Journal of Retailing and Consumer Services 70 (2023) 103158

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

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

Determinants of intention to use autonomous vehicles: Findings from PLS-SEM and ANFIS

Behzad Foroughi [a,*], Pham Viet Nhan [b], Mohammad Iranmanesh [c], Morteza Ghobakhloo [d,e], Mehrbakhsh Nilashi [f,g], Elaheh Yadegaridehkordi [h]

[a] Department of International Business Administration, I-Shou University, Kaohsiung, Taiwan
[b] College of Management, I-Shou University, Kaohsiung, Taiwan
[c] School of Business and Law, Edith Cowan University, Joondalup, WA, 6027, Australia
[d] School of Economics and Business, Kaunas University of Technology, Kaunas, Lithuania
[e] Division of Industrial Engineering and Management, Uppsala University, PO Box 534, Uppsala, Sweden
[f] UCSI Graduate Business School, UCSI University, No. 1 Jalan Menara Gading, UCSI Heights, 56000 Cheras, Kuala Lumpur, Malaysia
[g] Centre for Global Sustainability Studies (CGSS), Universiti Sains Malaysia, 11800, USM Penang, Malaysia
[h] Center for Software Technology and Management, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, Bangi, Malaysia

A R T I C L E I N F O

Keywords:
Autonomous vehicles
Intention to adopt
Technology acceptance
Driverless cars
UTAUT2

A B S T R A C T

Artificial intelligence (AI)-powered autonomous vehicles (AVs) are one of the most disruptive technologies with potentially wide-ranging social implications, including improvements in passenger/driver safety, environmental protection, and equity considerations. The current research extends the UTAUT2 model in the context of fully AVs (level 5 automation) to determine and rank determinants of intention to adopt AVs. Collected data from 378 respondents were analysed by a hybrid approach employing partial least squares (PLS) complemented by the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) technique. According to the findings, five major determinants emerged: trust, hedonic motivation, social influence, compatibility, and effort expectancy. Furthermore, compatibility positively moderates the association between performance expectancy and intention to use AVs. The findings shed light on determinant factors, their level of importance, and the potential interplay between them in shaping individuals' intention to adopt and use AVs. Furthermore, the current research provides valuable insights to carmakers, technology developers, and practitioners on determinants of AVs adoption, assisting them in devising effective AVs-related strategies.

1. Introduction

In today's digital world, we are benefiting from the growing technology infusion into various contexts, where humans are increasingly augmented, supported, and in some cases, replaced by machines (Meyer-Waarden and Cloarec, 2022). In this regard, many technological developments and disruptive innovations, such as autonomous vehicles (AVs), significantly influence marketing and society and change customer behaviours (McLeay et al., 2022). AVs, also called robotic vehicles, driverless, or self-driving, are believed to offer wide-ranging benefits in different ways, including improved access of elderly and physically impaired people to mobility, improved ecological footprint, optimized traffic flow, reduced fuel consumption, increased road safety, and reduced accidents (Fagnant and Kockelman, 2015; König and Neumayr, 2017; Nastjuk et al., 2020; Waung et al., 2021). Regardless of AVs' general desirability and beneficial aspects, their adoption seems to lag far behind the expectation (Rubio et al., 2020).

Previous studies offer important theoretical and methodological insights into the AVs adoption phenomenon. From the theoretical point of view, various studies have investigated the determinants of individuals' AVs adoption, employing common technology acceptance models such as the "technology acceptance model" (TAM) (e.g., Wu et al., 2019; Xu et al., 2018), integration of TAM and "theory of planned behaviour" (TPB) (e.g., Buckley et al., 2018; Lee et al., 2019; Moták et al., 2017; Robertson et al., 2019), "unified theory of acceptance and use of technology" (UTAUT) (e.g., Madigan et al., 2017, 2016), diffusion of

* Corresponding author.
E-mail addresses: foroughi@isu.edu.tw (B. Foroughi), phamvietnham96@gmail.com (P.V. Nhan), m.iranmanesh@ecu.edu.au (M. Iranmanesh), morteza_ghobakhloo@yahoo.com (M. Ghobakhloo), nilashidotnet@hotmail.com (M. Nilashi), yellahe@gmail.com (E. Yadegaridehkordi).

https://doi.org/10.1016/j.jretconser.2022.103158
Received 29 May 2022; Received in revised form 24 September 2022; Accepted 2 October 2022
Available online 13 October 2022

innovation (DOI) (Luo et al., 2019; Talebian and Mishra, 2018). Among all models and theories used to determine individuals' AVs adoption, UTAUT and its extended version (UTAUT2) are the most comprehensive, as they integrate different models and theories (Venkatesh et al., 2012). However, relatively few studies have employed UTAUT2 to investigate the influential factors determining individuals' acceptance of AVs (e.g., Kapser and Abdelrahman, 2020; Nordhoff et al., 2020). UTAUT2 is more suitable in the context of current research since it was specifically developed and tailored to users' perspectives (Venkatesh et al., 2012) and showed a more significant proportion of variance in individuals' acceptance of AVs than UTAUT, TPB, and TAM (e.g., Buckley et al., 2018; Nordhoff et al., 2020; Xu et al., 2018). According to Venkatesh et al. (2012), UTAUT2 extends the applicability of UTAUT from an organizational context to a consumer setting. Although customers are concerned about the monetary cost of technology, it does not matter to employees since a company should be responsible for the cost of adopting the technology (Venkatesh et al., 2012). Given the importance and the central role of UTAUT2 in a consumer adoption setting, current research employs UTAUT2 as the main theoretical underpinning to elucidate the determinants of users' intention to use AVs. Nevertheless, the majority of the existing studies on AVs have been conducted in developed countries such as France (Meyer-Waarden and Cloarec, 2022), Germany (Nastjuk et al., 2020), Spain (Montoro et al., 2019), and the US (Benleulmi and Ramdani, 2022; Guo et al., 2021). The studies that have applied UTAUT2 to investigate users' acceptance of AVs were mainly conducted in western countries. For instance, in their study, Kapser and Abdelrahman (2020) employed UTAUT2 to assess the determinants of users' acceptance of AVs in Germany but did not mention the level of car automation under study. Similarly, Nordhoff et al. (2020) evaluated drivers' intention to use AVs (level 3) in eight European countries. Although these studies applied UTAUT2 and confirmed its applicability for discovering the determinants of the users' acceptance with a focus on AVs, the study context was western countries, limiting the generalizability of their findings that merit scholarly attention. The studies that have compared the determinants of technology adoption among developed and developing countries have found the drivers are different among these countries (e.g., Chopdar et al., 2018; Jiménez and San-Martín, 2017). It is argued that cultural differences may affect users' acceptance of AV technologies (Haboucha et al., 2017; Kacperski et al., 2021). For instance, previous studies have argued that social influence has a higher effect on individuals' behaviours in developing countries in comparison to developed ones (Hong et al., 2022; Senali et al., 2022). Thus, the current study differentiates from the literature on AV acceptance by investigating the determinants of individuals' intention to use AVs (level 5) in Vietnam as a developing eastern country, extending our understanding of this emerging phenomenon.

Venkatesh et al. (2012) stressed the necessity of examining and extending UTAUT2 in various settings and cultures to improve its robustness and applicability, arguing that elements influencing the new information systems' adoption vary in different contexts. Accordingly, we incorporated trust (Yuen et al., 2020; Choi and Ji, 2015), image (Acheampong et al., 2021; Wu and Lu, 2013), and compatibility (Guo et al., 2021; Nastjuk et al., 2020) to extend the original model of UTAUT2. These factors have been selected based on a meta-analysis of AVs literature (e.g., Yuen et al., 2020; Acheampong et al., 2021; Guo et al., 2021). As the users' concern about cybersecurity may adversely influence their adoption intention, trust is an important factor in the context of AVs (Lim and Taeihagh, 2018). AVs operate without the need for human intervention, and cyber-attacks may result in serious security risks and accidents (Li et al., 2018). Furthermore, the social image of using AVs is expected to be an important driver of intention to use AVs in Vietnam, as previous studies have shown social image plays an important role in motivating people in developing countries to adopt an innovative technology (Pandey et al., 2022). Additionally, prior investigations found compatibility as an important determinant of individuals' adoption of new technology such as AVs (Guo et al., 2021; Nastjuk et al., 2020), and the study on the moderating role of compatibility in the formation process of individuals' behavioural intentions toward AVs is lack. Previous studies have shown that compatibility moderates the relationships between behaviours towards technologies and their determinants (Wong et al., 2015; Wang et al., 2021). Given the above explanation, this study introduces compatibility as a moderator to investigate its role in individuals' intention to adopt AVs.

From the methodological perspective, prior empirical evidence on the adoption of AVs explored various factors that might be crucial. However, the majority of them have relied on symmetrical analysis (e.g., regression and structural equation modelling (SEM)) (e.g., Kacperski et al., 2021; Panagiotopoulos and Dimitrakopoulos, 2018). Although employing symmetric analysis (e.g., variance-based method) help researcher uncover major determinants of an outcome of interest, it overlooks the possibility of nonlinear relationships (Liébana-Cabanillas et al., 2017; Ahani et al., 2017). In fact, relationships between psychological factors are rarely linear, and linear approaches cannot estimate these relationships precisely (Ho and Tsai, 2011). In order to overcome this drawback, the current study employs a combination of SEM technique and an asymmetric analysis as a complementary approach, namely "adaptive neuro-fuzzy inference systems" (ANFIS), to figure out both the linear and the potential nonlinear relationships that may have an impact on the results and deepen our understanding of elements contributing individuals' acceptance and intention to use AVs. The ANFIS method can explain nonlinear relationships better than linear methods such as multiple regression and SEM (Roham et al., 2012). Given the effectiveness and efficiency of employing both SEM and an asymmetric analysis (e.g., ANFIS) to prioritize drivers of technology adoption, their integration in the area of AVs adoption has not been studied. With that motivation, current research contributes to the growing body of evidence on AVs adoption by addressing the following objectives:

1. To extend the UTAUT2 model in the context of AVs by incorporating compatibility, trust, and image as well as investigating the moderating role of compatibility.
2. To apply a new SEM-ANFIS technique to identify and rank the importance of the contributing factors in AVs adoption from both linear and nonlinear perspectives.

Current research adds value to the existing body of knowledge on AVs by applying and enriching the UTAUT2 model with three additional factors identified and tested empirically in prior research: trust, image, and compatibility. The findings of this study enable us to deepen our understanding of influential factors associated with and contributing to the individuals' adoption of AVs. To achieve these goals, the present study undertakes a combined linear (e.g., SEM) and nonlinear (e.g., ANFIS) approach for the outcome of interest. The findings shed light on determinant factors, their level of importance, and their potential interplay in shaping individuals' intention to adopt and use AVs. Furthermore, current research provides valuable insights on key predictors of AVs adoption to carmakers, technology developers, and practitioners, assisting them in devising effective AVs-related strategies.

