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Exploring university students' acceptability of autonomous vehicles and urban air mobility

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ABSTRACT

AVs and UAM will provide many benefits. However, lack of user acceptance is the predominant barrier to the adoption of automated transport technologies. Yet, little is known about AV and UAM acceptability in developing countries. To this end, this study investigates the factors affecting the acceptability of AVs and UAM in Türkiye. The sample was drawn from 369 university students. An extended UTAUT model was established with additional hedonic motivation, perceived safety, and personal innovativeness constructs. Findings revealed that perceived safety and performance expectancy were the strongest determinants of behavioral intention to use AVs. On the other hand, social influence and hedonic motivation were the main drivers of UAM acceptability. Furthermore, personal innovativeness was a strong factor when estimating the utilitarian value in both models. The findings could guide the politicians, scholars, and stakeholders of the AV and the UAM market.

1. Introduction

Driverless and flying cars are no longer science fiction but will become a part of our lives. Most of the leading companies in the automotive and high-tech industry are working on fully automated, self-driving cars (i.e., autonomous vehicle (AV), SAE Level 4–5 automation in this study) (SAE, 2014; Condliffe, 2016; Heineke et al., 2017). On the other hand, urban air mobility (UAM) —or a more inclusive term referred to as advanced air mobility by NASA— is an emerging transportation concept. It covers local, regional, and inter-regional commuting and cargo operations through air transport by using vertical takeoff and landing (VTOL) aircraft (NASA, 2021). The history of UAM is classified into six phases (Cohen et al., 2021). The former three phases cover the first flying car concept, passenger transport with helicopters, and transport on-demand services. The latter three phases are introduced as short to long-range future, which consists of passenger transport with VTOLs called air shuttle services, air metro, and on-demand air taxi services respectively. In this study, the terms UAM and autonomous passenger drone (APD) are used interchangeably to refer to all automated passenger transportation services defined in phases four, five, and six.

AVs and UAM will provide many benefits. Some of these for AVs would be reduced crashes, eased congestion, reduced energy use, reduced pollution, reduced driver stress, improved fuel economy, reduced parking needs, and improved mobility for those who are unable to drive (Fagnant and Kockelman, 2015; Bagloee et al., 2016; Faisal et al., 2019; Litman, 2020). Moreover, increased mobility, decreased commuting and delivery time, and reduced surface congestion and pollution would be the expected benefits of APDs (Steiner, 2019). However, the potential positive impacts of the AVs could be seen after 2040 (Bertoncello and Wee, 2015; Litman, 2020), and a commercially effective air metro could be in operation by 2030 (Hasan, 2019). In addition, lack of customer/user acceptance is one of the predominant barriers to the adoption of AVs and APDs (Raj et al., 2020; Bezai et al., 2021; Thipphavong et al., 2018; Lascara et al., 2018; Straubinger et al., 2020).

The number of studies about AV acceptability has slowly increased in the last decade (Jing et al., 2020). Most of the studies proved that the early adopters of AVs are likely to be males, young, highly educated, and with higher incomes (Golbabaei et al., 2020). Similarly, males, young people, higher-income groups, tech-savvies, and those who have pro-environmental attitudes were more likely to be early adopters of APDs (Garrow et al., 2021; Kloss and Riedel, 2021; Çetin et al., 2022). However, the existing body of knowledge contains a small number of studies on APD acceptability. Yet, little is known about AV and APD acceptability in developing countries.

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Comprehending the acceptability of AVs and APDs is crucial for several reasons originating from sociotechnical dynamics. Examining behavior patterns provides valuable information for creating user-centric systems that meet the requirements and expectations of users. Beyond the technological factors, this investigation clarifies the complex web of public perception and cultural differences all of which are essential in adapting these breakthroughs to a range of society norms and values. Furthermore, as public acceptance is a prerequisite for market viability, understanding the psychological elements impacting adoption facilitates the formulation of well-informed investment and commercial strategy decisions. At this juncture, understanding the dynamic differences in adoption between the two modes of autonomous transportation is crucial for comprehensive planning, policy making, guiding campaigns and educational initiatives accurately. Comparatively analyzing the adoption dynamics of different autonomous transportation modes is essential to grasp these nuances fully.

To this end, this study investigates the factors affecting the acceptability of AVs and APDs by using an extended unified theory of acceptance and use of technology (UTAUT) in Türkiye. The study's target population is university students, who would be the potential users of AVs and APDs in the predicted deployment years. The study aims to find the antecedents that explain behavioral intention to use two emerging transport modes and provide early insight. In addition, the study presents evidence from a developing country in the field of autonomous transportation acceptability.

The remainder of this paper is organized as follows. Section 2 contains the relevant literature about technology acceptance models and the acceptability of AVs and UAM. Section 3 defines the conceptual framework. Hypotheses are developed in this section. The data and methods are introduced in Section 4. Section 5 reports the measurement and structural model results. Important implications of the study are discussed in Section 6. Finally, Section 7 concludes the paper.

2. Background

2.1. Technology acceptance models

Many models have been developed to explain the technology use behavior of individuals. UTAUT was synthesized from eight models in the literature including the Theory of Reasoned Action (TRA; Fishbein and Ajzen, 1975), the Theory of Planned Behavior (TPB; Ajzen, 1991), and the Technology Acceptance Model (TAM; Davis, 1989). UTAUT posits that performance expectancy, effort expectancy, and social influence are positively associated with behavioral intention. Also, behavioral intention and facilitating conditions are positively associated with the actual use of information technology (Venkatesh et al., 2003). Venkatesh et al. (2012) extended the UTAUT, namely UTAUT2, by adding hedonic motivation, price value, and habit constructs. UTAUT2 outperformed the previous model, significantly improving the explained variance of the behavioral intention. Although it was initially developed for information systems, UTAUT has been frequently used in general-purpose systems and specialized business systems research (Williams et al., 2015). Moreover, TPB, TAM, and UTAUT have been commonly adopted in the field of transportation to predict user acceptance (Rahman et al., 2017; Jing et al., 2020).

