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Factors influencing attitude and intention to use autonomous vehicles in Vietnam: findings from PLS-SEM and ANFIS

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Abstract

Purpose – This study aims to explore and ranks the factors that might determine attitudes and intentions toward using autonomous vehicles (AVs).

Design/methodology/approach – The "technology acceptance model" (TAM) was extended by assessing the moderating influences of personal-related factors. Data were collected from 378 Vietnamese and analysed using a combination of "partial least squares" and the "adaptive neuro-fuzzy inference system" (ANFIS) technique.

Findings – The findings demonstrated the power of TAM in explaining the attitude and intention to use AVs. ANFIS enables ranking the importance of determinants and predicting the outcomes. Perceived ease of use and attitude were the most crucial drivers of attitude and intention to use AVs, respectively. Personal innovativeness negatively moderates the influence of perceived ease of use on attitude. Data privacy concerns moderate positively the impact of perceived usefulness on attitude. The moderating effect of price sensitivity was not supported.

Practical implications – These findings provide insights for policymakers and automobile companies' managers, designers and marketers on driving factors in making decisions to adopt AVs.

Originality/value – The study extends the AVs literature by illustrating the importance of personal-related factors, ranking the determinants of attitude and intention, illustrating the inter-relationships among AVs adoption factors and predicting individuals' attitudes and behaviours towards using AVs.

Keywords Intention to adopt, Autonomous vehicles, Self-driving cars, Driverless cars, Technology acceptance model, Technology adoption

Paper type Research paper

1. Introduction

Autonomous vehicles (AVs) are game-changers in the urban transportation system (Wang and Zhao, 2019). Several leading automobile manufacturers deliver different levels of automation by incorporating various automation features such as collision avoidance systems, adaptive cruise

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control, parking assist and advanced driver assistance systems into their vehicles (Talebian and Mishra, 2018). Using AVs can reduce crashes, enhance roadway safety, reduce traffic congestion, reduce emissions and improve urban life (Greenwald and Kornhauser, 2019; Raj *et al.*, 2020). Accordingly, AVs have grabbed the attention of manufacturers, customers and policymakers (Raj *et al.*, 2020). Despite the potential benefits, the AVs adoption rate has been less than expected, and people have a low intention to use AVs (Hegner *et al.*, 2019).

Several studies have investigated drivers and barriers of intention to use AVs, aiming to shed light on the reasons for low adoption and consequently promote the usage of AVs (Yuen *et al.*, 2020; Acheampong and Cugurullo, 2019). Scholars have used different theoretical lenses, such as "technology diffusion theory" (TDT), "technology acceptance model" (TAM) and "universal theory of acceptance and use of technology" (UTAUT), to explain the determinants of AVs adoption (Yuen *et al.*, 2020; Acheampong and Cugurullo, 2019; Smyth *et al.*, 2021). Although TAM has illustrated a strong power to explain intention to adopt new technology, "perceived ease of use" (PEU) and "perceived usefulness" (PU), as determinants of attitude and intention to use new technologies in TAM, are highly technology-related factors. Several studies have illustrated that adopting AVs does not only drive by technology-related factors but also personal-related factors such as personal innovativeness, price sensitivity and data privacy concerns (Waung *et al.*, 2021; Kapser *et al.*, 2021). Furthermore, many scholars have recommended that TAM requires to be modified to enhance its explanatory power (Schiopu *et al.*, 2021; Zhong *et al.*, 2021). Following the recommendation of Guo *et al.* (2021), Kapser *et al.* (2021) and Waung *et al.* (2021), we included personal innovativeness, price sensitivity and data privacy concerns as moderators of the associations between PEU, PU and attitude towards using AVs. The study suggests that people are not homogenous, and the influence of PEU and PU on attitudes towards using AVs may be less among individuals with high personal innovativeness, low price sensitivity and high data privacy concerns.

The previous studies on determinants of AV adoption were based on the assumption that there is a linear relationship between determinants and adoption intention (e.g. Hegner *et al.*, 2019). In fact, psychology-related factors often exhibit nonlinear relationships and cannot be estimated accurately with linear approaches (Ho and Tsai, 2011). Artificial intelligence (AI)-based approaches like "adaptive neuro-fuzzy inference systems" (ANFIS) can tackle non-linearity and explain the nonlinear relationships better than linear techniques such as "structural equation modelling" (SEM) and multiple regression. Accordingly, this study combines SEM and ANFIS techniques to explain the nonlinear relationships, rank the importance of factors and predict the users' attitudes and behaviour towards using AVs. To our best knowledge, such hybrid analysis techniques have never been used for explaining the determinants of AV adoption and predicting individuals' attitudes and behaviours.

Moreover, the development and adoption of AVs have garnered significant attention from researchers, manufacturers and policymakers, particularly in developed countries where advancements in this technology are more radical (Etminani-Ghasrodashti *et al.*, 2022; Osburg *et al.*, 2022). However, understanding the influential drivers of AV adoption in developing countries, such as Vietnam, is equally essential to ensure a comprehensive understanding of the global implications of this technology. The context of developing countries presents unique challenges and opportunities, such as different infrastructure conditions, market dynamics and consumer preferences, which may impact the adoption of AVs. This research aims to analyse the influential drivers of attitudes and intentions to use AVs in the specific context of Vietnam, providing valuable insights for stakeholders involved in developing, promoting and regulating AVs in emerging markets. Therefore, this study aims:

(1) To extend TAM in the AV context by examining the moderating impacts of personal-related factors, namely personal innovativeness, price sensitivity and data privacy concerns.

(2) To assess the most critical predictors of attitude and intention to use AVs in Vietnam and the nonlinear relationships between determinants.

The findings contribute to current knowledge by expanding the TAM model in the AV context and identifying the most critical drivers of using AVs. The integration of ANFIS and SEM adds value by providing more precise results, illustrating the inter-relationships among AV adoption factors and their importance in predicting attitude and AV usage intention. The findings provide insight for policymakers and automobile manufacturers on the factors that may trigger the usage of AVs.

