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Sharing roads with automated vehicles: A questionnaire investigation from drivers', cyclists' and pedestrians' perspectives

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ABSTRACT

Despite the promised benefits, the introduction of Automated Vehicles (AVs) on roads will be confronted by many challenges, including public readiness to use those vehicles and share the roads with them. The risk profile of road users is a key determinant of their safety on roads. However, the relation of such risk profiles to road users' perception of AVs is less known. This study aims to address the above research gap by conducting a cross-sectional survey to investigate the acceptance of Fully Automated Vehicles (FAVs) among different non-AV-user groups (i.e., pedestrians, cyclists, and conventional vehicle drivers). A total of 1205 road users in Queensland (Australia) took part in the study, comprising 456 pedestrians, 339 cyclists, and 410 drivers. The Theory of Planned Behaviour (TPB) is used as the theoretical model to examine road users' intention towards sharing roads with FAVs. The risk profile of the participants derives from established behavioural scales and individual characteristics are also included in the acceptance model. The study results show that pedestrians reported lowest intention in terms of sharing roads with FAVs among the three groups. Drivers and cyclists in a lower risk profile group were more likely to report higher intention to share roads with FAVs than those in a higher risk profile group. As age increased, pedestrians were less likely to accept sharing roads with FAVs. Drivers who had more exposure time on roads were more likely to accept sharing roads with FAVs. Male drivers reported higher intention towards sharing roads than female drivers. Overall, the study provides new insights into public perceptions of FAVs, specifically from the non-AV-user perspective. It sheds light on the obstacles that future AVs may encounter and the types of road users that AV manufacturers and policymakers should consider closely. Specifically, groups such as older pedestrians and road users who engage in more risky behaviours might resist or delay the integration of AVs.

1. Introduction

1.1. Background

In recent years, the transport industry and academic research have directed lots of efforts towards the development of Automated Vehicles (AVs). With the commitment of a wide range of high-tech companies and automobile manufacturers, the deployment of Highly Automated Vehicles (SAE Level 4) is deemed as a matter of time (Shladover, 2016), and the arrival of Fully Automated Vehicles (FAVs, SAE Level 5) has become the ultimate goal (Hancock et al., 2019). Indeed, there are a large number of vehicles that are already equipped with Advanced Driver Assistance Systems on the roads (i.e., SAE Level 1 & 2 AVs) (Oviedo-Trespalacios et al., 2021; Kaye et al., 2022). The main cause for such efforts relates to the various benefits that AV technologies are expected to have, including improved safety, mobility and equity, and reduced traffic congestion and vehicle emissions (Wadud et al., 2016, Tafidis et al., 2022). Despite the attention paid to AV technical issues, there are important social challenges that must be overcome first, such as public perception of AVs and intention to use or share roads with these vehicles.

AV technology development trends suggest that AVs will be sharing roads with other road users, conventional vehicle drivers, and vulnerable road users (e.g., pedestrians and cyclists) (Pyrialakou et al., 2020; Martínez-Buelvas et al., 2022). To guide the safe and effective integration of AVs on roads, it is critical to understand how these road users view AVs, as they will directly interact with AVs on roads. Previous reports have shown that pedestrians might start taking advantage of AVs

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to the point that they could bully them (Liu et al., 2022a,b; Afghari et al., 2021). Without public acceptance of the technologies, the adoption of AVs will be limited, and the public might resist policy initiatives that ensure its safe deployment (Afghari et al., 2021).

AVs are expected to prevent human errors by reducing human engagement when operating a vehicle, especially for FAVs which do not need human driver intervention in any situations. However, this promise will largely benefit the driver group as their roles are replaced by the automation system. The benefits of AVs for other road users are not yet clear (Martínez-Buelvas et al., 2022), but the challenges regarding the interaction between AVs and other road users are already foreseeable. Over the past decade, a large body of research has focused on the potential AV users and investigated their acceptance of, and interaction with AVs (Kaye et al., 2020; Becker & Axhausen, 2017). In contrast, the view from the non-AV users regarding the introduction of AVs on roads has been underestimated (Kaye et al., 2022; Pyrialakou et al., 2020). This study investigates the perceptions of pedestrians, cyclists, and conventional vehicle drivers in terms of sharing roads with FAVs, with a specific focus on the relationship between their risk profiles, individual characteristics and the acceptance of FAVs. The findings of this study can help develop more public-receptive AV technologies and related policies to integrate AVs more effectively into the road transport system.

1.2. Public perception/acceptance of AVs

Most of the literature has focused on drivers' perceptions towards, and acceptance of AVs. However, and more recently, there has been an emergence of studies which examined vulnerable road users' acceptance of AVs (e.g., Rahman et al., 2019; Schrauth et al., 2021) and interactions between vulnerable road users' and AVs (e.g., Vondráčková et al., 2022), particularly in relation to pedestrians' intentions to cross in front of AVs (e.g., Rad et al., 2020; Zhao et al., 2022; Afghari et al., 2021). Rahman et al. (2019) recruited adults aged 60 years and older to examine acceptance of AVs from both drivers' perspective and pedestrians' perspective. Their study showed that acceptance of AVs differed depending on if participants were answering questions from a driver's perspective or from a pedestrian's perspective. As an example, and from a driver's perspective, participants' attitudes towards AVs were positive. However, from a pedestrian's perspective, participants' attitudes towards AVs were neutral. Further, Schrauth et al. (2021) examined 1,929 vulnerable road users' and 3,898 car drivers' acceptance of conditional AVs. Their findings highlighted that acceptance of conditional AVs differed between road user groups, with pedestrians and cyclists reporting slightly lower levels of acceptance of conditional AVs compared to car drivers. Given that previous research has reported that acceptance of AVs differs between different road user groups, it is important to examine drivers', cyclists', and pedestrians' acceptance of AVs separately. This research extends upon Schrauth et al. (2021) by assessing drivers', cyclists', and pedestrians' acceptance of FAVs as opposed to conditional AVs, and if there are any differences in perceptions between these road user groups of sharing roads with FAVs.