2.2. Acceptability of autonomous vehicles

Numerous studies have investigated perceptions, willingness to pay, and ownership issues of AVs with descriptive and multivariate statistical methods that relied on questionnaires. It was concluded that most of the respondents have positive attitudes toward using AVs (Payre et al., 2014; Schoettle and Sivak, 2014; Kyriakidis et al., 2015; Piao et al., 2016; Bansal et al., 2016; Becker and Axhausen, 2017; Hulse et al., 2018). The focus of this study being on acceptability of autonomous transportation modes, research pertaining to this subject has been examined in greater detail. The review has been conducted under three main headings: studies based on TAM, studies based on UTAUT, and studies based on mixed/integrated behavior models. The term acceptance represents a favorable assessment of a new technology that has been applied. On the other hand, acceptability is the prediction of the extent to which this technology will be accepted if implemented (Gärling et al., 2008). In many studies, these terms have been used interchangeably. In this study, using the term acceptability is considered more appropriate.

Several studies have examined AV acceptability with extended TAM. In addition to baseline TAM constructs, Choi and Ji (2015) found the significant effects of trust and external locus of control on behavioral intention to use AVs. Panagiotopoulos and Dimitrakopoulos (2018) added perceived trust and social influence factors to the baseline TAM. They indicated that these factors have significant impacts on behavioral intention to use AVs. Lee et al. (2019) pointed out that perceived risk is negatively associated with AVs' use intention. Also, relative advantage and self-efficacy significantly explain perceived usefulness and ease of use. Zhang et al. (2019) extended TAM by adding perceived safety risk, perceived privacy risk, and initial trust. They revealed significant effects of the perceived safety risk on trust, and trust on attitude. Wu et al. (2019) examined the effect of environmental concern as an additional factor to TAM for the acceptability of electric autonomous vehicles. They found the significant effects of environmental concern on behavioral intention, as well as green perceived usefulness and perceived ease of use. Similarly, Dirsehan and Can (2020) added sustainability concerns and trust to baseline TAM. They highlighted the significant effects of sustainability concerns and trust on behavioral intention to use AVs. Apart from the hypothetical studies, Xu et al. (2018) designed a field experiment with conditionally automated vehicles (SAE Level 3). This study assessed acceptability for full automation and willingness to re-ride for conditional automation with extended TAM. Results of the experiment showed that trust and perceived safety both significantly explain the willingness to re-ride and behavioral intention. The explanatory powers of perceived usefulness and behavioral intention were significantly increased after the AV experience.

Researchers have attempted to evaluate AV acceptability by using UTAUT. Madigan et al. (2017) constructed a model by adding hedonic motivation to baseline UTAUT to assess automated public transport acceptability. They found a significant and strong effect of hedonic motivation on behavioral intention. Kaur and Rampersad (2018) examined the effects of trust and performance expectancy on AV acceptability. They introduced trust with three constructs: reliability, security, and privacy. All these factors significantly explain trust; trust and performance expectancy also explain the use intention. The study conducted by Leicht et al. (2018) analyzed how consumer innovativeness impacts the relationship between the constructs of UTAUT and the intention to purchase autonomous cars. They found a significant positive effect of consumer innovativeness on these relationships. Garidis et al. (2020) extended the UTAUT and found the significant effects of various variables such as safety, security, privacy, desire for control, hedonic motivation, and cost on AVs' use intention. Morrison and Van Belle (2020) found significant effects of hedonic motivation and trust on behavioral intention to use AVs.

In addition to the abovementioned studies, several works have been carried out on the acceptability of autonomous public transportation by using the UTAUT as a baseline model. Korkmaz et al. (2021) conducted a study by adding trust and safety and perceived risk constructs to UTAUT2. However, they reported that the effect of perceived risk on behavioral intention to use automated public transport was non-significant. Yuen et al. (2022) integrated the perceived value and social exchange theories with UTAUT. They confirmed the significant effects of perceived value and trust on automated public transport acceptability.

A number of studies that were supported by mixed/integrated behavioral models (e.g., TPB, TAM, UTAUT) were also carried out.

Rahman et al. (2017) investigated the acceptance of advanced driver assistance systems with TPB, TAM, and UTAUT comparatively. They found that TAM (attitude + perceived usefulness) outperformed the other models by explaining 82 % of the variation in behavioral intention. Furthermore, in a simulated driving study that examines behavioral intention to use conditionally automated vehicles, Buckley et al. (2018) added trust to TPB and TAM constructs and compared the two models. As a result, trust increased the explained variance when joined with TPB and TAM. Jing et al. (2019) claimed that knowledge and perceived risk factors are possible determinants of behavioral intention to use AVs with TPB constructs. Kaye et al. (2020) found that TPB constructs explain behavioral intention to use highly automated cars in

Table 1
Previous studies on AV acceptability with behavioral models.