2. Literature review

2.1. Background of AVs

The technological advances in the driving process that help or replace human control are called vehicle automation (Guo et al., 2021). Based on the degree of autonomy, vehicle automation can be classified into five levels, varying from no automated functionality (level 1) to unconditional self-driving (level 5). The focus of this research is level 5 of automation, whereby "an automated driving system on the vehicle can do all the driving in all circumstances [and] the human occupants are just passengers and need never be involved in driving"(Xie et al., 2022, p. 2). Potential advantages and drawbacks of AVs are evident in various contexts, such as road safety (Papadoulis et al., 2019), virtual and data safety (Parkinson et al., 2017), sustainability (Cugurullo et al., 2021), as well as social inclusivity (Bennett et al., 2020). AVs are considered revolutionary technology that is expected to shape the future of urban transportation. Despite AVs' potential advantages and concerns, it is still being critically discussed and evaluated. Prior studies predict AVs will be commercially available by the late 2020s in some countries, but they will not be ubiquitous until as early as 2040 or as late as 2060 (Guo et al., 2021; Litman, 2022). China, various countries in the European Union (EU), and over 30 states in the United States support AVs testing and usage by introducing related legislation (Xu and Fan, 2019). The global market size of AVs is projected to be valued at US$106 billion in 2021 and will be worth about $400 billion in 2050 (Placek, 2021). Although this market is growing rapidly, the adoption of AVs is far from market expectations.

Prior studies have identified various determinants of the success or failure of AVs adoption. The standard theories that previous research applied to investigate the intention to use AVs are TAM (e.g., Wu et al., 2019; Xu et al., 2018), TPB (e.g., Dai et al., 2021; Gkartzonikas et al., 2022), UTAUT (e.g., Madigan et al., 2017, 2016), UTAUT2 (e.g., Kapser and Abdelrahman, 2020; Nordhoff et al., 2020), behavioural reasoning theory (BRT) (Huang and Qian, 2021), cognitive appraisal theory (CAT) (Ribeiro et al., 2022), DOI (Luo et al., 2019; Yuen et al., 2021). However, relatively few studies have employed UTAUT2 to explore factors that influence individuals' acceptance of AVs (e.g., Kapser and Abdelrahman, 2020; Nordhoff et al., 2020). From the methodological perspective, the majority of them has relied on symmetrical analysis (e.g., regression, SEM) (Anania et al., 2018; Ro and Ha, 2019). Table 1 summarizes recent studies dedicated to investigating individuals' acceptance of AVs.

Current research employs UTAUT2 as a theoretical foundation and extends it by adding three factors (trust, image, and compatibility) that can influence AVs adoption. Furthermore, this study applies a two-stage SEM-ANFIS technique to identify and rank the importance of the contributing factors in AVs adoption from both linear and nonlinear perspectives.

2.2. Extended UTAUT2

This research employs UTAUT2 as a key theoretical foundation to investigate the individuals' intention to use and adopt AVs. This theory is an extension of UTAUT and is explicitly developed to identify determinants of technology acceptance from users' perspectives (Venkatesh et al., 2012). UTAUT2 is a synthesis of eight common models for user acceptance research, such as TAM and TPB, to emphasize intrinsic motivation (hedonic value) of technology users. This resulted in the addition of three new factors, such as hedonic motivation, habit, and price value, to the original UTAUT. Compared with UTAUT, the UTAUT2 model has a substantially greater predictive power, capable of explaining roughly 74 percent of the variance in customers' behavioural intentions (Venkatesh et al., 2016). Prior studies have deployed UTAUT2 to investigate behavioural intentions towards new technologies in different settings, such as smartwatch for fitness and health monitoring (Beh et al., 2021), m-health (Dwivedi et al., 2016), mobile payment (Morosan and DeFranco, 2016), mobile commerce (Kalinić et al., 2020), and online banking (Khan et al., 2021). However, relatively few studies have employed UTAUT2 to investigate determinants of AVs adoption (e.g., Kapser and Abdelrahman, 2020; Nordhoff et al., 2020). Hence, this study practically and theoretically justified employing the UTAUT2 as a theoretical lens to assess individuals' AVs adoption.

Although the UTAUT2 has been employed in explaining users' intention to adopt several technologies, some modifications were necessary to fit it into the context of AVs. Even though habit has been proven influential (Venkatesh et al., 2012), it is impossible to evaluate in current research. In order to examine habit, respondents must have a comprehensive understanding of AVs and have used them many times to

Table 1
Summary of recent articles on AVs adoption.

Authors	Theoretical underpinning	Analytical approach	Core findings
Gkartzonikas et al. (2022)	Theory of Planned Behaviour (TPB) & Innovation Diffusion Theory (DOI)	Structural Equation Modelling (SEM)	The synergistic effects between TPB and IDT can better explain the behavioural intention to ride in AVs. the effect of the TBP components is similar across various areas; however, this is not the case for the IDT components.
Ribeiro et al. (2022)	Cognitive Appraisal Theory (CAT) & Artificially Intelligent Device Use Acceptance (AIDUA) model	SEM	Trust is the key predictor of performance expectancy and an influential element to reduce risk perceptions among travellers. Positive emotions can be determined by hedonic motivation and performance expectance, which in turn contribute to AVs adoption.
Huang and Qian (2021)	Behavioural Reasoning Theory (BRT)	SEM	Individuals' reasons have negative (positive) influences against (adopting) AVs. Moderating role of need for uniqueness on the relationship between users' reasoning for AVs and their adoption intention. Moderating role of risk aversion on the relationship between users' reasoning against AVs and their adoption intention.
Launonen et al. (2021)	TPB	Kruskal-Wallis H test and inductive content analysis	Security, safety, and trust are three predictors of individuals' attitude toward using AVs. There are no differences regarding passengers' perceptions of personal security, emergency management, and traffic safety.
Yuen et al. (2021)	TAM & IDT	SEM	Users' behavioural intention to use is predicted by perceived usefulness (PU) and perceived ease of use (PEOU). Perceived characteristics of innovation have a significant effect on both PU and PEOU.
Dai et al. (2021)	TPB	SEM	Experience satisfaction was positively associated with trust, attitude, SN, and PBC. Attitude, PBC, experience satisfaction, and trust mattered to intention to use AV.

(*continued on next page*)

Table 1 (*continued*)

Authors	Theoretical underpinning	Analytical approach	Core findings
Rezaei and Caulfield (2020)	Not specifically stated	Multinominal Logit Regression	Only 20% of respondents expressed high interest in driving AVs. Privacy concerns regarding the recording of driver-data severely diminished participants' level of interest. Participants expressed great uncertainty regarding the safety and security of autonomous vehicles.
Sharma and Mishra (2020)	Not specifically stated	Integrated choice and latent variable modelling	households with high income and frequent car buyers are more likely to adopt connected and autonomous vehicles (CAVs). CAV adoption will positively influence an individual's social values among his peers.
Wu et al. (2019)	TAM	SEM	Environmental concerns, green perceived usefulness, and perceived ease of use have a positive effect on behavioural intention
Ro and Ha (2019)	UTAUT & TRA	EFA, CFA, & SEM	Monetary costs, safety, licensing, ethics, and convenience affect attitudes, while monetary costs, safety, and convenience affect purchasing intentions for AVs.
Acheampong and Cugurullo (2019)	TAM, DOI, TPB	SEM	Social psychological factors impact individuals' perceptions and adoption of AVs. Sociodemographic factors, such as gender, age, and education, also impact the psychological mechanism towards adoption.
Bennett et al. (2019)	Not specifically stated	Regression analysis & structural topical modelling	Internal locus of control and generalized anxiety and internal locus of control can influence three attitude categories (freedom, fear, and curiosity). Fear and freedom influence respondents' willingness to use AVs.
Talebian and Mishra (2018)	DOI & resistance theory	Agent-based modelling	Measures willingness to pay for AVs and addresses how adoption rates can be predicted by marketing and customer satisfaction.
Anania et al. (2018)	Not specifically stated	Multivariate analysis	After hearing positive information about AVs, consumers are more willing to ride in AVs, and after being subject to negative information, they are less willing to ride in AVs. Gender and nationality differences exist.
Ruggeri et al. (2018)	DOI	Chi-square analysis	Patterns of adoption of previous technologies can influence AVs adoption. Older consumers are likely to be later adopters.
Kaur and Rampersad (2018)	UTAUT & TAM	SEM	Trust can be predicted by privacy concerns, security, and reliability. Concerns influence trust. Adoption is driven by the ability of AV to meet trust, and performance expectations are drivers of AVs adoption.
Madigan et al. (2017)	UTAUT	Hierarchical multiple regression	Hedonic motivation is the key driver of behavioural intention to use automated road transport systems (ARTS). Intention to use ARTS also can be driven by facilitating conditions, social influence, and performance expectancy.

develop habitual behaviour. Since AVs have not been regularly available in the Vietnam market, the habit was reasonably excluded from the original model. Furthermore, following the argument mentioned earlier, price value was replaced with price sensitivity. To investigate price value, individuals should know the actual price of AVs and their benefits upfront. Again, at this point of AVs introduction, it is illogical to investigate respondents' price value. However, in prior studies and different markets, the price has been proven critical in AVs adoption (Kapser and Abdelrahman, 2020). Accordingly, price sensitivity associated with individuals' willingness to pay is introduced in current research to address the pricing element (Tsai and LaRose, 2015).

3. Model conceptualisation and hypotheses development

Current research employed the UTAUT2 to investigate the determinants of individuals' intention toward AVs usage and adoption. Moreover, prior studies have pointed out that some influential factors are highly relevant to AVs acceptance. Accordingly, trust, image, and compatibility were incorporated into the model to provide a better understanding of individuals' behaviour toward AVs adoption. Moreover, compatibility was also incorporated as a moderator that may influence the relationship between AVs adoption and its predictors (Fig. 1). In the following, the proposed relationships are discussed in greater detail.

3.1. Performance expectancy

Performance expectancy in the current research is defined as "the degree to which using a technology will provide benefits to consumers" (Venkatesh et al., 2012, p. 159). In this study, performance expectancy refers to what extent AVs can be effective and efficient in completing users' mobility needs (Zhang et al., 2013). Prior research stated that AVs could offer their users several utilitarian benefits, such as time gain

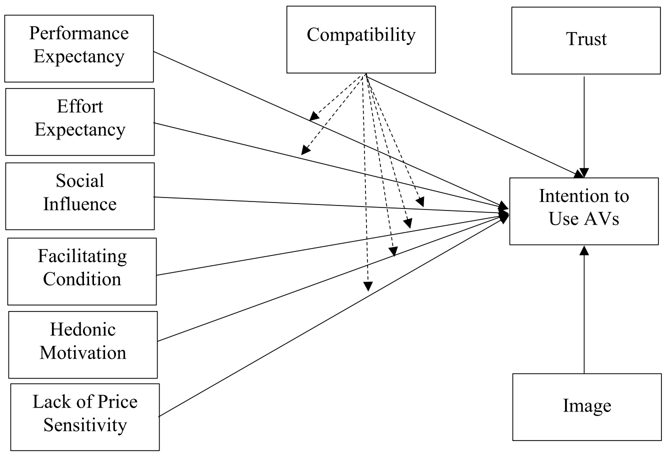

Fig. 1. Proposed conceptual framework.

(Penmetsa et al., 2019). According to Hohenberger et al. (2016), autonomous vehicles have a crucial role in improving traffic flow and reducing travel time, offering their users a time advantage. Furthermore, instead of driving, individuals can be engaged with other activities such as resting or entertaining themselves; consequently, they have more time to devote to other activities/tasks. Based on the above-mentioned argument, the more individuals perceive benefits from AV to have efficient and effective driving, the more they will be encouraged to use AV. Hence, we proposed:

H1. Performance expectancy positively influences intention to use AVs.

3.2. Effort expectancy

Effort expectancy refers to "the degree of ease associated with consumers' use of technology" (Venkatesh et al., 2012, p. 159). Individuals' intention to use technology is likely to increase as it requires less effort to use (Wong et al., 2015). Accordingly, if people feel that an AV is performing all driving-related activities, thus, riding an AV will more likely be perceived as effortless. Since a higher level of effort expectancy is linked to technology adoption, we proposed:

H2. Effort expectancy positively influences intention to use AVs.

