Delft University of Technology

Cyclists perception and self-reported behaviour towards interacting with fully automated vehicles

Li, Xiaomeng; Pooyan Afghari, Amir; Oviedo-Trespalacios, Oscar; Kaye, Sherrie Anne; Haworth, Narelle

DOI
10.1016/j.tra.2023.103713

Publication date
2023

Document Version
Final published version

Published in
Transportation Research Part A: Policy and Practice

Citation (APA)
Li, X., Pooyan Afghari, A., Oviedo-Trespalacios, O., Kaye, S. A., & Haworth, N. (2023). Cyclists perception and self-reported behaviour towards interacting with fully automated vehicles. *Transportation Research Part A: Policy and Practice*, *173*, Article 103713. https://doi.org/10.1016/j.tra.2023.103713

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright
Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy
Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

This work is downloaded from Delft University of Technology.
For technical reasons the number of authors shown on this cover page is limited to a maximum of 10.

Transportation Research Part A 173 (2023) 103713

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Cyclists perception and self-reported behaviour towards interacting with fully automated vehicles

Xiaomeng Li [a,*], Amir Pooyan Afghari [b], Oscar Oviedo-Trespalacios [a,b], Sherrie-Anne Kaye [a], Narelle Haworth [a]

[a] *Queensland University of Technology (QUT), Centre for Accident Research and Road Safety-Queensland (CARRS-Q), Institute of Health and Biomedical Innovation (IHBI), Kelvin Grove, Queensland 4059, Australia*
[b] *Safety and Security Science Section, Department of Values, Technology and Innovation, Faculty of Technology, Policy and Management, Delft University of Technology, 2628BX Delft, Netherlands*

A R T I C L E I N F O

Keywords:
Driverless cars
Cyclists
Road sharing
Technology acceptance
Human-robot interaction

A B S T R A C T

Fully automated vehicles (FAVs) have the potential to improve road safety and reduce traffic congestion and emissions. Most studies of acceptance of FAVs have focused on motor vehicle users, largely ignoring other road users, such as cyclists. This study investigates the factors that influence cyclists' receptivity towards sharing roads with FAVs and their behavioural intentions in interactions with FAVs. The online survey collected information on participant demographics (e.g. age, gender, crash experience), self-reported on-road cycling behaviours (e.g. violations, errors, positive behaviours) and their receptivity towards sharing roads with FAVs (e.g. attitude, social norms, trust). Three typical cyclist-vehicle interaction scenarios were presented to test the cyclists' intention to engage in self-protective behaviours (e.g. giving a hand signal, giving way or moving over) during the interaction with a FAV. Three hundred and fourteen Australian adults (106 females vs 208 males) who had ridden a bicycle at least once in the past year completed the survey. The results show that older cyclists and male cyclists had a lower receptivity towards sharing roads with FAVs than younger cyclists and female cyclists, respectively. Cyclists who reported being involved in a bicycle crash in the last two years and those who reported committing more errors on roads were more willing to share roads with FAVs. Cyclists who had a higher propensity to risky behaviours and positive behaviours were less likely to take intended self-protective behaviours during interaction with FAVs. Findings of the study provide some insights from the cyclist's perspective to facilitate the development and implementation of automated vehicles.

1. Introduction

Automated vehicle (AV) technologies have developed rapidly in the last decade with great potential for reducing traffic crashes, congestion and emissions. According to the SAE International classification system (SAE, 2018), Level 5 vehicles are fully automated vehicles (FAVs) and should be able to perform all types of driving tasks in any environment and conditions without driver intervention. Despite the powerful capabilities and potential benefits of FAVs, their introduction into the road transportation system still faces many

* Corresponding author.
E-mail address: xiaomeng.li@qut.edu.au (X. Li).

https://doi.org/10.1016/j.tra.2023.103713
Received 12 April 2021; Received in revised form 1 March 2023; Accepted 12 May 2023
Available online 24 May 2023
0965-8564/© 2023 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

challenges. Ensuring that all road users in the transportation system interact with FAVs safely and efficiently is a complex issue, which will directly influence the successful implementation of FAVs (Merat et al., 2018).

Cycling is a healthy, sustainable, and cost-effective form of transport and it is also an important leisure and health activity. All these benefits together with the need for more sustainable transport have resulted in the growth in cycling worldwide. For example, bicycle modal share is over 30% in both Copenhagen and Amsterdam (CIVITAS, 2016). In the U.S., the numbers of cyclists increased by 4.5 million between 2015 and 2017 (Statista, 2018). However, the integration of bicycles in current transport systems has been challenging due to present policies that have placed motorised vehicles at the centre of transport and city planning in many jurisdictions (Useche et al., 2018a; Aldred, 2013). Current safety issues between cyclists and motorised transport question a future when FAVs are ubiquitous.

The lack of effective integration between cycling and motor vehicles has resulted in important safety issues. In low cycling countries where cyclists are often not separated on the road from motor vehicles, the numbers of cyclist casualties have been increasing (Beck et al., 2017; Boufous et al., 2012; Useche et al., 2018a). A comprehensive study in Victoria, Australia, found that motor vehicles were involved in 90% of police reported cycling crashes with 34% of these resulting in serious injury to the cyclist (Boufous et al., 2012). Indeed, crashes between bicycles and motor vehicles are the primary contributor to cyclist trauma (Prati et al., 2018; Johnson et al., 2010). Drivers are more often at fault in these crashes than cyclists (Schramm et al., 2010; Haworth et al., 2019) though cyclists' lack of notice and misunderstanding of the situation are also contributing factors (Habibovic and Davidsson, 2012). It is predicted that FAVs have the potential to reduce or even eliminate these crashes.

1.1. FAV deployment and potential impact on cyclists

Conflicts between cyclists and motor vehicles have caused long-standing safety issues. The deployment of AVs is expected to have a significant impact on the future road transport system, as they promise to offer benefits by creating a safer, more inclusive and sustainable traffic environment (Booth et al., 2019). However, FAVs are not yet available in the market, and it is also difficult to foresee their arrival time. Up till now, little is known about the actual impacts of FAVs on cyclists and whether the impacts will be positive or negative in general.

Cyclists constitute as a group of vulnerable road users in road transport system whose safety has received continuous attention. Cyclists behaviour and their interaction with motor vehicles have been studied extensively in the past due to their close link with crash risk. When considering a comprehensive examination of cycling behaviours, the self-reported behaviour questionnaire paradigm has been widely used. For example, Useche et al. (2018b) developed and validated a Cycling Behaviour Questionnaire which has been increasingly applied by other studies to measure three dimensions of cyclist behaviours, i.e. violations, errors and positive behaviours. Using this paradigm, cyclists behaviour traits and its relation to individual characteristics and crash involvement have been consistently reported. Studies have shown that cyclists who reported more violations, errors and less positive behaviours on roads were more likely to be involved in crashes (O'Hern et al., 2020; Li et al., 2022). Cyclist characteristic also play a certain role in impacting behaviours. Male cyclists were found to engage in more violations and fewer positive behaviours than female cyclists in general (Useche et al., 2018c; Li et al., 2022). Younger cyclists were more likely to engage in risky riding behaviours than their older counterpart (Twisk et al., 2015; Li et al., 2022). Additionally, prior research has also identified typical collision scenarios involving cyclists and vehicles. For example, research has found that in a shared road space, vehicles overtaking cyclists created dangerous conflicts and imposed great risks on cyclists' safety (Dozza et al., 2016; Kovaceva et al., 2019). Cyclists' colliding with an open door from a parked vehicle was another event that received increasing attention worldwide (Lawrence et al., 2018; Johnson et al., 2013). As compared to other types of road users such as motor vehicles and pedestrians, cyclists' movement trajectory on roads is more flexible in nature. Thus, for the advanced automated vehicles, it is critical for them to be equipped with the ability to precisely detect cyclists and recognise their behavioural intentions.