2. Literature review

2.1 Background of autonomous vehicles (AVs)

AVs are robotic vehicles that operate without a human driver (Hegner *et al.*, 2019). Automation has different levels, from the complete lack of automation to fractional automation all the way to full automation. The AV automation level is classified into six levels, from no driving automation and assistance (level zero) to full automation and vehicle drives without human interaction (level five) (SAE International, 2018). This study focuses on full AV automation, which is relatively unexplored. The studies on AVs can be categorised into four main streams. The first stream of studies focuses on AV algorithms to improve the systems and address their weaknesses (Kim *et al.*, 2020; Rossi *et al.*, 2018). The commercialisation of AVs has raised concerns about privacy and cybersecurity risks (Lim and Taeihagh, 2018). AVs store highly sensitive information, and cyber-attacks may cause accidents and severe security risks (Li *et al.*, 2018). Accordingly, the second research stream has focused on addressing the unintended consequences (Kim *et al.*, 2021; Taeihagh and Lim, 2019). Kim *et al.* (2021) reviewed 151 articles on AVs and classified them against attacks into anomaly detection, intrusion detection and security architecture. The third stream of studies has investigated the social and environmental impacts of AVs diffusion (Tomás *et al.*, 2020; Sohrabi *et al.*, 2020). Tomás *et al.* (2020) investigated the emission impacts of AVs at three different penetration rates. They found that AV adoption has a low influence on emissions at a low penetration rate (10–20%). However, they found that at a 30% penetration rate, AV adoption may lead to a reduction of 3–5% in emissions. Finally, concerning the benefits of AVs, research has been conducted to determine the influential drivers of AV usage (Yuen *et al.*, 2020; Acheampong and Cugurullo, 2019). In most of these studies, the heterogeneity of users has not been considered. This study aims to tackle this gap by assessing the moderating impact of personal-related factors.

Furthermore, prior studies have assessed the determinants of AVs using linear analysis techniques (Zhou *et al.*, 2021; Abbasi *et al.*, 2022). Several studies have demonstrated that human adoption behaviour is not linear and proposed using the machine learning approach as a complementary analysis. Accordingly, we used a combination of "partial least squares structural equation modelling" (PLS-SEM) and ANFIS.

2.2 PLS-SEM and ANFIS in nonlinear modelling

ANFIS has been used in several studies as a complementary method to PLS-SEM. The PLS-SEM results show the significant factors that will be used as input for the ANFIS. Çakıt *et al.* (2020b) used PLS-SEM and ANFIS techniques to investigate the determinants of workplace safety. They identified the significant factors driving workplace safety using PLS-SEM. By using ANFIS, they identified the most critical predictor of workplace safety. In another study, Çakıt *et al.* (2020a) used PLS-SEM and ANFIS as complementary techniques to identify significant determinants and the most critical driver of personnel error behaviour, personnel safety motivation and violation behaviour. Yadegaridehkordi *et al.* (2018) also used this hybrid approach to identify determinants and the most critical predictor of hotel success.

PLS results revealed that empowerment, employee training, location, hotel interior and exterior, top management support, service quality, customer satisfaction, service standardisation, benchmarking, financial performance and information technology (IT) usage significantly influence hotel success and development. ANFIS provided further insight into these findings by showing that customer satisfaction is the most critical driver. Khaw *et al.* (2023) used ANFIS, a nonlinear and compensatory interaction-based model, as a complementary method to PLS-SEM sustainability commitment strategies. Băban *et al.* (2022) used PLS-SEM, "artificial neural networks" (ANN) and ANFIS techniques in the context of university collaboration in open innovation. Drawing on the UTAUT2 model, Foroughi *et al.* (2023a, b, c) used PLS in the AV context. They use PLS-SEM to identify direct and moderating effects. They concluded that the relationships between AV use intentions and their determinants are not linear, and the findings of studies relying solely on linear approaches are unreliable. Accordingly, they recommended using nonlinear approaches such as ANFIS as complementary to PLS-SEM. In light of the aforementioned studies, it is concluded that PLS-SEM combined with soft computing techniques can offer promising outcomes when modelling nonlinear relationships.

3. Technology acceptance model (TAM)

TAM, developed by Davis (1989), proposes PU and PEU as driving factors of attitude and intention to use a new system. PEU refers to "the extent to which a person considers whether using a particular system would be free of effort" (Davis, 1989, p. 320). PU refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, 320). Studies have shown the power of TAM factors in explaining technology adoption in various contexts, such as augmented reality (Alam *et al.*, 2021), e-learning (Thongsri *et al.*, 2020), mobile apps (Mehra *et al.*, 2021) and Internet banking (Patel and Patel, 2018). Many scholars have argued the importance of extending the TAM model by incorporating contextual factors (Patel and Patel, 2018; Mehra *et al.*, 2021). Although a vast number of studies extended TAM, little attention was given to moderating factors (Chung *et al.*, 2010). Personal-related factors are the potential moderators that have been recommended by scholars. Hegner *et al.* (2019) also argued that a lack of attention to personal-related factors is the main drawback of the TAM model. In this study, we assessed the moderating influences of three personal-related factors, namely personal innovativeness, data privacy concerns and price sensitivity (Figure 1), as previous studies in the AVs context found them as important factors (Dong *et al.*, 2020; Kaye *et al.*, 2022; Lim and Taeihagh, 2018).

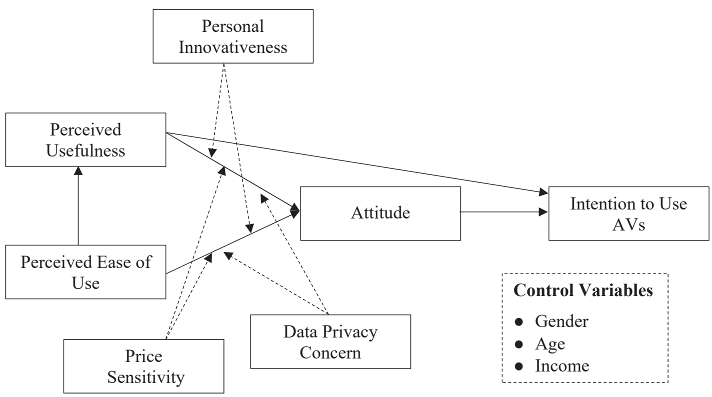

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Figure 1.
Proposed conceptual framework

4. Hypotheses development

4.1 Perceived usefulness (PU)

TAM posits that PU is a powerful driver of attitude and technology adoption (Verma *et al.*, 2018). Several studies have shown the significant role of PU in shaping attitude and usage intention (To and Trinh, 2021; Huarng *et al.*, 2022; Iranmanesh *et al.*, 2017). The significant influences of PU on attitude and intention to use various technologies such as chatbots (Chocarro *et al.*, 2023), mobile wallets (To and Trinh, 2021), wearable devices (Huarng *et al.*, 2022), social media (Hyun *et al.*, 2022, Iranmanesh *et al.*, 2022a, b, c) and online shopping (Yang *et al.*, 2022) have been proven in the literature. Individuals believing that their performance can be improved by using a system would be more willing to use it (Verma *et al.*, 2018). Verma *et al.* (2018) believe that PU is the most important determinant of adopting a system. In this study, PU measures the extent to which individuals believe using AVs may enhance their driving effectiveness and performance (Lee *et al.*, 2019). The features of AVs, such as parking assist, adaptive cruise control and advanced driver assistance systems, can enhance driving performance (Talebian and Mishra, 2018). Baccarella *et al.* (2021) and Lee *et al.* (2019) found PU as a driving factor of attitude and intention to use AVs. Accordingly, we proposed that:

H1. PU positively influences attitudes towards using AVs.

H2. PU positively influences the intention to use AVs.