Previous research typically applies psychosocial models to examine public perceptions and acceptance of AVs. Examples of these models include the Technology Acceptance Model (TAM; Davis, 1989), the Theory of Planned Behaviour (TPB; Ajzen, 1991), and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003). Some of the constructs in these models have been shown to significantly predict intentions to use AVs. For example, Buckley et al. (2018) applied the TAM and TPB to assess users' future intentions to use conditional AVs (SAE Level 3). They found that attitudes, subjective norms, and perceived behavioural control (PBC) were significant positive predictors of users' intentions. In addition, perceived usefulness was also a significant positive predictor of intentions. Further, Smyth et al. (2021) applied a UTAUT framework to examine acceptance of driver state monitoring for AVs. They found that performance expectancy, effort expectancy, and social influence predicted attitudes, which in turn predicted intentions. In a recent systematic review and *meta*-analysis of 35 articles, Kaye et al. (2021a) found support for using these psychosocial models to assist in understanding users' acceptance of private Level 3–5 AVs. Other studies have also provided support for applying these models to examine users' acceptance of shared automated shuttle buses (e.g., Madigan et al., 2017), robo-taxi services (e.g., Liu et al., 2022a,b), and fully automated public transport (e.g., Yuen et al., 2022). Collectively, the above studies show that psychosocial models can be applied to assess user acceptance of AVs.

In addition to the aforementioned constructs, road users' characteristics may also influence perception towards, and acceptance of AVs. However, research findings about the influence of sociodemographic characteristics on AV acceptance have been mixed. For example, some studies have found that younger adults reported more favourable attitudes or greater intentions to use AVs than older adults (e.g., Hulse et al., 2018; Sener et al., 2019). In contrast, other studies have found age had no significant effect on intentions to use AVs (e.g., Smyth et al., 2021). Kaye et al. (2021a) also reported that age did not show a significant pooled relationship with attitudes towards AVs and intentions and willingness to use AVs. For gender, research has typically found that males reported more favourable attitudes towards AVs (e.g., Hulse et al., 2018; König & Neumayr, 2017) and higher levels of willingness to use AVs (e.g., Hohenberger et al., 2016) than females. Lee et al. (2019) found that a higher proportion of males than females were more likely to report that they would be comfortable with FAVs. Lee et al. (2019) also reported that individuals with a higher level of formal education (i.e., bachelor's degree or graduate education) were more likely to report that they would be comfortable with FAVs compared to individuals with a lower level of formal education (i.e., high school diploma or less). Considering that many factors may influence road users' acceptance of AVs and behaviours around them, it is necessary to conduct prospective studies to identify those factors but also link them with individual characteristics. This will help identify groups who are more prone to engaging in maladaptive interactions with AV (e.g., bullying) or groups that are less likely to accept policies aimed at facilitating mass introduction of AVs.

1.3. Road user risk profile and behaviours on roads

The road transport system is a complex, dynamic unity consisting of multiple types of road users, vehicles, roads, and environments. Road user behaviour is one of the most critical and unpredictable factors that influence the system's operational safety (Petridou & Moustaki 2000; Papadimitriou et al., 2022). Previous studies have highlighted several forms of road user behaviours that are associated with high crash risks. These behaviours are generally known as risky behaviours, which are typically conceptualised as low compliance of traffic laws or traffic rule violations, errors, and aggressive and hostile actions on roads (Ellison et al., 2012; Twisk et al. 2015; Scott-Parker and Oviedo-Trespalacios, 2017).

It should be noted that the occurrence of risky road behaviour depends on the factors that are often outside the control of a road user. Road user behaviour, risky or not, is driven by the transport system itself. For example, road infrastructure and traffic characteristics have been found to influence the speeding behaviour of drives on highways (Afghari et al, 2018). They were also found to determine the behaviour of cyclists over individual differences or even the reason for the travel (Oviedo-Trespalacios et al., 2022). Other examples of this are that vehicles and emerging driver support technologies are not easy to use and may result in distraction (Kaye et al., 2022; Oviedo-Trespalacios et al, 2021) or risk-compensating behaviour (Afghari et al, 2022), or that policy initiatives fail to take into account the health status of the road users (Vaezipour et al., 2022; Hasan et al., 2022). Additionally, factors associated with the capability and beliefs of a road user can influence the emergence of risky behaviours, for example driving skills, risk-taking personality, and attitudes towards road safety (Oltedal & Rundmo, 2006; Ellison et al., 2015; Twisk et al., 2015). Regardless of the determinants, an understanding of how risky behaviours interact with future challenges in the transport systems can support the technological evolution of the transport system, resulting in better mobility outcomes.

Research has shown that risky road behaviours are associated with certain types of road users, and road users who frequently commit certain types of risky behaviours are also more likely to engage in other forms of risky behaviours (Taubman-Ben-Ari and Yehiel, 2012; Twisk and Senserrick, 2021). For instance, young drivers (aged 17–25 years) have been reported to engage in speeding behaviour, drink driving, fatigue, not wearing a seatbelt, and distraction more frequently than other groups of drivers and this population group are over-represented in road deaths and injuries worldwide (Oviedo-Trespalacios et al., 2017; Scott-Parker and Oviedo-Trespalacios, 2017). A study by Li et al. (2022) found that cyclists who reported more errors (e.g., abrupt brake, misjudge a turn, inattention) on roads were also correlated with a higher frequency of traffic violations (e.g., drink/drug riding, red-light-running, cycling against traffic). These findings highlight the necessity of road user risk profiling to identify the homogeneous risk group among others. This is especially important when a new element is introduced into the road transport system, such as AVs.

