China and South Korea on N = 998 drivers to investigate the human road users' intention to bully automated vehicles, and the results showed that drivers were more likely to drive aggressively toward automated vehicles than toward other human drivers. A study conducted by Tennant et al. (2017) on how drivers feel about interacting with automated vehicles on the road reported that some "combative" drivers are more open and technologically optimistic to automated vehicles, and this might be due to the fact that they see automated vehicles as easier agents to deal with on the road than human drivers. The possible increase of risk-taking behaviours of road users in the presence of automated vehicles may offset the safety benefits promised by automated vehicles and further lead to negative impacts on the traffic flow. Although some naturalistic observations and field experiments did not report significant changes in the interactions with automated vehicles compared to conventional vehicles (Dey et al., 2017; Merat et al., 2018; Rothenbücher et al., 2016), it is necessary to study how road users' behavioural intentions might have changed in front of FAVs.

2. Research objectives

In a foreseeable future when FAVs are integrated into the road transportation system, manual vehicle drivers will be the largest group of road users that need to share roads and interact with FAVs. However, research on the acceptance of FAVs has mostly focused on the potential buyers, while the perspective of drivers who will share roads with FAVs has been underestimated. These drivers' acceptance of FAVs and interaction behaviour tendencies are critical for a smooth integration of FAVs and a harmonious road transport system. This study aims to bridge the current research gaps by (1) conducting an online experiment to study conventional vehicle drivers' behavioural intentions during the interaction with FAVs in a typical lane-changing scenario; (2) identifying the underlying factors associated with different behavioural responses in the interaction, including driver characteristics (e.g., age, gender), general driving behaviours (e.g., self-reported risky and positive driving behaviours), past benchmark behaviour in the same scenario and their acceptance of FAVs; (3) exploring if there are cross-cultural differences between countries in terms of drivers' acceptance and behaviour tendency when interacting with FAVs. This research was exploratory and therefore, no hypotheses were made.

3. Method

3.1. Instruments

3.1.1. Experimental scenario

A lane-changing scenario was designed in the study to investigate the drivers' behavioural tendency when interacting with FAVs. The scenario was selected as it frequently occurs in daily driving and drivers' behaviour options are safety–critical, which involve certain level of risks (Yang et al., 2018). In the US, it was reported that 9 % of all police-reported motor vehicle crashes were two-vehicle lane-change crashes (Sen et al., 2003).

The scenario was described as, "*You are driving your car to work on a one-way road with two lanes. You are driving in the right-hand lane. There is a fully automated vehicle (FAV) driving in the left lane ahead of you. At this moment, the right-turn indicator light of the FAV showing that it wants to change to your lane.*" The scenario figure was provided as in Fig. 1 (note that Australia adopts left-hand traffic and China adopts right-hand traffic). Three questions were asked to the participants following the scenario descriptions: Q1 – "*How likely are you to slow down and give way to the FAV?*"; Q2 – "*How likely are you to keep driving at the same speed and ignore the FAV's indicator?*"; Q3 – "*How likely are you to accelerate to pass the FAV before it changes lane?*". All participants needed to answer each question on a 5-point likelihood-based Likert scale, where 1 = "extremely unlikely", 2 = "unlikely", 3 = "neutral", 4 = "likely", 5 = "extremely likely".

It should be noted that drivers in this scenario are not obligated to slow down and give way to the lane-changing vehicle although such yielding behaviour could be commonly observed in real life. The scenario did not provide detailed information about vehicle speed or gap as participants may use this information to speculate what the FAV would do, instead of treating it as a general situation. In our case, we are more interested in collecting participants' attitude and response toward an FAV's lane-changing request. The three questions in this scenario were designed to measure three different types of behavioural tendency. Specifically, Q1 measures the tendency of a positive interaction behaviour of the driver by yielding to the FAV; Q2 measures the likelihood of disregardful behaviour of the driver by ignoring the FAV's lane-changing request; and Q3 measures the tendency of aggressive behaviour by accelerating and potentially increasing the collision risk.

3.1.2. Questionnaires

The study considered four potential factors that may influence a driver's interaction tendency with FAVs, namely, driver characteristics, their general driving behaviours on roads, past benchmark behaviour in the same situation and their acceptance of FAVs. To collect the information, the questionnaire instrument was divided into four sections: a 6-item demographic questionnaire, a 38-item driver behaviour questionnaire, a past benchmark behaviour question, and a 16-item FAV acceptance questionnaire. The complete questionnaire can be found in the Appendix.

The demographic questionnaire was used to collect participant characteristics information, such as their age, gender, education level, years of holding a driver license, weekly driving hours and crash experience.