4.2 Perceived ease of use (PEU)

Scholars have shown that PEU and PU are positively associated (Daragmeh *et al.*, 2021; Hegner *et al.*, 2019). If individuals can easily use technology, they can better take advantage of its benefits and, consequently, find it useful (Foon *et al.*, 2020). Furthermore, a favourable belief that using a new system will be free of effort leads to a positive attitude towards using it (Munoz-Carril *et al.*, 2021). The positive influence of PEU on attitude towards using new technology has been proven in various contexts, such as mobile apps (Huang and Chueh, 2022), mobile banking (Firmansyah *et al.*, 2022), electric vehicles (Jaiswal *et al.*, 2021) and augmented reality (Cabero-Almenara *et al.*, 2019). In several cases, PEU has been shown as a significant driver of PU and attitude (Cabero-Almenara *et al.*, 2019; Jing *et al.*, 2021). In this study, PEU measures the degree to which individuals believe that using AVs will be effortless (Lee *et al.*, 2019). Jing *et al.* (2021) identified PEU as a determinant of PU and attitude towards using AVs. Therefore, we hypothesised that:

H3. PEU positively influences PU.

H4. PEU positively influences attitudes towards using AVs.

4.3 Attitude

Attitude refers to "the degree to which a person has a favourable or unfavourable evaluation or appraisal of the behaviour in question" (Ajzen, 1991, p. 188). The previous studies introduce attitude to act as a determinant of intention to use various technologies. For instance, Lee and Lee (2018) found attitude as the most significant driver of intention to use a wearable healthcare device. Patil *et al.* (2020) found a positive association between attitude and intention to use mobile payment. In another study, Huang and Chueh (2022) found that individuals' attitude towards mobile apps has a positive effect on their intention to use mobile apps. Zhang *et al.* (2020) demonstrated a positive association between attitude towards AVs and AVs usage intention. Accordingly, we proposed that:

H5. Attitude positively influences the intention to use AVs.

4.4 Personal innovativeness

Intention to use and adopt technology is only driven by technology characteristics but also by adopter characteristics (Hegner *et al.*, 2019). Although personal-related factors were not considered in the original TAM, the previous studies have shown that people have different needs and characteristics, and consequently, the drivers of their attitude towards using new technology are not similar (Mohammadi, 2015). Personal innovativeness is a personally related factor that many scholars found as a significant driver of attitudes and behaviours towards using new technology or service (Patil *et al.*, 2020; Gu *et al.*, 2021). Personal innovativeness measures the tendency to use a new technology or service relatively earlier than the majority of people (Bhat *et al.*, 2022). Mohammadi (2015) found personal innovativeness as a significant driver of attitude towards using mobile banking. Tan *et al.* (2014) showed that personal innovativeness acts as the most critical determinant that develops the intention to use mobile payment.

Innovative individuals are more open and ready for new technology adoption and less risk-averse to adopting a new system (Lee *et al.*, 2012). As innovators are prone to experience a new technology even if they are uncertain about its potential value and performance (Hegner *et al.*, 2019), it is expectable that personal innovativeness moderates the influences of PEU and PU on attitude. The moderating role of personal innovativeness has been shown in previous studies (Keszey, 2020; Khazaei and Tareq, 2021). Mohammadi (2015) found that the association between PEU and attitude is moderated by personal innovativeness. Accordingly, we proposed that PEU and PU have less effect on attitudes among innovators in comparison to late adopters as they are more self-confident and tolerant of adventures and uncertainty (Gu *et al.*, 2021). Therefore, we proposed that:

H6. Personal innovativeness moderates negatively the influences of (a) PU and (b) PEU on attitudes towards using AVs.

4.5 Data privacy concerns

Data privacy concerns hinder the adoption of technologies that gather and communicate personal information (Xu, 2019). Data privacy concerns is "a person's vulnerability due to loss of control over the management of individually identifiable personal information by other parties, such as firms or organizations" (Keszey, 2020, p. 7). Data privacy has a negative impact on the adoption of technology that relies on data such as e-commerce (Anic *et al.*, 2019), mobile phone (Zhang *et al.*, 2021), location-based applications (Budi *et al.*, 2021) and AVs (Keszey, 2020). The existence of privacy risks and concerns and security threats negatively influence the attitude towards using a technology (Anic *et al.*, 2019). Budi *et al.* (2021) argued that the lack of control over collected information, such as personal information and location information and the lack of knowledge on how collected information will be used, arouse the intention to not disclose personal information.

AVs are able to collect and communicate users' geographical locations and destinations and store sensitive information such as video and audio (Schoonmaker, 2016). While gathering and communicating such a category of data could be critical for effectual traffic management, the users' concerns about cybersecurity and misuse of personal information may negatively influence their decisions to use AVs (Lim and Taeihagh, 2018). Unauthorised access to AV networks may have serious consequences, such as using private information with malicious intent and undermining a vehicle's safety (Kohler and Colbert-Taylor, 2014). Budi *et al.* (2021) argued that the attention of individuals to data privacy is different and although some users of data-driven technologies may pay serious attention to data privacy, some others may have less concern about it. Accordingly, we proposed data privacy concerns may offset the impact of PEU and PU on attitudes towards using AVs. It means that individuals who are highly concerned about privacy risks may have less intention to use AVs regardless of the level of their usefulness and ease of use. Accordingly, we hypothesised that:

H7. Data privacy concerns moderate negatively the influences of (a) PU and (b) PEU on attitudes towards using AVs.

4.6 Lack of price sensitivity

Price is a crucial factor for consumers when deciding to purchase products and services (Hsu *et al.*, 2017). The customers compare the price of products with their internal price, and if the price exceeds their internal price thresholds, it may negatively influence their intention to purchase (Hahnel *et al.*, 2014). However, individuals have different levels of price sensitivity, and the intention to purchase products is negatively influenced by price sensitivity (Brandão and da Costa, 2021). It means that high price-sensitive customers tend to react strongly to price changes, while the reactions of low price-sensitive customers are moderate to price changes (Hahnel *et al.*, 2014). Price sensitivity is "the extent to which people differ in their responses towards price changes" (Hahnel *et al.*, 2014, p. 307).

Dong *et al.* (2020) and Lopes *et al.* (2014) found cost factors as one of the most important determinants of intention to purchase eclectic vehicles. Since AVs are more expensive than conventional vehicles, price sensitivity may hinder individuals' intention to purchase and use these vehicles regardless of their PU and PEU. The moderating role of price sensitivity has been shown in various contexts, such as green products (Hsu *et al.*, 2017) and hybrid vehicles (Bhutto *et al.*, 2022). Accordingly, it is expectable that price sensitivity plays a vital role in translating the PEU and PU into the attitude towards using AVs. Therefore, we proposed the following hypotheses:

H8. Lack of price sensitivity moderates positively the influences of (a) PU and (b) PEU on attitude towards using AVs.