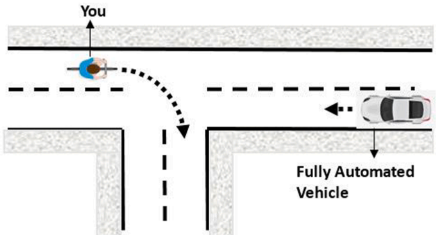
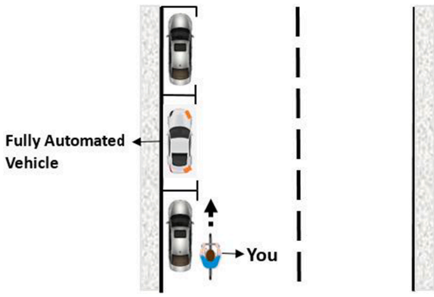
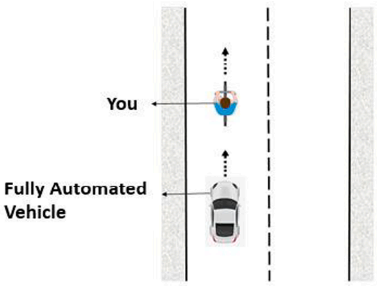
From a technical perspective, FAVs are equipped with advanced devices (e.g. sensors and cameras) and technologies to detect road environment and other road users, and they are expected to follow strict safety rules. However, this safety features might lead to unexpected outcomes. A critical one is the road users' over-reliance on FAVs' capability, thus generating a false sense of security (Harper et al., 2016). This false sense may encourage road users to exhibit unsafe or risk-taking behaviours in front of FAVs (Liu et al., 2020). To minimise risks, the implications of FAVs for cycling safety should be considered in a prospective manner, and a preceding step is to understand cyclists' perceptions of FAVs and their behavioural intention during the interaction with FAVs.

To achieve a smooth and successful adoption of AVs, public acceptance is important. It should be highlighted that public acceptance of AVs not only include the potential buyers' acceptance of using this kind of technology but also other road users' willingness to share roads with them. The literature shows that research relating to public acceptance of private (Level 3–5) AVs has typically focused on assessing drivers' a priori acceptability of AVs (i.e., acceptability before experiencing an AV; Regan et al., 2014; Payre et al., 2014; Kaye et al., 2020; Jing et al., 2020). Nevertheless, research on vulnerable road users' perceptions of AVs is now emerging. Deb et al. (2017) developed a questionnaire to assess pedestrians' receptivity towards FAVs, and their study found that pedestrians who show more positive behaviours on roads tend to have more positive belief regarding FAVs' improvement on traffic safety. Penmesta et al. (2019) examined perceptions towards Uber self-driving AVs in Pittsburgh, US. Compared to pedestrians and cyclists who had not previously interacted with these AV, those pedestrians and cyclists who had interacted with these AVs were significantly more likely to have positive attitude towards self-driving AVs and perceive that self-driving AVs had the potential to reduce traffic-related injuries and fatalities. In another US study, Pyrialakou et al. (2020) used ordered probit models to examine perceived safety near self-driving AVs. They found that participants perceived driving near a self-driving AV to be safer than walking and cycling near a self-driving AV. Further, walking near a self-driving AV was perceived to be safer than cycling near a self-driving AV. Merat et al. (2018) examined pedestrians’ and cyclists’ perceptions towards interacting with fully automated passenger shuttles across three countries: France, Switzerland, and Greece. The findings emphasised the importance of road markings, with participants reporting higher perceptions of safety when the vehicle was operating in designated lanes. Receiving communication of the vehicle’s intention was also important to participants. Rodrígues (2017) examined vulnerable road users’ ($N = 198$) perceptions towards interacting with traditional motor vehicles compared to WEpods (a type of shared FAV). They found that over 50% of the sample reported that they currently base their actions on eye contact or gestures provided by the driver of a vehicle. Further, cyclists reported that they would feel significantly safer sharing the roads with traditional vehicles at unsignalized interactions compared to WEpods. However, when sharing roads in general, cyclists reported that they would feel significantly safer sharing roads with WEpods compared to traditional vehicles. Collectively, these studies highlights some of the key factors influencing users’ acceptance of private and shared FAVs. The current study extends upon this research by examining the perceptions that cyclists residing in Australia have towards sharing roads with FAVs.

1.2. Research objectives

Public acceptance will play a vital role in the widespread adoption of FAVs. Many studies have investigated the acceptance of conditional to FAVs from the potential users’ or buyers’ point of view. Few studies were conducted from the vulnerable road users’

Table 1
Online experiment scenarios.

Scenario description	Question
Scenario 1 - Crossing the path of an oncoming FAV: You are riding a bicycle on a busy urban street when you decide to turn right a long way in front of a FAV. Based on this scenario, please answer the following question.  	How likely are you to give a hand signal that you are turning right?
Scenario 2 - Cycling beside a parked FAV: You are riding a bicycle next to parked vehicles on a busy urban street. A FAV pulls into a parking spot and you think passengers are about to get out of the right-hand-side of the FAV. Based on this scenario, please answer the following question.  	How likely are you to move over or slow down to avoid a door collision?
Scenario 3 - Cycling in front of a FAV: You are riding a bicycle on a street with other vehicles. You notice a FAV approaching from behind in the same lane, needing to overtake you. Based on this scenario, please answer the following questions.  	How likely are you to maintain your position in the lane?

perspective, especially cyclists who are expected to have frequent interactions with FAVs. Besides, most of the previous studies that involved cyclists focused on a specific AV prototype and investigated cyclists' general safety perceptions when interacting with that AV. A major difference of future FAV and the present AV prototype is that FAV will be capable to handle all driving conditions without human intervention (SAE, 2018). This essential difference could generate more uncertainties of other road users' responses and interaction behaviours once they are aware of the vehicle's capabilities. However, up to date little is known about cyclists' receptivity towards sharing roads with FAVs, their behavioural intentions in the presence of FAVs and the underpinning factors (especially their current behaviour traits). To bridge these research gaps, the study conducted an online survey with two research objectives: (1) to examine cyclists' receptivity towards sharing roads with FAVs and its relationship with their current cycling behaviours on roads and individual characteristics; and (2) to identify the factors rising from the first research objective that impact cyclists' interaction behaviour intentions in front of FAVs. The main research question to be addressed in this study is whether and how cyclists' general behaviours at present can predict their future interaction behavioural tendency with FAVs.

2. Method

This research involved an online experiment and questionnaire following a cross-sectional design. The research was approved by the Ethics Review Committee of the Queensland University of Technology (QUT) (Approval Number: 1900000669).

2.1. Participants

A total of N = 314 participants, including N = 106 females and N = 208 males, fully completed the survey. Another N = 105 participants started the survey but did not complete all items and were excluded. The participants' average age was 39.44 (SD = 14.92) years old ranging from 18 to 79 years old. Of all the participants, 18.15% had Completed Year 12 (equivalent to high school degree), 20.06% had Certificate or Diploma, 38.22% had a Bachelor's Degree, and 19.11% had a Master's Degree or higher. Participants primarily rode a bicycle for commuting or utilitarian (37.26%), recreation or leisure (37.26%), or fitness or health purposes (25.48%). Their average riding time was 3.71 h/week (SD = 4.08 h/week) and about 70% (N = 220) of the participants reported riding a bicycle for at least 2 h/week. Overall, 15.6% of the participants reported having least one crash in the past two years when riding a bicycle on the road.

