Consumers' behavioural intention to adopt AV technology: China and Australia studies

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1. Introduction

Autonomous vehicles (AVs) are expected to significantly change the transport industry, with several automobile manufacturers and telecommunication companies developing autonomous driving systems. Drivers and non-drivers alike stand to benefit from enhanced road safety, lower congestion levels, independent mobility for those presently challenged, lower emissions and in-vehicle productivity. For AVs to enter the transport function, government authorities and car manufacturers must be prepared and implement AV-related infrastructure and technologies. Therefore, understanding the public's perceptions of AVs is critical. AV literature speculates that driverless technologies will accelerate recent ridesharing trends, and research must inquire about people's openness to adopting ridesharing and ride-pooling as their usual travel mode. Furthermore, research should shed light on travellers' willingness to share their personal space with strangers in pooled shared AVs (PSAVs) because no driver also means no onboard monitor or authority.

The research aims to investigate respondents' willingness to accept AVs, incorporating the antecedents of the Technology Acceptance Model (TAM) into the estimation to explore the influence of people's perceptions and their intentions. Two surveys of TAM antecedent items, along with attitudes and concerns, collected during a qualitative pre-survey data collection (Tang, 2022) were administered and used to validate an extended TAM model.

The paper is as follows. Section 2 reviews the related literature. Section 3 describes the methods and proposed hypotheses. Section 4 presented the empirical inquiry, including the results of the measurement and structural equation models and the discussions. Section 5 concludes this paper.

2. Related literature

The development of autonomous vehicles (AVs) has become a popular topic in transport research, with some on-market vehicles already equipped with semi-autonomous technologies. Improving road safety is thought to offer the greatest advantage for replacing human drivers with autonomous vehicles (Hulse *et al.*, 2018). AVs provide mobility for those who presently cannot drive, people with disabilities or underlying health conditions, the elderly and adolescents, offering independent and individual mobility (Anania *et al.*, 2018). Enhancing mobility for these community segments not only increases their quality of life by enhancing inclusion, but also reduces the burden on family members who may need to act as chauffeurs. AVs have the potential to address traffic congestion and reduce energy consumption at a larger scale through cooperative adaptive cruise control (CACC). The platooning of AVs can be achieved using vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. By shortening gaps between vehicles, intersection delays and fuel consumption levels can be reduced significantly. One in three respondents showed aversion to AVs and would never buy

one, according to a national report targeting US residents between 12 to 64 years old on the perceptions and misconceptions of AVs (Kelly Blue Book, 2016). Another aspect widely discussed is of experience, which can improve trust, attitudes, and likely adoption (Dennis *et al.*, 2021; McAslan *et al.*, 2021; Tan *et al.*, 2023). People expressed more positive attitude towards AVs and enhanced perceived safety after riding in a real AV bus (Mouratidis and Serrano, 2021).

Despite the anticipated benefits of AVs, there is persistence of apprehension by would-be adopters. Safety is a major barrier to AV adoption, due to concerns that AVs might fail to correctly recognise objects on the road or that the sensors might experience partial or complete failures (Yeong *et al.*, 2021). The fatal crash of Tesla's trial AV in 2016, the uncertainty surrounding AVs, and their inability to avoid emergencies was brought to the fore through mass media coverage, including The New York Times¹, The Guardian², USA Today³, and Forbes⁴.

With the widespread use of AVs approaching, it is important to understand public perceptions and the factors affecting their adoption. Several behavioural theories and models have emerged to predict consumers' behavioural intentions to use AVs and their antecedents. These include the Technology Acceptance Model (TAM) (Lee *et al.*, 2019; Zhang *et al.*, 2020), the Theory of Planned Behaviour (TPB) (Kaye *et al.*, 2020), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Morrison and Belle, 2020). Some studies combine two behavioural theories to generate more complex models, such as TAM and TPB (Acheampong and Cugurullo, 2019) or TPB and UTAUT (Yuen *et al.*, 2020). Understanding the determinants behind AV adoption is crucial as AVs may alter travel behaviours and mobility styles, hence researchers explore psychological factors affecting the acceptance of AVs and compare studies based on behavioural theories.