4.7 Control variables

Previous studies on AVs argued that demographic factors might influence decisions to use AVs. For instance, several studies have reported that age negatively influences the intention to purchase and use AVS (Guo *et al.*, 2021; Wang *et al.*, 2021). This relationship can be explained by a few factors. Compared to young individuals, elderly individuals tend to be less tech-savvy, which might make them less comfortable with the idea of using a vehicle that operates entirely on advanced technology. They are generally less open to new experiences, possibly as a result of long-standing habits and routines, which can serve as an additional barrier to AV usage (Wang *et al.*, 2021). Furthermore, elderly individuals are often more safety-conscious than younger ones. Given the novel nature of AVs and the occasional media reports of safety concerns, this group may perceive AVs as riskier than traditional vehicles (Asmussen *et al.*, 2020). Gender has also been found to significantly influence AV-related decisions. Studies by Zoellick *et al.* (2019) and Guo *et al.* (2021) have found that men are generally more inclined to use AVs than women. This could be because women tend to be more risk-averse than men. The uncertainty surrounding AVs may discourage women more than men from using AVs. Men often exhibit more overconfidence in uncertain circumstances, leading them to be more open to using AVs (Asmussen *et al.*, 2020). Income is another demographic factor that appears to influence the intention to use AVs significantly (Guo *et al.*, 2021; Spurlock *et al.*, 2019). The cost of AVs is currently higher than that of non-automated vehicles, which means that their adoption may be limited to individuals with sufficient disposable income (Berliner *et al.*, 2019). Moreover, high-income individuals may be more willing to invest in new, potentially risky technologies, while lower-income individuals may be more risk-averse due to their financial constraints. Consequently, individuals with lower incomes might be more hesitant to adopt AVs, even if they recognise the potential benefits of these vehicles (Berliner *et al.*, 2019; Wang and Zhao, 2019). In light of these insights, this study considered age, gender and income as control variables.

5. Research design

5.1 Measurement of constructs

The study developed and employed a structured questionnaire to collect data and test the relationships hypothesised. The items were adapted from validated measurements. The items related to intention to use. We adapted PEU and PU from Lee *et al.* (2019). Personal innovativeness, data privacy concerns, price sensitivity and attitude were measured by the items adapted from Lu *et al.* (2005), Keszey (2020), Kapser and Abdelrahamn (2020) and Nastjuk *et al.* (2020), respectively. All the items were assessed on a 5-point Likert scale from 1, "Strongly Disagree," to 5, "Strongly Agree." A pre-test was conducted with three academicians and two AV experts from the industry to determine the content and face validity. Based on their inputs, minor changes were made. The original questionnaire was translated into Vietnamese by a professional translator. Later, the Vietnamese version was translated back into English by another translator. Three experts compared the original and translated items and confirmed that both versions are equivalent. The final version of the questionnaire was pilot tested by 37 potential respondents. The Cronbach's alpha values of all constructs were above 0.7, indicating that the questionnaire is reliable.

5.2 Sample and data collection

The population of this study included Vietnamese who planned to purchase a car within three years and had no AVs in the past. Data were collected from the target population through an online survey executed within the Facebook platform in which groups of users with Vietnamese members were approached. We included two screening questions to verify that the respondents (1) had active plans to purchase a car within three years and (2) had no AVs in the past. A total of 393 data were received, and 15 data were excluded due to incomplete data. We used G*Power to test the robustness of the sample. The power of the sample was 0.999, indicating the study sample has adequate power to examine the hypotheses (Faul *et al.*, 2009). The final sample comprises 196 females (51.9%) and 182 males (48.1%). A total of 131 respondents (34.7%) were between the ages of 18 and 25, followed by 101 (26.7%) between 26 and 35, 88 (23.3%) between 35 and 45 and 58 (15.3%) above the age of 46. Results revealed that most respondents had a Bachelor's degree (64.3%). Around 27.2% of respondents held a Master's degree, while 3.4% had a Ph.D. The remaining 5% merely had the schooling education. Approximately the income of 21% of respondents was less than \$500 (32.0%), followed by \$500–1000 (29.1%), \$1001–2000 (24.1%) and above \$2000 (14.8%). As a self-reported questionnaire was used to collect data, the responses are subject to "common method bias" (CMB) (Fuller *et al.*, 2016). The research team followed Lindell and Whitney's (2001) approach and calculated the correlation values between the study's constructs and the marker variable "attitude towards the colour blue." The results identified all correlation values within the data (Lindell and Whitney, 2001).

5.3 Data analysis

This study used PLS-SEM and ANFIS to analyse the data. The significance of the proposed relationships was tested using PLS-SEM. Later, the significant factors were analysed with ANFIS. PLS-SEM is selected because the study is explanatory in nature and draws on a complex conceptual framework to address its objectives (Hair *et al.*, 2019). Furthermore, the data were not normally distributed, and PLS-SEM is a suitable technique for a non-normal distribution (Chin, 1998). We used SmartPLS software to run PLS-SEM analysis. As PLS-SEM only can analyse linear models, it may oversimplify a technology adoption concept that is more likely to be nonlinear (Ho and Tsai, 2011). As a complementary technique to PLS-SEM, soft computing techniques have been used in numerous studies in order to overcome the linearity issue (Ahani *et al.*, 2017; Yadegaridehkordi *et al.*, 2020). ANFIS allows for tackling nonlinear relationships, ranking the input variables and predicting the output (Roham *et al.*, 2012). However, ANFIS is unsuitable for testing causal relationships and building theory (Liébana-Cabanillas *et al.*, 2017). Accordingly, PLS-SEM and ANFIS are complementary techniques and have been used in this study together. We run ANFIS in MATLAB software.

6. PLS-SEM results

6.1 Assessment of measurement model

The validity and reliability of the measurements were investigated by assessing the factor loadings and calculating two well-known measures of "Composite Reliability" (CR) and "Average Variance Extracted" (AVE). The loadings of all items were above the threshold of 0.4 proposed by Hair *et al.* (2019). Furthermore, AVE and CR were above 0.5 and 0.7, indicating acceptable reliability and convergent validity (Hair *et al.*, 2019; Iranmanesh *et al.*, 2022a, b, c) (Table 1).

We assessed the discriminant validity by employing the "heterotrait-monotrait" (HTMT) (Henseler *et al.*, 2015). There were no HTMT values greater than 0.85, indicating good discriminant validity (Foroughi *et al.*, 2023a, b, c; Kline, 2016; Sulaiman *et al.*, 2022) (Table 2).

6.2 Assessment of structural model

Scholars have used the proportion of variance explained (R^2) to validate the model's accuracy (Hair *et al.*, 2019; Foroughi *et al.*, 2023a, b, c). The variables used in the study explained 0.562, 0.598 and 0.605 of the variance in PU, attitude and intention to use AVs, respectively. Furthermore, the Stone-Geisser Q^2 values of PU (0.339), attitude (0.418) and intention to use (0.449) were above zero, indicating that the model has high predictive relevance (Chin, 2010; Foroughi *et al.*, 2022).