Although risky road behaviour has an important link with road safety, it has been rarely taken into account in research related to AV acceptance. In a study that investigated road users' safety perception and acceptance of AVs, Hulse et al. (2018) considered the road users' risk-taking propensity as a potential factor. Their study found that the propensity of taking road user risks did not significantly influence road users' attitudes towards AVs. From a user perspective, Payre et al. (2014) and Demeulenaere (2020) reported that drivers with higher sensation seeking inclination tend to report higher intention to use FAVs. Risk-taking (or sensation-seeking) as a scale, has been commonly used to measure road users' willingness to take various types of risks on roads (Hatfield and Fernandes, 2009). However, the difference of the road user risk profile and risk-taking propensity should be highlighted, with the former established based on real-world committed behaviours while the latter represents more of a personality trait. Based on the Behaviour Questionnaire paradigm, this study uniquely uses measures of multiple behaviour dimensions across various types of road users to classify the road user risk profiles and examines the association between risk profile and intention towards sharing roads with FAVs. Determining the link between risk profile and road-sharing intention could help identify the underlying risk factors that lead to different attitudes and perceptions of AVs. It also helps guide the design of AVs to be more risk-tailored so that they can take into account the variety and range of risk profile that different road users may present during the interaction. Additionally, it is important to maintain current efforts in improving behaviours of road users today as it will also represent challenges in a more connected and automated transport system in the future.

1.4. The present study

The overall aim of the present study is to investigate different types of road users' perception of sharing roads with FAVs. Specifically, the study has a focus on:

(1) Road users' risk profile and its relation to the acceptance of FAVs;
(2) The different types of road users and whether they have differences in the perception of sharing roads with FAVs;
(3) The individual characteristics of road users and the roles they play in influencing the acceptance of FAVs.

2. Method

Three types of road users (i.e., pedestrians, cyclists and drivers) were invited to take part in an online questionnaire. The questionnaire was developed based on a cross-sectional design, and participants were assigned to different questionnaires depending on their role. The research was conducted in Queensland, Australia and it was approved by the Ethics Review Committee of Queensland University of Technology (approval number: 1900000669).

2.1. Participants

A total of 1205 road users in Queensland (Australia) completed the online questionnaire, consisting of 456 pedestrians, 339 cyclists, and 410 drivers. The common criteria for participating in the study was that they were required to reside in Australia and to be at least 18 years old. The cyclist questionnaire required participants to have ridden a bicycle on a road during the past 12 months. The driver questionnaire contained participants who had driven a private car on a road during the past 12 months. No specific requirement was added for pedestrians, assuming all participants had walking experience on roads during the past 12 months. The question "which of the following have you used on roads for the past 12 months" were used to separate participants into different road user type, and options included "private car", "bicycle", "both" and "neither". Participants who chose "private car" were half directed to the driver group questionnaire and half directed to the pedestrian questionnaire. Participants who chose "bicycle" or "both" were directed to the cyclist group questionnaire, and participants who chose "neither" were directed to the pedestrian group questionnaire. This division strategy helped ensure a relatively balanced amount of sample collected for each group.

The pedestrian group comprised 239 females and 217 males. Their average age was 36.1 years (S.D. = 16.4), ranging between 18 and 85. Note that at least 87.1% pedestrian participants in this study had a driver license (the rest 12.9% participants who did not use a private car or bicycle for the past 12 months may also have a driver license). The pedestrians' exposure time on roads was measured by asking their weekly walking time on footpaths next to roads, and the average time was 4.0 h/week with a standard deviation of 4.2 h/week. Their highest education level was asked, with 175 (38.4%) reporting completed or less than Year 12, 130 (28.5%) reporting a certificate or diploma, 104 (22.8%) reporting a Bachelors' degree, and 47 (10.3%) reporting a Masters' degree or higher. For crash experience, 305 (66.9%) pedestrians reported that they had never been hit or nearly hit by a car in the past two years, with 60 (13.2%) pedestrians reported once and 91 (20.0%) pedestrians reported being hit or nearly hit by a car at least twice.

The cyclist group consisted of 117 females and 222 males, with an average age of 39.7 years (S.D. = 14.9, aged between 18 and 79). Note that at least 92.0% of cyclist participants in this study had a driver licence (the rest 8.0% of cyclists who reported using a bicycle for the past 12 months may also have a driver licence). The cyclists' average riding time on roads was 3.9 h/week with a standard deviation of 4.0 h/week. The education distribution of the cyclists was 68 (20.1%) with completed or less than Year 12, 67 (19.8%) with a certificate or diploma, 126 (37.2%) with a Bachelors' degree, and 78 (23%) with a Masters' degree or higher. The majority of cyclists (n = 284, 84.7%) reported that they had not experienced any crashes in the past two years. Thirty four (10.0%) reported one crash experience and 18 (5.3%) reported at least two crashes. Crash of a cyclist refers to any incident involving a vehicle or pedestrian that resulted in a personal injury, damage to a vehicle or other property.

The driver group consisted of 199 females and 211 males, with an average age of 43.0 years (S.D. = 15.9, aged between 18 and 87). The average driving time of the drivers was 8.9 h/week with a standard deviation of 9.1 h/week. For the reported highest education, 101 (24.6%) drivers had completed Year 12 or less, 135 (32.9%) completed a certificate or diploma, 113 (27.6%) completed a Bachelors' degree, and 61 (14.9%) completed a Masters' degree or higher. Most of the drivers (n = 349, 85.1%) reported zero crash while driving a car in the past two years, 46 (11.2%) reported once and 15 (3.7%) reported at least twice. Crash for a driver was defined as any incident involving a vehicle that resulted in a personal injury, damage to a vehicle or other property.

2.2. Measures

The questionnaire of the three types of road users contained three sections, including demographics questions, behaviours on roads, and acceptance of FAV. It should be noted that the three types of road users may have an overlapped role in the real world. For example, a pedestrian is likely to be a driver or cyclist at the same time. To accurately measure participants' response in relation to their role's position, the questionnaire emphasised the participant's specific role in each question. For instance, instructions such as "the following questions relate to your behaviour on road as a pedestrian", or "the following questions relate to your beliefs and attitude as a pedestrian" were provided to pedestrian group. Moreover, some questions themselves could specify road users' role and position on roads (e.g., for pedestrians' acceptance of FAVs, the situation described was about crossing roads in the front of the FAVs while for drivers or cyclists, the situation was driving or riding a bicycle on roads in the presence of FAVs, respectively). A complete version of the questionnaire can be found in the Appendix.