2.2. Online experiment

Three scenario-based questions were designed to investigate the cyclist's intentions of initiating self-protective behaviours when interacting with a FAV in specific situations. In this study, the self-protective behaviour is defined as a momentary action or response that cyclists take at a particular situation to increase their safety on road. The selected scenarios described typical interactions with motor vehicles that a cyclist in Queensland (Australia) would commonly encounter while riding on the road. These scenarios all involved a certain extent of crash risk, which could result in cyclists initiating intended self-protective behaviours during the interaction with vehicles. The following introduction text was provided to participant before the scenario: "*As a cyclist, please imagine the following described scenarios in which you will interact with a FAV on the road. In these scenarios, it is assumed that you can tell whether a car is a FAV without difficulty*". Participants then viewed the image and written text of each scenario outlined in Table 1.

As shown in Table 1, the first scenario describes a cyclist intending to turn right in front of an oncoming FAV, and response to the question represents the cyclist's intention to give a hand signal to a FAV. For the interaction between cyclists and motor vehicles, using hand/arm signal is deemed as an effective way to communicate the cyclists' intention (Walker, 2005). The second scenario describes a cyclist riding past a parked FAV, and the response indicates the likelihood that the cyclist would move over or slow down to avoid a door collision (both behavioural options were deemed as cyclists' self-protective behavioural intention). This scenario was considered as the cyclist-open vehicle door collision, which is a frequent cyclist crash type and could result in fatal outcomes for cyclists in Australia (Johnson, et al., 2013). The third scenario describes a cyclist riding on the road with a FAV approaching from behind, and the response reflects the likelihood that the cyclist would maintain his/her position in the lane, rather than making way for the vehicle. This scenario specifically tested the cyclist's attitude and behavioural intention when they were sharing the same lane with FAVs with the interaction initiated by the FAV. This scenario was selected because previous research reported that cyclists are frequently harassed by drivers who follow them too closely in Australia which increase the overall risk perception of cycling (Heesch et al., 2011&2018).

It can be seen from Table 1 that only general information was provided for each scenario without detailed descriptions of the situation such as the vehicle speed, vehicle distance, speed limit, cyclist position or surrounding traffic. The purpose was to identify participants' generic response in this type of situation, without being biased by a specific environment element. For example, a speed limit of 20 km/h or the vehicle being far away may reduce the likelihood of using a hand signal in Scenario 1. Moreover, as the study focused particularly on cyclists' self-protective behavioural intention across various situations, only one type of behaviour option was provided following each corresponding scenario. The intention was measured by the likelihood on a 5 point Likert-scale (1 = "extremely unlikely", 2 = "unlikely", 3 = "neutral", 4 = "likely", 5 = "extremely likely").

2.3. Questionnaire

Before the participants were presented with the experimental scenarios and questions, they firstly needed to complete an online questionnaire which mainly includes three sections as described below.

1) Cyclist demographic questions (6 items), which include participants' age, gender, education level, riding motivation, riding time and crash experience.
2) Cycling Behaviour Questionnaire (CBQ, 44 items, adapted from Useche et al., 2018b). The CBQ consists of three types of behaviours: violations (16 items), errors (16 items) and positive behaviours (12 items). All CBQ items used a 5-level frequency-based response scale with 1 = "never", 2= "hardly ever", 3 = "sometimes", 4 = "frequently", 5 = "almost always". The CBQ has been validated in prior research as a self-report tool to measure cyclists' risky and positive riding behaviours (Useche et al., 2018b).
3) Cyclist receptivity towards sharing roads with FAVs (18 items, adapted from Deb et al., 2017). This section includes 18 items to measure five factors of behavioural intention: five items for attitude, three for social norms, five for trust, two for compatibility, two for system effectiveness, and one shared item for both compatibility and system effectiveness. Specifically, the "attitude" factor measures the individual's overall positive or negative feelings towards FAVs; "social norms" refers to the individual's perception of what other people whose opinion is important to them think about FAVs; "trust" is defined as the individual's belief that a FAV can perform its intended task efficiently; "system effectiveness" means the extent to which a FAV successfully detects other road users and obstacles on the road and takes appropriate actions accordingly; and "compatibility" represents the degree to which a FAV is perceived as being compatible with the existing transportation system. The items of the receptivity questionnaire were scored on a 7 point Likert-scale (1 = "strongly disagree", 2 = "moderately disagree", 3 = "somewhat disagree", 4 = "neutral", 5 = "somewhat agree", 6 = "moderately agree", 7 = "Strongly agree").

Additionally, between the CBQ and FAV receptivity sections, an item to assess the participants' prior knowledge of AVs was asked ("Before today, have you heard of the term 'automated vehicle'?"). A comprehensive text introduction of FAV (Deb et al., 2017) was also provided to participants before they started to answer the receptivity questionnaire. The complete questionnaire can be found in the Appendix.

2.4. Data collection

The survey was created using the Qualtrics online survey design platform (https://www.qualtrics.com). Data collection was conducted in different ways. A global online market search firm, Dynata (https://www.dynata.com), was invited to provide survey administration and dissemination, and data collection and cleaning services. Dynata has access to a large, diverse pool of participants with whom they have built ongoing relationships. In addition, the online survey was disseminated using social media (e.g. Facebook, Twitter) and electronic mail through QUT mailing lists. Respondents were required to be living in Australia, over 18 years old and have ridden a bicycle on roads during the past 12 months. The survey took about 20 min to complete and the respondents were assured that participation was voluntary. The 314 complete participant samples included 254 collected from social media and emails and 60 collected from Dynata. Participants who joined the study through social media or email were provided a chance to win 1 of 10*50AUD shopping gift cards to thank for their participation. For participants recruited through Dynata, the incentives were provided by Dynata in a form of membership rewards.

3. Results

3.1. Data analysis

Cyclists' behavioural intentions when interacting with FAVs in specific situations are measured in this study using a series of questions such as "How likely are you to give a hand signal that you are turning right?". Since participants' responses to these questions are discrete and ordered, e.g. "extremely unlikely", "unlikely", "neutral", "likely", "extremely likely", ordered discrete response models are needed to evaluate these types of responses (Oviedo-Trespalacios et al., 2020). Unordered or nominal discrete choice models ignore the order of these responses and treat the above discrete categories as nominal categories. A consequence of this mistreatment is that the parameter estimates will have larger variance (i.e. loss of efficiency) if unordered models are used for the ordered dependent variables (Washington et al., 2020). As a result, ordered discrete response models are used for the data analysis in this study. However, an important limitation of these models is that model parameters are assumed to be fixed across individuals. This assumption may not always hold due the unobserved differences among individuals in the sample data. These unobserved differences may arise from the lack of available information and may result in varying effects of explanatory variables on the dependent variable. This phenomenon is referred to as unobserved heterogeneity in the sample (Mannering et al., 2016) and needs to be accounted for within ordered response models. Mixed specification of ordered response models is one of the most common approaches in addressing unobserved heterogeneity in transport applications (Mannering et al., 2016; Afghari et al., 2020) and thus is used in this study. In addition, Principal Component Analysis (PCA) is used in this study to minimize autocorrelation and summarize data to be used in the mixed ordered probit models (more on this will be presented in the following). The details of mixed ordered response model specification and the PCA are presented in the following sections.