TAM is a widely used model to understand and predict technology adoption. It includes three psychological constructs: perceived ease of use (PEOU), perceived usefulness (PU), and behavioural intention (BI) to use. PEOU refers to the ease of using a particular system or technology, while PU reflects its potential benefits. Both PEOU and PU directly affect BI. For their study on the adoption of AVs, Choi and Ji (2015) extended the TAM by adding two new constructs: trust and perceived risk. Trust mediates the relationship between humans and automation and is a major determinant of acceptance of automation. They proposed three dimensions of trust: system transparency, technical competence, and situation management, and introduced perceived risk as a crucial component of trust models. Xu *et al.* (2018) modified the extended TAM by adding the path from trust to PEOU. The authors believed that trust impacted cognitive processes of forming and weighing AV technologies' perceived ease of use.

3. Method

This section describes the proposed hypotheses and the Structural Equation Model (SEM) used to test these hypotheses and identify the direct/undirect influence from one construct to another. Confirmatory factor analysis (CFA) is used to develop and validate a measurement model for six latent constructs in the TAM: PEOU, PU, perceived safety and risks (PSR), perceived privacy and risks (PPR), trust, and personal innovativeness (PI). Responses were collected using five-point Likert scale indicators of these constructs. The following hypotheses are proposed for the SEM, with the structure diagram shown in Figure 1:

¹ <u>Autopilot Cited in Death of Chinese Tesla Driver - The New York Times (nytimes.com)</u>

² Tesla driver dies in first fatal crash while using autopilot mode | Tesla | The Guardian

³ <u>Tesla crash in China renews spotlight on Autopilot (usatoday.com)</u>

⁴ <u>Tesla Autopilot Enthusiast Killed In First Self-Driving Car Death (forbes.com)</u>

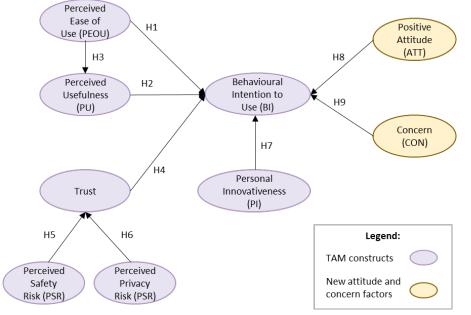
- H₀1: PEOU positively influences people's BI to use AVs.
- H₀2: PU positively influences people's BI to use AVs.
- H₀3: PEOU positively influences PU.
- H_04 : People who trust AVs have stronger BI to use AVs.
- H₀5: PSR negatively influences people's trust.
- H₀6: PPR negatively influences people's trust.
- H₀7: PI positively influences people's BI to use AVs.

In addition, the attitudinal and concern constructs reported in Tang (2022) were added to the model suggesting two further hypotheses:

H₀8: Positive attitude (ATT) positively influences people's BI to use AVs.

H₀9: Concern (CON) negatively influences people's BI to use AVs.

Figure 1: Enhanced Technology Acceptance Model: structure and hypotheses



4. Empirical inquiry

Two surveys were administered in October 2021 (Australian undergraduate students) and in February 2022 (Chinese online panel survey, representative population). Whilst the two samples are difficult to compare due to the sampling frame, we find a notable difference in travel behaviour and suggest there is a contextual difference between the samples.