3.3. Social influence

Social influence refers to "the extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology" (Venkatesh et al., 2012, p. 159). Consumers generally act in a specific manner in order to satisfy the expectations of their friends, families, relatives, and society (Singh et al., 2020). Before adopting new technologies, individuals evaluate the opinions of friends and family, and they are less likely to accept them if others' opinion is unfavourable. (He et al., 2022). Social influence has been determined as an influential factor in motivating consumers to use AVs (Leicht et al., 2018). These findings imply that social pressure is an important element in compelling individuals to quickly decide and adopt or use new technology to conform to their social communities (Park et al., 2019). Accordingly, we proposed:

H3. Social influence positively influences intention to use AVs.

3.4. Facilitating condition

Facilitating condition is defined as "consumers' perceptions of the resources and support available to perform a behaviour" (Venkatesh et al., 2012, p. 159). Indeed, using AVs usually requires specific knowledge, resources, and skill. Individuals could be more encouraged to use technology if they possess the needed level of resources, knowledge, and supporting devices (Upadhyay et al., 2022). Bearing the perception that consumers have the necessary knowledge and tools to operate technology and the availability of a support system when they have a problem shapes their behavioural intention to use and adopt that technology (Budi et al., 2021). Taken together, in the context of AVs, it is believed that factors such as mobile devices, the internet, help hotlines, and personal knowledge facilitate individuals' adoption of AVs. Therefore, the following hypothesis was proposed:

H4. Facilitating conditions positively influence intention to use AVs.

3.5. Hedonic motivation

Hedonic motivation refers to "the fun or pleasure derived from using a technology" (Venkatesh et al., 2012, p. 161). Hedonism's importance has been recognized particularly with regard to emotion, enjoyment, and fun elicited when individuals interact with new technology (Ribeiro et al., 2022). If users' intrinsic motivations can be satisfied by new technology, they are likely to adopt technology (Lin et al., 2020). The hedonic benefits in the context of AVs can be related to their driving experience, design, aesthetic, entertainment, fun, and exploration (Meyer-Waarden and Cloarec, 2022). Furthermore, the notion of chauffeured driving for individuals who commute along congested roads might evoke feelings of enjoyment (Erskine et al., 2020). As a result, driving an autonomous car can arouse thoughts of experiential hedonism, pleasure, and fun and significantly motivate individuals to use AVs. Hence, in the light of the above evidence, we posited:

H5. Hedonic motivation positively influences intention to use AVs.

3.6. Lack of price sensitivity

Price sensitivity refers to the "way in which buyers react to price changes" (Goldsmith et al., 2005, p. 501). It is "the extent to which a customer accepts a rise in price for a specific product in terms of economic and psychological gains" (Bhutto et al., 2022, p. 68). Consistent with the setting of this research, Kacperski et al. (2021) also described price sensitivity as "willingness to pay more" for autonomous delivery vehicles. In their study, Ng et al. (2018) demonstrated that consumers' purchase intention for electric cars could be driven by price sensitivity. Furthermore, the positive influence of price sensitivity on consumers' purchase intention has been shown in the context of hybrid vehicles (Bhutto et al., 2022). As the price of AVs is higher than driver-controlled cars, consumers' willingness to pay premium prices for AVs emerges as a challenging factor in their purchase behaviour. On the other hand, AVs offer dominant and promising benefits (e.g., minimized driving effort). Consequently, we might expect individuals to have greater price tolerance for using and adopting AVs. Therefore, current research hypothesized that:

H6. Lack of price sensitivity positively influences intention to use AVs.

3.7. Trust

Trust is an essential element in accepting new technology because it can help people overcome the uncertainty of technological advancement (Meyer-Waarden and Cloarec, 2022). It can be defined as "the attitude that an agent will help achieve an individual's goals in a situation characterised by uncertainty and vulnerability" (Lee and See, 2004, p. 51). Trust has been discovered as a vital factor in determining human-automation interaction (Zhang et al., 2019). Over-trusting an automated system can lead to abuse or misuse, whereas distrust in an automated system may result in disuse (Liu et al., 2019). Several studies have supported this argument in the context of AVs (Lee and Kolodge, 2020; Meyer-Waarden and Cloarec, 2022; Yuen et al., 2021). Built-in automated systems control deceleration, acceleration, and steering in AVs. AVs are completely automated cars that do not require human intervention. As a result, individuals must relinquish some control and rely on AVs to perform the driving task safely and reliably (Yuen et al., 2020). Accordingly, trust in systems like automated systems is widely regarded as an essential driver of adoption (Nastjuk et al., 2020). If individuals possess trust in AVs, it signifies that they believe the AV system is understandable and predictable, performs tasks correctly and accurately, and gives users the option of regaining control of their cars at any desired time (Molnar et al., 2018). The existence of these components would increase people's trust and confidence in AVs, leading to their acceptance. Hence, we hypothesized as follow:

H7. Trust in AVs positively influences intention to use AVs.

3.8. *Image*

Image refers to "the degree to which use of an innovation is perceived to enhance one's status in one's social system" (Moore and Benbasat, 1991, p. 195). Prior studies have employed similar terms to explain the identical definition, such as social image (Rejón-Guardia et al., 2020) or self-image (Mijin et al., 2019). The desire to obtain a better social image or respect has been recognized as an effective extrinsic motivator in accepting and using an innovation (Wamba et al., 2017). For specific technologies, gaining social status is the only advantage conveyed by the product to its users (Meyer-Waarden and Cloarec, 2022). It is argued that individuals look for innovative products to establish social differentiation or to gain higher social status (Nie et al., 2020). Therefore, staying up-to-date with adopting AVs as "vehicles of tomorrow" allows individuals to achieve a certain social recognition and status level. It is therefore hypothesized that:

H8. Image positively influences intention to use AVs.

3.9. *Direct and moderating role of compatibility*

Compatibility is defined as "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (Moore and Benbasat, 1991, p. 195). It determines how well an innovation fits into an individual's current social and technical environment (Wang et al., 2018). In this study, compatibility refers to "the extent to which autonomous driving accords with the individual's usual mobility needs and behaviour" (Nastjuk et al., 2020, p. 8). Several studies within various domains have evidenced the influential role of compatibility on people's acceptance of new technology. For instance, in their study, Joia and Altieri (2018) pointed out a positive association between compatibility and individuals' intention to use e-hailing apps. Similar findings can be noticed in the research conducted by Sánchez-Prieto et al. (2019), who confirmed compatibility as one of the main drivers of intention to use mobile learning technologies. These results are in line with the findings of Groβ (2018), who asserted that consumers' behavioural intention for mobile shopping could be driven by compatibility. In the context of the current research, compatibility can be reflected from various points of view. For instance, AVs' benefits for people who care about the natural environment can be consistent with their green lifestyle. For the elderly, the automatic driving systems' easy-to-operate characteristics can fulfil their specific travel requirements. According to the above-mentioned argument, we expect a positive association between compatibility and the intention to use AVs. Thus, the following hypothesize is postulated:

H9. Compatibility positively influences intention to use AVs.

Based on task-technology fit theory, individuals are more likely to employ available technology to accomplish the tasks if technology matches with requirements of tasks (Goodhue and Thompson, 1995). Moreover, the degree of fit between the task and technology determines the level of work outcomes (Wang et al., 2021). High congruence means that potential adopters need to make fewer adjustments to their routines or exert less effort to accept new technology (Yuen et al., 2021). If users believe that AVs fit their lifestyle and their usual mobility behaviours, then they are more likely to consider other benefits of AVs, such as ease of use and higher driving performance. Motivations such as performance expectancy, effort expectancy, social influence, facilitating condition, and hedonic motivation may have less effect on the adoption decision of individuals who believe that AVs are less compatible with their lifestyles. For instance, large households may find AVs are more compatible with their lifestyle as the vehicle needs to go to several pick-up and drop-off locations (Yuen et al., 2020). As such, the performance expectancy of AVs may play a more important role in their decision to adopt AVs. Accordingly, it can be argued that when people consider AVs highly congruent with their present mobility needs and routines, determinants of AVs have a higher influence on their intention to use. Wang et al. (2015) and Wang et al. (2021) found that compatibility moderates the associations between behaviours towards technologies and their determinants. As such, the following hypothesis was structured:

H10. Compatibility positively moderates the influence of (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating condition, (e) hedonic motivation, and (f) lack of price sensitivity on intention to use AVs.

4. Research methods

4.1. *Research instruments*

The present study designed an online survey for data collection. To ensure the content validity of the questionnaire, measurements of the study were adapted from prior research. The items to measure performance expectancy, effort expectancy, and individuals' intention to use AVs were adapted from Lee et al. (2019). Measures of social influence were borrowed from Madigan et al. (2017). Facilitating condition, hedonic motivation, and price sensitivity were measured using the items recommended by Kapser and Abdelrahman (2020). Image, trust, and compatibility were assessed by the measures adapted from Acheampong and Cugurullo (2019), Nastjuk et al. (2020), and Yuen et al. (2020), respectively. All items were measured with a five-point Likert scale anchored by "strongly disagree (=1)" to "strongly agree (=5)". All items can be seen in Table 3. Before commencing the data collection at a large scale, the questionnaire was piloted among 36 potential respondents. The pilot test results showed that Cronbach's α values were above 0.7, indicating the reliability of the questionnaire.

4.2. *Participants and procedure*

Vietnamese who had no AVs in the past and planned to buy a car within the next three years form the population of the study. Using a Google Form, data were gathered via an online questionnaire. We posted the link to the online survey on Facebook pages with Vietnamese members and asked the participants to share the questionnaire with their Vietnamese friends via their Facebook accounts. Two filtering questions were included to ensure the respondents (1) had not owned an AV in the past and (2) were planning to purchase a vehicle within the next three years. An information page was provided to explain a concise description of AVs in general and the type of AVs we are referring to in our survey to ensure a common understanding between responses received. Particularly, the term "self-driving cars" was used to describe fully AVs. Its definition was based on the SAE International (2018) for vehicles with level-5 automation (full driving automation): "self-driving

Table 2
Full collinearity analysis.

	PE	EE	SI	FC	HM	PC	TR	COMP	IM	INT
VIF	2.083	2.109	1.696	2.339	1.807	1.821	1.136	2.228	1.982	2.517

Note(s): PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, HM = Hedonic Motivation, PC = Price Sensitivity, TR = Trust, COMP = Compatibility, IM = Image, INT = Intention.

cars can drive themselves everywhere in all conditions without any human interaction. A self-driving car is neither bound by geofencing nor affected by weather and transports human beings comfortably and efficiently without requiring a driver. The only human involvement will be to set a destination". The research drew on a sample of 378, of which 48.1% (182) were male and 51.9% (196) were female. A total of 131 (34.7%) respondents were 18–25 years old, 101 (26.7%) were 26–35 years old, 88 (23.3%) were 35–45 years old, and 58 (15.3%) were above 46 years old. Respondents with a bachelor's degree form 64.3% of the sample, followed by a master's degree (27.2%), schooling education (5%), and Ph.D. (3.4%). Since data were gathered from a single source, thus, the current research evaluated common method bias (CMB). We evaluated the full collinearity suggested by Kock and Lynn (2012) to assess the CMB. As indicated in Table 2, the variance inflation factor (VIF) for all variables is below 3.3, specifying that CMB was not a concern.