The findings of non-parametric bootstrapping confirmed the significance of all TAM relationships. The moderating effects of personal innovativeness, data privacy concerns and lack of price sensitivity were assessed using the two-stage approach. According to the results, personal innovativeness moderates negatively the association between PEU and attitude ($\beta = -0.097; p < 0.05$). Furthermore, data privacy concerns moderate positively the relationships between PU and attitude ($\beta = 0.131; p < 0.05$). Price sensitivity does not moderate the impacts of PU and PEU on attitude. Based on the literature, we expected data privacy concerns to moderate the influence of PU on attitude negatively. Accordingly, although the interaction is significant, H7a was rejected. Accordingly, H1 to H5, H6b and H8a were supported (Table 3).

Figure 2 illustrates that the impact of PEU on attitude is greater among respondents with low personal innovativeness in comparison to innovators. Furthermore, PU has a higher effect on attitudes among individuals with high data privacy concerns than those with low data privacy concerns.

7. ANFIS results

We used ANFIS to explain the nonlinear relationship, reveal the importance of the inputs and predict the outputs. The significant factors from PLS-SEM results were used to develop ANFIS models (Figure 3). Totally, three ANFIS were used in this study, as shown in Figure 3. ANFIS 1–3 were used to predict PU, attitude and intention to use AVs, respectively. These models were constructed to find the importance level of factors impacting the corresponding outputs, PU, attitude and AV usage intention. The importance of each determinant of PU, attitude and intention to use and the nonlinear relationships between them were illustrated in 2D plots (Figure 4) and 3D plots (Figure 5). This plot clearly demonstrates the interactions between the inputs and outputs of the models. In ANFIS modelling, several Membership

Constructs	Items	Loadings	CR	AVE
Perceived Usefulness (PU)	Using an autonomous vehicle would enhance my driving effectiveness	0.872	0.922	0.747
	Using an autonomous vehicle would increase my productivity	0.833		
	Using an autonomous vehicle would enhance my driving performance	0.886		
	I would find an autonomous vehicle is useful	0.867		
Perceived Ease of Use (PEU)	Interacting with an autonomous vehicle would be clear and understandable	0.742	0.896	0.684
	I would find an autonomous vehicle is easy to use	0.861		
	Interacting with an autonomous vehicle would not require much mental effort	0.861		
	Learning to operate an autonomous vehicle would be easy for me	0.837		
Attitude (ATT)	I think that using autonomous vehicles is a wise idea	0.870	0.934	0.738
	I think that using autonomous vehicles is a good idea	0.891		
	In my opinion, it is desirable to use autonomous vehicles	0.855		
	I like the idea of using autonomous vehicles	0.837		
	I think that using autonomous vehicles would be beneficial for me	0.841		
Intention to Use AVs (INT)	Assuming I have access to an autonomous vehicle, I would intend to use it	0.893	0.913	0.779
	Given I have access to an autonomous vehicle, I predict I would use it	0.847		
	In the future, I would not hesitate to use an autonomous vehicle	0.906		
Personal Innovativeness (PI)	If I heard about a new technology, I would look for ways to experiment with it	0.865	0.909	0.716
	Among my peers, I am usually the first to explore new technologies	0.746		
	I like to experiment with new technologies	0.904		
	In general, I am hesitant to try out new technologies	0.861		
Data Privacy Concern (DPC)	I am afraid that the data (e.g. position, routes) collected about me during my travels will be stolen	0.812	0.902	0.755
	I am afraid that the autonomous vehicle I am using will be attacked by hackers	0.868		
	I am afraid that data entry during my travel will be breached and the autonomous vehicle will miss-navigate	0.923		
Lack of Price Sensitivity(PS)	I would not mind paying more to use autonomous vehicles	0.802	0.862	0.556
	I would not mind spending a lot of money to use autonomous vehicles	0.736		
	I would be less willing to pay for autonomous vehicles if I thought it to be high in price	0.722		
	If using autonomous vehicles are likely to be more expensive than conventional vehicles, that would not matter to me	0.787		
	A really great transportation option would be worth paying a lot of money for	0.674		

Note(s): CR: Composite Reliability; AVE: Average Variance Extracted
Source(s): Author's own creation/work

Table 1.
Measurement model evaluation

Functions (MFs) were introduced for each factor. We used Gaussian MFs to fuzzify the inputs (Boyacioglu and Avci, 2010) (see Figure 4). For each input variable, three linguistic terms, namely low, moderate and high, were considered based on the responses to the five-point Likert scale. These MFs played an important role in accurately predicting models' output. Note that these MFs can be extended for other MFs, such as Triangular and trapezoidal MFs.

We provide the results of ANFIS prediction in Figure 5. The results are obtained from training the ANFIS models by using the collected data and defied MFs for each output. Each ANFIS used 200 epochs to refine the prediction models. Figure 4 demonstrates the relationship between determinants and PU, attitude and AV usage intention. As seen from

	PU	PEU	ATT	INT	PI	DPC	PS
PU							
PEU	0.834						
ATT	0.765	0.788					
INT	0.749	0.799	0.821				
PI	0.691	0.742	0.735	0.813			
DPC	0.195	0.147	0.122	0.124	0.212		
PS	0.308	0.298	0.260	0.203	0.224	0.634	

Source(s): Author's own creation/work

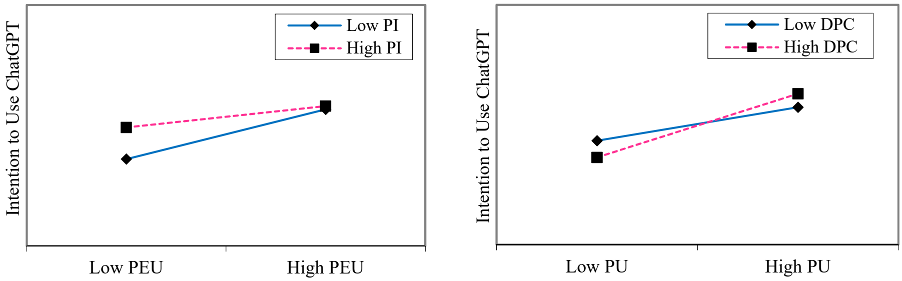
Table 2. Heterotrait-monotrait (HTMT)