Author(s)	Location (Sample Size)	Object	Model	Explained Variance of Behavioral Intention	Additional Constructs
Studies based on TAM					
Choi and Ji (2015)	n. m. (552)	Autonomous vehicles (NHTSA Lv 4)	TAM (Extended)	67.6 %	***Trust, n.s.Perceived risk, **External locus of control, n.s.Sensation seeking
Panagiotopoulos and Dimitrakopoulos (2018)	n.m. (483)	Autonomous driving	TAM (Extended)	43.7 %	**Perceived trust, **Social influence
Xu et al. (2018)	China (300)	Automated vehicles (WTR, SAE Lv 3; BI, SAE Lv 5)	TAM (Extended)	BI: 55 % WTR: 40 %	*Trust, **Perceived safety
Lee et al. (2019)	Korea (313)	Autonomous vehicles	TAM (Extended)	52 %	*Perceived risk, **Self-efficacy, n.s.Relative advantage, ***Psychological ownership
Zhang et al. (2019)	Shenzhen, China (216)	Autonomous vehicles (SAE Lv 3)	TAM (Extended)	61 %	***Perceived Safety Risk, n.s.Perceived Privacy Risk, ***Trust
Wu et al. (2019)	China (470)	Autonomous electric vehicles	TAM (Extended)	–	***Environmental concern
Dirsehan and Can (2020)	Türkiye (391)	Autonomous vehicles (NHTSA Lv 5)	TAM (Extended)	57 %	**Trust, ***Sustainability concerns
Studies based on UTAUT					
Madigan et al. (2017)	Trikala, Greece (315)	Automated road transport systems (SAE Lv 4)	UTAUT	59 %	**Hedonic motivation, n.s.Age, n.s.Gender, n.s.No. times using ARTS
Kaur and Rampersad (2018)	Flinders University, Australia (101)	Driverless cars	UTAUT (only PE)	–	***Reliability, †Security, **Privacy, †Trust
Leicht et al. (2018)	France (241)	Autonomous car (SAE Lv 5)	UTAUT	–	*Consumer innovativeness (moderator)
Garidis et al. (2020)	Germany (470)	Autonomous driving	UTAUT (Extended)	82 %	*Hedonic motivation, *Cost, n.s.Environmental friendliness, **Desire for control, n.s.Loss of driving pleasure, *Safety, *Security, †Privacy, n.s.Legal
Morrison and Van Belle (2020)	South Africa (441)	Autonomous vehicles (Fully autonomous)	UTAUT (Extended)	71.1 %	***Hedonic motivation, *Trust in safety
Korkmaz et al. (2021)	Istanbul, Türkiye (303)	Automated public transport	UTAUT2 (Extended)	72 %	***Trust and safety, n.s.Perceived risk
Yuen et al. (2022)	Beijing, China (476)	Autonomous public transport (SAE Lv 5)	UTAUT (Extended)	71 %	*Hedonic motivation, *Perceived value, *Trust
Studies based on mixed/integrated behavior models					
Rahman et al. (2017)	USA (430)	Advanced driver assistance systems	TAM, TPB, UTAUT	UTAUT: 71 % TAM (PU + PEoU): 73 % TPB: 80 % TAM (A + PU): 82 %	–
Buckley et al. (2018)	Michigan, USA (78)	Autonomous vehicles (SAE Lv 3)	TPB and TAM (Extended)	TPB: 49 % TAM: 44 %	*Trust
Jing et al. (2019)	China (906)	Autonomous vehicles and shared autonomous vehicles	TPB (Extended)	–	*Knowledge, ***Perceived risk
Kaye et al. (2020)	Australia (558), France (625), Sweden (380)	Highly automated cars (SAE Lv 4)	TPB and UTAUT	TPB: 57.9 %–74.1 % UTAUT: Additional %3-6	n.s.Age, n.s.Gender, n.s.Pre-existing knowledge#
Yuen et al. (2020)	Da Nang, Vietnam (268)	Shared autonomous vehicles	Integrated TPB and UTAUT2	87 %	–
Gkartzonikas et al. (2022)	Chicago (400), Indianapolis (400), Phoenix (400)	Autonomous vehicles (Lv 2 or higher)	TPB and DoI (Extended)	–	**Self-efficacy, **Personal Moral Norms, **Safety Perceptions, **Driving Related Sensation Seeking, **Environmental Concerns, *Affinity to Innovativeness
Farzin et al. (2022)	Tehran, Iran (641)	Autonomous vehicles (NHTSA Lv 4)	UTAUT and DoI (Extended)	50.3 %	*Trialability, †Observability, ***Perceived risk
Nordhoff et al. (2021)	Berlin-Schöneberg (340)	Driverless automated shuttles	DoI and UTAUT (Extended)	UTAUT: 39.7 % DoI + UTAUT: 48.5 %	*Trust, *Automated shuttle sharing

n.m. (Not mentioned) n.s.Non-significant, †$p < 0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, #Only significant ($p < 0.01$) for the Australian sample.
SAE: Society of Automotive Engineers, NHTSA: National Highway Traffic Safety Administration, PU: perceived usefulness, PeoU: perceived ease of use, A: attitude, BI: behavioral intention, WTR: willingness to re-ride.

Australia, France, and Sweden. Yuen et al. (2020) integrated the UTAUT2 constructs into TPB constructs for explaining the factors affecting the acceptability of shared autonomous vehicles in Vietnam. They found that perceived behavioral control in TPB has the greatest effect on behavioral intention while hedonic motivation has the greatest effect on attitude. Gkartzonikas et al. (2022) integrated TPB and Diffusion of Innovation Theory (DoI), adding several additional factors. They demonstrated that the behavioral intention to use AVs can be better explained by the synergistic effects of TPB and DoI. In a recent study, Farzin et al. (2022) integrated the DoI constructs with baseline UTAUT. They demonstrated the positive effect of trialability and observability and, the negative effect of perceived risk on AV acceptability. On the other hand, Nordhoff et al. (2021) found that none of the UTAUT constructs significantly explain the acceptability of driverless automated shuttles when joined together with the DoI constructs. Table 1 presents previous autonomous vehicle acceptability studies briefly.