5. Data analysis

The current research employed both symmetric and asymmetric approaches to examine the significance of proposed relationships. For symmetric analysis, partial least squares (PLS) was applied. The PLS was chosen because it corresponds well to the characteristics of the collected data (non-normal data) (Hair and Sarstedt, 2011), the predictive nature of the research, and the complexity of the model (Hair et al., 2019). The study evaluated multi-variate normality using the online tool named Web Power. The results indicated that the gathered data are not multi-variate normal with Mardia's multi-variate skewness ($b = 8.5051$, $p < 0.01$) and kurtosis ($b = 73.919$, $p < 0.01$), fortifying the logical for choosing PLS-SEM.

Although employing PLS-SEM helps researchers uncover major determinants of an outcome of interest and general tendencies, it over-simplifies the complicated decision-making process and overlooks the possibility of nonlinear relationships (Ahani et al., 2017). In order to overcome this drawback, prior studies have recommended the application of soft computing techniques as the complementary approach to PLS-SEM (Yadegaridehkordi et al., 2018; Sharma et al., 2016). Accordingly, the current study employs a two-stage SEM-ANFIS methodology to figure out both the linear and the potential nonlinear relationships that may impact the results and deepen our understanding of elements contributing to individuals' acceptance and intention to use AVs. PLS-SEM was employed to evaluate the proposed relationships. The confirmed direct relationships were further analysed using ANFIS.

5.1. PLS-SEM results

5.1.1. Assessment of measurement model

To assess the measurement model, convergent validity and discriminant validity were tested. Hair et al. (2017) suggested that convergent validity is confirmed if the loadings, the average variance explained (AVE), and the composite reliability (CR) are greater than 0.7, 0.5, and 0.7, respectively. The loadings of all items, except PS2 (0.699), PS3 (0.650), and PS5 (0.663), are higher than 0.7 (Table 3). All AVE and CR values are higher than the proposed thresholds. Although the loading of PS2, PS3, and PS5 are slightly lower than the suggested value of 0.7, these items are retained due to the satisfactory level of AVE and CR (Jozef et al., 2019).

The study examined discriminant validity using the heterotrait-monotrait ratio (HTMT). The results indicated that the HTMT values are below 0.9 (Iranmanesh et al., 2022; Kline, 2016), indicating discriminant validity was fulfilled (Table 4).

5.1.2. Structural model assessment

The variance explained (R^2) value of endogenous construct was higher than 0.10 (Falk and Miller, 1992), specifying that the research framework has the ability to explain sufficient variance in behavioural intention to adopt (BI) AVs ($R^2_{INT} = 0.641$). Using the blindfolding procedure, the result indicated that the predictive relevance Q^2 value of BI ($Q^2_{INT} = 0.469$) was higher than zero, indicating that the research exhibits predictive relevance (Fornell and Cha, 1994; Foroughi et al., 2022). We used non-parametric bootstrapping to test the proposed hypotheses. According to the results, effort expectancy ($\beta = 0.176$; $p < 0.01$), hedonic motivation ($\beta = 0.241$; $p < 0.001$), trust ($\beta = 0.361$; $p < 0.001$), and compatibility ($\beta = 0.148$; $p < 0.05$) were the significant drivers of behavioural intention to adopt AVs. In contrast to our assumption, the direct influence of performance expectancy ($\beta = 0.080$; $p > 0.05$), social influence ($\beta = -0.137$; $p < 0.05$), facilitating condition ($\beta = -0.049$; $p > 0.05$), price sensitivity ($\beta = 0.017$; $p > 0.05$), and image ($\beta = -0.039$; $p > 0.05$) on behavioural intention to use AVs does not reach significance. The summary of the findings of this study can be seen in Table 5.

The two-stage approach was applied to assess the moderating effect of compatibility. Based on the findings, compatibility ($\beta = 0.103$; $p < 0.05$) positively moderates the relationship between perceived expectancy and intention to use AVs. However, the moderating role of compatibility on the influences of other determinants was not supported. Fig. 2 depicts that performance expectancy positively affects the intention to use AVs of individuals with a high level of perceived compatibility and almost has no effect on the intention of individuals with a low level of perceived compatibility.

5.2. ANFIS results

This study used ANFIS as a complementary method to PLS. The ANFIS method enables the identification of nonlinear relationships, the prediction of outcomes, and the ranking of input variables (Roham et al., 2012). ANFIS combines fuzzy logic and neural network to deal with nonlinear relationships (Khoshnevisan et al., 2014). However, for testing causal relationships and developing theories, ANFIS is not an appropriate technique (Liébana-Cabanillas et al., 2017). Accordingly, we used ANFIS and PLS-SEM together as complementary techniques in this study. We used MATLAB software to run ANFIS.

The significant determinants in PLS were used as inputs for ANFIS to explain the nonlinear relationship between determinants and intention to use AVs, identify the importance level of determinants, and predict the intention to use AVs. Inputs[1] were fuzzified using Gaussian Membership Functions (MFs) (Boyacioglu and Avci, 2010). The responses on a 5-point Likert scale were converted to low, moderate, and high linguistics terms. Fig. 3 demonstrates the non-linear relationships between determinants and intention to use AVEs. The inputs for determinants and defied MFs for intention to use AVEs were used to train the ANFIS model using 200 epochs. The slops of the lines in Fig. 3 illustrate the influence of determinants at different input values. According to the results, trust is the most important driver, followed by hedonic motivation, social influence, compatibility, and effort expectancy. It is worthwhile to highlight that the influence of trust is less when its value

Table 3
Measurement model evaluation.

Constructs	Items	Loadings	CR	AVE
Performance Expectancy (PE)	Using an autonomous vehicle would enhance my driving effectiveness.	0.875	0.922	0.747
	Using an autonomous vehicle would increase my productivity.	0.839		
	Using an autonomous vehicle would enhance my driving performance.	0.881		
	I would find an autonomous vehicle is useful.	0.861		
Effort Expectancy (EE)	Interacting with an autonomous vehicle would be clear and understandable.	0.741	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.	0.859		
	Learning to operate an autonomous vehicle would be easy for me.	0.841		
Social Influence (SI)	People who are important to me think that I should use autonomous vehicles.	0.885	0.919	0.741
	People who influence my behaviour think that I should use autonomous vehicles.	0.862		
	People whose opinions I value would like me to use autonomous vehicles.	0.844		
	In general, the authority would support the use of autonomous vehicles.	0.851		
Facilitating Condition (FC)	I have the resources necessary to use autonomous vehicles (i.e., mobile devices).	0.826	0.887	0.663
	I have the knowledge necessary to use autonomous vehicles.	0.776		
	Autonomous vehicles are compatible with other technologies I use (e.g., smartphones).	0.797		
	I can get help from others when I have difficulties using autonomous vehicles.	0.856		
Hedonic Motivation (HM)	Using autonomous vehicles would be fun.	0.895	0.903	0.756
	Using autonomous vehicles would be enjoyable.	0.872		
	Using autonomous vehicles would be very entertaining	0.841		
Lack of Price Sensitivity (PS)	I would not mind paying more to use autonomous vehicles.	0.868	0.852	0.538
	I would not mind spending a lot of money to use autonomous vehicles.	0.699		
	I would be less willing to pay for autonomous vehicles if I thought it to be high in price.	0.650		
	If using autonomous vehicles are likely to be more expensive than conventional vehicles, that would not matter to me.	0.765		
	A really great transportation option would be worth paying a lot of money for.	0.663		
Trust (TR)	I trust that autonomous vehicles can drive without assistance from me.	0.781	0.920	0.658
	I trust autonomous vehicles to be safe and reliable in severe weather conditions.	0.840		
	I would trust the driving skills of autonomous vehicles more than my own driving skills.	0.764		
	Autonomous vehicles can be trusted to carry out journeys effectively.	0.884		
	My trust in autonomous vehicles will be based on the car manufacturer's reputation for safety and reliability.	0.816		
	My trust in autonomous vehicles will be based on the reliability of the underlying technologies.	0.774		
Image (IM)	Travelling in an autonomous vehicle, I would gain respect and recognition in my community	0.950	0.942	0.890
	Travelling in an autonomous vehicle, I would gain respect and recognition among my friends and colleagues	0.937		
Compatibility (COMP)	Using autonomous vehicles would be compatible with my mobility behaviour.	0.921	0.891	0.733
	I think using autonomous vehicles would not fit well into mobility behaviour.	0.812		
	I think using autonomous vehicles is compatible with all aspects of my mobility behaviour.	0.831		
Intention to Use AVs (INT)	Assuming I have access to an autonomous vehicle, I would intend to use it.	0.897	0.913	0.779
	Given I have access to an autonomous vehicle, I predict I would use it.	0.846		
	In the future, I would not hesitate to use an autonomous vehicle	0.904		

Note. CR: Composite Reliability; AVE: Average Variance Extracted.

is low (between 1 and 4) in comparison to the time the value of trust is more than 4. It means that although trust is the most important factor, a minimum level of trust is required to adopt AVs. Furthermore, the effect of compatibility between the values of 3 and 5 is less than the time that its values are between 1 and 3. Accordingly, the medium level of compatibility is sufficient, and high efforts and investment in enhancing the compatibility level of AVs may not lead to higher adoption. The association between social influence and intention to use AVs is positive, whereas PLS results showed a negative association.

As psychological factors are interrelated, we generated 3D plots to identify the relationships between every two determinants and intention to use AVs (Fig. 4). The results reveal that the influence of each determinant on intention to use AVs depends on other determinants. Furthermore, 3D results provide an explanation for contradictory findings on the influence of social influence between PLS and ANFIS results. At a low level of hedonic motivation and a high value of trust, social influence positively influences the intention to use when its value is less than 3.5, and it has a negative influence at values higher than 3.5. It indicates that the positive or negative influences of social value depend on other factors.

6. Discussion

Current research attempts to validate the UTAUT2 model to

Table 4
Heterotrait-monotrait (HTMT).

	PE	EE	SI	FC	HM	PS	TR	IM	INT	COMP
PE										
EE	0.824									
SI	0.735	0.746								
FC	0.808	0.832	0.813							
HM	0.831	0.826	0.717	0.807						
PS	0.308	0.298	0.167	0.243	0.347					
TR	0.790	0.798	0.791	0.828	0.766	0.229				
IM	0.569	0.537	0.627	0.592	0.603	0.204	0.691			
INT	0.749	0.799	0.581	0.725	0.797	0.203	0.816	0.530		
COMP	0.691	0.728	0.722	0.748	0.739	0.179	0.814	0.768	0.732	

Note(s): PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Condition, HM = Hedonic Motivation, PC = Price Sensitivity, TR = Trust, COMP = Compatibility, IM = Image, INT = Intention.

Table 5
Path coefficients and hypotheses testing.

Hypotheses	Relationships	Path Coefficients	STD	T Values	P Values	Decisions
Main Model						
H1	PE - > INT	0.080	0.062	1.283	0.100	Not Supported
H2	EE - > INT	0.176	0.060	2.926	0.002**	Supported
H3	SI - > INT	−0.137	0.053	2.559	0.005**	Not Supported
H4	FC - > INT	−0.049	0.064	0.771	0.220	Not Supported
H5	HM - > INT	0.241	0.057	4.241	0.000***	Supported
H6	PS - > INT	0.017	0.034	0.507	0.306	Not Supported
H7	TR - > INT	0.361	0.058	6.222	0.000***	Supported
H8	IMG - > INT	−0.039	0.049	0.798	0.212	Not Supported
H9	COMP - > INT	0.148	0.053	2.809	0.003**	Supported
Moderating Effect of Compatibility						
H10a	PE*COMP - > INT	0.103	0.061	1.675	0.047*	Supported
H10b	EE*COMP - > INT	−0.065	0.051	1.271	0.102	Not Supported
H10c	SI*COMP - > INT	−0.038	0.061	0.632	0.264	Not Supported
H10d	FC*COMP - > INT	−0.144	0.073	1.969	0.025*	Not Supported
H10e	HM*COMP - > INT	0.031	0.074	0.418	0.338	Not Supported
H10f	PS*COMP - > INT	0.014	0.036	0.387	0.349	Not Supported

Note. *p < 0.05; **p < 0.01; ***p < 0.001.