Hypotheses	Relationships	Path coefficients	STD	*T* values	*P* values	Decisions
Main model						
H1	PU → ATT	0.393	0.059	6.633	0.000***	Supported
H2	PU → INT	0.265	0.053	5.010	0.000***	Supported
H3	PEU → PU	0.760	0.032	23.80	0.000***	Supported
H4	PEU → ATT	0.412	0.054	7.662	0.000***	Supported
H5	ATT → INT	0.579	0.049	11.710	0.000***	Supported
Moderating effect of personal innovativeness						
–	PI → ATT	0.145	0.051	2.873	0.004**	–
H6a	PU*PI → ATT	−0.006	0.045	0.124	0.901	Not Supported
H6b	PEU*PI → ATT	−0.118	0.051	2.323	0.021*	Supported
Moderating effect of data privacy concerns						
–	DPC → ATT	−0.013	0.034	0.378	0.706	–
H7a	PU*DPC → ATT	0.126	0.065	1.928	0.045*	Not Supported
H7b	PEU*DPC → ATT	−0.031	0.053	0.590	0.556	Not Supported
Moderating effect of lack of price sensitivity						
–	PS → ATT	0.054	0.042	1.294	0.196	–
H8a	PU*PS → ATT	0.097	0.066	1.460	0.145	Not Supported
H8b	PEU*PS → ATT	0.023	0.059	0.388	0.698	Not Supported
Control variables						
–	Gender → ATT	−0.036	0.069	0.517	0.605	–
–	Gender → INT	−0.044	0.064	0.683	0.494	–
–	Age → ATT	−0.062	0.033	1.861	0.063*	–
–	Age → INT	0.012	0.031	0.377	0.706	–
–	Income → ATT	0.007	0.034	0.212	0.832	–
–	Income → INT	−0.013	0.029	0.430	0.667	–

Note(s): $*p < 0.05$; $**p < 0.01$; $***p < 0.001$
Source(s): Author's own creation/work

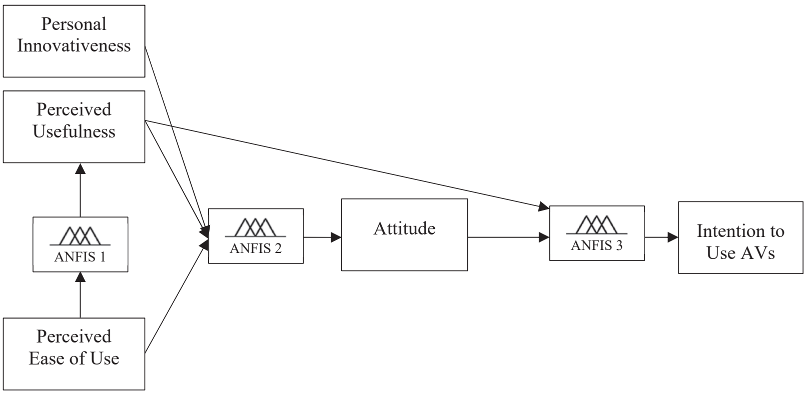
Table 3. Path coefficients and hypotheses testing

the plots in Figure 5, the results are interesting by ANFIS for the nonlinear relationships. The slope of the lines demonstrates the importance level of each factor in shaping the outcomes. According to the findings, PEU is the most important driver of attitude, and the importance level of personal innovativeness and PU are almost similar. Furthermore, attitude plays a more critical role in shaping AV usage intention in comparison to PU. These outcomes clearly demonstrate the users' behaviour in intention to use AVs.



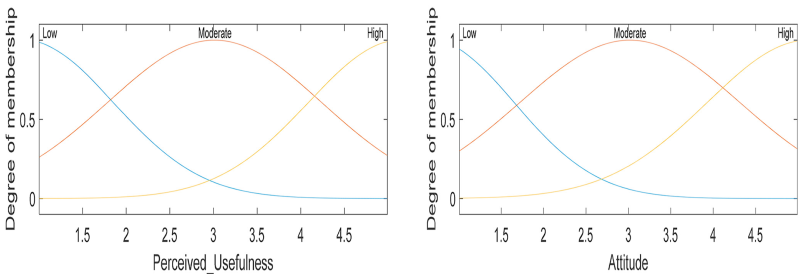
Source(s): Author's own creation/work

Figure 2.
Moderating effect of personal innovativeness and data privacy concerns



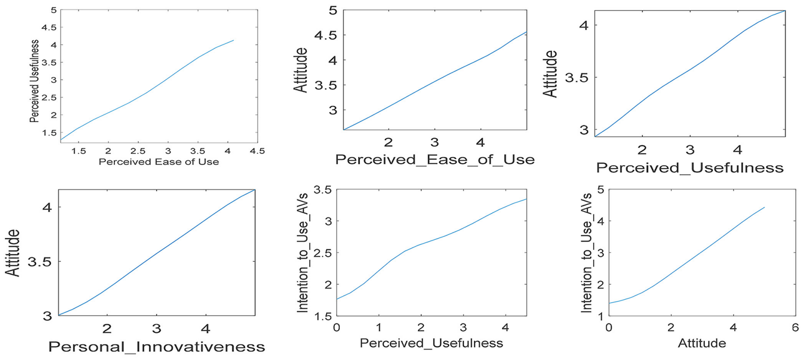
Source: Author's own creation/work

Figure 3.
Proposed ANFIS model



Source(s): Author's own creation/work

Figure 4.
MFs used for PU and Attitude

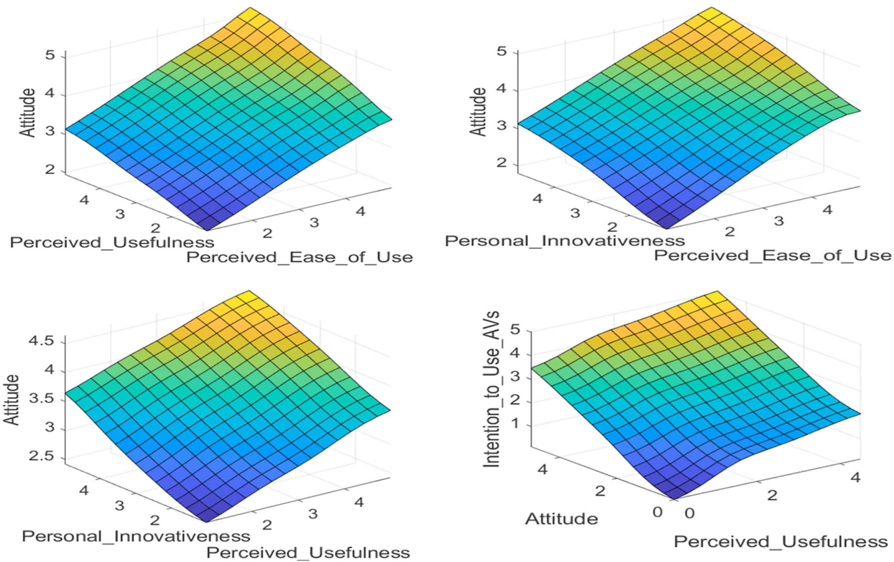


Source(s): Author's own creation/work

Figure 5. The importance of determinants of PU, attitude, and intention to use

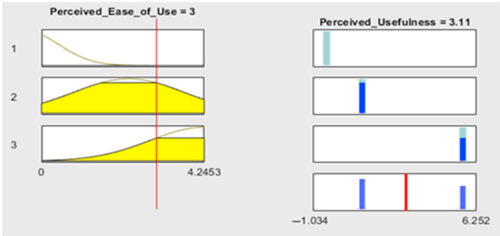
To better reveal the relationships between the factors and the outputs, 3D plots were generated from three ANFIS models. Figure 6 demonstrates the relationships between every two input variables and the outputs. According to these 3D plots, the influence of each input variable on output depends on other input variables. For instance, the level of attitude at the PEU value of 3 is different when the PU value is 3 compared to the time that PU is 5. It means the effect of PEU on attitude depends on the value of PU. These findings indicate that the input variables are interrelated, and their influences on output depend on each other.