2.3. Acceptability of UAM

Previous studies showed that public attitudes toward UAM are unclear (Çetin et al., 2022). For instance, a pain-gain acceptance test measured low acceptability for air mobility in Germany (Duwe and Sprenger, 2019). Contrarily, a qualitative study in Germany pointed out that although flying taxis are little known by the interviewees, they have favorable attitudes toward flying taxis (Behme and Planing, 2020). Keller et al. (2021) surveyed 412 individuals in the Czech Republic and found that UAM user acceptability is independent of familiarity with UAM, gender, age, and frequent long trips. Nevertheless, the study confirmed the association between dissatisfaction with current means of transport, willingness to pay for services, opinions regarding traffic in low-level air space and air transportation, and UAM acceptability. A similar study in Lisbon with 207 respondents indicated that UAM user acceptability differs with gender, safety perceptions, expected benefits, and satisfaction with ride-hailing services (Ferreira and Kalakou, 2020). Besides the socio-demographics, Rothfeld et al. (2018) revealed that access/egress times and process times are highly effective in passenger acceptability of UAM. Also, Fu et al. (2019) found that mode choice between autonomous taxis and autonomous flying taxis varies by individuals' current commuting mode and trip purposes. Additionally, Chancey and Politowicz (2020) revealed the importance of trust in automation and remote/onboard pilot control on the public acceptability of UAM.

In addition to the abovementioned studies, several researchers have investigated the acceptability of drones based on behavioral models. Chamata (2017) proposed a theoretical framework to explain the factors delaying the acceptability of unmanned aircraft without empirical evidence. He claimed that perceived risk, which is associated with public acceptability, is increased by social and economic concerns. Chamata and Winterton (2018) introduced a framework regarding drone acceptability by replacing perceived usefulness and perceived ease of use factors of TAM with perceived benefit, perceived risks, and perceived control factors. Rohlik and Stasch (2019) conducted a questionnaire with 321 individuals living in more than 50 different metropolitan areas. They found that perceived usefulness explains attitude, while subjective norms, travel cost, and personal innovativeness are associated with behavioral intention to use UAM. Furthermore, Kellermann and Fischer (2020) examined the public acceptability of both delivery and passenger drones among focus groups. Findings revealed that safety and security, environmental friendliness, traffic problems, noise, price and exclusivity, usefulness, transport volume, and time are the object-related factors affecting the public acceptability of drones. Al Haddad et al. (2020) demonstrated the relevance of safety concerns, affinity to automation, data, and ethical issues, high affinity to social media, socio-demographics, the value of time savings, automation costs, and service reliability in UAM user acceptability. In a recent study, Kim et al. (2022) examined the UAM acceptability by extending TAM. They introduced time-saving, availability, flight comfort, and perceived cost as the antecedents of service quality and reliability, safety, security, and resilience as the antecedents of trust. The findings of the study verified that trust, which is mostly affected by perceived safety, is a significant determinant of UAM user acceptability, while service quality factors are significant determinants of perceived usefulness and perceived ease of use.

3. Conceptual framework and hypotheses development

Looking at the literature according to AV acceptability reveals that behavioral models have been extended mostly with trust, perceived safety, and anxiety (i.e., perceived risk) constructs. Also, the importance of safety and security has been highlighted in the context of UAM acceptability. However, the literature on passenger UAM user acceptability is still developing. Many studies have focused on conducting exploratory surveys or building theoretical frameworks. In this study, baseline UTAUT constructs (performance expectancy, effort expectancy, social influence, and behavioral intention) were used along with further factors such as hedonic motivation, perceived safety, and personal innovativeness to provide empirical evidence in terms of AV and UAM acceptability. Several studies (e.g., Fu et al., 2019; Garrow et al., 2021) claimed that AVs and UAM are modes of transport that are in some respect similar and competitive. Therefore, the same acceptability models were proposed and tested for both transportation modes. Fig. 1 presents the research model.

The proposed hypotheses for AV and APD acceptability models are separated by a slash. The former shows the hypotheses of the AV model, and the latter shows the hypotheses of the APD model.

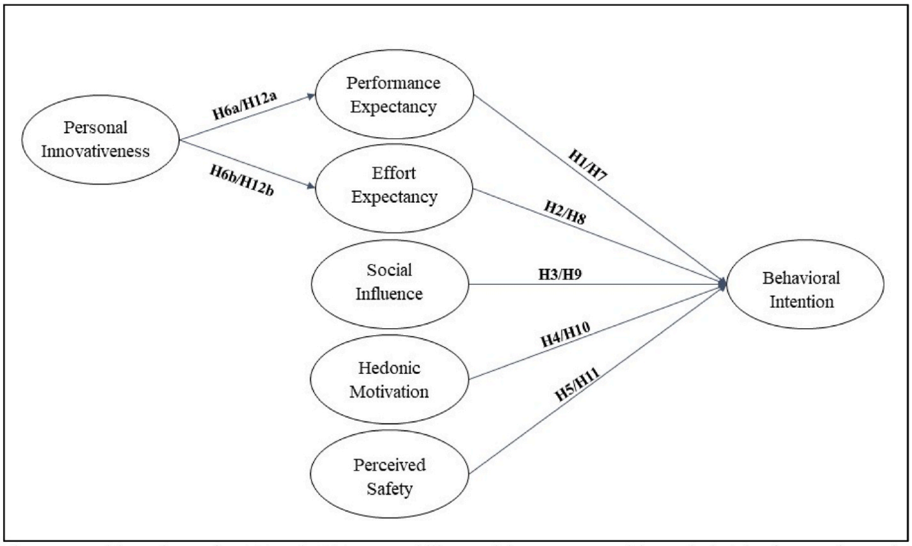
Performance expectancy is the first construct from the baseline UTAUT model, which is described as a person's belief that by using the system, he or she would be able to improve his or her work performance (Venkatesh et al., 2003). Previous studies have already proved the significant effect of performance expectancy (i.e., perceived usefulness) on behavioral intention to use AVs (e.g., Choi and Ji, 2015; Madigan et al., 2017; Buckley et al., 2018; Kaur and Rampersad, 2018; Leicht et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Xu et al., 2018; Lee et al., 2019; Wu et al., 2019; Zhang et al., 2019; Dirsehan and Can, 2020; Morrison and Van Belle, 2020; Farzin et al., 2022). In the context of UAM, various studies have indicated the importance of usefulness in determining user acceptability (e.g., Chamata and Winterton, 2018; Al Haddad et al., 2020; Behme and Planing, 2020; Kellermann and Fischer, 2020; Kim et al., 2022). As a result, it is expected that individuals with high-performance expectations will have a high willingness to accept AVs/APDs. Therefore, the following hypotheses were proposed:

H1. Performance Expectancy has a significant positive effect on behavioral intention to use AVs.

H7. Performance Expectancy has a significant positive effect on behavioral intention to use APDs.

Effort expectancy is the second UTAUT construct, which is described as the level of simplicity with which the system may be used (Venkatesh et al., 2003). Several studies have revealed the significant effect of effort expectancy (i.e., perceived ease of use) on behavioral intention to use AVs (e.g., Choi and Ji, 2015; Leicht et al., 2018; Xu et al., 2018; Wu et al., 2019; Dirsehan and Can, 2020; Garidis et al., 2020; Morrison and Van Belle, 2020; Farzin et al., 2022). Furthermore, Winter et al. (2020) found a significant effect of perceived value, which is associated with the benefits and ease of use in acceptance models, on willingness to fly in APDs. Also, Kim et al. (2022) demonstrated a significant association between perceived ease of use and attitude toward using UAM. Consequently, it is predicted that believing that AV/APD can be used with low effort will have a positive effect on individuals' intention to use those vehicles.

H2. Effort Expectancy has a significant positive effect on behavioral



The proposed hypotheses for AV and APD acceptability models are separated by a slash. The former shows the hypotheses of the AV model, and the latter shows the hypotheses of the APD model.

Fig. 1. The research model.

intention to use AVs.

H8. Effort Expectancy has a significant positive effect on behavioral intention to use APDs.

Social influence is the last construct from the baseline UTAUT model, which is defined as an individual's perception of how important others feel he or she should adopt the new system (Venkatesh et al., 2003). The effect of social influence (i.e., subjective norms) on use intention has been found significant in previous AV acceptability studies (e.g., Madigan et al., 2017; Leicht et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Garidis et al., 2020; Morrison and Van Belle, 2020; Gkartzonikas et al., 2022; Farzin et al., 2022). Moreover, Rohlik and Stasch (2019) found a significant effect of social norms on behavioral intention to use UAM. It is estimated that individuals who think that they are supported by their peers when they use AV/APD will have a positive intention to use those vehicles. Therefore, the following hypotheses were proposed:

H3. Social Influence has a significant positive effect on behavioral intention to use AVs.

H9. Social Influence has a significant positive effect on behavioral intention to use APDs.

As explained in the first paragraph of this section, the baseline UTAUT model was extended with three additional constructs. The first additional construct is hedonic motivation from UTAUT2. It is referred to as enjoyment or pleasure gained while using technology (Venkatesh et al., 2012). A similar construct to hedonic motivation was proposed in Car Technology Acceptance Model (CTAM) (Osswald et al., 2012) and Autonomous Vehicle Acceptance Model (AVAM) (Hewitt et al., 2019), which is called the attitude towards using technology. Also, recent studies have validated the significant effect of hedonic motivation on behavioral intention to use AVs (Madigan et al., 2017; Garidis et al., 2020; Morrison and Van Belle, 2020). In the context of UAM, Winter et al. (2020) revealed the importance of happiness and fun factor as predictors of willingness to fly in APDs. It is expected that individuals who think that it will be interesting and fun to travel in AV/APD will have a high tendency to use AV/APD. Therefore, the following hypotheses were proposed:

H4. Hedonic Motivation has a significant positive effect on behavioral intention to use AVs.

H10. Hedonic Motivation has a significant positive effect on behavioral intention to use APDs.

The second additional construct is perceived safety. Osswald et al. (2012) defined perceived safety as "the degree to which an individual believes that using a system will affect his or her well-being." (p. 55). Perceived safety was proposed in CTAM (Osswald et al., 2012) and AVAM (Hewitt et al., 2019) frameworks as a direct antecedent of behavioral intention to use information technology in the vehicle. Perceived safety has been featured under the name of trust in various AV acceptability studies. Most of the previous studies have found a significant association between perceived safety (i.e., trust) and behavioral intention to use AVs (e.g., Choi and Ji, 2015; Buckley et al., 2018; Kaur and Rampersad, 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Xu et al., 2018; Zhang et al., 2019; Dirsehan and Can, 2020; Morrison and Van Belle, 2020; Gkartzonikas et al., 2022). In addition to this, Fu et al. (2019) indicated that safety is a substantial factor when choosing autonomous transportation modes. In line with this, Behme and Planing (2020) found that safety and security concerns are mostly pronounced as reasons for refusal to use autonomous flying taxis. Al Haddad et al. (2020) revealed the negative association between safety concerns and UAM acceptability. Also, Kim et al. (2022) verified that trust is a strong determinant of attitude and behavioral intention to use UAM. It is expected that individuals with a high perception of safety towards AV/APD will also have a high tendency to use these vehicles. Therefore, the following hypotheses were proposed:

H5. Perceived Safety has a significant positive effect on behavioral intention to use AVs.