3.1.1. Mixed ordered response model specification

Let Y_i be the dependent variable representing the likelihood of cyclist i intending to behave in a particular way when interacting with a FAV in specific situations (e.g. moving to the left, giving hand signals, staying in the middle of the lane), and let s $(s = 1, 2, 3, \ldots, S)$ represent ordinal categories of this dependent variable (i.e. *extremely unlikely*, *unlikely*, *neutral*, *likely, extremely likely*). To construct the mixed ordered response model, an underlying latent variable is defined by a linear propensity function for the dependent variable as in the following:

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

Where β is the vector of parameters, X_i is the vector of covariates (cyclist's demographic characteristics, behaviours on road, attitude, trust, etc.) and ε_i is idiosyncratic error terms assumed to be identically and independently distributed across observations in this equation. To account for the unobserved heterogeneity in the effects of explanatory variables on the dependent variable, model parameters are allowed to vary across respondents:

$$\beta_i = \overline{\beta_j} + \delta_i \text{ and } \delta_i \ \ \text{Normal}\,(0,\ \upsilon) \tag{2}$$

where $\overline{\beta_j}$ and υ are the mean and standard deviation of parameters across respondents. If the standard deviation of the normal distributions are zero ($\upsilon = 0$), the model will reduce to the regular ordered response model. The latent variable is then mapped to the actual categories of the dependent variable by thresholds (τ) such that:

$$Y_i = S \text{ if } \tau^{(s)} < Y^*{}_i < \tau^{(s+1)} \tag{3}$$

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

$$E(Y_i^s|X_i) = H_i^s(.) \text{ where } 0 \leq H_i^s(.) \leq 1 \text{ and } \sum_{s=1}^{S} H_i^s = 1 \tag{4}$$

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 a mixed ordered probit model of cyclists' receptivity towards automated vehicles. The probability of each category of the dependent variable is then presented as:

$$P(Y_i = s) = \varphi\{\tau^{(s+1)} - (\beta_i X_i)\} - \varphi\{\tau^{(s)} - (\beta_i X_i)\} \tag{5}$$

Here $\varphi(.)$ is the standard normal cumulative probability density function. The probability of initiating behaviour by cyclist i can be obtained as:

$$P(Y_i) = \prod_{s=1}^{S} P(Y_i = s)^I \tag{6}$$

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:

$$l = \prod_{i=1}^{N}(\int_{\beta} P(Y_i) d\beta) \tag{7}$$

The above likelihood function can be estimated by the Maximum Simulated Likelihood Estimation technique (Bhat and Srinivasan, 2005). Finally, the Akaike Information Criterion (AIC) is used to compare the goodness of fit among different variants (mixed or regular) 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, 2011):

$$\text{AIC} = -2\log(\text{L}) + 2\text{P} \tag{8}$$

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 is generally preferred over the other models.

3.1.2. Principal component analysis

Autocorrelation or the correlation among several variables of the same kind is a common problem in statistical analysis of survey data in behavioural research (Huitema, 1986; Huitema and McKean, 1991). Autocorrelation arises when there are too many questions in the survey that may capture the same behaviour. One way of dealing with autocorrelation is to simply use the average of all items within a category as a representative of that category. The average, however, may not properly capture the variability in the original items. Principal Component Analysis (PCA) is an alternative approach used in the statistical literature (Tipping et al, 2001) to summarize data when there are too many variables in the analysis (Henry and Hidy, 1979). The PCA creates a set of new variables, referred to as *principal components (PC)*, each of which is a linear and orthogonal combination of the original variables in such a way that each orthogonal combination captures the maximum variability in the original set of variables and has the minimum autocorrelation with other linear combinations:

$$PC_i = \sum_{j=1}^{m} w_j x_j \tag{9}$$

where PC_i is the i^{th} principal component, w_j are factor loadings, and x_j are the standardized form of the original variables. The principal components can be obtained by applying the orthogonal transformation and finding the Eigenvectors and Eigenvalues of the Spearman correlation matrix of the original set of explanatory variables. The principal components are then arranged based on their decreasing contribution to the total variance of the original set of explanatory variables: the first principal component explains the highest variability in the explanatory variables; the second principal component explains the second highest variability in the explanatory variables, and so forth (the cumulative contribution of all principal components is equal to 1). These principal components can then be used in the analysis as representatives of the original set of variables. The number of principal components to be used in the model depends on the specific research objective, though the common practice is to use all principal components with Eigenvalues greater than one. However, in the context of this study, the first principal component is selected as the most appropriate representative of all items within each category of variables.

3.2. Data base

Table 2 shows the descriptive statistics for all the variables in this study. The responses are displayed as percentages except for age, riding time and crash count. For convenience of presentation of the cyclist receptivity questionnaire, responses of moderately disagree and somewhat disagree were merged into a new category, disagree. Similarly, responses of moderately agree and somewhat agree were merged into a new category, agree.

3.3. Correlation analysis

Pearson correlation coefficients were first calculated for the variables in this study to obtain an initial understanding of the data and to identify the associations between cyclists' characteristics, behaviours on road, and their receptivity towards sharing roads with FAVs. The correlations (see Table 3) show that older cyclists showed lower receptivity towards FAVs compared to younger cyclists, as age had significantly negative correlations with all the constructs of the receptivity questionnaire. Male cyclists reported lower ratings of system effectiveness and compatibility compared to females. Cyclists who had more crashes gave higher ratings of FAV compatibility than those who had less crash experience. Few significant correlations were found between cyclists' on-road behaviour and receptivity towards FAVs, except that cyclists reporting more errors were more likely to give higher ratings on FAV compatibility.

3.4. Cyclists' interaction behaviours with FAVs

3.4.1. Model selection

The goodness of fit across model candidates is listed in Table 4. The AIC of mixed ordered probit model is slightly lower than that of

Table 2
Descriptive statistics of all variables.

Variables		Mean	S. D.	Min	Max	
Age		39.44	14.92	18.00	79.00	
Riding time (hours/week)		3.91	4.08	0.10	30.00	
Crash count		0.29	0.94	0.00	10.00	
Gender (male)		65.92%				
Riding motivation	Fitness	25.48%				
	Commuting	37.26%				
	Recreational	37.26%				
Education	Less than year 12	2.23%				
	Completed year 12	18.15%				
	Certificate or diploma	20.06%				
	Bachelors	38.22%				
	Masters	19.11%				
	Other	2.23%				
Prior knowledge of AVs (yes)		91.08%				
Cyclist behaviour on road		**Never**	**Hardly ever**	**Sometimes**	**Frequently**	**Almost always**
Violations		61.72%	15.61%	13.50%	5.45%	3.72%
Errors		68.25%	19.73%	8.86%	1.89%	1.27%
Positive behaviours		5.47%	6.00%	16.51%	23.59%	48.43%
Cyclist receptivity towards FAV		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
Attitude		10.89%	13.82%	18.47%	32.87%	23.95%
Social norms		6.16%	15.29%	40.98%	27.92%	9.66%
Trust		13.57%	14.76%	21.71%	31.29%	18.67%
System effectiveness		12.95%	16.24%	25.80%	31.95%	13.06%
Compatibility		19.32%	20.70%	24.42%	26.54%	9.02%
Cyclist interaction with FAV		**Extremely unlikely**	**Unlikely**	**Neutral**	**Likely**	**Extremely likely**
Scenario 1		3.50%	4.78%	11.78%	29.62%	50.32%
Scenario 2		1.27%	2.87%	8.28%	33.12%	54.46%
Scenario 3		28.66%	34.71%	13.38%	15.61%	7.64%