Both surveys collected data on choice tasks, willingness to use, psychological statements, attitudes and concerns, and demographic and travel information. The Chinese survey gathered 942 valid responses, representing a valid response rate of 88.7%. The surveyed sample had a similar gender distribution (51% males) to the national population. Two-thirds of the respondents were aged 25 to 34, held at least a bachelor's degree and were employed. A third of the respondents worked in large cities, with another half in provincial capitals. Almost 90% of the sample had higher income levels than the Chinese urban residents' monthly income, 88% were car owners, and 92% were driver's licence holders. Most (60%) reported estimated market prices of their private vehicles ranging from CNY 100,000 to 200,000 (AUD 22,500 to 45,000) and that this was their primary mode for commuting and leisure trips. The average scores for both driving enjoyment and driving confidence were 3.14 out of five (five for strongly enjoy/confident), respectively. Just under one-third of the sample reported frequent ridership on public transport or using taxi/ridesharing services. Almost all respondents (97%) reported

using ridesharing services in the previous month, with 70% having used them on three or more occasions.

The Australian study was undertaken with a cohort of undergraduate students (N=351), of which 41% were male, 56% were female, and 3% did not indicate gender. Almost all respondents belonged to Generation Z, born after 1996, with more than 80% of participants under 20 years of age. Around one-third of students did not work, and nearly two-thirds worked part-time, with only 1.4% working full-time. Of the 351 respondents, two-thirds owned a car, and almost all had a driver's license. However, 13% of respondents stated they did not drive. The average driving enjoyment and driving confidence scores were 3.28 and 3.47. Half of the respondents travelled to education or work by car, one-third travelled by public transport, and 10% travelled on foot for commute trips. Approximately 70% of respondents reported using ridesharing services in the last month, and more than half used them on three or more occasions.

4.1. Measurement models

The basis of the empirical study is to estimate an extended TAM with trust attributes (Xu *et al.*, 2018) along with attitude and concerns items (Tang, 2022) based on each sample data. The analysis focuses on how applicable the model is to the data and whether there are parameter differences or potential structural differences in the models estimated for each sample. Exploratory FA and CFA (results not reported here) revealed that the items for the Australian sample aligned with the constructs as suggested by the extended TAM, but not for the China sample. A multi-group analysis was run, with results presented in Table 1. The percentage of explained variance for all six constructs decreased in China's dataset, with only 26.3% variance explained in PU and 10.2% in PI, thus adopting the same factor structure for China's dataset in IBM SPSS and confirmed in IBM Amos. Whilst the results are not given here, the path diagrams given in the next section reveal the new structure of the model for the China sample.

Chinese respondents had higher scores in the items under PEOU, PU, TRUST and PI, but lower scores for PSR than Australian respondents. The PPR items did not differ between the two groups of respondents. This comparison reveals that Chinese respondents generally have a more positive attitude towards AVs and fewer concerns than Australian respondents. Moreover, all items under PU and PI were higher than four out of five for Chinese respondents, indicating that they perceive AVs as useful and are open to new technologies.

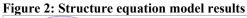
	Australian sample (n=351)		China Sample (n=942)		
Estimated Constructs	Mean for all items	%Var explained by factor	Mean for all items	%Var explained by factor	Difference in means
Perceived Ease of Use (PEOU)	3.52	79.1%	3.87	41.7%	0.348***
Perceived Usefulness (PU)	3.71	64.0%	4.21	26.3%	0.503***
Perceived Safety Risk (PSR)	4.04	60.6%	3.59	64.4%	-0.450***
Perceived Privacy Risk (PPR)	3.52	75.3%	3.64	69.8%	0.115
Trust (TRUST)	3.33	58.1%	3.83	44.1%	0.503***
Personal Innovativeness (PI)	4.18	42.0%	4.35	10.2%	0.165**

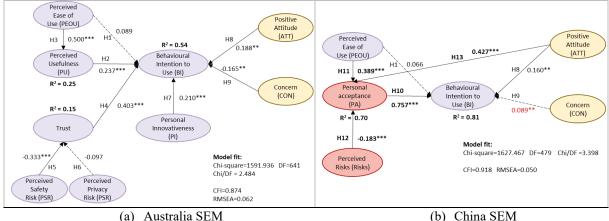
Table 1: Multi-group analysis

4.2. Structural equation models

Two SEMs were adopted to test the hypotheses for two datasets. As the China dataset revealed different measurement structures, two new 'hyper' factors were identified, with four more hypotheses being proposed. The results are shown in Figure 2, with solid line paths supporting the corresponding hypothesis and dotted line paths not supporting it.