H11. Perceived Safety has a significant positive effect on behavioral intention to use APDs.

The final additional construct is personal innovativeness. Rogers (2002) defined innovativeness as "the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than other members of a social system." (p. 990). Although personal innovativeness is omitted in the UTAUT and UTAUT2, it is often used as a variable to extend the baseline model. Several studies have confirmed the role of personal innovativeness as an external variable to explain perceived usefulness and perceived ease of use (i.e., utilitarian value) in the domain of technology acceptance (e.g Lu et al., 2005; Fagan et al., 2012; Hong et al., 2017). Moreover, Venkatesh et al. (2016) suggested that the baseline UTAUT/UTAUT2 model can be extended with individual-level contextual factors and higher-level contextual factors. On this basis, Nordhoff et al. (2019) introduced a 4-stage process for autonomous vehicle acceptability studies in the multi-level automated vehicle acceptance model (MAVA). In MAVA, technology savviness is identified as an individual difference factor that affects the factors at the meso-level such as domain-specific factors including performance expectancy, effort expectancy, facilitating conditions, safety, and service/vehicle characteristics (Nordhoff et al., 2019). Furthermore, Leicht et al. (2018) found the moderating effect of consumer innovativeness on the relationships between performance expectancy/effort expectancy and AVs' purchase intention. Finally, Winter et al. (2019) revealed that interest in technology and the perceived utility of automated buses are positively correlated. It is expected that those who define themselves as innovators are estimated to both expect high performance from AVs/APDs and believe that these vehicles can be used with little effort. In light of the above findings, the following hypotheses were proposed:

H6a. Personal Innovativeness has a significant positive effect on the performance expectancy of AVs.

H6b. Personal Innovativeness has a significant positive effect on the effort expectancy of AVs.

H12a. Personal Innovativeness has a significant positive effect on the performance expectancy of APDs.

H12b. Personal Innovativeness has a significant positive effect on the effort expectancy of APDs.

4. Data & methods

4.1. Sampling & Questionnaire design

An online questionnaire was designed by the author. The questionnaire consists of two parts. The first part includes socio-demographic questions such as gender, age, education, employment, and car ownership. Driving/air travel experience and general knowledge about AVs/APDs were also asked in this part. The second part includes AV and UAM acceptability questions (Table 2). All 39 items in the second part utilized a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). Before the questions, brief information was given about autonomy levels and the concept of UAM. The information includes the SAE autonomy levels in vehicles, no automation, driver assistance, partial automation, conditional automation, high automation and full automation, categorized as levels 0 to 5 respectively (SAE, 2014). According to the survey, autonomous vehicles are reported to be at levels 4 and 5 of autonomy. Additionally, the UAM concept is presented involves short-distance urban and inter-city travel conducted using VTOL vehicles. One visual was used to illustrate a VTOL vehicle.

The questionnaire was distributed to online platforms. The responses were collected from 14th April 2021 to 7th June 2021. Respondents were recruited using snowball sampling. As explained in the introduction section, today's young adults in education will be an important audience in the automated transportation market. Therefore, a sampling frame was drawn from this target group. A total of 369 respondents completed the questionnaire.

Table 2
Items used in estimating the acceptability of AVs and UAM.

Indicator	Items for AV acceptability	Items for UAM acceptability	Source of adoption/adaptation
Performance Expectancy			
PE1	Using the vehicle would enable me to reach my destination quickly.	Using the APD would enable me to reach my destination quickly.	Hewitt et al. (2019)
PE2	AVs will be useful.	APDs will be useful.	Osswald et al. (2012)
PE3	AVs will reduce traffic congestion.	APDs will help me avoid traffic congestion.	Liu (2020)
Effort Expectancy			
EE1	Using an AV will be easy.	Access to an APD will be easy.	Hewitt et al. (2019)
EE2	Learning an AV will be easy.	Traveling by an APD will be easy.	Hewitt et al. (2019)
EE3	AVs will be easily understandable.	APDs will be easily understandable.	Hewitt et al. (2019)
Social Influence			
SI1	If most people start using it, I will use it too.	If most people start using it, I will use it too.	Hewitt et al. (2019)
SI2	I will use it if people close to me start using it.	I will use it if people close to me start using it.	–
SI3	If people whose opinions are important to me recommend it, I will use it.	If people whose opinions are important to me recommend it, I will use it.	Osswald et al. (2012)
Hedonic Motivation			
HM1	Using an AV would be fun.	Using an APD would be fun.	Hewitt et al. (2019)
HM2	I can do fun things during the trip with an AV.	I can do fun things during the trip with an APD.	–
HM3	Traveling by AV would be interesting.	Traveling in APD would be interesting.	Osswald et al. (2012)
Perceived Safety			
PS1	I feel safe while using the system.	I feel safe while using the system.	Osswald et al. (2012)
PS2	Using the system decreases the accident risk.	I believe the probability of an accident is low.	Osswald et al. (2012)
PS3	I don't think it will be a problem with the car.	I don't think it will be a problem with the vehicle.	–
Behavioral Intention			
BI1	If I have a chance, I will try to use it.	If I have a chance, I will try to use it.	Osswald et al. (2012)
BI2	I intend to use it.	I intend to use it.	–
BI3	I plan to use it in the future.	I plan to use it in the future.	Osswald et al. (2012)
Personal Innovativeness			
PI1	I often use smartphone apps.	Same items and responses were used in both models for personal innovativeness.	Sener et al. (2019)
PI2	It is important to keep up with the latest trends in technology.		Sener et al. (2019)
PI3	Technology will provide solutions to many of our problems.		Sener et al. (2019)