To measure driver general behaviours, the Driver Behaviour Questionnaire (DBQ) (Stephens and Fitzharris, 2016) was used, which contains 28 items categorised into Violations (8 items), Errors (11 items), Lapses (6 items) and Aggressions (3 items). Additionally, another 10 items for measuring positive behaviours (adapted from Özkan and Lajunen (2005)) were added to the DBQ. In the DBQ, violations refer to deliberate behaviours that contravene safe driving practices, e.g., disregard the speed limit on a freeway. Errors, on the other hand, encompass the unintended behaviours that lead to unplanned outcomes, e.g., brake too quickly on a slippery road. Lapses measure the involuntary deviation in the action due to attention or memory failures, e.g., misread the signs and exit from a roundabout on the wrong road. Aggressions correspond to behaviours of aggressive interpersonal violence towards other road users, e.g., use horn to indicate annoyance to another road user. Positive behaviours refer to behaviours that appease social interactions, e.g., adjust speed to help a driver trying to overtake. The past benchmark behaviour question asks about the participant's yielding behaviour frequency in the same lane-changing scenario as a benchmark. The 38 DBQ items and the past benchmark behaviour

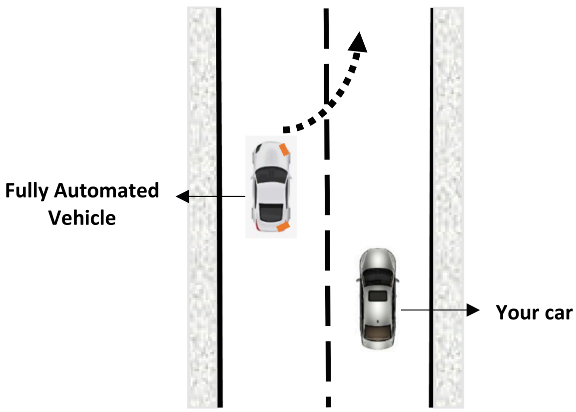


Fig. 1. Lane-changing scenario.

question were all answered on a 6-point frequency-based Likert scale, where 1 = “never”, 2 = “hardly ever”, 3 = “occasionally”, 4 = “frequently”, 5 = “quite often”, 6 = “nearly all the time”.

The FAVs acceptance questionnaire was developed upon Ajzen (1991)’s Theory of Planned Behaviour. It included five items for Attitudes, three items for Subjective Norms, and three items related to Perceived Behaviour Control (PBC). Attitudes refers to the degree to which a person has a positive or negative evaluation of performing the behaviour (i.e., driving on roads in the presence of FAVs in this study). Subjective norms represent the person’s perception of social pressure to perform or not to perform the behaviour. PBC measures the perceived ease or difficulty of performing the behaviour. Moreover, another five items measuring trust on FAVs were also included in the questionnaire (Deb et al., 2017), which corresponds to individual belief that a FAV can be relied on to perform its intended task. For all the 16 items, participants needed to respond on a 7-point Likert scale with 1 = “strongly disagree”, 2 = “moderately disagree”, 3 = “somewhat disagree”, 4 = “neutral”, 5 = “somewhat agree”, 6 = “moderately agree”, 7 = “strongly agree”.

3.2. Participants

Participants were recruited from Australia and China for a cross-country analysis. A total of 838 participants took part in the study and completed the online survey, consisting of 465 Australian participants and 373 Chinese participants. Table 1 provides an overview of the Australian and Chinese sample characteristics.

3.3. Data collection

The research was approved by the Ethics Review Committee of the Queensland University of Technology (QUT) (Approval Number: 1900000669). Online survey design platforms were used to create the questionnaire (Qualtrics for Australian questionnaire and Wenjuanxing for Chinese questionnaire). The Australian data were collected using different approaches. An online market research firm, i.e., Dynata (https://www.dynata.com), was invited to provide data collection service. The online survey was also disseminated using social media (e.g., Facebook, Twitter) and emails through QUT mailing lists. The Chinese questionnaire was translated from the English version and adapted according to the Chinese traffic operation rules. All Chinese data were collected by the Wenjuanxing platform (https://www.wjx.cn/) using their panel service. Requirements for the participants to take part in the study were that (a) they need to be living in Australia (or China), (b) at least 18 years old, and (c) hold a valid driver license. The survey took about 15–20 min to complete and the participants were assured that their participation was anonymous and voluntary.

3.4. Data analysis

The lane-changing scenario measured drivers’ positive, disregardful and aggressive interaction behaviour tendencies, respectively. Since participants’ responses to the three scenario questions are discrete and ordered (1 = “extremely unlikely”, 2 = “unlikely”, 3 = “neutral”, 4 = “likely”, 5 = “extremely likely”), ordered discrete response models are needed to evaluate these types of responses (Oviedo-Trespalacios et al., 2020). The details of ordered response model specification are presented in the following.

Let Y_i be the dependent variable representing the likelihood of initiating certain behaviour in the above lane changing scenario (i.e., slowing down, maintaining the speed, or accelerating) for driver *i*, and let *s* (*s* = *1, 2, 3, 4 and 5*) represent ordinal categories of this dependent variable (i.e., *extremely unlikely*, *unlikely*, *neutral*, *likely, extremely likely*). To construct the ordered response model, an underlying latent variable Y^*_i is defined by a linear propensity function for the dependent variable as in the following Equation (1):

$$Y_i = \beta X_i + \varepsilon_i \tag{1}$$

Where β is the vector of parameters, X_i is the vector of covariates (driver’s characteristics, on-road driving behaviours and acceptance of FAVs, etc.) and ε_i is idiosyncratic error terms assumed to be identically and independently distributed across observations in this equation. The latent variable is then mapped to the actual categories of the dependent variable by thresholds (τ) such that:

$$Y_i = S \text{ if } \tau^{(s)} < Y^*_i < \tau^{(s+1)}$$

Table 1
Sample characteristics.