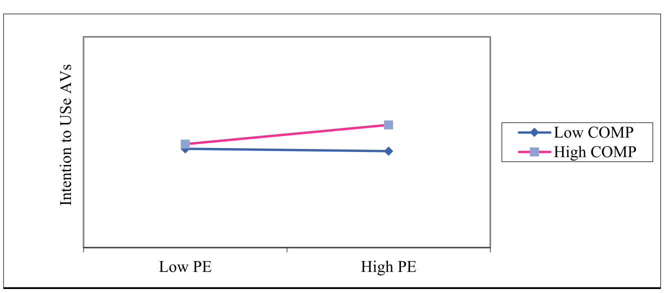

Fig. 2. Moderating effect of compatibility.

understand the determinants of intention to use AVs. Price sensitivity, trust, compatibility, and image were further included in the original model to tailor it to the context of Avs. Furthermore, current research explored the moderating role of compatibility. The findings of PLS showed that effort expectancy, social influence, hedonic motivation, compatibility, and trust significantly affect the intention to use AVs. According to ANFIS, trust is the most important determinant of using AVs, followed by hedonic motivation, social influence, compatibility, and effort expectancy.

The findings revealed that there was no significant association between performance expectancy and intention to adopt AVs, which is inconsistent with the results of Kacperski et al. (2021) and Penmetsa et al. (2019). This finding implies that individuals in Vietnam are impacted by factors other than performance expectancy when it comes to adopting AVs. It means that regardless of their perception about the extent to which AVs may enhance driving performance and effectiveness, individuals may or may not be encouraged to accept and use AVs. A plausible reason for this finding can be due to the lack of marketing communication and proper knowledge of the benefits of AVs in Vietnam, given that they are still considered a new technology worldwide. Furthermore, if individuals do not have enough experience using a specific technology (e.g., AVs), they will not care or realize its outcomes or benefits (Loureiro et al., 2018). The insignificant association between performance expectancy and behavioural intention has been found in some other contexts, such as e-learning (Mailizar et al., 2021) and the Internet of Things (IoT) in the medical context (Arfi et al., 2021).

In alignment with the findings of Madigan et al. (2017) and Leicht et al. (2018), current research confirms the predicting role of effort expectancy in AV adoption. This result is inconsistent with the finding of Kapser and Abdelrahman (2020) in a developed country, who found an insignificant relationship between effort expectancy and AV adoption in Germany. As AVs are operated via a mobile app and people in developed countries consider themselves to be experienced in the use of similar applications such as electric bike (e-bike) apps and electric scooter (e-scooter) apps, effort expectancy plays a less important role in shaping their intention to adopt AVs compared to developing ones. This result suggests that Vietnamese care about the required efforts to use AVs. It means the notion that lower effort in using AVs may lead to a higher propensity to adopt AVs. As such, AVs should be carefully designed to require the least effort from users to navigate. Hence, carmakers should aim to design AVs that are easy to use and user-friendly to sustain the positive intention of AV users.

The PLS results posited a significant but negative influence of social influence on AVs adoption, which is contrary to the previous research

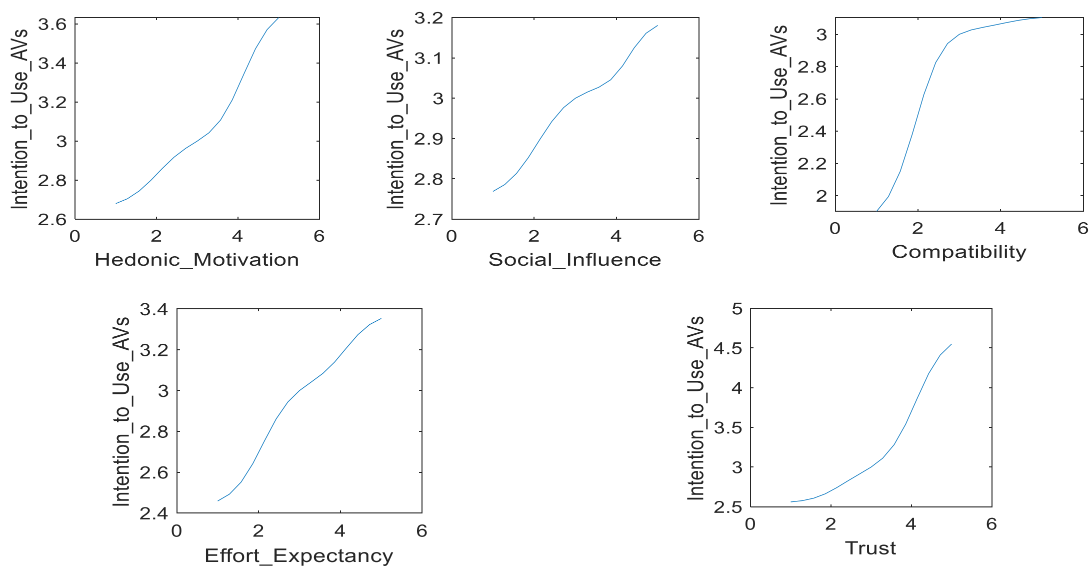

Fig. 3. The importance of determinants of intention to use AVs.

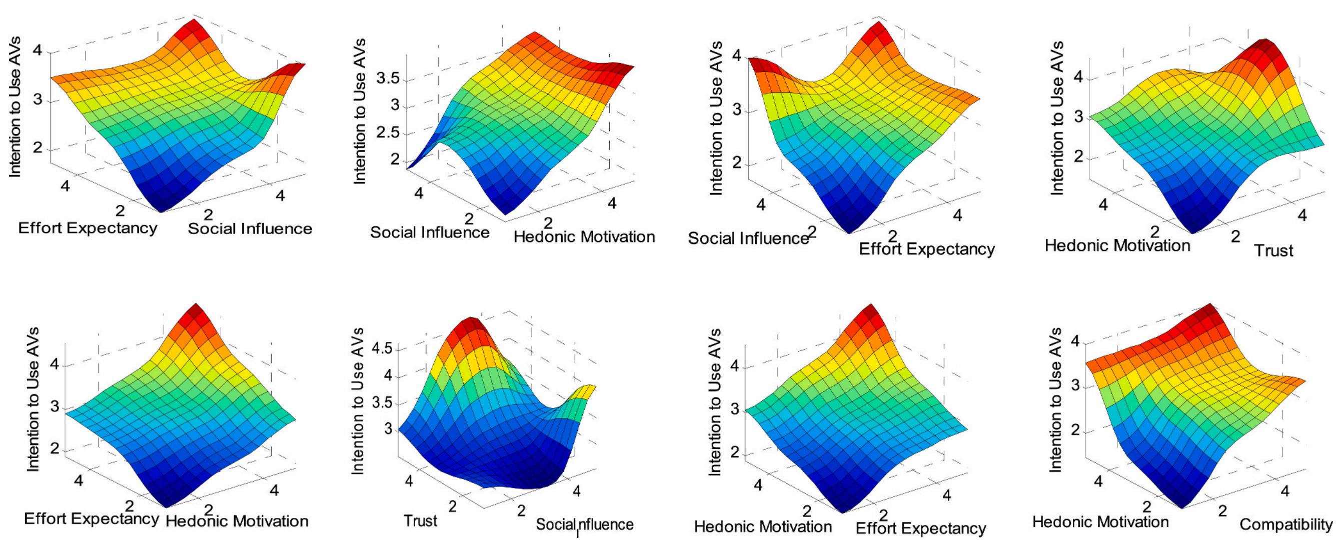

Fig. 4. The relationships between determinants and intention to use AVs.

that affirmed that social influence has a positive effect on the intention to adopt AVs (e.g., Buckley et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018). However, the 2D plots of ANFIS showed a positive association between social influence and the intention to adopt AVs. The contractive result between PLS and ANFIS approaches can be explained by referring to 3D plots. Based on these plots, the influence of social influence is more look like a bell curve. When hedonic motivation is low, and trust is high, social influence has a positive effect in the social value range of 1–3.5 and has a negative influence in the range of 3.5–5. It indicates that when individuals have high trust in AVs and do not find it an enjoyable experience, a medium level of social influence positively influences their decision to use AVs. However, in this circumstance, a high social influence can adversely influence the intention to use AVs. It means that when individuals have high trust and low hedonic motivation, a medium level of support and favourable opinion of friends, family, and society may form the feeling that using AVs is a wise decision. However, when individuals have high trust in AVs, they may think that a very high level of favourable opinion of society about AVs is because AVs are highly trustworthy. So, as they also have other expectations from AVs, strong social influence negatively influences their decision. Furthermore, when people have low hedonic motivation, they may interpret a strong social influence as a mere rational choice, and as hedonic factors are also important for them, high social influence negatively influences their decision.

In contrast to our expectation, facilitating condition is insignificant in predicting the intention to use AVs. This result is also inconsistent with the prior studies in the context of AVs, which pointed out that facilitating condition plays a significant role in encouraging people to accept and use AVs (Madigan et al., 2017; Park et al., 2021). Facilitating conditions in the AVs context includes the necessary knowledge, resources, and help (in difficult situations) for individuals to use AVs. One plausible explanation for the insignificant role of facilitating conditions may be due to the increased use of mobile devices (as a required resource) and mobile applications. With 63.1% of the population possessing a smartphone, Vietnam has among the highest smartphone penetration rates in the world (BankMyCell, 2022). Generally, Vietnamese are highly familiar with mobile apps and platforms to operate AVs. Hence, the facilitating condition is no longer necessary for them to adopt AVs. This result is further supported by Gao et al. (2015), who asserted that m-health apps usage could not be influenced by facilitation conditions due to the advancement of smartphone interfaces.

Hedonic motivation is found to be significant in explaining the behavioural intention to adopt AVs, which is consistent with the findings of Keszey (2020), Moták et al. (2017), and Kacperski et al. (2021) who found that hedonic motivation is an influential factor in predicting intention to use AVs. ANFIS result revealed that among UTAUT2 factors, hedonic motivation is the most important one. As a result, it appears that the entertainment and fun obtained from using AVs are critical in determining user acceptance. As a result, if AV marketers promote hedonic consumption among individual users, people are more inclined to accept and use AVs. Certainly, breakthrough technologies like AVs can foster aspects of hedonic motivation, resulting in enjoyment and a stronger desire to accept and use the technology.

For the lack of price sensitivity, the current study postulated that AVs adoption could not be influenced by the lack of price sensitivity, which is in contradict the findings of Kapser and Abdelrahman (2020) and Kacperski et al. (2021), who asserted that price sensitivity could negatively contribute to the behavioural intention to use autonomous delivery vehicles. This result implies that individuals value other advantages of AVs, such as increased users' satisfaction, safety, and security, decreased car accident and environmental footprint, lane departure warning systems, automatics paring, and collision avoidance, more than the cost advantage (Baccarella et al., 2021; Cugurullo et al., 2021). They may be less price-sensitive as, in the long term, AVs can reduce their costs by reducing car accidents and enhancing fuel consumption efficiency. Furthermore, other values of AVs, such as improving urban life, reducing traffic congestion, reducing greenhouse gas emissions, and enhancing roadway safety, may reduce the sensitivity to price.