4.2. Data preparation & modeling approach

At the stage of preparing the data for the model, first, the sample size requirement was checked. Although several researchers suggested different sufficient sample sizes for structural equation modeling (SEM), $N > 200$ is considered a rule of thumb (Iacobucci, 2010; Bagozzi and Yi, 2012; Barrett, 2007). Accordingly, this study has a sufficient sample size ($N = 369$) for the SEM. Then, univariate, and multivariate normality conditions were checked. When the absolute skewness $|2|$ and kurtosis $|7|$ values stated by Curran et al. (1996) were taken as reference, the univariate normality condition was met for all the indicators in both models. However, the distribution of the data departed from the multivariate normality for both models since the multivariate kurtosis values were above the critique value of 5 (Bentler, 2006; Byrne, 2016). Nevertheless, maximum likelihood estimation could be used when the sample size is more than 100 even under severe nonnormality conditions (Lei and Lomax, 2005). Parameter estimates with maximum likelihood and generalized least squares are robust to depart from multivariate normality (Finch et al., 1997). Since all the indicators were reflective and the sample size was sufficient, the two-step covariance-based structural equation modeling (CB-SEM) technique with maximum likelihood estimation was employed in this study. The first step was composed of a measurement model. It consists of assessing construct validity and testing measurement model fit. The second step was composed of a structural model. It consists of testing the structural theory (Anderson and Gerbing, 1988; Hair et al., 2018). The measurement and structural models were performed using IBM SPSS AMOS 26 with 369 valid answers.

5. Findings

According to the 369 answers, females consisted of 55.83 % of the sample. Respondents aged between 18 and 25. The median age was 20. 52.30 % of the respondents had a driver's license. While 44.44 % of the respondents stated that they had never driven a car before, the rest of the sample had at least 1 year of driving experience. 63.69 % of the respondents stated that they had traveled by plane at least once. Looking at the answers given to the question "How much do you know about AVs?", 42.82 % of the respondents indicated they know or know well, while 34.69 % indicated they don't know or don't know at all. The same question was asked for UAM. 26.02 % of the respondents indicated they know or know well, while 49.05 % indicated they don't know or don't know at all. The rest of the respondents stated that they were unsure.

5.1. Measurement model

In the first step of the measurement model, standardized factor loadings were calculated. According to the results of the analysis (Table 3), all the standardized factor loadings in both models exceed the satisfactory cut-off value of 0.6 (Hair et al., 2018). In the next step, convergent validity and discriminant validity were assessed based on the cut-off criteria for composite reliability (CR) (>0.7) and average variance extracted (AVE) (>0.5) (Fornell and Larcker, 1981). To ensure discriminant validity, the square root of the AVE should exceed the inter-construct correlations. CR and AVE values were found satisfactory for both models to provide evidence of discriminant validity and convergent validity (Tables 4 and 5). The standardized residuals were between the cut-off range of |4.0| in both models (Hair et al., 2018).

After establishing satisfactory factor loadings and construct validity, the model fit was evaluated. Since the chi-square statistic (χ^2) is sensitive to sample size, additional fit parameters including the chi-square/degrees of freedom ratio ($\chi^2/df \leq 3$), standardized root mean squared residual (SRMR≤0.08), comparative fit index (CFI≥0.90) and root mean square error of approximation (RMSEA≤0.08) were used for the assessment of the model fit (Browne and Cudeck, 1992; Hu and Bentler, 1998, 1999; Kline, 2005). Findings revealed that all the model fit parameters were acceptable for both measurement models (Table 3).

5.2. Structural model

In this step, the relationship between latent constructs was established and the structural model fit was assessed. Table 6 shows the estimated standardized path coefficients and their significance levels, fit statistics, and results of the hypotheses of AV and APD acceptability models. Both structural models provided an acceptable fit to the data.

The findings confirmed that all the constructs significantly explain behavioral intention to use AVs. The association between effort expectancy and hedonic motivation with the behavioral intention to use AVs was found marginally significant ($p < 0.10$). Performance expectancy and social influence were significantly associated with behavioral intention at the 0.05 significance level, while perceived safety had a significant and positive effect on behavioral intention at the 0.001 significance level. Moreover, personal innovativeness was significantly associated with performance expectancy and effort expectancy at the 0.001 significance level. Thus, all the hypotheses (H1-H6) were supported by the AV acceptability model.

In line with the AV acceptability model, all the constructs significantly explain behavioral intention to use APDs. The association between effort expectancy and perceived safety with the behavioral intention to use APDs was found marginally significant ($p < 0.10$). Performance expectancy was significantly associated with behavioral

Table 3
CFA results for AV and APD models.

Autonomous vehicle			Autonomous passenger drone		
		Standardized Factor Loading			Standardized Factor Loading
Construct	Indicator		Construct	Indicator	
AV_PE	AV_PE1	0.711	APD_PE	APD_PE1	0.833
	AV_PE2	0.733		APD_PE2	0.796
	AV_PE3	0.695		APD_PE3	0.771
AV_EE	AV_EE1	0.864	APD_EE	APD_EE1	0.655
	AV_EE2	0.853		APD_EE2	0.808
	AV_EE3	0.810		APD_EE3	0.831
AV_SI	AV_SI1	0.898	APD_SI	APD_SI1	0.925
	AV_SI2	0.908		APD_SI2	0.901
	AV_SI3	0.769		APD_SI3	0.788
AV_HM	AV_HM1	0.822	APD_HM	APD_HM1	0.881
	AV_HM2	0.819		APD_HM2	0.820
	AV_HM3	0.757		APD_HM3	0.751
AV_PS	AV_PS1	0.899	APD_PS	APD_PS1	0.846
	AV_PS2	0.744		APD_PS2	0.865
	AV_PS3	0.671		APD_PS3	0.835
PI	PI_1	0.742	PI	PI_1	0.738
	PI_2	0.774		PI_2	0.774
	PI_3	0.761		PI_3	0.766
AV_BI	AV_BI1	0.756	APD_BI	APD_BI1	0.844
	AV_BI2	0.811		APD_BI2	0.899
	AV_BI3	0.860		APD_BI3	0.848
χ^2:422.651; df:168; $p < 0.001$ χ^2/df: 2.516 CFI: 0.941 RMSEA: 0.064 SRMR: 0.047			χ^2:440.260; df:168; $p < 0.001$ χ^2/df: 2.621 CFI: 0.945 RMSEA: 0.066 SRMR: 0.047		