		Australia	China
Gender	Males	216	172
	Female	249	201
Age	Range	18–87 years	20–56 years
	M (SD)	40.0 (16.8)	32.8 (6.2)
Education	Completed Year 12 (High School) or lower	151 (32.5 %)	8 (2.1 %)
	Certificate or Diploma (Junior College)	149 (32.0 %)	40 (10.7 %)
	Bachelors	111 (23.9 %)	287 (76.9 %)
	Masters or higher	54 (11.6 %)	38 (10.2 %)
Number of years holding a driver’s licence	M (SD)	21.5 (16.8)	7.5 (5.0)

Implying that when the latent variable is within $\tau^{(s)}$ and $\tau^{(s+1)}$, the likelihood of driver *i* initiating a certain type of behaviour in the scenario is equal to category *s*. To estimate the latent propensity of the dependent variable, it is assumed that:

$$E(Y_i^s|X_i) = H_i^s() \text{ where } 0 \leq H_i^s() \leq 1 \text{ and } \sum_{s=1}^{S} H_i^s = 1$$

Where $H_i^s(.)$ is the probability density function for the category *s* of the dependent variable. $H_i^s()$ can take standard normal or standard logistic probability density functions for the ordered probit or ordered logit models, respectively. The former functional form is used in this study to construct an ordered probit model of driver's behaviour in front of the FAV. The probability of each category of the dependent variable is then presented as:

$$P(Y_i = s) = \varphi\{\tau^{(s+1)} - (\beta X_i)\} - \varphi\{\tau^{(s)} - (\beta X_i)\} \tag{4}$$

Where $\varphi(.)$ is the standard normal cumulative probability density function. The probability of initiating a certain behaviour by driver *i* can be obtained as:

$$P(Y_i) = \prod_{s=1}^{S} P(Y_i = s)^I \tag{5}$$

Where *I* is an indicator variable taking binary values –1 for the chosen category and 0 for the non-chosen category of the dependent variable. The corresponding likelihood of the dependent variable over the entire observations is obtained as:

$$l = \prod_{n=1}^{N} P(Y_i) \tag{6}$$

The ordered probit model can be estimated by regular Maximum Likelihood Estimation technique (Washington et al., 2020). Finally, Akaike Information Criterion (AIC) is used to compare the goodness of fit among different variants of the ordered probit model and to select the final parsimonious model for making inferences about explanatory variables. AIC is defined as (Washington et al., 2020):

$$\text{AIC} = -2\log(\text{L}) + 2\text{P} \tag{7}$$

Where *L* is the likelihood of the model at convergence and *p* is the number of estimated parameters and the model with a lower AIC

Table 2
Summary statistics of variables (Australia | China).

Demographic variables		Mean	S. D.		
Age		40.0|32.8	16.8|6.2		
Years of license		21.5|7.5	16.8|5.0		
Driving time (%)	≤7h/week	57.2|49.6			
	>7h/week	42.8|50.4			
Gender (%)	Male	46.5|46.1			
	Female	53.5|53.9			
Crash experience (%)	0	81.7|58.2			
	1	14.0|26.0			
	≥2	4.3|15.8			
Education (%)	Completed Year 12 (High School) or lower	32.5|2.1			
	Certificate or Diploma (Junior College)	32.0|10.7			
	Bachelors	23.9|76.9			
	Masters or higher	11.6|10.2			

Driver behaviour on roads (%)	Never	Hardly ever	Occasionally	Quite often	Frequently	Nearly all the time
Lapses	41.5|18.8	34.7|35.7	18.1|31.9	3.3|10.6	1.6|2.6	0.8|0.4
Aggressions	53.4|36.6	23.3|32.4	15.6|19.0	4.3|8.2	2.5|2.8	0.9|1.0
Violations	55.5|47.0	23.8|29.2	12.6|14.6	4.3|6.3	2.8|2.3	1.0|0.6
Errors	80.4|33.6	15.7|39.5	2.8|20.8	0.4|4.3	0.6|1.5	0.0|0.3
Positive behaviour	13.4|1.3	10.8|4.8	18.7|9.8	18.6|23.1	18.9|34.9	19.5|26.1
Past benchmark behaviour	8.0| 0.5	3.7|4.6	14.6|11.3	25.6|27.1	25.2|41.8	23.0|14.7
Acceptance of FAV (%)	**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**	
Attitudes	9.7|1.1	20.1|10.7	22.8|15.2	34.3|56.8	13.1|16.1	
Subjective norms	5.9|1.9	17.9|15.3	46.8|17.3	23.0|56.0	6.3|9.5	
Perceived behaviour control	9.5|0.2	16.8|6.2	18.0|8.1	40.1|58.4	15.6|27.1	
Trust	8.6|3.9	19.5|18.6	24.6|15.6	32.2|50.9	15.2|11.2	
Interaction scenario with FAV (%)	**Extremely unlikely**	**Unlikely**	**Neutral**	**Likely**	**Extremely likely**	
Option 1 – Positive interaction	3.9|0.3	7.5|0.8	11.2|4.0	41.5|49.1	35.9|45.8	
Option 2 – Disregardful interaction	30.8|20.6	40.4|61.1	11.8|10.5	12.7|5.9	4.3|1.9	
Option 3 – Aggressive interaction	43.4|35.9	28.8|39.1	13.8|13.9	9.0|8.6	4.9|2.4	

is generally preferred over the other models. However, it is acknowledged that AIC or any other measure of fit should not be the only criterion for model selection. The parameter estimate and the theoretical justification behind the inclusion in the model is another criterion that need to be considered when selecting the model.