2.2.1. Demographic questions

The demographic questions collected participants' age, gender, education, weekly walking/riding/driving (exposure) time on roads and their crash experience (number of crashes in the past two years).

2.2.2. Behaviours on roads

The general behaviours of pedestrians, cyclists, and drivers on roads were measured using the Behavioural Questionnaire paradigm. This paradigm has been widely applied to understand road user behaviours by measuring their self-reported frequency of performing both positive and risky behaviours (Reason et al., 1990; Özkan & Lajunen, 2005). The paradigm refers to Walking Behaviour Questionnaire (WBQ; Useche et al., 2020), Cycling Behaviour Questionnaire (CBQ) (Useche et al., 2018), and Driving Behaviour Questionnaire (DBQ) (Stephens and Fitzharris, 2016; Özkan & Lajunen, 2005) for pedestrians, cyclists, and drivers, respectively. Three dimensions of behaviours on roads were consistently measured among the three groups, which were violations, errors, and positive behaviours. Violations refer to the deliberate behaviours that contravene road traffic rules. Errors describe the unintended behaviours or failure of planned actions that lead to undesirable outcomes. Positive behaviours, on the contrary, are conceptualised as proactive safe behaviours that can potentially reduce the likelihood of being involved in a traffic crash.

The WBQ contains 12 questions (4 items for each dimension), with Cronbach's $\alpha = 0.826$ (violations), 0.679 (errors) and 0.623 (positive behaviours). They were measured on a 6-point frequency-based Likert scale, where 1 = "very infrequently or never", 2 = "quite infrequently", 3 = "infrequently", 4 = "frequently", 5 = "quite frequently", 6 = "very often or always". The CBQ consists of 16 items of violations (Cronbach's $\alpha = 0.879$), 16 items of errors (Cronbach's $\alpha = 0.956$) and 12 items of positive behaviours (Cronbach's $\alpha = 0.868$). All items of CBQ were measured on a 5-point frequency-based response scale, with 1 = "never", 2= "hardly ever", 3 = "sometimes", 4 = "frequently", 5 = "almost always". The DBQ comprises 8 items of violations (Cronbach's $\alpha = 0.877$), 11 items of errors (Cronbach's $\alpha = 0.933$) and 10 items of positive behaviours (Cronbach's $\alpha = 0.885$). All the items of DBQ were measured 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".

2.2.3. Acceptance of FAVs

Before participants started the acceptance of FAVs questions, they were asked about whether they have heard of the term "automated vehicles" before their participation and an objective description of FAVs' definition and main features was provided for them to read so that participants obtained similar amount of knowledge regarding FAVs. In this study, the majority of participants (91.0% of drivers, 91.7% of cyclists and 93.2% of pedestrians) reported that they have heard about AVs prior to the study.

Acceptance of FAV was measured by the Theory of Planned Behaviour (TPB), comprising four key constructs, attitudes, subjective norms, PBC, and intention (Ajzen, 1991). Attitudes measure the overall positive or negative perception towards sharing roads with FAVs (4 items), with Cronbach's $\alpha = 0.952$ (pedestrians), 0.956 (cyclists), and 0.969 (drivers). Subjective norms measure an individual's perception of important others' opinion about sharing roads with FAVs (2 items), with Cronbach's $\alpha = 0.571$ (pedestrians), 0.713 (cyclists), and 0.766 (drivers). PBC measures the perceived ease or difficulty of sharing roads with FAVs (2 items), with Cronbach's $\alpha = 0.735$ (pedestrians), 0.910 (cyclists), and 0.901 (drivers). Behavioural intentions refers to a person's willingness to share roads with FAVs (2 items), with Cronbach's $\alpha = 0.967$ (pedestrians), 0.972 (cyclists), and 0.958 (drivers). All the items were measured 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".

2.3. Procedure

The online questionnaire was created using the Qualtrics survey platform (http://www.qualtrics.com). A global online market search firm, Dynata (http://www.dynata.comhttp://www.dynata.com), was invited to provide survey administration, dissemination, and data collection services. The online questionnaire was also disseminated using the university social media accounts (e.g., Facebook, Twitter). The survey took about 15–20 min to complete, and the respondents were acknowledged that their participation was voluntary. Participants who completed the questionnaire were provided a chance to win 1 of 10 $50AUD shopping gift cards to thank for their participation. Invalid samples were excluded if the questionnaire contained incomplete answers or it took over short or long time (i.e., <5 min or more than 40 min) for one participant to finish.

2.4. Data analysis

The data analysis contained three components: (1) road user risk profiling, (2) comparing the acceptance among road user types, and (3) hierarchical regression modelling. Firstly, K-means clustering was used to classify each type of road users into two (low vs. high) risk groups based on the self-reported scores of violations, errors, and positive behaviours obtained through the Behavioural Questionnaire paradigm. The K-means clustering method was selected as it is a simple but powerful unsupervised machine learning algorithm with high performance in grouping data into distinct non-overlapping subgroups (Kanungo et al., 2000). The differences in the two risk groups of each user type were further examined by Mann-Whitney tests.

Secondly, the TPB constructs of attitudes, subjective norms, PBC, and intentions were examined by Krustkal-Wallis tests to identify whether there were significant differences of the constructs among the three types of road users. For each construct that was identified with significant result, Mann-Whitney Test was performed for pairwise comparisons with a Bonferroni adjustment applied to the alpha values to control for Type 1 errors.

Lastly, hierarchical regression models were developed to identify the significant predictors of road users' intention towards sharing roads with FAVs. During the modelling, the TPB constructs of attitudes, subjective norms, and PBC were entered into Step 1 as they were supposed to contribute most in explaining the variance in intentions. The road user risk profiles and demographic variables including on-road exposure time and crash experience were entered into Step 2 to examine the extent to which they could add to explaining the variance in intentions. The hierarchical regression model was used as it can effectively determine whether newly added variables of interest explain a statistically significant amount of variance in the dependent variable after accounting for all other variables. The proportion of explained variance in the dependent variable were measured by R^2 and F Statistics, and the improvement in the explained variance after added new variables were measured by ΔR^2 and ΔF statistics.