The finding of PLS confirmed that trust influences intention to use AVs and, hence, is congruent with prior research in the literature (e.g., Nastjuk et al., 2020; Panagiotopoulos and Dimitrakopoulos, 2018). ANFIS results revealed that not only trust is a significant factor, but also it is the most important determinant. Trust towards autonomous vehicles is developed when AVs perform tasks correctly and accurately, are predictable and understandable, and allow users to regain control of the cars whenever they want; users develop trust towards them (Yuen et al., 2020). This can bolster individuals' confidence in the use of AVs, leading to their acceptance. The bad news about the safety and security of AVs may destroy the trust of people and lead to a less positive evaluation of AVs.

Contrary to our expectation, the image was not significantly correlated with the intention to use AVs. This result is inconsistent with prior studies that confirmed the meaningful link between image and individuals' intention to adopt AVs (e.g., Meyer-Waarden and Cloarec, 2022; Yuen et al., 2021) and, conversely, is in line with the finding of Acheampong et al. (2021). Our research findings suggest that reputational benefits have no impact on their adoption intentions. One potential explanation for the above finding is that since AVs are not commercially introduced and available in the market, the use of AVs is not considered a powerful common concept that can help individuals capture status benefits. Consistent with Yuen et al. (2020) and Nastjuk et al. (2020), our finding confirmed the role of compatibility as a significant predictor of AVs adoption. This suggests that if using AVs is compatible with individuals' mobility needs and routines, they are more likely to accept and use AVs. Moreover, this result backs up the argument that if innovation is considered a "radical departure" from the current needs and approaches to decision-making, it is less likely to be implemented (Lee and Blouin, 2019).

Finally, our result confirmed the moderating role of compatibility on the association between performance expectancy and AVs adoption. The finding indicates that performance expectancy positively influences intention to use AVs when people find AVs as a compatible system and has no effect when people believe AVs are not compatible with their mobility behaviour (Fig. 2). It means enhancing driving effectiveness and performance is important when people find AVs compatible. As such, the insignificant direct effect of performance expectancy should not be interpreted as a lack of importance of the extent to which AVs enhance driving effectiveness and performance. When AVs are not compatible, their contribution to driving performance may not lead to adoption. It means lack of compatibility may offset the influence of performance expectancy, and people decide not to adopt AVs regardless of the extent to which AVs may enhance their driving effectiveness.

7. Overall contributions

7.1. Theoretical implications

The current study addresses a major limitation of previous research on AVs adoption, as stated by Gkartzonikas and Gkritza (2019): "studies have investigated the likelihood that AVs [autonomous vehicles] will be adopted and the process by which that might happen, the questions included in those studies' respective surveys have not been based on well-established theories" (p. 335). Extant literature studying the elements that drive the uptake of AVs has drawn heavily on DOI, UTAUT, TRA, TPB, TAM, and other related models to technology adoption to investigate individuals' beliefs and perceptions. The present research advances the contemporary knowledge on AVs adoption based on the foundations of the well-established UTAUT2 model, unlocking variables accountable for a richer understanding of autonomous driving acceptance. Although the UTAUT2 has been employed in explaining users' intention to adopt several technologies, some modifications and extensions were necessary to fit it into the context of AVs. To do so, we incorporated compatibility, trust, and image as extensions to the original UTAUT2 model and modified price value to price sensitivity. The findings confirmed the importance of contextual factors (trust and compatibility) besides UTAUT2 factors (effort expectancy, social influence, and hedonic motivation). This integrated model can demonstrate a greater explanatory power in predicting individuals' behavioural intention to use AVs. Moreover, we tested the moderating role of compatibility on the relationships between AVs adoption and its determinants in the UTAUT2 model. It is worth mentioning that compatibility moderated the relationship between performance expectancy and individuals' behavioural intention to use AVs. Even though UTAUT2 was developed to investigate the acceptance of consumer technologies, to the best of our knowledge, no study could be identified that utilised UTAUT2 in the Eastern cultural context to discover the determinants of AVs. Thus, some of the constructs investigated in the present research have been found to account for some variance in user intentions to use AV in a Vietnamese sample.

Besides, the present research integrated PLS and ANFIS to investigate the adoption of AVs, thereby contributing to the advancement of methodology in technology adoption research. Such a combination can appropriately overcome the weaknesses of PLS and ANFIS while maintaining accurate prediction of performance. The findings of ANFIS showed that the associations between determinants and AVs are not linear. These findings indicate that the results of the previous studies, which assumed that the relationships between determinants and adoption intention are linear, are not trustworthy and reliable. Furthermore, the findings illustrated that the determinants are interrelated, and their influence on intention to use AVs depends on the values of other factors. As such, the findings of this study provide a more precise picture of the associations between the intention to use AVs and its determinants in comparison to the previous studies.

7.2. Practical implications

From a practical perspective, current research provides valuable insights on key predictors of AVs adoption to carmakers, technology developers, and practitioners, assisting them in devising effective AVs-related strategies to encourage the public to adopt AVs. The finding revealed that trust in AVs is a vital pre-condition and the most imperative factor in predicting individuals' acceptance and adoption of AVs. Defining self-driving maturity standards with an independent, certified quality label endorsed by authorities could improve AVs carmakers' brand image and, as a result, be effective in fostering trust in AVs. Furthermore, Nastjuk et al. (2020) affirmed that being transparent about the functionality of technology can build a strong foundation for trust in it. Furthermore, Nastjuk et al. (2020) proved that being transparent about the functionality of technology can build a strong foundation for trust in it. Thus, manufacturers and policymakers could furnish the public with transparent information regarding the AVs' functionality that is simply available and accessible to the general public. Test drives can assist in forming or improving trust in AVs, and policymakers should collaborate with fleets operators and manufacturers to promote and encourage supervised test zones outside real-traffic territories. Such test zones may be beneficial in overcoming trust barriers, as it is shown that the initial encounters with AVs are related to a sense of unease because of the transfer of control from the driver to the car (Nunez, 2017). Effort expectancy was found to have an important role in explaining individuals' behavioural intention towards acceptance and usage of AVs. This recommends that AV designers not overlook the required efforts to operate AVs. Instead, they should strive to simplify and clarify the human-automation interactions. The hedonic motivation was also significant in determining users' acceptance of AVs. Developers and designers of AVs should concentrate on the hedonic elements for prototype improvement and incorporate features and aspects of the technology that are truly entertaining and enjoyable. Compatibility is identified as a factor that contributes a significant amount of strength to AVs acceptance. AVs should be promoted and marketed in ways that align with the public's lifestyle, existing values, mobility, and transport needs to make them more appealing and enhance their public acceptability. AVs can be explicitly targeted at pro-environmental individuals, active households, and working professionals who may find AVs a better-suited alternative to their mobility needs.

8. Conclusions

The current research extends and modifies the UTAUT2 model to predict individuals' behavioural intention toward AVs adoption by incorporating context-related factors, namely lack of price sensitivity, compatibility, trust, and image. Moreover, the moderating role of compatibility was tested on the relationships between AVs adoption and its drivers. We evaluated the proposed hypotheses with a two-stage SEM-ANFIS approach. The findings revealed that effort expectancy, hedonic motivation, compatibility, and trust are critical in motivating people to accept and use AVs. According to the results, trust in AVs is identified as the strongest predictor of AVs adoption. Furthermore, compatibility positively moderates the influence of performance expectancy on the acceptance and use of AVs. The results contribute to the current knowledge on autonomous driving by extending the UTAUT2 model to identify the influential factors contributing to AVs adoption, evaluate the importance of determinants, and demonstrate the interrelationship among constructs. Furthermore, current research provides valuable insights to carmakers, technology developers, and practitioners, assisting them in devising effective AVs-related strategies.

The present research is bounded in several ways. The study's first limitation is its geographical restriction, as it was conducted in Vietnam, which is a developing country. Future research can apply the proposed model in different contexts (e.g., developed and non-Asian countries) to validate the generalizability of the findings. Any disparities in the findings would encourage strategies and policies that are tailored to each context to enhance automated vehicle acceptance. The current study has developed a research model based on only one theoretical lens, namely UAUT2, to determine individuals' AVs adoption. Future studies can apply and integrate other technology adoption theories such as TAM3 or IDT to explain individuals' intention to accept and use AVs. The present study employed a hybrid approach by integrating variance-based SEM and ANFIS. Future studies in AVs adoption can employ covariance-based SEM such as AMOS and decision-making techniques to sheds further light on the understanding of factors that pertain to AVs acceptance. This study extended the UTAUT2 model by incorporating compatibility, trust, and image. Future research can include other potential factors that may influence AVs adoption, such as privacy, security (Kacperski et al., 2021), anxiety (Tan et al., 2022), and innovativeness (McLeay et al., 2022), and extend the findings of this research.

Data availability

Data will be made available on request.

References

Acheampong, R.A., Cugurullo, F., 2019. Capturing the behavioural determinants behind the adoption of autonomous vehicles: conceptual frameworks and measurement models to predict public transport, sharing and ownership trends of self-driving cars. Transport. Res. part F traffic Psychol. Behav. 62, 349–375.

Acheampong, R.A., Cugurullo, F., Gueriau, M., Dusparic, I., 2021. Can autonomous vehicles enable sustainable mobility in future cities? Insights and policy challenges from user preferences over different urban transport options. Cities 112, 103134.

Ahani, A., Rahim, N.Z.A., Nilashi, M., 2017. Forecasting social CRM adoption in SMEs: a combined SEM-neural network method. Comput. Hum. Behav. 75, 560–578.

Anania, E.C., Rice, S., Walters, N.W., Pierce, M., Winter, S.R., Milner, M.N., 2018. The effects of positive and negative information on consumers' willingness to ride in a driverless vehicle. Transp. policy 72, 218–224.

Arfi, W.Ben, Nasr, I.Ben, Kondrateva, G., Hikkerova, L., 2021. The role of trust in intention to use the IoT in eHealth: application of the modified UTAUT in a consumer context. Technol. Forecast. Soc. Change 167, 120688.

Baccarella, C.V., Wagner, T.F., Scheiner, C.W., Maier, L., Voigt, K.-I., 2021. Investigating consumer acceptance of autonomous technologies: the case of self-driving automobiles. Eur. J. Innovat. Manag. 24, 1210–1232.

BankMyCell, 2022. How Many People Have Smartphones Worldwide [WWW Document]. https://www.bankmycell.com/blog/how-many-phones-are-in-the-world. accessed 02.24.2022.

Beh, P.K., Ganesan, Y., Iranmanesh, M., Foroughi, B., 2021. Using smartwatches for fitness and health monitoring: the UTAUT2 combined with threat appraisal as moderators. Behav. Inf. Technol. 40, 282–299.

Benleulmi, A.Z., Ramdani, B., 2022. Behavioural intention to use fully autonomous vehicles: instrumental, symbolic, and affective motives. Transport. Res. part F traffic Psychol. Behav. 86, 226–237.

Bennett, R., Vijaygopal, R., Kottasz, R., 2020. Willingness of people who are blind to accept autonomous vehicles: an empirical investigation. Transport. Res. part F traffic Psychol. Behav. 69, 13–27.

Bennett, R., Vijaygopal, R., Kottasz, R., 2019. Willingness of people with mental health disabilities to travel in driverless vehicles. J. Transport Heal. 12, 1–12.

Bhutto, M.H., Tariq, B., Azhar, S., Ahmed, K., Khuwaja, F.M., Han, H., 2022. Predicting consumer purchase intention toward hybrid vehicles: testing the moderating role of price sensitivity. Eur. Bus. Rev. 34, 62–84.

Boyacioglu, M.A., Avci, D., 2010. An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: the case of the istanbul stock exchange. Expert Syst. Appl. 37, 7908–7912.