4. Results

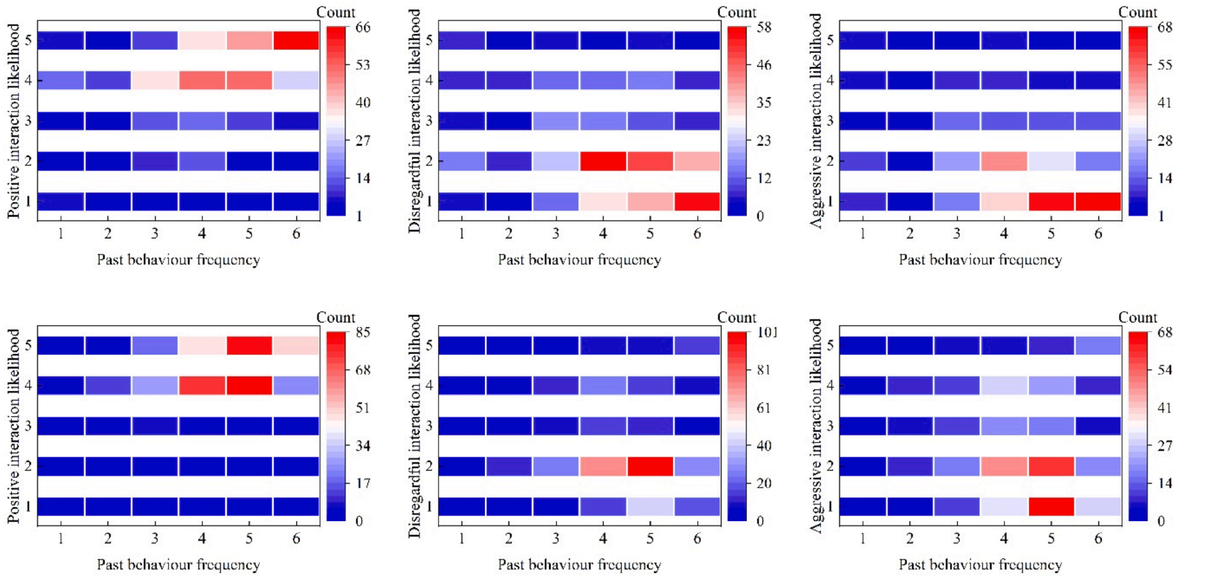
This section mainly presented three ordered model results for three scenarios to identify the significant factors of drivers' positive, disregardful, and aggressive interaction behaviour likelihoods, respectively. Before that, a correlation analysis was performed to (1) examine whether there were any significant correlations between driver characteristics, general driving behaviours, past benchmark behaviour and their acceptance of FAVs, and (2) help identify and exclude explanatory variables in the model with unacceptably high ($r > 0.7$) correlation coefficients.

The Cronbach's alpha coefficient was calculated for both datasets to ensure reliability and consistency of responses in the three scenarios (Bravo & Potvin, 1991). The results indicated that the Cronbach's alpha coefficients for the Australian and Chinese datasets were 0.8 (with 95 % confidence interval ranging from 0.77 to 0.84) and 0.67 (with 95 % confidence interval ranging from 0.62 to 0.72), respectively. These findings indicate a high reliability for the Australian dataset and a relatively acceptable reliability for the Chinese dataset (Bland and Altman, 1997).

4.1. Descriptive and correlation analysis

A summary of all variables collected in this study was listed as in Table 2, and the results of correlation analysis results for Australian and China were provided in Appendix B. In terms of driver characteristics, older drivers in Australia were associated with less positive/favourable attitudes and lower trust toward FAV compared to younger drivers. They were associated with higher perceived behaviour control for driving in the presence of FAVs and higher likelihood of taking positive action when interacting with FAVs. Those correlations were not observed among the Chinese participants. For the Australian drivers, the number of years that a driver held a driver license was negatively associated with attitudes, trust and subjective norms and positively associated with perceived behaviour control (same for the Chinese drivers). The Australian drivers' years of holding a driver license were also positively associated with the likelihood of positive interactions and negatively associated with the likelihood of disregardful and aggressive interactions. The weekly driving time of the Australian drivers was positively correlated with the likelihood of disregardful and aggressive interactions. The Australian female drivers had lower perceived behaviour control and trust of FAVs and higher possibility of positive interactions with FAVs than the Australian male drivers. There were not many significant correlations observed regarding drivers' crash experience except that the Chinese drivers' crash number positively associated with their subjective norms. For both countries, drivers' education level was positively associated with their attitudes and subjective norms toward FAVs. A positive correlation between education level and trust of FAVs was also observed on the Chinese drivers.