3. Results

3.1. Road user risk profiling

The K-means clustering method was used to classify the road users into two risk groups (K = 2; low-risk vs. high-risk) according to their scores on the behaviour questionnaire dimensions. The cluster results are listed in Table 1. The low-risk group represents lower scores in reported violations, errors, and higher score in positive behaviours while the high-risk group represents the opposite. For all three types of road users, the low-risk group contains more members than the high-risk group, especially for the cyclists, with the majority of them in the low-risk group (accounting for 89.7%).

To examine whether the two risk groups were significantly different in the three behaviour dimensions, Mann-Whitney tests were conducted regarding each type of road users. The results (see Table 2) show that for all three types of road users, the two risk groups had statistically significant differences in the scores of violations, errors, and positive behaviours. The low-risk group reported significantly lower frequencies of violations, errors, and higher frequency of positive behaviours than the high-risk group.

3.2. Comparison among road user types

The TPB constructs were compared among three types of road users by Krustkal-Wallis tests and the results are listed in Table 3. The test results showed that road users' attitudes, subjective norms, PBC, and intentions towards sharing roads with FAVs were significantly different among pedestrians, cyclists, and drivers. Specifically, according to the Mann-Whitney pairwise comparison results (see Table 4), cyclist's attitudes and subjective norms towards sharing roads with FAVs were significantly higher than those of pedestrians and drivers (as shown in Fig. 1). Drivers' subjective norms ratings were significantly higher than those of pedestrians while their ratings of PBC were lower than both cyclists and pedestrians. In terms of intentions, pedestrians provided lower ratings on intentions towards sharing roads with FAVs than cyclists and drivers.

3.3. Hierarchical regression analysis

3.3.1. Pedestrian

The results of hierarchical regression model for pedestrians are presented in Table 5. The TPB constructs of attitudes, subjective norms, and PBC were entered at Step 1 and they significantly explained 35.3% of the variance in intentions to share roads with FAVs, $F(3, 455) = 82.106$, $p < 0.001$. Pedestrian risk profile and individual characteristics were entered at Step 2, and the total variance explained by the model as a whole was 36.9%, $F(9, 455) = 28.972$, $p < 0.001$. However, age was the only significant predictor of intentions among the new entries at Step 2, accounting for an additional 1.6% of the variance in intentions (though the contribution was not significant) after controlling for the TPB constructs, $\Delta R^2 = 0.016$, $\Delta F(6, 446) = 1.909$, $p = 0.078$.

In addition to identifying the significant predictors of intentions, the model demonstrates all TPB constructs were positively associated with intentions, with subjective norms the strongest predictor. This indicates that pedestrians with higher ratings of attitude, subjective norms, and PBC had higher intentions to share roads with FAVs. Age was negatively associated with intentions, meaning that older pedestrians had lower intentions to share roads with FAVs.

3.3.2. Cyclists

For the cyclist group, the TPB constructs of attitudes, subjective norms, and PBC significantly explained 47.6% of the variance in intentions to share roads with FAVs at Step 1, $F(3, 338) = 101.420$, $p < 0.001$, as shown in Table 6. After entry of cyclist risk profile and individual characteristics at Step 2, the total variance explained by the model as a whole was 50.9%, $F(9, 338) = 37.871$, $p < 0.001$. Among all the entries at Step 2, cyclist risk profile was a significant predictors of intentions, accounting for an additional 3.3% of the variance in intentions after controlling for the TPB constructs, $\Delta R^2 = 0.033$, $\Delta F(6, 329) = 3.671$, $p < 0.01$.

The model results confirmed that cyclists with higher ratings of attitudes, subjective norms, and PBC showed higher intentions to share roads with FAVs. Cyclists in the lower risk group were more likely to report higher intentions to share roads with FAVs compared to those in the higher risk group.

3.3.3. Drivers

For the driver group, the three TPB constructs significantly explained 32.2% of the variance in intentions to share roads with FAVs at Step 1, $F(3, 409) = 64.133$, $p < 0.001$, as shown in Table 7. After entry of driver risk profile and individual characteristics at Step 2, the total variance explained by the model as a whole was 36.5%, $F(9, 409) = 25.576$, $p < 0.001$. Driver risk profile, gender, and exposure time on roads were significant predictors, accounting for an additional 4.4% of the variance in intentions after controlling for the TPB constructs, $\Delta R^2 = 0.044$, $\Delta F(6, 400) = 4.594$, $p < 0.01$.

Similar to the pedestrian and cyclist groups, drivers who reported higher attitudes, subjective norms, and PBC were more likely to report higher intentions to share roads with FAVs. Drivers with lower risk profile were more likely to report higher intentions to share roads with FAVs than those with higher risk profile. Males were more likely to report higher intentions than females. As the driving exposure time increased, the likelihood of drivers reporting higher intentions to share roads with FAVs increased.

4. Discussion

The present study analysed road users' acceptance of FAVs and the

Table 1
K-means clustering results of road user risk group.

Road user type	Risk group	N	Violations		Errors		Positive behaviours	
			Mean	S.D.	Mean	S.D.	Mean	S.D.
Pedestrian	Low-risk	290	1.76	0.59	1.35	0.35	4.21	1.06
	High-risk	166	3.61	0.76	2.27	0.77	3.98	0.88
Cyclist	Low-risk	304	1.60	0.38	1.32	0.29	4.12	0.60
	High-risk	35	3.06	0.68	3.00	0.78	3.40	0.83
Driver	Low-risk	248	1.49	0.43	1.24	0.26	4.44	0.67
	High-risk	162	2.14	0.98	1.56	0.78	2.69	0.92

Table 2
Mann-Whitney test results of behaviour dimensions of road users in different risk groups.

Behaviour dimension	Pedestrian			Cyclist			Driver		
	Mann-Whitney U	Z	p	Mann-Whitney U	Z	p	Mann-Whitney U	Z	p
Violations	580.2	−17.405	<0.001	5764.5	−13.706	<0.001	19799.0	−3.164	0.002
Errors	174.5	−9.382	<0.001	104.0	−9.531	<0.001	2458.0	−5.220	<0.001
Positive behaviours	12446.0	−6.539	<0.001	16306.0	−3.268	0.001	1606.5	−15.764	<0.001

Table 3
Kruskal-Wallis test results of TPB constructs across three road user groups.