Buckley, L., Kaye, S.-A., Pradhan, A.K., 2018. Psychosocial factors associated with intended use of automated vehicles: a simulated driving study. Accid. Anal. Prev. 115, 202–208.

Budi, N.F.A., Adnan, H.R., Firmansyah, F., Hidayanto, A.N., Kurnia, S., Purwandari, B., 2021. Why do people want to use location-based application for emergency situations? The extension of UTAUT perspectives. Technol. Soc. 65, 101480.

Choi, J.K., Ji, Y.G., 2015. Investigating the importance of trust on adopting an autonomous vehicle. Int. J. Hum. Comput. Interact. 31, 692–702.

Chopdar, P.K., Korfiatis, N., Sivakumar, V.J., Lytras, M.D., 2018. Mobile shopping apps adoption and perceived risks: a cross-country perspective utilizing the Unified Theory of Acceptance and Use of Technology. Comput. Hum. Behav. 86, 109–128.

Cugurullo, F., Acheampong, R.A., Gueriau, M., Dusparic, I., 2021. The transition to autonomous cars, the redesign of cities and the future of urban sustainability. Urban Geogr. 42, 833–859.

Dai, J., Li, R., Liu, Z., 2021. Does initial experience affect consumers' intention to use autonomous vehicles? Evidence from a field experiment in Beijing. Accid. Anal. Prev. 149, 105778.

Dwivedi, Y.K., Shareef, M.A., Simintiras, A.C., Lal, B., Weerakkody, V., 2016. A generalised adoption model for services: a cross-country comparison of mobile health (m-health). Govern. Inf. Q. 33, 174–187.

Erskine, M.A., Brooks, S., Greer, T.H., Apigian, C., 2020. From driver assistance to fully-autonomous: examining consumer acceptance of autonomous vehicle technologies. J. Consum. Market. 37, 883–894.

Fagnant, D.J., Kockelman, K., 2015. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transport. Res. Part A Policy Pract. 77, 167–181.

Falk, R.F., Miller, N.B., 1992. A Primer for Soft Modeling. University of Akron Press, AKron, OH.
Fornell, C., Cha, J., 1994. Partial least squares. In: Bagozzi, R.P. (Ed.), Advanced Method of Marketing Research. Blackwell, Cambridge, MA, pp. 52–78.
Foroughi, B., Arjuna, N., Iranmanesh, M., Kumar, K.M., Tseng, M.-L., Leung, N., 2022. Determinants of hotel guests' pro-environmental behaviour: past behaviour as moderator. Int. J. Hospit. Manag. 102, 103167.
Gao, Y., Li, H., Luo, Y., 2015. An empirical study of wearable technology acceptance in healthcare. Ind. Manag. Data Syst. 115, 1704–1723.
Gkartzonikas, C., Gkritza, K., 2019. What have we learned? A review of stated preference and choice studies on autonomous vehicles. Transport. Res. C Emerg. Technol. 98, 323–337.
Gkartzonikas, C., Losada-Rojas, L.L., Christ, S., Pyrialakou, V.D., Gkritza, K., 2022. A multi-group analysis of the behavioral intention to ride in autonomous vehicles: evidence from three US metropolitan areas. Transportation 1–41.
Goldsmith, R.E., Kim, D., Flynn, L.R., Kim, W.-M., 2005. Price sensitivity and innovativeness for fashion among Korean consumers. J. Soc. Psychol. 145, 501–508.
Goodhue, D.L., Thompson, R.L., 1995. Task-technology fit and individual performance. MIS Q. 19, 213–236.
Groß, M., 2018. Mobile shopping loyalty: the salient moderating role of normative and functional compatibility beliefs. Technol. Soc. 55, 146–159.
Guo, Y., Souders, D., Labi, S., Peeta, S., Benedyk, I., Li, Y., 2021. Paving the way for autonomous Vehicles: understanding autonomous vehicle adoption and vehicle fuel choice under user heterogeneity. Transport. Res. Part A Policy Pract 154, 364–398.
Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transport. Res. C Emerg. Technol. 78, 37–49.
Hair, J.F., Hult, G.T.M., Ringle, C., Sarstedt, M., 2017. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Sage Publications.
Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M., 2019. When to use and how to report the results of PLS-SEM. Eur. Bus. Rev. 31, 2–24.
Hair, Ringle C.M., Sarstedt, M., 2011. PLS-SEM: indeed a silver bullet. J. Market. Theor. Pract. 19, 139–152.
He, P., Lovo, S., Veronesi, M., 2022. Social networks and renewable energy technology adoption: empirical evidence from biogas adoption in China. Energy Econ. 106, 105789.
Ho, Y.-C., Tsai, C.-T., 2011. Comparing ANFIS and SEM in linear and nonlinear forecasting of new product development performance. Expert Syst. Appl. 38, 6498–6507.
Hohenberger, C., Spörrle, M., Welpe, I.M., 2016. How and why do men and women differ in their willingness to use automated cars? The influence of emotions across different age groups. Transport. Res. Part A Policy Pract. 94, 374–385.
Hong, W.C.H., Chi, C., Liu, J., Zhang, Y., Lei, V.N.-L., Xu, X., 2022. The influence of social education level on cybersecurity awareness and behaviour: a comparative study of university students and working graduates. Educ. Inf. Technol. 1–32.
Huang, Y., Qian, L., 2021. Understanding the potential adoption of autonomous vehicles in China: the perspective of behavioral reasoning theory. Psychol. Market. 38, 669–690.
Iranmanesh, M., Foroughi, B., Nunkoo, R., Shan, C.L., 2022. Travellers' loyalty toward Airbnb: the moderating effect of relative attractiveness of the reward program. Curr. Issues Tourism 1–17.
Jiménez, N., San-Martín, S., 2017. Attitude toward m-advertising and m-repurchase. Eur. Res. Manag. Bus. Econ. 23, 96–102.
Joia, L.A., Altieri, D., 2018. Antecedents of continued use intention of e-hailing apps from the passengers' perspective. J. High Technol. Manag. Res. 29, 204–215.
Jozef, E., Kumar, K.M., Iranmanesh, M., Foroughi, B., 2019. The effect of green shipping practices on multinational companies' loyalty in Malaysia. Int. J. Logist. Manag. 30, 974–993.
Kacperski, C., Kutzner, F., Vogel, T., 2021. Consequences of autonomous vehicles: ambivalent expectations and their impact on acceptance. Transport. Res. part F traffic Psychol. Behav. 81, 282–294.
Kalinić, Z., Marinković, V., Djordjevic, A., Liebana-Cabanillas, F., 2020. What drives customer satisfaction and word of mouth in mobile commerce services? A UTAUT2-based analytical approach. J. Enterprise Inf. Manag. 33, 71–94.
Kapser, S., Abdelrahman, M., 2020. Acceptance of autonomous delivery vehicles for last-mile delivery in Germany–Extending UTAUT2 with risk perceptions. Transport. Res. C Emerg. Technol. 111, 210–225.
Kaur, K., Rampersad, G., 2018. Trust in driverless cars: investigating key factors influencing the adoption of driverless cars. J. Eng. Technol. Manag. 48, 87–96.
Keszey, T., 2020. Behavioural intention to use autonomous vehicles: systematic review and empirical extension. Transport. Res. C Emerg. Technol. 119, 102732.
Khan, I.U., Hameed, Z., Khan, S.N., Khan, S.U., Khan, M.T., 2021. Exploring the effects of culture on acceptance of online banking: a comparative study of Pakistan and Turkey by using the extended UTAUT model. J. Internet Commer. 1–34.
Khoshnevisan, B., Rafiee, S., Omid, M., Mousazadeh, H., 2014. Prediction of potato yield based on energy inputs using multi-layer adaptive neuro-fuzzy inference system. Measurement 47, 521–530.
Kline, R.B., 2016. Principles and Practice of Structural Equation Modeling, fourth ed. The Guilford Press, New York.
König, M., Neumayr, L., 2017. Users' resistance towards radical innovations: the case of the self-driving car. Transport. Res. part F traffic Psychol. Behav. 44, 42–52.
Launonen, P., Salonen, A.O., Liimatainen, H., 2021. Icy roads and urban environments. Passenger experiences in autonomous vehicles in Finland. Transport. Res. part F traffic Psychol. Behav. 80, 34–48.
Lee, J., Lee, D., Park, Y., Lee, S., Ha, T., 2019. Autonomous vehicles can be shared, but a feeling of ownership is important: examination of the influential factors for intention to use autonomous vehicles. Transport. Res. C Emerg. Technol. 107, 411–422.
Lee, J.D., Kolodge, K., 2020. Exploring trust in self-driving vehicles through text analysis. Hum. Factors 62, 260–277.
Lee, J.D., See, K.A., 2004. Trust in automation: designing for appropriate reliance. Hum. Factors 46, 50–80.
Lee, R.L., Blouin, M.C., 2019. Factors affecting web disclosure adoption in the nonprofit sector. J. Comput. Inf. Syst. 59, 363–372.
Leicht, T., Chtourou, A., Ben Youssef, K., 2018. Consumer innovativeness and intentioned autonomous car adoption. J. High Technol. Manag. Res. 29, 1–11.
Li, Y., Tu, Y., Fan, Q., Dong, C., Wang, W., 2018. Influence of cyber-attacks on longitudinal safety of connected and automated vehicles. Accid. Anal. Prev. 121, 148–156.
Liébana-Cabanillas, F., Marinković, V., Kalinić, Z., 2017. A SEM-neural network approach for predicting antecedents of m-commerce acceptance. Int. J. Inf. Manag. 37, 14–24.
Lim, H.S.M., Taeihagh, A., 2018. Autonomous vehicles for smart and sustainable cities: an in-depth exploration of privacy and cybersecurity implications. Energies 11, 1062.
Lin, H., Chi, O.H., Gursoy, D., 2020. Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. J. Hospit. Market. Manag. 29, 530–549.
Litman, T., 2022. Autonomous Vehicle Implementation Predictions: Implications for Transport Planning.
Liu, P., Yang, R., Xu, Z., 2019. Public acceptance of fully automated driving: effects of social trust and risk/benefit perceptions. Risk Anal. 39, 326–341.
Loureiro, S.M.C., Cavallero, L., Miranda, F.J., 2018. Fashion brands on retail websites: customer performance expectancy and e-word-of-mouth. J. Retailing Consum. Serv. 41, 131–141.
Luo, Q., Saigal, R., Chen, Z., Yin, Y., 2019. Accelerating the adoption of automated vehicles by subsidies: a dynamic games approach. Transp. Res. Part B Methodol. 129, 226–243.
Madigan, R., Louw, T., Dziennus, M., Graindorge, T., Ortega, E., Graindorge, M., Merat, N., 2016. Acceptance of automated road transport systems (ARTS): an adaptation of the UTAUT model. Transport. Res. Procedia 14, 2217–2226.
Madigan, R., Louw, T., Wilbrink, M., Schieben, A., Merat, N., 2017. What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. Transport. Res. part F traffic Psychol. Behav. 50, 55–64.
Mailizar, M., Burg, D., Maulina, S., 2021. Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: an extended TAM model. Educ. Inf. Technol. 26, 7057–7077.
McLeay, F., Olya, H., Liu, H., Jayawardhena, C., Dennis, C., 2022. A multi-analytical approach to studying customers motivations to use innovative totally autonomous vehicles. Technol. Forecast. Soc. Change 174, 121252.
Meyer-Waarden, L., Cloarec, J., 2022. "Baby, you can drive my car": psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles. Technovation 109, 102348.
Mijin, N., Jang, H., Choi, B., Khongorzul, G., 2019. Attitude toward the use of electronic medical record systems: exploring moderating effects of self-image. Inf. Dev. 35, 67–79.
Molnar, L.J., Ryan, L.H., Pradhan, A.K., Eby, D.W., Louis, R.M.S., Zakrajsek, J.S., 2018. Understanding trust and acceptance of automated vehicles: an exploratory simulator study of transfer of control between automated and manual driving. Transport. Res. part F traffic Psychol. Behav. 58, 319–328.
Montoro, L., Useche, S.A., Alonso, F., Lijarcio, I., Bosó-Seguí, P., Martí-Belda, A., 2019. Perceived safety and attributed value as predictors of the intention to use autonomous vehicles: a national study with Spanish drivers. Saf. Sci. 120, 865–876.
Moore, G.C., Benbasat, I., 1991. Development of an instrument to measure the perceptions of adopting an information technology innovation. Inf. Syst. Res. 2, 192–222.
Morosan, C., DeFranco, A., 2016. It's about time: revisiting UTAUT2 to examine consumers' intentions to use NFC mobile payments in hotels. Int. J. Hospit. Manag. 53, 17–29.
Moták, L., Neuville, E., Chambres, P., Marmoiton, F., Monéger, F., Coutarel, F., Izaute, M., 2017. Antecedent variables of intentions to use an autonomous shuttle: moving beyond TAM and TPB? Eur. Rev. Appl. Psychol. 67, 269–278.
Nastjuk, I., Herrenkind, B., Marrone, M., Brendel, A.B., Kolbe, L.M., 2020. What drives the acceptance of autonomous driving? An investigation of acceptance factors from an end-user's perspective. Technol. Forecast. Soc. Change 161, 120319.
Ng, M., Law, M., Zhang, S., 2018. Predicting purchase intention of electric vehicles in Hong Kong. Australas. Mark. J. 26, 272–280.
Nie, J., Zheng, C., Zeng, P., Zhou, B., Lei, L., Wang, P., 2020. Using the theory of planned behavior and the role of social image to understand mobile English learning check-in behavior. Comput. Educ. 156, 103942.
Nordhoff, S., Louw, T., Innamaa, S., Lehtonen, E., Beuster, A., Torrao, G., Bjorvatn, A., Kessel, T., Malin, F., Happee, R., 2020. Using the UTAUT2 model to explain public acceptance of conditionally automated (L3) cars: a questionnaire study among 9,118 car drivers from eight European countries. Transport. Res. part F traffic Psychol. Behav. 74, 280–297.
Nunez, M., 2017. My First Ride in A Self-Driving Car Was Harrowing as Hell [WWW Document]. https://www.gizmodo.com.au/2017/01/my-first-ride-in-a-self-driving-car-was-harrowing-as-hell/. accessed 02.27.2022.
Panagiotopoulos, I., Dimitrakopoulos, G., 2018. An empirical investigation on consumers' intentions towards autonomous driving. Transport. Res. C Emerg. Technol. 95, 773–784.
Pandey, S., Chawla, D., Puri, S., 2022. Food delivery apps (FDAs) in Asia: an exploratory study across India and the Philippines. Br. Food J. 124, 657–678.