Table 3
Correlation analysis results.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Age	–																
2. Gender (male)	0.196**	–															
3. Riding time	0.066	0.032	–														
4. Crash experience	−0.134*	0.071	0.111*	–													
5. Education level	0.160**	0.051	0.060	0.035	–												
6. Riding motivation (fitness)	0.082	0.112*	−0.033	0.013	−0.024	–											
7. Riding motivation (commute)	−0.065	−0.071	0.113*	0.087	0.071	−0.451**	–										
8. Riding motivation (recreation)	−0.009	−0.030	−0.083	−0.099	−0.049	−0.451**	−0.594**	–									
9. AV knowledge	0.079	0.034	−0.058	−0.117*	0.059	0.029	0.079	−0.106	–								
10. Violations	−0.213**	0.090	0.143*	0.291**	0.056	−0.040	0.136*	−0.100	−0.151**	–							
11. Errors	−0.243**	0.028	0.058	0.268**	0.011	−0.064	0.064	−0.006	−0.261**	0.766**	–						
12. Positive behaviours	0.230**	−0.132*	0.026	−0.131*	0.012	0.120*	−0.086	−0.023	−0.065	−0.226**	−0.197**	–					
13. Attitude	−0.122*	−0.045	−0.055	0.043	0.063	−0.069	0.064	−0.002	0.002	−0.012	−0.045	0.030	–				
14. Social norms	−0.105	−0.054	−0.084	0.033	0.035	−0.022	−0.019	0.038	−0.02	0.011	0.001	0.033	0.674**	–			
15. Trust	−0.127*	−0.053	−0.024	0.089	0.052	−0.099	0.065	0.024	0.016	0.068	0.038	−0.054	0.826**	0.641**	–		
16. System effectiveness	−0.127*	−0.112*	−0.089	0.056	0.016	−0.043	0.093	−0.054	0.078	0.032	0.026	0.051	0.771**	0.597**	0.748**	–	
17. Compatibility	−0.22**	−0.16**	−0.042	0.134*	−0.008	−0.055	0.083	−0.034	0.092	0.085	0.137*	−0.021	0.709**	0.548**	0.73**	0.727**	–

** represent $p < 0.01$; * represent $p < 0.05$.

the ordered probit model in both Scenario 1 and Scenario 3 while the AIC of the two models are equal in Scenario 2. This finding implies that the mixed ordered probit model is performing slightly better than the ordered probit model. However, it is recognized that goodness of fit is only one criterion for model selection. The ability of explaining unobserved differences in individuals' behaviour is another important model selection criterion (Afghari et al., 2018) which is unique to the mixed ordered probit model. As such, the mixed ordered probit model is selected to evaluate the effects of explanatory variables on cyclists' behavioural intentions when interacting with FAVs in the previously mentioned scenarios.

When developing the models, explanatory variables were tested for multicollinearity by computing the Pearson correlation coefficients, and the variables with unacceptably high correlation coefficients ($r > 0.7$) were excluded from the models. The explanatory variables were inserted into the mixed ordered probit model using stepwise variable selection criterion. In addition, principal component analysis was applied to the items within violations, errors, positive behaviours, attitude, social norms, trust, system effectiveness and compatibility, and the first principal components were used as the explanatory variables in the models. The results of the principal component analysis i.e. the Eigenvalues, Eigenvectors and proportion of explained variability, are provided in the Appendix. The estimated parameters of the mixed ordered probit models for the three scenarios are presented in Table 5.

3.4.2. Scenario 1 - crossing the path of an oncoming FAV

The modelling results for the first scenario indicated that riding purpose (commuting), errors, positive behaviours and compatibility are statistically significant variables in explaining the likelihood of a cyclist giving a hand signal for turning maneuvers. The negative parameter of these variables show that cyclists who ride a bicycle for commuting, who have more errors and more positive behaviours, are associated with decreased likelihood of giving hand signals before turning. The parameter of compatibility is random and statistically significant with a negative mean. These results indicate that cyclists' rating on FAV compatibility decreases the likelihood of giving a hand signal in average, although this effect significantly varies across participants.

3.4.3. Scenario 2 - cycling beside a parked FAV

The modelling results of the second scenario show that violations, positive behaviours, compatibility and social norms are statistically significant variables in explaining the likelihood of a cyclist moving over or slowing down to avoid a door collision. The negative parameters of violations and positive behaviours indicate that higher frequencies of cyclists' violations and positive behaviours on roads are associated with a decreased likelihood of taking actions to avoid door collisions. In contrast, the positive parameter of compatibility suggests that a higher rating of FAV compatibility is associated with an increased likelihood of moving over or slowing down. The parameter of social norms is random with a positive mean, indicating that social norms is, in average, positively associated with the likelihood of taking actions to avoid door collisions, although its effect varies across participants.

3.4.4. Scenario 3 - cycling in front of a FAV

The modelling results of the third scenario show that riding time, violations, the highest level of education, prior knowledge of AVs and attitude are significantly associated with the likelihood of a cyclist maintaining his/her position in the lane. Among the significant variables, the parameters of riding time and violations are fixed across participants while the rest of the parameters are random. The positive parameters of riding time and violations indicate that longer riding time and higher frequency of violations on roads are associated with increased likelihood of maintaining the position in the lane. The parameters of education and attitude are random with statistically significant means and standard deviations, indicating that they influence the likelihood of maintaining the position in the lane but their effects vary across participants. The parameter of prior knowledge of AVs is also random with a not statistically significant mean but a statistically significant standard deviation. This finding implies that prior knowledge of AVs increases the likelihood of cyclist maintaining his/her position in the lane for some individuals and decreases this likelihood for others. However, the average effect of this variable is not statistically significant across the sample.

4. Discussion

4.1. Cyclists' receptivity towards sharing roads with FAVs

Findings from the present investigation revealed important insights into cyclists' receptivity towards sharing roads with FAVs and the associated factors. Receptivity towards sharing roads with FAVs among cyclists was highly correlated with their demographic characteristics but less with their cycling behaviours. Older cyclists reported lower receptivity of riding a bicycle in the presence of a FAV compared to younger cyclists and this was reflected in lower ratings of most constructs of the receptivity including attitude, trust,

Table 4
Comparison of goodness of fit across model candidates.

	Scenario 1		Scenario 2		Scenario 3	
	OP	MOP	OP	MOP	OP	MOP
Number of estimated parameters	8	10	8	10	8	13
Log likelihood at convergence	−357	−354	−312	−310	−440	−432
AIC	729	728	640	640	896	891

OP: ordered probit model; **MOP:** mixed ordered probit model.

Table 5
Results of mixed ordered probit regression model for three scenarios.

Scenario 1 - Crossing the path of an oncoming FAV				
Variable	**Estimate**	**St. Error**	**t-value**	**p-value**
Threshold values:				
Threshold 1|2	0.860	0.205	4.190	0.000
Threshold 2|3	1.922	0.237	8.120	0.000
Threshold 3|4	3.530	0.269	13.120	0.000
Non-random parameters				
Riding purpose (commuting)	−0.448	0.153	−2.930	0.003
Errors - PC1	−0.094	0.024	−3.950	0.000
Positive behaviours - PC1	−0.246	0.033	−7.560	0.000
Means of random parameters				
Constant	3.647	0.264	13.800	0.000
Compatibility - PC1	−0.197	0.055	−3.600	0.000
Standard deviation of random parameters				
Constant	1.147	0.099	11.560	0.000
Compatibility - PC1	0.621	0.067	9.290	0.000
Scenario 2 - Cycling beside a parked FAV				
Variable	**Estimate**	**St. Error**	**t-value**	**p-value**
Threshold values:				
Threshold 1|2	0.692	0.229	3.020	0.003
Threshold 2|3	1.457	0.256	5.680	0.000
Threshold 3|4	2.771	0.272	10.200	0.000
Non-random parameters				
Violations - PC1	−0.066	0.029	−2.270	0.023
Positive behaviours - PC1	−0.137	0.033	−4.200	0.000
Compatibility - PC1	0.140	0.060	2.340	0.019
Means of random parameters				
Constant	2.893	0.266	10.870	0.000
Social norms - PC1	0.259	0.069	3.750	0.000
Standard deviation of random parameters				
Constant	0.343	0.070	4.880	0.000
Social norms - PC1	0.358	0.062	5.740	0.000
Scenario 3 - Cycling in front of a FAV				
Variable	**Estimate**	**St. Error**	**t-value**	**p-value**
Threshold values:				
Threshold 1|2	1.653	0.137	12.040	0.000
Threshold 2|3	2.398	0.160	15.000	0.000
Threshold 3|4	3.763	0.221	17.030	0.000
Non-random parameters				
Riding time	0.225	0.029	7.690	0.000
Violations - PC1	0.037	0.013	2.840	0.004
Means of random parameters				
Constant	0.947	0.245	3.870	0.000
Education (Bachelor's degree or more)	0.403	0.139	2.900	0.004
Attitude - PC1	−0.127	0.037	−3.470	0.001
Prior knowledge of AVs	−0.320	0.229	−1.400	0.162
Standard deviation of random parameters				
Constant	0.536	0.072	7.480	0.000
Education (Bachelor's degree or more)	0.978	0.101	9.720	0.000
Attitude - PC1	0.499	0.046	10.750	0.000
Prior knowledge of AVs	0.462	0.073	6.290	0.000