Constructs	Groups	N	Mean	S.D.	Kruskal-Wallis H	df	p
Attitudes	Pedestrian	456	4.40	1.67	18.834	2	<0.001
	Cyclist	339	4.86	1.71			
	Driver	410	4.50	1.76			
Subjective norms	Pedestrian	456	3.79	1.18	26.723	2	<0.001
	Cyclist	339	4.24	1.33			
	Driver	410	3.94	1.29			
PBC	Pedestrian	456	5.23	1.41	66.445	2	<0.001
	Cyclist	339	5.08	1.84			
	Driver	410	4.24	1.87			
Intentions	Pedestrian	456	4.19	1.77	72.837	2	<0.001
	Cyclist	339	5.10	1.75			
	Driver	410	5.01	1.55			

Table 4
Mann-Whitney test results of TPB constructs for pair groups.

Constructs	Pairs	Mann-Whitney U	Z	p
Attitudes	Driver-Cyclist	60405.5	−3.095	0.002
	Cyclist-Pedestrian	63458.5	−4.332	<0.001
	Driver-Pedestrian	90369.0	−0.849	0.396
Subjective norms	Driver-Cyclist	60678.0	−3.049	0.002
	Cyclist-Pedestrian	61113.5	−5.138	<0.001
	Driver-Pedestrian	85545.5	−2.201	0.028
PBC	Driver-Cyclist	51262.0	−6.237	<0.001
	Cyclist-Pedestrian	77099.0	−0.061	0.951
	Driver-Pedestrian	65523.0	−7.669	<0.001
Intentions	Driver-Cyclist	65078.0	−1.522	0.128
	Cyclist-Pedestrian	53675.5	−7.458	<0.001
	Driver-Pedestrian	68271.5	−6.949	<0.001

influence of their characteristics. A key innovation of the present research is an in-depth analysis of the relationship between risky behaviour profile and the acceptance of AVs. This is also one of the first studies that considered and compared perspectives of cyclists, pedestrians, and non-AV drivers.

4.1. Differences in acceptance of FAVs across cyclists, pedestrians and non-AV drivers

We found that, in general, cyclist's attitudes and subjective norms towards sharing roads with FAVs were significantly higher than those of pedestrians and drivers, indicating a higher FAV acceptance level among the cyclist group. This result can be explained by the fact that in Australia, cyclists are often one of the most vulnerable groups of road users in terms of safety and security, as they are often harassed and intimidated by motorists (Delbosc et al., 2019). Arguably, vehicles that do not have human drivers, with their biases and beliefs, would be considered as a positive change to the current situation, resulting in higher acceptance.

Drivers and pedestrians had the lowest scores in terms of PBC and subjective norms, respectively. The finding of drivers might be that they see AVs as more complex for the driver group, and it is less likely to have an alternative to sharing the roads as pedestrians or cyclists who often have their own footpaths or bicycle lanes. On the other hand, the finding of pedestrians might be related to the fact that this study specifically considered the road crossing scenario because this is the moment where pedestrians are more likely to interact and have conflicts with AVs. As interactions with motor vehicles are particularly risky for pedestrians (Jang et al., 2013), it is not surprising that participants will assess the perceptions of people important to them as less favourable towards road sharing with uncertain technologies such as AVs.

A road user normally represents multiple roles in their daily life, e.g., a pedestrian could be a driver and/or cyclist, or a driver could be a cyclist and/or pedestrian. It would be interesting to explore whether this multi-role perspective plays a role in changing individual's perception of FAVs, especially when compared with single-role road users. It is expected that multi-role road users may consider the introduction of FAVs from a more thorough and systematic perspective than the single-role road users. Australia is one of the most car-dependent country in the world, which somehow restricts the recruitment of single-role road users (e.g., at least 87.1% pedestrians and 92.0% of cyclists in this study were drivers at the same time). It is suggested that in the future, this type of study could be conducted in countries that are not heavily reliant on cars.

4.2. TPB in explaining intentions to share roads with FAVs

The current findings showed that the TPB can be applied to assess road users' intentions towards sharing roads with FAVs. Specifically, the current results revealed that the three predictors of the TPB (attitudes, subjective norms, and PBC) accounted for 35.3%, 47.6%, and 32.2% of variance in intentions towards sharing roads with FAVs for the pedestrian, cyclist, and driver groups, respectively. These findings are in line with previous research which has shown that the TPB is a suitable model to predict drivers' intentions to use AVs (e.g., Buckley et al., 2018; Kaye et al., 2020; Rejali et al., 2023). Further, and for pedestrian and cyclist groups, subjective norms were found to be the strongest positive predictor of intentions while for driver group, attitudes were the strongest positive predictor of intentions. Previous research has reported similar findings that subjective norms or attitudes in TPB were the strongest significant unique predictor of drivers' intentions to use AVs, depending on the investigating country and the type of vehicles (e.g., Kaye et al., 2020, 2021b; Rahman et al., 2017; Rejali et al., 2023). For example, Rahman et al. (2017) found attitudes to be the strongest significant positive predictor of intentions to use advanced driver assistance systems. Kaye et al (2020) found that attitudes were the strongest unique predictor of intentions to use Highly Automated Vehicles for residents in France and Sweden. Further, Kaye et al. (2021b) found that subjective norms were the strongest significant unique predictor of young Australian drivers' (aged 17–25 years) self-reported intentions to use conditional AVs after they had experienced automated driving in a driving simulator. Rejali et al. (2023) also reported that subjective norms were the strongest significant unique predictor of intentions to use FAVs in a sample of drivers from Iran. It should be noted that the mixed findings were all from user perspective. The present study further identified that attitudes may be an important factor for conventional vehicles drivers, while vulnerable road users considered more about important others' opinion in terms of sharing roads with FAVs in the future.