For the present driving behaviours, the frequencies of lapses, errors and violations were positively associated with driver attitudes



(1) Positive interaction (2) Disregardful interaction (3) Aggressive interaction

Fig. 2. Split distribution of past benchmark behaviour frequency and interaction behaviour intention with FAV (the upper line refers to the Australian drivers and the lower line refers to the Chinese drivers).

toward FAVs among the Australian drivers. For the Chinese drivers, their attitudes toward FAVs was negatively associated with the frequency of violations and positively associated with the frequency of positive behaviours. For both countries, drivers perceived behaviour control negatively correlated with the frequency of lapses and positively correlated with the frequency of positive behaviours. In Australia a higher trust of FAV was observed among drivers who reported more lapses and violations, while in China a higher trust was correlated with more positive behaviours on roads. Moreover, drivers' present driving behaviours had significant correlations with their interaction behaviour tendency in front of an FAV. For both countries, the self-reported frequency of risky driving behaviours (i.e. lapse, errors, and violations) was positively associated with the likelihood of disregardful and aggressive interactions, while the frequency of positive driving behaviours was positively associated with the likelihood of positive interactions.

Drivers' past benchmark behaviour in the lane-changing situation had significant correlations with their interaction behaviour tendency when they encountered an FAV. In both countries, drivers who adjusted speed for a lane-changing vehicle more frequently in the real-world was associated with a higher likelihood of yielding to the lane-changing FAVs in the same situation and a lower likelihood of disregarding its request or adopting aggressive responses, as shown in Fig. 2.

Regarding the TPB constructs, the Chinese sample showed that driver attitudes, subjective norms, perceived behaviour control, and trust toward FAVs had positive associations with the likelihood of positive interactions and negative associations with the likelihood of disregardful and aggressive interactions. For the Australian drivers, perceived behaviour control was positively associated with the likelihood of positive interactions and negatively associated with the likelihood of disregarding the FAV's lane-changing request.

4.2. Modelling results

4.2.1. Scenario 1 – Positive interaction

The first scenario identified statistically significant factors associated with the likelihood of positive responses to the FAV in the lane-changing scenario (e.g., slowing down and giving way). A pairwise selection criterion was used to include the explanatory variables in the model based on the statistical fit (AIC) and theoretical justification of the parameters. The modelling results for both countries are listed in Table 3. For the Australian drivers, age, gender, weekly driving time, present aggressive behaviours on roads and trust on FAV were statistically significant with 95 % certainty. Older drivers were more likely to slow down and give way to the FAV than younger drivers. Female drivers were more likely to slow down and give way compared to male drivers. Drivers who drove more time per week were less likely to show positive interactions. Drivers who reported more aggressive behaviours on roads were less likely to slow down and give way. Drivers who rated higher trust on FAVs were more likely to behave positively in the interaction scenario.

For the Chinese drivers, none of the driver characteristics factors were statistically significant, but drivers' self-reported driving behaviours (i.e., aggressions and errors) and their attitudes toward FAVs were statistically significant with 95 % certainty. Drivers who reported more aggressive behaviours and driving errors on roads were less likely to slow down and give way to the FAV, and drivers who reported more positive/favourable attitudes toward FAV were more likely to show positive interaction behaviour.

4.2.2. Scenario 2 – Disregardful interaction

The second scenario identified statistically significant factors associated with the likelihood of disregardful responses of drivers in the lane-changing scenario, i.e., driving at the same speed without giving way to the FAV. The modelling results for both countries are listed in Table 4. For the Australian drivers, the driving hours per week, frequencies of lapses and positive behaviours on roads, and the

Table 3
Results of scenario 1 model - positive interaction.

Variables	Australia					
	Estimate	St. Error	Z	P-value	95% CI	
Constant	1.759	0.253	6.940	<0.001	1.263	2.256
Age	0.009	0.003	2.830	<0.01	0.003	0.016
Gender (Male)	−0.281	0.109	−2.580	<0.05	−0.494	−0.067
Driving hours per week	−0.017	0.006	−2.730	<0.01	−0.029	−0.005
DBQ (Aggressions)	−0.242	0.063	−3.840	<0.001	−0.366	−0.119
Trust	0.112	0.036	3.120	<0.01	0.042	0.183
Thresholds:						
τ1	0.624	0.068	9.140	<0.001	0.490	0.758
τ2	1.113	0.063	17.710	<0.001	0.990	1.236
τ3	2.293	0.074	30.890	<0.001	2.148	2.439
Variables	**China**					
	Estimate	**St. Error**	**Z**	**P-value**	**95 % CI**	
Constant	3.202	0.410	7.800	<0.001	2.398	4.006
DBQ (Aggressions)	−0.183	0.076	−2.400	<0.05	−0.332	−0.033
DBQ (Errors)	−0.309	0.109	−2.840	<0.01	−0.522	−0.095
Attitudes	0.150	0.062	2.420	<0.05	0.028	0.271
Thresholds:						
τ1	0.518	0.173	2.990	<0.01	0.179	0.857
τ2	1.234	0.117	10.540	<0.001	1.005	1.463
τ3	3.085	0.124	24.850	<0.001	2.842	3.329

Table 4
Results of scenario 2 model - disregardful interaction.