system effectiveness and compatibility. The finding is consistent with the age difference reported in most studies about user acceptance of Avs (e.g. Liu et al., 2019; Bansal et al., 2016). These studies have suggested that younger people hold stronger positive attitudes toward AVs (Liu et al., 2019) while older people are less likely to accept AVs and less likely to pay for AVs due to their low level of trust (Bansal et al., 2016). An earlier study of Connor and Brown (2010), which investigated cyclists' perceptions of sharing the road with motorists, provides possible explanations for our results. Their study reported that younger cyclists (aged < 25 years) are less concerned for their safety when passing motor vehicles. The reason for this could be attributed to the findings in personality research that younger people have a greater propensity for risk taking and sensation seeking and the propensity tends to decline as age increases (Mata et al., 2016).

It should be noted that in our study, male cyclists reported lower receptivity of riding around FAVs due to lower ratings of system effectiveness and compatibility. This is surprising as many previous studies reported that males have more positive attitudes and less safety concerns regarding AVs and they are more inclined to buy one than females (Payre et al., 2014; Hulse et al., 2018). However, our result is supported by a focus-group study with vehicle owners from Los Angeles, Chicago and Iselin (Silberg et al., 2013). Women in the focus groups were more receptive to self-driving vehicles as they perceived more benefits of being free to focus on their children in the back seat and less restrictions on drivers who might be influenced by alcohol, illness and other limitations. In contrast, males were more resistant to FAVs as they believed that the vehicle would force them to stay in lane and follow speed limits. This is consistent with the male cyclists' concern on the system effectiveness of FAVs reported in our study. Together, the results reflect that males tend to have higher expectations on the FAV system effectiveness and compatibility than females in terms of both driving and interaction with other road users.

FAVs are expected to improve road safety by reducing crashes related to human errors or violations, and according to the results of our study, this expectation seems to be especially important for people who have suffered from crashes and human errors. In our study, crash-involved cyclists and those who reported more errors when cycling had a higher receptivity in terms of FAV compatibility compared to cyclists without crash history and cyclists with less errors on roads. Similarly, Bansal et al. (2016), in a survey of people's willingness to pay for AVs, found that respondents perceive fewer crashes to be the main benefit of AVs and the number of past crashes experienced is positively associated with the willingness to pay. Overall, the findings indicate that this specific group of people who suffered from crashes and errors may appreciate and benefit more from the enhanced safety brought by FAVs and will also rely more on the FAVs to take human errors out of the road traffic.

4.2. Cyclists' intended self-protective behaviours when interacting with FAVs

4.2.1. The role of current cycling behaviours on road

The study revealed factors that influence the likelihood of cyclists to engage in intended self-protective behaviours during interactions with FAVs. Cyclists who self-reported higher propensity to risky riding behaviours, more violations (i.e. deliberate infringement of some regulated or socially accepted code) and more errors (i.e., failure of planned actions to achieve their desired outcome), were less likely to initiate self-protective behaviours near FAVs. Cyclists who reported more violations were less likely to move over or slow down when approaching parked vehicles. These are behaviours that cyclists often engage in to prevent "door-open" crashes, which are a major safety concern among cyclists in Australia (Johnson et al., 2013). In addition, cyclists who committed more violations were less likely to move over when followed by a motor vehicle, which could reduce the safety margin if the vehicle overtakes. These findings are not surprising since previous studies found strong correlations between the lack of self-protective behaviour and violations (Twisk et al., 2015). Australian cyclists are exposed to a hostile environment that includes frequent harassment and aggressive behaviour by motorists, and self-protective behaviours play an important role to ensure their safety on roads (Poulos et al., 2019; Heesch et al., 2011, 2018). Regarding errors, cyclists who reported more errors were less likely to engage in protective behaviours such as giving a hand signal when crossing the path of oncoming traffic. Potentially, cyclists with a tendency to riding errors are seeing FAVs as an opportunity to lower their guard and reduce the engagement of protective behaviours. These results suggest that high-risk groups of cyclists could have reduced safety margins whilst interacting with FAVs.

Another interesting finding is that positive behaviour appears to be negatively associated with intended self-protective behaviour when cycling beside parked cars and crossing the path of oncoming traffic. This finding is surprising because drivers who generally engage in safe behaviours also avoid risky behaviours. In the case of car drivers, Özkan et al. (2005) argue that positive driver behaviours could buffer the effects of errors and violations in some circumstances. Additionally, Useche et al (2018a) identified that cyclists who report engaging in more positive behaviours also report less errors and violations. In this study, it is suspected that cyclists who engage in positive behaviours more often would possibly wait for the FAV to cross first instead of using a hand signal. It is also likely that those cyclists may hold positive view on FAVs' capability to avoid door collisions.

4.2.2. The role of cyclists' perception towards FAVs

Among all the receptivity variables, perception of FAV compatibility was significantly associated with cyclists' responses to the scenarios though the association direction was not consistent across scenarios. Cyclists who believed that FAVs will be compatible with transport system were, in average, less likely to use hand signal while they were more likely to take actions to avoid door collisions. This result emphasises that whether FAVs could be integrated into the present transport system in a compatible and effective way could directly influence other road users' behavioural responses towards them. It also highlights the importance of ensuring that FAVs are capable of delivering the high levels of performance that cyclists expect them to have, as otherwise safety–critical situations could be increased.

Attitude and social norms were also associated with the likelihood of engaging in specific self-protective behaviours. When cycling beside parked cars, cyclists who reported higher social norms on average tended to pay more attention to door collisions. Similarly, previous research of Feenstra et al. (2010) reported that cyclists who had a higher score on personal norm tended to have a lower score on risky cycling behaviours and risky cycling intentions. When being followed by a vehicle, cyclists who reported more positive attitudes towards sharing the road with FAVs were, in average, more likely to move over and give way to the FAV. According to Australian traffic rules, cyclists in this situation are not required to move over. Potentially, cyclists do so to allow a larger safety margin in case of an overtaking maneuver from the following vehicle, as a courtesy to prevent delay of the vehicle, lack of knowledge of the road rules, or because they feel that they are harassed. Further research is needed to confirm the reasons underlying this behaviour.