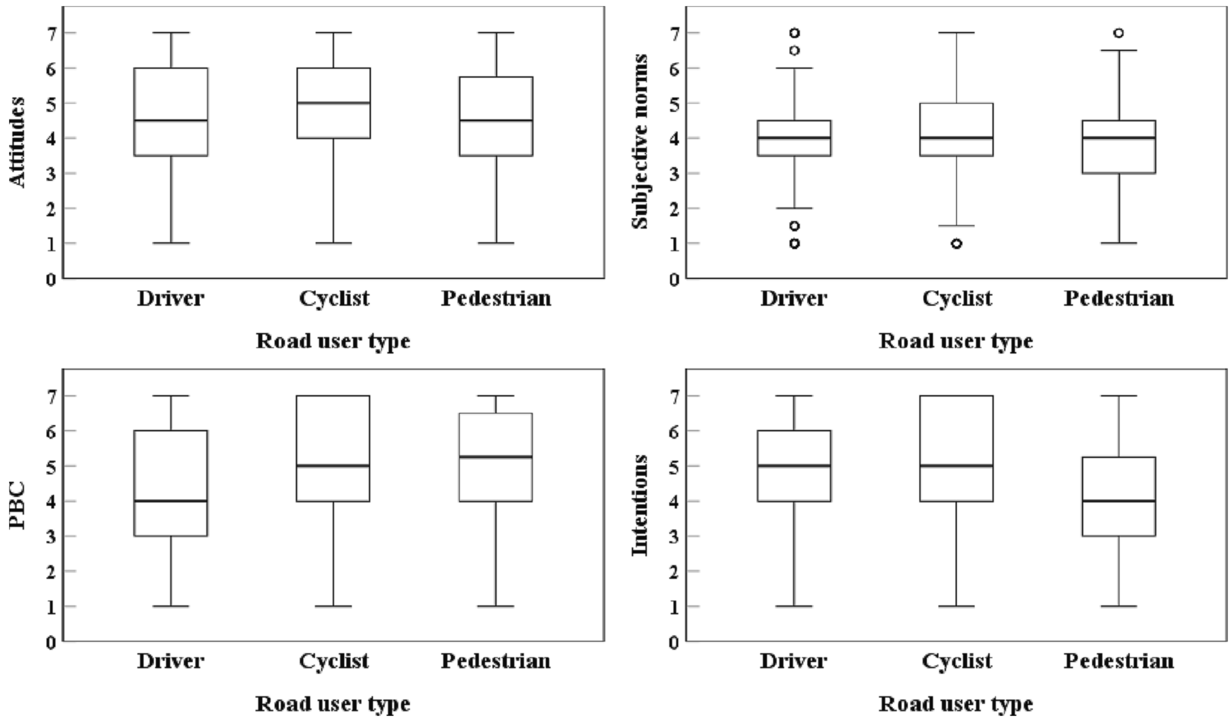

Fig. 1. TPB construct ratings for three types of road users.

Table 5
Hierarchical regression model results of pedestrian group.

	B	S.E.	β	t	p
Step 1 ($R^2 = 0.353$)					
Attitudes	0.252	0.045	0.237	5.541	<0.001
Subjective norms	0.618	0.064	0.411	9.714	<0.001
PBC	0.157	0.049	0.125	3.224	0.001
Step 2 ($\Delta R^2 = 0.016$)					
Attitudes	0.242	0.046	0.227	5.309	<0.001
Subjective norms	0.588	0.064	0.391	9.151	<0.001
PBC	0.163	0.049	0.129	3.333	<0.001
Risk profile	−0.050	0.145	−0.014	−0.349	0.727
Age	−0.013	0.005	−0.117	−2.785	0.006
Gender	0.246	0.139	0.069	1.774	0.077
Education	−0.047	0.068	−0.027	−0.692	0.490
Exposure time	−0.006	0.016	−0.014	−0.354	0.723
Crash	−0.042	0.036	−0.046	−1.177	0.240

Table 6
Hierarchical regression model results of cyclist group.

	B	S.E.	β	t	p
Step 1 ($R^2 = 0.476$)					
Attitudes	0.234	0.048	0.229	4.931	<0.001
Subjective norms	0.548	0.064	0.416	8.561	<0.001
PBC	0.213	0.041	0.224	5.182	<0.001
Step 2 ($\Delta R^2 = 0.033$)					
Attitudes	0.251	0.047	0.245	5.320	<0.001
Subjective norms	0.546	0.064	0.414	8.578	<0.001
PBC	0.200	0.041	0.210	4.887	<0.001
Risk profile	−0.796	0.245	−0.138	−3.249	0.001
Age	0.003	0.005	0.029	0.677	0.499
Gender	0.171	0.146	0.046	1.172	0.242
Education	0.117	0.068	0.070	1.709	0.088
Exposure time	0.023	0.018	0.052	1.270	0.205
Crash	0.098	0.079	0.052	1.242	0.215

Table 7
Hierarchical regression model results of driver group.

	B	S.E.	β	t	p
Step 1 ($R^2 = 0.322$)					
Attitudes	0.324	0.043	0.367	7.584	<0.001
Subjective norms	0.289	0.058	0.240	4.977	<0.001
PBC	0.130	0.034	0.157	3.825	<0.001
Step 2 ($\Delta R^2 = 0.044$)					
Attitudes	0.332	0.042	0.376	7.900	<0.001
Subjective norms	0.264	0.058	0.219	4.577	<0.001
PBC	0.116	0.034	0.140	3.409	<0.001
Risk profile	−0.353	0.132	−0.111	−2.669	0.008
Age	−0.007	0.004	−0.076	−1.785	0.075
Gender	0.361	0.130	0.116	2.784	0.006
Education	0.103	0.064	0.067	1.623	0.105
Exposure time	0.021	0.007	0.121	2.986	0.003
Crash	−0.038	0.126	−0.012	−0.300	0.765

4.3. The role of road users' risk profile

Risk profile significantly predicted intention for the cyclist and driver groups, and it was not a significant predictor for the pedestrian group. Road users (drivers and cyclists) with lower risk profile were more likely to report higher intention to share roads with FAVs than those with higher risk profile. This means that safer drivers and cyclists are more receptive to the technology. Two possible explanations of this are that safer road users might be more confident and optimistic in terms of sharing roads with FAVs in a safe and effective way as long as each one follows road rules strictly. Another possible reason is that safer road users might be more conscious of the risks that human drivers bring to the road network, and thus expect this advanced technology to help mitigate or eliminate this. On the other hand, risky drivers and cyclists who engage in more risky behaviour were less receptive to FAVs. It could be possible that these road users saw FAVs as a new technology with high uncertainty in terms of responding to risky behaviours, and they may give low tolerance to behaviours that do not comply with traffic rules, which may restrict road users' engagement of risky behaviours. Future research is needed to further contextualise these findings, which can also shed light on current determinants of risky behaviours.