Predicting the output of each model according to the inputs is an important task that ANFIS does. Figure 7 enables us to predict the outcomes based on various values of inputs. Three predictions for PU at different levels of PEU were provided (Figure 7a). For instance, at the PEU value of 3, it is expectable that the users' PU level be 3.11. Figure 7b demonstrates 9 predictions for AV usage intention based on different values of PU and attitude. At a PU

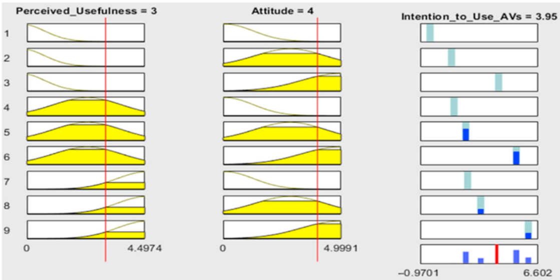


Source(s): Author's own creation/work

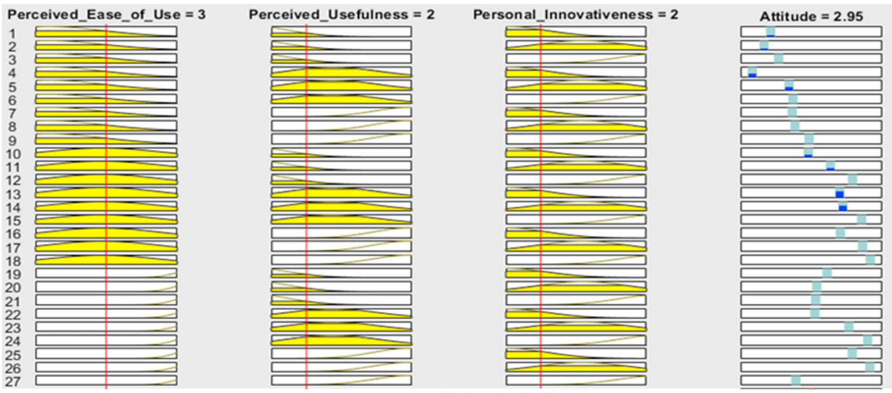
Figure 6. The relationships between determinants and outcomes



Predicting Perceived Usefulness
(a)



Predicting Intention to Use AVs
(b)



Predicting Attitude
(c)

Source(s): Author's own creation/work

Figure 7.
The prediction of PU, attitude, and intention to use based on inputs

value of 3 and an attitude level of 4, the level of intention to use AVs is predicted to be 3.95. Finally, Figure 7c illustrates 37 predictions for attitude at different levels of PEU, PU and personal innovativeness.

8. Discussion

The study used a hybrid PLS-ANFIS approach to test the determinants of AV usage intention by considering personal innovativeness, data privacy concerns and price sensitivity as moderators. PLS enables us to identify influential drivers and test moderating effects. PLS revealed that PU and PEU significantly influence attitude, which, in turn, leads to the intention to use AVs. PLS results also confirmed the direct effects of PU on intention to use and PEU on PU. PLS showed that personal innovativeness moderates negatively the relationship between PEU and attitude, and data privacy concerns moderate positively the effect of PU on attitude. The study used ANFIS to identify the most critical driver of attitude and determine how factors interact in order to affect attitude. According to ANFIS results, PEU is the most critical driver of attitude towards using AVs. Furthermore, ANFIS revealed that the influence of one factor on attitude depends on the extent of other factors (Figure 6). For instance, the influence of PEU on attitude is greater at higher levels of PU compared to low levels of PU. This finding extends PLS results which show a fixed effect between two factors. Although PLS indicated that the path coefficient of PEU on attitude is 0.404, ANFIS showed that the effect of PEU on attitude varies and depends on the extent of PU and personal innovativeness.

The findings of the studies confirmed the significance of all the proposed relationships of TAM, which illustrate the power of this theory in explaining the behaviours towards adopting new technology. It is worth highlighting that according to the findings of ANFIS, PEU is the most critical predictor of attitude towards using AVs and its influence is greater than PU. It has been found in most previous studies that PU has a greater influence on attitudes and behaviours in comparison to PEU (Huang and Chueh, 2022; Munoz-Carril *et al.*, 2021). Many studies even found PEU as an insignificant driver of intention to use new technology (Baccarella *et al.*, 2021; Lee *et al.*, 2019). The level of familiarity with the system can explain these results. The users' experience of working with a system with similar features offsets the importance of PEU. For instance, in the mobile app development context, software developers commonly try to make their applications easier to use by adopting the visual appeals of popular apps and integrating them into their mobile applications (Iranmanesh *et al.*, 2022a, b, c). Consequently, PEU is not the concern of individuals in the adoption decision. However, as people are unfamiliar with AVs and have no experience working with a system with similar features, PEU becomes a key determinant of their attitude towards AVs.

The findings reveal that while personal innovativeness negatively moderates the influence of PEU on attitude, it does not moderate the influence of PU. It means PEU is a more important factor in the adoption decision process of individuals with a low level of personal innovativeness (i.e. late majority or laggards) in comparison to innovators and early adopters. Figure 2 shows that PEU contributes significantly to the attitude of both early and late adopters, but its importance is significantly higher among late adopters. Accordingly, the early adopters' positive comments on the ease of working with AVs on social media and review websites may trigger the late adopters' intention to use (Filieri *et al.*, 2017; Moldovan *et al.*, 2015). The insignificant moderating effect of personal innovativeness on the association between PU and attitude indicates the importance of finding AVs useful in enhancing driving effectiveness and performance in the adoption decision of both early and late adopters. Accordingly, in the early diffusion stage of AVs, marketers should give more attention to the benefits of AVs, and by moving to the stage of public acceptance of AVs, besides the benefits of AVs, they should emphasise their ease of use.

Data privacy concerns moderate the relationship between PU and attitude, according to the findings. Surprisingly, in contrast to our expectation, data privacy concerns moderate positively the PU-attitude relationship. It means that finding AV as a useful device has a higher effect on the attitude of individuals with high data privacy concerns than those with low privacy concerns. The comparison of gained values and risks can explain this finding. Individuals with high privacy concerns may have a favourable attitude towards AVs if they find the benefits of using AVs surpass their risks. As such, having a positive perception of AV usage is crucial in the adoption decision process of individuals with high privacy concerns. The findings also revealed that data privacy concerns do not moderate the influence of PEU on attitude. It indicates that PEU is vital for individuals with high and low data privacy concerns. The nature of usefulness, risk and ease of use can explain this observation. Although usefulness and risk are related to gaining or threatening values, ease of use is related to the required efforts for using the technology. Accordingly, the users need to assess usefulness and risk simultaneously to make a decision, and consequently, PU and data privacy concerns have an interactive effect.