4.2.3. The role of cyclist characteristics

Some demographic characteristics were also found to influence participants' responses to FAVs during the online experiment. In the scenario where the cyclist is followed by the FAV, participants who were more educated and spent more time riding were less likely to move over. Additionally, cycling commuters reported being less likely to give hand signals when crossing the path of oncoming traffic. This could be related to more experienced and educated cyclists having a better knowledge of the road rules. As explained earlier, cyclists are not legally required to move over in this scenario but they likely do so for self-protection or altruistic reasons. Previous research has revealed that cyclists with more experience (i.e., those who reported cycling regularly for two years) report a reduced concern for traffic risks when compared to less experienced cyclists (O'Connor and Brown, 2010). Additionally, this study also found a discrete effect of prior knowledge of AVs on cyclists' decision to move over when being followed by a FAV. A group of cyclists who had heard about AVs before the study tended to maintain their position in the lane, which is probably due to their awareness that the FAV would follow strict safety rules. The other group of cyclists who had heard about AVs before were more likely to move over. The moving over action in this scenario is deemed more as a courtesy gesture than a self-protective behaviour by this group of people. Previous studies also reported that participants who had pre-existing knowledge of AVs held more optimistic view towards using AVs in the future than those who had no such knowledge (Kaye et al., 2020). Further research still need to investigate the uncaptured influence of cyclists' familiarity with FAV (e.g. the extent of pre-existing knowledge about FAVs) on their interaction behaviour choice.

4.3. Limitations and future research suggestions

Some limitations in the study should be noted. First, the participants did not have practical interaction experience with FAVs, which is a common issue in the current social science studies related to FAVs, and thus the responses of the participants might be biased. Future research is required to examine cyclists' receptivity towards sharing roads by exposing cyclists to these vehicles in a real-world driving environment. Second, although the participants were aware that the survey was completely anonymous and voluntary, it is possible that participants may have been influenced by social desirability biases and reported inaccurate responses. Third, the study is more exploratory in nature and the sample size in the study is relatively small. A larger sample size will help increase the validity of the results and enhance the generalizability of our findings to the general population. Moreover, FAV traits and features that may play an important role in cyclists' perceptions and decisions are not thoroughly considered in the study. It is suggested to conduct a stated-preference experiment with different FAV traits to deeply understand cyclists' concerns or recognitions on FAV features on a larger sample base in the future. Fourth, the study did not consider participants' prior experience with advanced driver assistance technology. This experience may influence the receptivity of FAVs and their behaviours towards them, and thus future studies should involve these potential factors. Regarding the selection of models, mixed ordered probit model can efficiently capture the unobserved heterogeneity in the effects of explanatory variables on the dependent variables. However, given many of the variables analysed this study are indicators of latent constructs (e.g. errors, violations and trust), future research should investigate the use of hybrid choice models to better understand these latent constructs and their effects on cyclists' behavioural intentions.

5. Conclusion

The study conducted an online experiment and questionnaire to investigate cyclist receptivity towards FAVs and their behavioural responses when sharing the road with FAVs. Cyclists' receptivity towards FAVs was associated with several factors regarding their individual characteristics and riding behaviours on roads. Generally, younger and female cyclists are more likely to have favourable receptivity. Cyclists who reported crash experience and more frequent riding errors had a higher receptivity towards FAVs. Three interaction scenarios between cyclist and FAV were designed in the study to test cyclists' self-protective behavioural intention. The study found that cyclists who were less likely to engage in intended self-protective behaviours were those who self-reported higher propensity to risky riding behaviours and positive riding behaviours. Moreover, cyclists' perceptions of social norms, attitude and FAV compatibility directly influenced their behavioural response during the interaction. The study suggested that high-risk groups of cyclists are not going to actively increase safety margin when interacting with FAVs. Prior to being introduced into the transport systems, AVs should manage to improve and perfect their functions to match the cyclists' high level of expectations on their performance.

CRediT authorship contribution statement

Xiaomeng Li: Project administration, Conceptualization, Investigation, Validation, Methodology, Formal analysis, Writing – original draft. **Amir Pooyan Afghari:** Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft. **Oscar Oviedo-Trespalacios:** Conceptualization, Methodology, Investigation, Writing – original draft. **Sherrie-Anne Kaye:** Conceptualization, Methodology, Investigation, Writing – original draft. **Narelle Haworth:** Conceptualization, 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.

Acknowledgement

This research was funded by a 2019 Injury Prevention Program Seeding Grant provided by the (former) Institute of Health and Biomedical Innovation (IHBI), Queensland University of Technology (QUT). This work is also supported by the Motor Accident Instance Commission (MAIC), Queensland. The views expressed herein are those of the authors and are not necessarily those of the funders.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2023.103713.