The indifference of pedestrians to road sharing with FAVs is also interesting as it may be expected that in a car-centric country such as Australia, pedestrians would like to share the road with vehicles with more reliable driving patterns. Notwithstanding, it appears that this group of pedestrians, independently of their risk profile, do not see any direct advantages of adopting the AVs. There is a need to demonstrate to pedestrians how these technologies could improve their safety, but to do that, the industry needs to show commitment on developing the technology by keeping an eye on the needs of pedestrians, a group that have been traditionally disadvantaged on roads. Martínez-Buelvas et al. (2022) has argued that industries have shown very little interest in supporting the safe integration between vulnerable road users and FAVs.

4.4. The role of road user characteristics

The study identified several demographic factors of road users that significantly influenced their intentions towards sharing roads with FAVs. Age has shown consistent effects among pedestrians. As age increased, pedestrians' intentions towards sharing roads with FAVs decreased. Similarly, Deb et al. (2017) found that younger pedestrians showed higher receptivity towards FAVs than older pedestrian groups. These findings imply the older pedestrians' reluctance to have FAVs on roads and their doubts on the reliability and benefits of the new technology.

Gender was a significant factor among the driver group, with male drivers reporting higher intentions than female drivers. This is in line with findings in previous research that males tend to show a higher acceptance of AVs than females. For instance, Pyrialakou et al. (2020)'s study showed that females (younger than 45 years old) tend to hold more negative safety perceptions of cycling or walking near AVs than males. In a study that focused on pedestrians' receptivity towards FAVs, Deb et al. (2017) found that males were more inclined to accept FAVs than females. The gender difference found in the driver group might be related to the participants' confidence in their driving ability and handling unfamiliar situations, as studies have suggested that males have more confidence and reported higher scores on driving skills than females (Bergdahl, 2005; Özkan & Lajunen, 2006).

The study also identified that drivers who had more exposure time on roads reported higher intentions to share roads with FAVs. One of the potential explanations could be that drivers' crash risks increased along with their exposure time on roads (Shen et al., 2020), and thus they were more likely to hold a positive expectation on the safety benefits brought by FAVs. Significant association was not observed for cyclists and pedestrians, probably because they can use footpaths (or bicycle lanes for cyclists sometimes) instead of sharing lanes with FAVs directly as drivers do. The finding was supported by a relevant study of Schrauth et al. (2021) who investigated the acceptance of conditionally AVs from the view of different road user groups. Their study collected the respondents' number of trips per day as a measure of travel demand and on-road exposure and found that this variable had a positive influence on road users' acceptance of AVs.

5. Limitations

Inevitably, the study has some limitations that should be acknowledged. Firstly, the study has the common limitation of all questionnaire studies, in which validity of results depends on the authenticity of participants in answering the questions. To encourage the honest answers from participants, the questionnaire was set as entirely voluntary and anonymous for participants and sensitive questions in relation to personal privacy were avoided (e.g., commitment of illegal driving behaviours at specific time and location). Secondly, the road sharing scenario for pedestrians was different from that of drivers and cyclists. For pedestrians, the questions were mostly asked about their perceptions of crossing roads in front of FAVs, as this is the only occasion on Australian roads that pedestrians would interact directly with motor vehicles. The difference in scenarios might lead to a higher risk perceived by pedestrians and thus result in lower intention in road sharing. However, it is believed that the road sharing case should be different for different types of road users, and the road crossing scenarios offered a more concrete picture for pedestrians to imagine their future interaction with FAVs on roads. Thirdly, the Cronbach's alpha value of some constructs (e.g., subjective norms, errors and positive behaviours of pedestrians) was less than ideal, and this could be a result of a low number of items measuring the construct or heterogenous items in a scale. Future study is needed to further examine the questions to increase their internal consistency and the reliability of the scales. Lastly, the sample size of cyclists with high risk profile was relatively small. A possible reason is that the cyclists in this study presented as a homogenous group in riding behaviours. Although the finding regarding cyclists' risk profile was consistent with the driver group and complied with our expectation, it is suggested to increase the sample size of the high-risk cyclist group to further verify the finding.

6. Conclusion

The present study investigated road user groups' perceptions of FAVs and the factors that influence their intention towards sharing roads with FAVs, with special consideration for the risk profile of the road users. Pedestrians as the most vulnerable road users showed lowest intention to share roads as compared to cyclists and drivers. On the contrary, cyclists reported highest attitudes and subjective norms among the three groups. Risk profile has a significant association with drivers' and cyclists' road sharing intention, and safer road users were more likely to accept sharing roads with FAVs. Age, gender, and exposure time on roads were significant factors for specific groups. As age increased, pedestrians showed lower intentions towards sharing roads with FAVs. For driver group, intentions to share roads increased with their exposure time on roads. Male drivers were more likely to accept sharing roads with FAVs than female drivers. A critical implication of this research is that the responses to FAVs appear to be different across groups of road users and, as such, policy and other initiatives must consider those individual differences. Specifically, response to acceptance also seems to be linked to current road user behaviour. Moreover, the study findings suggest that working on improving current risky road user behaviours today, by targeting the systemic causes of the risky behaviours, is a way to improve road sharing outcomes now and in the future by harnessing the power of technology.

CRediT authorship contribution statement

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

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 data

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