Papadoulis, A., Quddus, M., Imprialou, M., 2019. Evaluating the safety impact of connected and autonomous vehicles on motorways. Accid. Anal. Prev. 124, 12–22.
Park, J., Ahn, J., Thavisay, T., Ren, T., 2019. Examining the role of anxiety and social influence in multi-benefits of mobile payment service. J. Retailing Consum. Serv. 47, 140–149.
Park, J., Hong, E., Le, H.T.P.M., 2021. Adopting autonomous vehicles: the moderating effects of demographic variables. J. Retailing Consum. Serv. 63, 102687.
Parkinson, S., Ward, P., Wilson, K., Miller, J., 2017. Cyber threats facing autonomous and connected vehicles: future challenges. IEEE Trans. Intell. Transport. Syst. 18, 2898–2915.
Penmetsa, P., Adanu, E.K., Wood, D., Wang, T., Jones, S.L., 2019. Perceptions and expectations of autonomous vehicles–A snapshot of vulnerable road user opinion. Technol. Forecast. Soc. Change 143, 9–13.
Placek, M., 2021. Worldwide - Driverless Car Market Size 2025. Statista [WWW Document]. https://www.statista.com/statistics/1224515/av-market-size-worldwide-forecast/. accessed 02.12.2022.
Rejón-Guardia, F., Polo-Peña, A.I., Maraver-Tarifa, G., 2020. The acceptance of a personal learning environment based on Google apps: the role of subjective norms and social image. J. Comput. High Educ. 32, 203–233.
Rezaei, A., Caulfield, B., 2020. Examining public acceptance of autonomous mobility. Travel Behav. Soc. 21, 235–246.
Ribeiro, M.A., Gursoy, D., Chi, O.H., 2022. Customer acceptance of autonomous vehicles in travel and tourism. J. Trav. Res. 61, 620–636.
Ro, Y., Ha, Y., 2019. A factor analysis of consumer expectations for autonomous cars. J. Comput. Inf. Syst. 59, 52–60.
Robertson, R.D., Woods-Fry, H., Vanlaar, W.G.M., Hing, M.M., 2019. Automated vehicles and older drivers in Canada. J. Saf. Res. 70, 193–199.
Roham, M., Gabrielyan, A.R., Archer, N.P., 2012. Predicting the impact of hospital health information technology adoption on patient satisfaction. Artif. Intell. Med. 56, 123–135.
Rubio, F., Llopis-Albert, C., Valero, F., Besa, A.J., 2020. Sustainability and optimization in the automotive sector for adaptation to government vehicle pollutant emission regulations. J. Bus. Res. 112, 561–566.
Ruggeri, K., Kácha, O., Menezes, I.G., Kos, M., Franklin, M., Parma, L., Langdon, P., Matthews, B., Miles, J., 2018. In with the new? Generational differences shape population technology adoption patterns in the age of self-driving vehicles. J. Eng. Technol. Manag. 50, 39–44.
SAE International, 2018. Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles [WWW Document]. https://www.sae.org/standards/content/j3016_201806/. accessed 02.15.2022.
Sánchez-Prieto, J.C., Hernández-García, Á., García-Peñalvo, F.J., Chaparro-Peláez, J., Olmos-Migueláñez, S., 2019. Break the walls! Second-Order barriers and the acceptance of mLearning by first-year pre-service teachers. Comput. Hum. Behav. 95, 158–167.
Senali, M.G., Cripps, H., Meek, S., Ryan, M.M., 2022. A comparison of Australians, Chinese and Sri Lankans' payment preference at point-of-sale. Market. Intell. Plann. 23, 96–102.
Sharma, I., Mishra, S., 2020. Modeling consumers' likelihood to adopt autonomous vehicles based on their peer network. Transport. Res. part D Transp. Environ. 87, 102509.
Sharma, S.K., Joshi, A., Sharma, H., 2016. A multi-analytical approach to predict the Facebook usage in higher education. Comput. Hum. Behav. 55, 340–353.
Singh, N., Sinha, N., Liébana-Cabanillas, F.J., 2020. Determining factors in the adoption and recommendation of mobile wallet services in India: analysis of the effect of innovativeness, stress to use and social influence. Int. J. Inf. Manag. 50, 191–205.
Talebian, A., Mishra, S., 2018. Predicting the adoption of connected autonomous vehicles: a new approach based on the theory of diffusion of innovations. Transport. Res. C Emerg. Technol. 95, 363–380.
Tan, H., Zhao, X., Yang, J., 2022. Exploring the influence of anxiety, pleasure and subjective knowledge on public acceptance of fully autonomous vehicles. Comput. Hum. Behav. 131, 107187.
Tsai, H.S., LaRose, R., 2015. Broadband Internet adoption and utilization in the inner city: a comparison of competing theories. Comput. Hum. Behav. 51, 344–355.
Upadhyay, N., Upadhyay, S., Abed, S.S., Dwivedi, Y.K., 2022. Consumer adoption of mobile payment services during COVID-19: extending meta-UTAUT with perceived severity and self-efficacy. Int. J. Bank Market. 40, 960–991.
Venkatesh, V., Thong, J.Y.L., Xu, X., 2016. Unified theory of acceptance and use of technology: a synthesis and the road ahead. J. Assoc. Inf. Syst. Online 17, 328–376.
Venkatesh, V., Thong, J.Y.L., Xu, X., 2012. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Q. 36, 157–178.
Wamba, S.F., Bhattacharya, M., Trinchera, L., Ngai, E.W.T., 2017. Role of intrinsic and extrinsic factors in user social media acceptance within workspace: assessing unobserved heterogeneity. Int. J. Inf. Manag. 37, 1–13.
Wang, C., Teo, T.S.H., Dwivedi, Y., Janssen, M., 2021. Mobile services use and citizen satisfaction in government: integrating social benefits and uses and gratifications theory. Inf. Technol. People 34, 1313–1337.
Wang, X., Yuen, K.F., Wong, Y.D., Teo, C.C., 2018. An innovation diffusion perspective of e-consumers' initial adoption of self-collection service via automated parcel station. Int. J. Logist. Manag. 29, 237–260.
Waung, M., McAuslan, P., Lakshmanan, S., 2021. Trust and intention to use autonomous vehicles: manufacturer focus and passenger control. Transport. Res. part F traffic Psychol. Behav. 80, 328–340.
Wong, C.-H., Tan, G.W.-H., Tan, B.-I., Ooi, K.-B., 2015. Mobile advertising: the changing landscape of the advertising industry. Telematics Inf. 32, 720–734.
Wu, J., Liao, H., Wang, J.-W., Chen, T., 2019. The role of environmental concern in the public acceptance of autonomous electric vehicles: a survey from China. Transport. Res. F Traffic Psychol. Behav. 60, 37–46.
Wu, J., Lu, X., 2013. Effects of extrinsic and intrinsic motivators on using utilitarian, hedonic, and dual-purposed information systems: a meta-analysis. J. Assoc. Inf. Syst. Online 14, 153–191.
Xie, H., David, A., Mamun, M.R. Al, Prybutok, V.R., Sidorova, A., 2022. The formation of initial trust by potential passengers of self-driving taxis. J. Decis. Syst. 1–30.
Xu, X., Fan, C.-K., 2019. Autonomous vehicles, risk perceptions and insurance demand: an individual survey in China. Transport. Res. part A policy Pract. 124, 549–556.
Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., Liu, P., 2018. What drives people to accept automated vehicles? Findings from a field experiment. Transport. Res. C Emerg. Technol. 95, 320–334.
Yadegaridehkordi, E., Nilashi, M., Nasir, M.H.N.B.M., Ibrahim, O., 2018. Predicting determinants of hotel success and development using Structural Equation Modelling (SEM)-ANFIS method. Tourism Manag. 66, 364–386.
Yuen, K.F., Cai, L., Qi, G., Wang, X., 2021. Factors influencing autonomous vehicle adoption: an application of the technology acceptance model and innovation diffusion theory. Technol. Anal. Strat. Manag. 33, 505–519.
Yuen, K.F., Wong, Y.D., Ma, F., Wang, X., 2020. The determinants of public acceptance of autonomous vehicles: an innovation diffusion perspective. J. Clean. Prod. 270, 121904.
Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., Zhang, W., 2019. The roles of initial trust and perceived risk in public's acceptance of automated vehicles. Transport. Res. C Emerg. Technol. 98, 207–220.
Zhang, X., Wang, K., Hao, Y., Fan, J.-L., Wei, Y.-M., 2013. The impact of government policy on preference for NEVs: the evidence from China. Energy Pol. 61, 382–393.