References

Afghari, A.P., Washington, S., Haque, M.M., Li, Z., 2018. A comprehensive joint econometric model of motor vehicle crashes arising from multiple sources of risk. Anal. Methods Accident Res. 18, 1–14.
Afghari, A.P., Haque, M.M., Washington, S., 2020. Applying a joint model of crash count and crash severity to identify road segments with high risk of fatal and serious injury crashes. Accid. Anal. Prev. 144, 105615.
Aldred, R., 2013. Incompetent or too competent? Negotiating everyday cycling identities in a motor dominated society. Mobilities 8 (2), 252–271.
Bansal, P., Kockelman, K.M., Singh, A., 2016. Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. Transport. Res. Part C: Emerg. Technol. 67, 1–14.
Beck, B., Ekegren, C.L., Cameron, P., Edwards, E.R., Bucknill, A., Judson, R., Gabbe, B.J., 2017. Predictors of recovery in cyclists hospitalised for orthopaedic trauma following an on-road crash. Accid. Anal. Prev. 106, 341–347.
Bhat, C.R., Srinivasan, S., 2005. A multidimensional mixed ordered-response model for analyzing weekend activity participation. Transp. Res. B Methodol. 39 (3), 255–278.
Booth, L., Norman, R., Pettigrew, S., 2019. The potential implications of autonomous vehicles for active transport. J. Transp. Health 15, 100623.
Boufous, S., de Rome, L., Senserrick, T., Ivers, R., 2012. Risk factors for severe injury in cyclists involved in traffic crashes in Victoria, Australia. Accid. Anal. Prev. 49, 404–409.
CIVITAS. Smart Choices for Cities. Cycling in the City. 2016. Available online: https://civitas.eu/sites/default/files/civ_pol-09_m_web.pdf.
Deb, S., Strawderman, L., Carruth, D.W., DuBien, J., Smith, B., Garrison, T.M., 2017. Development and validation of a questionnaire to assess pedestrian receptivity toward fully autonomous vehicles. Transport. Res. Part C: Emerg. Technol. 84, 178–195.
Dozza, M., Schindler, R., Bianchi-Piccinini, G., Karlsson, J., 2016. How do drivers overtake cyclists? Accid. Anal. Prev. 88, 29–36.
Feenstra, H., Ruiter, R.A., Kok, G., 2010. Social-cognitive correlates of risky adolescent cycling behavior. BMC Public Health 10 (1), 408.
Habibovic, A., Davidsson, J., 2012. Causation mechanisms in car-to-vulnerable road user crashes: Implications for active safety systems. Accid. Anal. Prev. 49, 493–500.
Haworth, N., Legge, M., Twisk, D., Bonham, J., O'Hare, T., Johnson, M., 2019. Young driver crashes with cyclists: Identifying training opportunities. Transp. Res. Rec. 0361198119860118.
Heesch, K.C., Sahlqvist, S., Garrard, J., 2011. Cyclists' experiences of harassment from motorists: Findings from a survey of cyclists in Queensland Australia. Prevent. Med. 53 (6), 417–420.
Heesch, K.C., Schramm, A., Debnath, A.K., Haworth, N., 2018. Cyclists' perceptions of motorist harassment pre-to post-trial of the minimum passing distance road rule amendment in Queensland Australia. Health Promot. J. Australia 28 (3), 247–250.
Henry, R.C., Hidy, G.M., 1979. Multivariate analysis of particulate sulfate and other air quality variables by principal components-Part I: Annual data from Los Angeles and New York. Atmospheric Environment (1967), 13(11), 1581-1596.
Huitema, B.E., 1986. Autocorrelation in behavioral research. In: Research methods in applied behavior analysis. Springer, Boston, MA, pp. 187–208.
Huitema, B.E., McKean, J.W., 1991. Autocorrelation estimation and inference with small samples. Psychol. Bull. 110 (2), 291.
Hulse, L.M., Xie, H., Galea, E.R., 2018. Perceptions of autonomous vehicles: Relationships with road users, risk, gender and age. Saf. Sci. 102, 1–13.
Jing, P., Xu, G., Chen, Y., Shi, Y., Zhan, F., 2020. The determinants behind the acceptance of autonomous vehicles: A systematic review. Sustainability 12, 1719.
Johnson, M., Charlton, J., Oxley, J., Newstead, S., 2010. Naturalistic cycling study: identifying risk factors for on-road commuter cyclists. In Annals of advances in automotive medicine/annual scientific conference. Association for the Advancement of Automotive Medicine.
Johnson, M., Newstead, S., Oxley, J., Charlton, J., 2013. Cyclists and open vehicle doors: crash characteristics and risk factors. Saf. Sci. 59, 135–140.
Kaye, S.A., Lewis, I., Forward, S., Delhomme, P., 2020. A priori acceptance of highly automated cars in Australia, France, and Sweden: A theoretically-informed investigation guided by the TPB and UTAUT. Accid. Anal. Prev. 137, 105441.
Kovaceva, J., Nero, G., Bärgman, J., Dozza, M., 2019. Drivers overtaking cyclists in the real-world: Evidence from a naturalistic driving study. Saf. Sci. 119, 199–206.
Lawrence, B.M., Oxley, J.A., Logan, D.B., Stevenson, M.R., 2018. Cyclist exposure to the risk of car door collisions in mixed function activity centers: A study in Melbourne Australia. Traffic Injury Prevention 19 (sup1), S164–S168.
Li, X., Useche, S.A., Zhang, Y., Wang, Y., Oviedo-Trespalacios, O., Haworth, N., 2022. Comparing the cycling behaviours of Australian, Chinese and Colombian cyclists using a behavioural questionnaire paradigm. Accid. Anal. Prev. 164, 106471.
Liu, P., Zhang, Y., He, Z., 2019. The effect of population age on the acceptable safety of self-driving vehicles. Reliab. Eng. Syst. Saf. 185, 341–347.
Liu, P., Du, Y., Wang, L., Da Young, J., 2020. Ready to bully automated vehicles on public roads? Accid. Anal. Prev. 137, 105457.
Mannering, F.L., Shankar, V., Bhat, C.R., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. Anal. Methods Accident Res. 11, 1–16.
Mata, R., Josef, A.K., Hertwig, R., 2016. Propensity for risk taking across the life span and around the globe. Psychol. Sci. 27 (2), 231–243.
Merat, N., Louw, T., Madigan, R., Wilbrink, M., Schieben, A., 2018. What externally presented information do VRUs require when interacting with fully Automated Road Transport Systems in shared space? Accid. Anal. Prev. 118, 244–252.
O'Connor, J.P., Brown, T.D., 2010. Riding with the sharks: Serious leisure cyclist's perceptions of sharing the roads with motorists. J. Sci. Med. Sport 13 (1), 53–58.
O'Hern, S., Stephens, A.N., Young, K.L., Koppel, S., 2020. Personality traits as predictors of cyclist behaviour. Accid. Anal. Prev. 145, 105704.
Oviedo-Trespalacios, O., Afghari, A.P., Haque, M.M., 2020. A hierarchical Bayesian multivariate ordered model of distracted drivers' decision to initiate risk-compensating behaviour. Anal. Methods Accident Res. 26, 100121.
Özkan, T., Lajunen, T., 2005. A new addition to DBQ: Positive driver behaviours scale. Transport. Res. F: Traffic Psychol. Behav. 8 (4–5), 355–368.
Payre, W., Cestac, J., Delhomme, P., 2014. Intention to use a fully automated car: Attitudes and a priori acceptability. Transport. Res. F: Traffic Psychol. Behav. 27, 252–263.
Penmesta, P., Adanu, E., Wood, D., Wang, T., Jones, S.L., 2019. Perceptions and expectations of autonomous vehicles: A snapshot of vulnerable road user opinion. Technol. Forecast. Soc. Change 143, 9–13.
Poulos, R.G., Hatfield, J., Rissel, C., Flack, L.K., Grzebieta, R., McIntosh, A.S., 2019. Cyclists' self-reported experiences of, and attributions about, perceived aggressive behaviour while sharing roads and paths in New South Wales, Australia. Transport. Res. F: Traffic Psychol. Behav. 64, 14–24.
Prati, G., Marín Puchades, V., De Angelis, M., Fraboni, F., Pietrantoni, L., 2018. Factors contributing to bicycle–motorised vehicle collisions: a systematic literature review. Transp. Rev. 38 (2), 184–208.
Pyrialakou, V.D., Gkartzonikas, C., Gatlin, J.D., Gkritza, K., 2020. Perceptions of safety on a shared road: Driving, cycling, or walking near an autonomous vehicle. J. Saf. Res. 72, 249–258.
Regan, M.A., Stevens, A., Horberry, T., 2014. Driver acceptance of new technology: Overview. In: Regain, M.A., Horberry, T., Stevens, A. (Eds.), Driver Acceptance of New Technology: Theory, Measurement and Optimisation. Ashgate Publishing Limited, Surry, England, pp. 3–8.
Rodrígues, P., 2017. Safety of pedestrians and cyclists when interacting with automated vehicles: A case study of the WEpods. Delft University of Technology, Netherlands. Masters thesis.

SAE International, 2018. Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. Standard J3016_201806. https://saemobilus.sae.org/content/j3016_201806.
Schramm, A.J., Rakotonirainy, A., Haworth, N.L., 2010. The role of traffic violations in police-reported bicycle crashes in Queensland. J. Australasian College Road Saf. 21 (3), 61–67.
Silberg, G., Manassa, M., Everhart, K., Subramanian, D., Corley, M., Fraser, H., Sinha, V., 2013. Self-driving cars: Are we ready. KPMG Llp 1–36.
Statista, 2018. Cycling - Statistics & Facts. Retrieved from https://www.statista.com/topics/1686/cycling/.
Twisk, D.A., Commandeur, J.J., Vlakveld, W.P., Shope, J.T., Kok, G., 2015. Relationships amongst psychological determinants, risk behaviour, and road crashes of young adolescent pedestrians and cyclists: Implications for road safety education programmes. Transport. Res. F: Traffic Psychol. Behav. 30, 45–56.
Useche, S., Montoro, L., Alonso, F., Oviedo-Trespalacios, O., 2018a. Infrastructural and human factors affecting safety outcomes of cyclists. Sustainability 10 (2), 299.
Useche, S.A., Montoro, L., Tomás, J.M., Cendales, B., 2018b. Validation of the Cycling Behavior Questionnaire: a tool for measuring cyclists' road behaviors. Transport. Res. F: Traffic Psychol. Behav. 58, 1021–1030.
Useche, S.A., Montoro, L., Alonso, F., Tortosa, F.M., 2018c. Does gender really matter? A structural equation model to explain risky and positive cycling behaviors. Accid. Anal. Prev. 118, 86–95.
Walker, I., 2005. Signals are informative but slow down responses when drivers meet bicyclists at road junctions. Accid. Anal. Prev. 37 (6), 1074–1085.
Washington, S.P., Karlaftis, M.G., Mannering, F.L., 2011. Statistical and econometric methods for transportation data analysis, 2nd ed. Chapman and Hall/CRC, BocaRaton, FL.
Washington, S., Karlaftis, M.G., Mannering, F., Anastasopoulos, P., 2020. Statistical and econometric methods for transportation data analysis. CRC Press.