Variables	Australia					
	Estimate	St. Error	Z	P-value	95 % CI	
Constant	1.451	0.273	5.320	<0.001	0.917	1.985
Driving hours per week	0.023	0.006	3.810	<0.001	0.011	0.036
DBQ (Lapses)	0.172	0.069	2.510	<0.05	0.038	0.307
DBQ (Positive behaviours)	−0.277	0.046	−6.010	<0.001	−0.367	−0.187
Perceived behaviour control	−0.087	0.037	−2.350	<0.05	−0.159	−0.014
Thresholds:						
τ1	1.149	0.061	18.920	<0.001	1.030	1.267
τ2	1.575	0.069	22.770	<0.001	1.439	1.710
τ3	2.403	0.111	21.600	<0.001	2.185	2.621
Variables	**China**					
	Estimate	**St. Error**	**Z**	**P-value**	**95 % CI**	
Constant	1.654	0.407	4.070	<0.001	0.857	2.452
DBQ (Errors)	0.401	0.097	4.150	<0.001	0.212	0.590
Perceived behaviour control	−0.280	0.060	−4.690	<0.001	−0.397	−0.163
Thresholds:						
τ1	1.842	0.084	21.990	<0.001	1.678	2.006
τ2	2.387	0.099	24.020	<0.001	2.193	2.582
τ3	3.093	0.164	18.900	<0.001	2.773	3.414

perceived behaviour control were statistically significant factors with 95 % certainty. Drivers who drove longer time per week were more likely to ignore the FAV's lane-changing request. Drivers who reported more lapses and less positive behaviours on roads were more likely to ignore the request. Drivers who rated higher levels of perceived behaviour control were less likely to show disregardful behaviours.

For the Chinese drivers, the driving errors and perceived behaviour control were statistically significant factors. Drivers who reported more errors when driving were more likely to ignore the FAV's lane-changing request. Similarly, the Chinese drivers who rated higher levels of perceived behaviour control were less likely to behave in a disregardful way.

4.2.3. Scenario 3 – Aggressive interaction

The last scenario examined the likelihood of aggressive response (i.e., accelerating) in the scenario and the statistically significant factors. Table 5 lists the modelling results of both countries. For the Australian drivers, age, present aggressive and positive behaviour frequency on roads were statistically significant factors with 95 % uncertainty. Older drivers were less likely to adopt aggressive response compared to younger drivers. Drivers who reported more aggressive behaviours and less positive behaviours in daily driving were more likely to behave aggressively in the scenario. For the Chinese drivers, the statistically significant factors included self-reported aggressive behaviours, errors and subjective norms. Drivers who reported more aggressive behaviours and more errors were more likely to accelerate in the scenario. Drivers who perceived higher social pressure from important others were less likely to accelerate in the scenario.

Table 5
Results of scenario 3 model - aggressive interaction.

Variables	Australia					
	Estimate	St. Error	Z	P-value	95 % CI	
Constant	0.924	0.256	3.610	<0.001	0.422	1.426
Age	−0.006	0.003	−1.960	<0.05	−0.012	0.000
DBQ (Aggressions)	0.289	0.062	4.690	<0.001	0.168	0.410
DBQ (Positive behaviours)	−0.270	0.047	−5.730	<0.001	−0.363	−0.178
Thresholds:						
τ1	0.824	0.057	14.500	<0.001	0.713	0.935
τ1	1.364	0.072	18.950	<0.001	1.223	1.506
τ1	1.998	0.105	18.990	<0.001	1.791	2.204
Variables	**China**					
	Estimate	**St. Error**	**Z**	**P-value**	**95 % CI**	
Constant	0.538	0.361	1.490	<0.136	−0.170	1.247
DBQ (Aggressions)	0.166	0.070	2.350	<0.05	0.028	0.303
DBQ (Errors)	0.250	0.101	2.490	<0.05	0.053	0.447
Subjective norms	−0.208	0.060	−3.480	<0.001	−0.325	−0.091
Thresholds:						
τ1	1.089	0.068	15.940	<0.001	0.955	1.223
τ1	1.672	0.086	19.420	<0.001	1.503	1.840
τ1	2.452	0.144	17.000	<0.001	2.170	2.735

5. Discussion

A holistic implementation and regulation of FAVs on roads need to take other road users into account (Hancock et al., 2020). The present study shed lights on some road policy challenges that FAVs may bring in the future. In particular, this study analysed, in a cross-cultural setting, responses of drivers facing a lane-changing request of FAVs. The study classified three possible behaviour tendencies, which were positive, disregardful, and aggressive interactions when a FAV indicates to change its lane in front of the participant. The variables used to understand these behavioural responses were individual characteristics (demographics), general driving behaviours (DBQ), past benchmark behaviour in the same situation and acceptance of FAVs. The findings of this research can be used to support the development of policies and guidelines that embrace behavioural adaptation and foster more positive interactions with emerging transport tools.