The Australia study supported all hypotheses except for H_01 and H_06 , while the China study supported all except for H_01 and H_09 . PEOU (H_01) was not found to directly affect BI in either study, but indirectly affected BI through PU in Australia study and through PA in China study. For the Australia study, the proposed model explained 52% of the variance in BI, 25% of variance in PU and 15% of variance in trust. As for the China study, the construct BI was explained by 81% of variances of other constructs, which is considered high. Moreover, PEOU, Risks and ATT explained 70% of variances in PA. Both studies showed trust as a significant factor to BI.





4.3. Discussion

Although the two structures are not identical, they share something in common in terms of the hypothesis testing. The hypotheses H1 from PEOU to BI and H9 from CON to BI were not supported in either of the structures, while H8 from ATT to BI was supported in both structures.

While PEOU shaped the technology adoption behaviour theoretically and empirically in many papers (Lee *et al.*, 2019; Zhang *et al.*, 2020), both structures failed to confirm the path from PEOU to BI, but indirectly through PU, similar to some previous findings (Hein *et al.*, 2018). This finding indicates that it might be more important for potential AV users to think of AVs as useful rather than how easy they are to use (Lee *et al.*, 2019). Because AVs operate fully autonomously without the need for human intervention, the influence of PEOU on BI might be counteracted relative to conventional human-driven vehicles that drivers need to control.

Trust in the Australian structure positively influenced BI (H4). Similarly, in the China structure, the 'hyper-construct' PA — integrating trust, PU and PI — also strongly influenced BI (H10). In both structures, trust and PA were the strongest indicators of BI. Besides, people's perceived safety risks due to vehicle malfunctions affect their trust in AVs but perceived privacy risks, such as data leakage, do not affect their trust in AVs. Kenesei *et al.* (2022) defined respondents' trust in AVs in three dimensions: trust in AV performance, trust in AV manufacturers, and trust in authoritative institutions that influence rules and regulations. Kenesei *et al.* (2022) results supported the positive effect of trust in AV performance on people's intention to use AVs, but did not support the trust in manufacturers and institutions. In this paper, we refer to trust in AV performance, a major stream in the definition of trust in behavioural theories.

The support of hypothesis H7 confirmed that people who are more innovative have a greater intention to use AVs than those who are not. Although rarely included in behavioural theories, the positive path from PI to BI has been confirmed in recent studies (Hegner *et al.*, 2019; Manfreda *et al.*, 2021). In addition, the openness of the Big Five Personality reportedly indirectly affects BI through the trust (Zhang *et al.*, 2020). Because AVs are new technologies, tech-savvy people are more likely to adopt AVs than other customers (Zhang *et al.*, 2020).

Comparing the two studies' measurement and structure models, the Australia study identified more assertive and distinguished constructs with high reliability and discriminant validity. In contrast, while the China study had high internal consistency within each construct, the discriminant validity revealed some strong correlations between constructs, for example, risks and concerns (CON). BI was also highly correlated with several constructs, including PA and ATT. Nevertheless, the SEM revealed statistically significant paths from PA and ATT to BI. While the constructs and measures were more robust using the Australian sample, the goodness-of-fit of the SEM was superior with the Chinese sample.

5. Conclusion

This study examined the extended Technology Acceptance Model (TAM) with two datasets in Australia and China. While the Australian sample is not representative for the population and full comparisons cannot be made, the similarities in findings, as well as the distinctive measurement structures, are valuable for further research in this field. Two separate SEM models were estimated and both support most of the hypotheses, confirming that BI for AVs is positively affected by PU, Risks, Trust, PI and ATT, with trust being the strongest indicator. However, PU and CON are not found to affect BI.

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