Finally, the results did not support the moderating effects of price sensitivity. It indicates that price sensitivity cannot offset the influences of PU and PEU on attitude towards using AVs. These insignificant relationships can be due to the fact that price sensitivity may have a low effect on individuals' beliefs and thoughts about AVs compared to their purchase decisions. As attitude measures the thoughts and beliefs of individuals, price sensitivity does not play a moderating role. We expect that price sensitivity moderates the impacts of PEU and PU on purchase intention, and future studies are recommended to test it.

9. Theoretical and practical implications

The findings of the study have several theoretical contributions. Firstly, the study illustrated the power of TAM factors in explaining attitudes and intentions to use AVs. All the proposed relationships of TAM were accepted in this study. These findings contribute to the literature by illustrating that TAM is a robust model in explaining attitude and behaviour towards adopting new disruptive technologies. Secondly, we found that PEU has a higher effect on attitude in the context of AVs in comparison to PU. It can be interpreted that when individuals are not familiar with the features of a new system, PEU has a greater influence on attitudes towards using the technology. Chung *et al.* (2010) asserted that the impact of PEU depends on the level of familiarity with new technology. As AVs are a revolutionary technology, PEU is a crucial factor in the process of deciding to use AVs.

Thirdly, the study extends TAM by incorporating three personal-related factors: personal innovativeness, data privacy concerns and price sensitivity. The results affirmed the importance of personal-related factors. Personal innovativeness negatively moderates the impact of PEU on attitude. Data privacy concerns moderate positively the effect of PU on attitude towards using AVs. To the best of our knowledge, personal-related factors have rarely been considered in technology adoption studies and theories and models related to technology adoption. We contribute to the literature by demonstrating that individual heterogeneity is a crucial factor in adopting a disruptive technology, and besides technology-related factors, personal-related factors should be considered. The extent to which technological factors influence attitude towards using a new technology depends on users' personal-related factors.

Fourthly, the study contributes to AVs literature by using a hybrid analysis approach. This PLS approach enables us to investigate the significant determinants of attitude and intention to use AVs and test the moderating effects of personal innovativeness, data privacy concerns and price sensitivity. ANFIS extends the findings of PLS by ranking the importance of determinants and demonstrating interrelationships among factors. According to ANFIS, PEU is the most critical determinant of attitude and the importance of PU and personal innovativeness are almost equal. Furthermore, attitude has a stronger influence on the intention to use AVs compared to PU. Furthermore, ANFIS showed that determinants are interrelated, and the influence of one factor on attitude and usage intention depends on the extent of other factors. It means that one single path coefficient cannot reflect the relationships between two factors, and the impact of one factor on attitude and intention fluctuates depending on other factors. To our best knowledge, no study has used the PLS-ANFIS approach in the AV context.

The findings also provide practical implications for policymakers and automobile companies' managers, designers and marketers. The findings provide guidelines for the future development of AVs. Both PEU and PU are vital factors in triggering the adoption of AVs. As such, marketers should highlight the usefulness of AVs (e.g. reducing crashes, reducing traffic congestion, enhancing roadway safety and reducing greenhouse gas emissions) and their ease of use in marketing communication activities. Furthermore, the designers should give special attention to developing a user-friendly system. Developing a system with similar features to commonly used apps can be an effective practice for enhancing the perception of ease of use (Iranmanesh *et al.*, 2022a, b, c; Senali *et al.*, 2023). Furthermore, as PEU has a higher influence on attitudes towards using AVs in comparison to PU, the marketers should give more attention in their commercial advertisement to ease of use at the point of AVs introduction and in the early diffusion stages. However, as the determinants are interrelated and the influence of one factor depends on the extent of other factors, marketers should also pay attention to its usefulness.

Furthermore, the study also illustrated that the importance of PU and PEU depends on users' personal-related factors. Accordingly, marketers should develop marketing practices based on the target groups and stage of technology diffusion. According to the findings, personal innovativeness moderates the impact of PEU negatively and has no moderating impact on the relationship between PEU and attitude towards using AVs. Accordingly, in the introduction stage, marketers should communicate the benefits of AVs to convince innovators and early adopters. In the following stages of AVs diffusion, marketers should provide a platform for early adopters to share their experience of ease of use with non-adopters. Likewise, user-friendliness should be one of the core messages of commercial advertisements to motivate late adopters to decide to adopt AVs. Finally, data privacy concerns moderate the influence of PU on attitude. As usefulness is a more critical factor for those with a high data privacy concern, marketers can consider the communication of benefits as a technique to trigger the intention of these sorts of customers (Immonen and Koivuniemi, 2018). Furthermore, marketers can also communicate the security of AVs and assure the system security to address the concerns of individuals with high data privacy concerns.

10. Conclusion

This research expands the TAM model in the AV context by incorporating personal-related factors, namely personal innovativeness, data privacy concerns, and price sensitivity, as moderators. The proposed conceptual framework was tested using a combination of PLS-SEM and ANFIS techniques. The findings confirmed that all TAM relationships are significant, and TAM has high explanatory power in explaining attitudes and behaviours towards using AVs. Furthermore, we found PEU as the most important determinant of attitude towards AVs. According to the findings, personal innovativeness negatively moderates the impact of PEU on attitude. Data privacy concerns moderate positively the impact of PU on Attitude. The findings contribute to the knowledge by expanding the TAM in the AV context, assessing the moderating influences of personal-related factors, ranking the importance of determinants, and demonstrating the interrelationships among factors. The findings provide directions for policymakers and automotive companies.

This study has some limitations that should be considered in interpreting the results. Firstly, the data were collected from Vietnam, which is a developing country with low purchasing power. As the price of AVs is currently high, future studies are recommended to test the model of this study in countries with a higher purchasing power. Secondly, previous studies have discussed the importance of hedonic and social factors (Kapser and Abdelrahman, 2020) and equipment/system failure (Baskutis *et al.*, 2022; Sankeerthana and Kadali, 2022) in the decision to adopt AVs. Future studies can extend this study by adding these factors. Finally, our results may be influenced by the current market situation in

Vietnam, where AVs are not yet widely available. Consequently, the participants in our study have had limited exposure to and experience with this technology, which could impact their evaluation of AVs' usefulness and ease of use. Future research is recommended to investigate how perceptions, attitudes and intentions of individuals evolve over time and consider conducting comparative studies in different markets or settings to provide a broader insight into the factors influencing the adoption of AVs.

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Further reading

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