Among the two countries, the role of age, gender and driving time per week seems to be exclusively important in Australia as opposed to China where driver characteristics were not statistically significant predictors of the interaction responses. In the sample data from Australia, as age increased, drivers were more likely to engage in positive interactions by allowing the FAV to complete the lane-changing, whilst younger drivers were more likely to behave aggressively. This finding is in line with previous studies showing that older drivers are more likely to engage in positive behaviours (i.e., behaviours to take care of the traffic environment or other road users, to help and to be polite with or without safety concerns) than younger drivers (e.g., Özkan and Lajunen, 2005). Younger drivers in previous studies have been observed to be more aggressive while driving (Shinar and Compton, 2004). The effect of age on drivers' behaviour tendencies was not statistically significant for the Chinese participants. This might be because the Chinese sample had a narrower range of age distribution and represent a more younger driver group than the Australian sample, with over 80 % of the participants aged between 21 and 40 years old. Future work might need to expand the age distribution among the Chinese sample to confirm whether age influences the interaction responses with FAVs.

Male drivers were less likely to have positive interaction responses toward FAVs. Compared to female drivers, male drivers had less positive prosocial behaviours, more aggressive driving and a higher threshold to risk which means they can tolerate smaller safety margins (Brañas-Garza et al., 2016; Shinar and Compton, 2004). Driving time per week was identified as a significant factor associated with positive and disregardful interactions in Australia, and more experienced drivers were less likely to show positive responses and more likely to disregard the FAV. This could be related to their larger exposure to traffic interactions such as vehicles merging in front of them, which sometimes requires hazard perception and avoidance in the process (Jackson et al., 2009). Thus, more experienced drivers could handle the situation better without necessary speed adjustment. The impact of driver gender and driving time was not observed among Chinese drivers, especially for Scenario 1 (positive interaction) and Scenario 2 (disregardful interaction) where significant impact was found among Australian drivers. A possible reason might be due to the focused (or less distributed) responses among Chinese drivers in these scenarios. For Scenario 1, 94.9 % Chinse participants chose "likely" or "extremely likely" to show positive interaction with FAVs while the percentage was 77.4 % for Australian participants. For scenario 2 (disregardful interaction), 81.7 % Chinese participants reported "unlikely" or "extremely unlikely" while the percentage was 71.2 % for Australian participants. The limited sample size and homogeneity in response may have led to the insignificant role of categorical/ordinal variables such as gender and driving time. However, more research is needed to investigate the underlying factors (e.g., traffic cultural, driver training history) and explain the lack of these associations among Chinese drivers.

The projection of drivers' present driving behaviours on future interactions with FAVs was achieved by using the well-established DBQ. Driving behaviour is a multidimensional construct, which means that no single driving performance measure can capture all the effects. Therefore, the DBQ was used given that its capability to reflect on-road driving behaviours has been widely demonstrated (de Winter et al. 2015). Within DBQ, the study identified that the measure which had more associations with the interaction tendencies in front of FAVs was the aggressive behaviours. Both in China and Australia, drivers who reported more frequent aggressive behaviours were more likely to act in an aggressive way that impeded the lane-changing of FAVs. Aggressive driving behaviours represent a reckless driving style that reduces safety margins and increases crash risk (Chliaoutakis et al., 2002; Habtemichael and de Picado Santos, 2014; Lajunen and Parker, 2001). Therefore, and prior to the introduction of connected and automated vehicles, more research is required to examine the extent to which aggressive driving behaviours may interact with the safety of these advanced vehicles and identify practical solutions to reduce drivers' aggressive behaviours in front of these vehicles.

Associations regarding other behavioural responses seem to be more dependent on the country of origin. In China, driver errors significantly associated with all three types of responses while no significant impact of driver errors was observed in any of the scenarios among Australian drivers. It is possibly because in this study, the Australian participants had more driving experience as measured by the number of years holding a valid driver license than the Chinese participants (21.5 years vs. 7.5 years), and Australian drivers reported lower frequency of errors in general. Driver errors are deviations from proper behaviours and are usually linked with risky driving behaviours such as distracted or drowsy driving. The findings of the study suggested that an aggressive response toward FAVs may not necessarily be related to an aggressive driver, but caused by potential human errors. Therefore, vehicle manufacturers, policy-makers and related transport stakeholders need to ensure that these deviations from proper behaviours of other road users are recognised and accounted from the FAV perspective to enhance safety and prevent disruptions of the traffic.

In Australia, driver lapses were associated with a disregardful behavioural response toward FAV. This finding is in accordance with expectations given that lapses are associated with attentional and/or memory failures (López-Ramón et al., 2011). As mentioned earlier, disregard of a vehicle's lane-changing request does not indicate a positive or negative nature of the behaviour as drivers are not obligated to yield in this situation. However, the significant impacts of lapses and errors among the Australian and Chinese participants, respectively, imply that Australian drivers may perceive the disregardful behaviour toward FAV as a sort of lapses while the Chinese drivers were more likely to perceive it as an erroneous behaviour. Generally, a good practice is to always maintain safety gaps between vehicles.

The positive behavioural response toward an FAV was predicted by trust (for the Australia drivers) and attitudes (for the Chinese drivers). This means that people who held a more positive view toward road-sharing with FAVs were also more likely to report polite behaviours in front of them. Increasing favourable views in the driver community could help safely integrate FAVs by creating larger safety margins with non-automated vehicles. Additionally, perceived behavioural control predicted disregardful behaviour both in the Chinese and Australian participants. Perceived behavioural control is a reflection of individuals having actual control over performing a behaviour (Terry and O'Leary, 1995). In this study, positive and aggressive behavioural responses toward FAVs are opposite intentional behaviours that require action from the driver. It is worth noting that subjective norms played a significant role in predicting the aggressive interaction tendency among the Chinese drivers and those who perceived higher subjective norms were less likely to behave aggressively. This might be somehow related to the collectivist of nations (Oyserman et al., 2002), which means individuals' public behaviours are highly likely to be influenced by the social and cultural norms to gain social recognition. Fleiter et al. (2011)'s research stated that road user behaviours should be strongly influenced by social relationships in China, as the Chinese society is strongly based on social rules and customs. An early cross-cultural study of Feather (1986) compared the different culture value systems between the Australian and Chinese students, and reported that the Chinese students assigned higher importance to social recognition than the Australian students. These prior findings may help explain the significant role of subjective norms in the interaction with FAVs among the Chinese sample. Overall, the present study implies that promoting a high acceptance and trust of FAVs among the non-AV users could facilitate positive interactions and restrain potential risk-taking and bully behaviours toward FAVs.

5.1. Limitations and future research suggestions

The study has some limitations that should be noted. Firstly, for questionnaire studies, the validity of results largely depends on the authenticity of the participants when they answer the questions. In this study, the participants were made aware that their participation was completely anonymous, and we encouraged participants to answer the questions honestly and frankly with no need to worry about any negative outcomes from their participation. Secondly, as FAVs are not yet available on roads, the lack of actual interactive experience with FAVs may lead to biases in answering the questions related to them. Thus, prior to answering the questions, a thorough introduction of FAVs to participants could help them understand the FAVs features and mitigate the bias. Thirdly, the study only examined lane-changing as a typical interaction scenario. Although several questions were asked regarding the scenario and the consistency between the answers could, to a certain extent, self-validate the study results, it is suggested that other scenarios could be tested in future studies to verify the generalisability of the findings. Fourthly, the Australian and Chinese samples have deviated largely in terms of age distribution, driving experience, and education. This may have led to some inconsistent factors identified in the models. To facilitate a direct comparison of the model results between the two countries, a similar sample structure should be used in the future. Lastly, the study did not ask the likelihood of three behaviour options in the scenario when the vehicle was a human driven one. This has limited the direct comparison of drivers' responses between the two types of vehicles. Drivers' perception constructs regarding FAVs (e.g. trust, attitudes, subjective norms) were found to play a significant role in impacting drivers' interaction behaviour tendency with FAVs. It will be interesting to further explore to what extent these perception constructs impact drivers' behaviour adaptation in front of FAVs as compared to conventional vehicles.

6. Conclusion

The study focused on conventional vehicle drivers' acceptance and interaction behavioural tendency toward FAVs. A scenario-based survey was designed to examine factors that may influence drivers' interaction behaviour tendency, including driver characteristics, general driving behaviours, past benchmark behaviour and acceptance of FAVs. Cross-cultural differences in the behavioural responses and related factors were observed between Australia and China. Driver characteristics such as age, gender and driving time influenced the Australian drivers' interaction tendency, but they did not play significant roles on the Chinese drivers. Drivers present driving behaviours were important predictors of their interaction behaviours with FAVs in both countries. The three constructs of TPB, i.e., attitudes, subjective norms and perceived behaviour control, influenced drivers' positive, disregardful and aggressive behavioural responses, respectively. Generally, the results suggest that drivers' present driving behaviours on roads could to a certain extent reflect their interaction patterns with future FAVs. This implies the importance of future driver training and education when FAVs are introduced, especially for the risk-taking and aggressive driver group as they are more likely to cause safety issues with FAVs. The study also delivers a critical message to the transportation department and automated vehicle manufacturers that non-automated vehicle users' perceptions and feedback should be valued and taken into consideration prior to deploying automated vehicles. To ensure a successful integration of automated vehicles and deliver their promised benefits, it is necessary to achieve a high acceptance and trust among the non-automated vehicle users.

CRediT authorship contribution statement

Xiaomeng Li: Conceptualization, Investigation, Methodology, Data curation, Formal analysis, Writing – original draft, Project administration, Funding acquisition. **Oscar Oviedo-Trespalacios:** Conceptualization, Investigation, Methodology, Writing – original draft, Funding acquisition. **Amir Pooyan Afghari:** Conceptualization, Investigation, Methodology, Formal analysis, Writing – original draft, Funding acquisition. **Sherrie-Anne Kaye:** Conceptualization, Investigation, Methodology, Writing – original draft, Funding acquisition. **Xuedong Yan:** Validation, Writing – review & editing.

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. Supplementary material

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