AV: autonomous vehicle, APD: autonomous passenger drone, PE: performance expectancy, EE: effort expectancy, SI: social influence, HM: hedonic motivation, PS: perceived safety, PI: personal innovativeness, BI: behavioral intention.

Table 4
Convergent and discriminant validity results for the AV model.

Construct	Mean	Std. Dev.	CR	AVE	PE	EE	SI	HM	PS	PI	BI
PE	3.751	0.821	0.757	0.509	**0.713**						
EE	4.040	0.751	0.880	0.710	0.468	**0.843**					
SI	3.898	0.821	0.895	0.741	0.644	0.485	**0.861**				
HM	4.266	0.673	0.842	0.639	0.589	0.437	0.630	**0.799**			
PS	3.675	0.813	0.818	0.604	0.598	0.598	0.561	0.498	**0.777**		
PI	4.200	0.716	0.803	0.577	0.278	0.395	0.374	0.421	0.438	**0.760**	
BI	4.042	0.747	0.852	0.657	0.621	0.540	0.592	0.552	0.691	0.557	**0.811**

AVE: average variance extracted, CR: composite reliability, PE: performance expectancy, EE: effort expectancy, SI: social influence, HM: hedonic motivation, PS: perceived safety, PI: personal innovativeness, BI: behavioral intention. The square root of AVE for the constructs is shown as bold at the diagonal. All correlations are significant at the 0.001 level.

Table 5
Convergent and discriminant validity results for the APD model.

Construct	Mean	Std. Dev.	CR	AVE	PE	EE	SI	HM	PS	PI	BI
PE	4.146	0.696	0.842	0.641	**0.800**						
EE	3.706	0.853	0.811	0.591	0.654	**0.769**					
SI	3.858	0.820	0.906	0.763	0.630	0.667	**0.873**				
HM	4.293	0.676	0.859	0.671	0.639	0.544	0.580	**0.819**			
PS	3.564	0.859	0.885	0.720	0.474	0.657	0.522	0.392	**0.849**		
PI	4.197	0.718	0.803	0.577	0.438	0.406	0.443	0.438	0.371	**0.759**	
BI	3.904	0.823	0.898	0.747	0.662	0.648	0.667	0.637	0.524	0.349	**0.864**

AVE: average variance extracted, CR: composite reliability, PE: performance expectancy, EE: effort expectancy, SI: social influence, HM: hedonic motivation, PS: perceived safety, PI: personal innovativeness, BI: behavioral intention. The square root of AVE for the constructs is shown as bold at the diagonal. All correlations are significant at the 0.001 level.

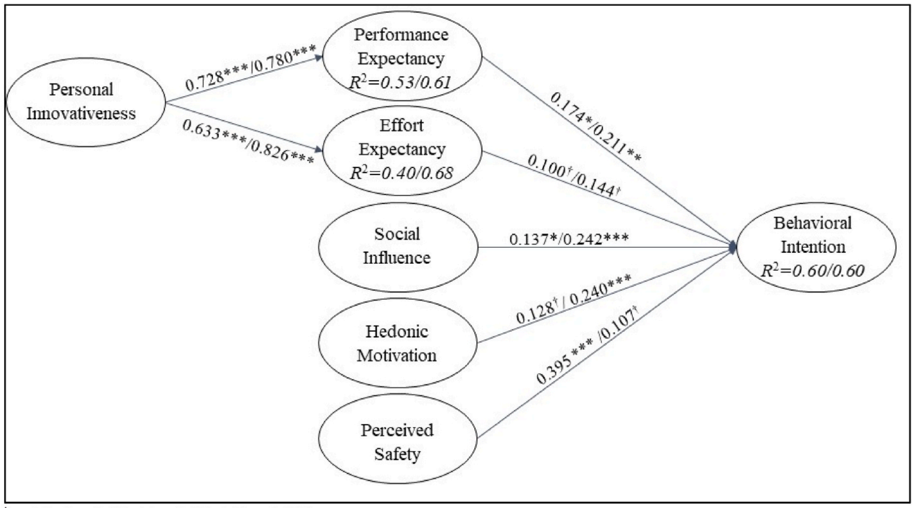
Table 6
Standardized path coefficients, significance levels, and fit statistics of AV and APD acceptability models.

Hypothesis	Predictor	Outcome	Std. Coefficient	z-value	p-value	Decision
Autonomous Vehicle Acceptability Model						
H1	AV_PE	AV_BI	0.174	2.202	0.028	Supported
H2	AV_EE	AV_BI	0.100	1.695	0.090	Supported
H3	AV_SI	AV_BI	0.137	2.028	0.043	Supported
H4	AV_HM	AV_BI	0.128	1.913	0.056	Supported
H5	AV_PS	AV_BI	0.395	5.041	<.001	Supported
H6a	PI	AV_PE	0.728	6.197	<.001	Supported
H6b	PI	AV_EE	0.633	6.254	<.001	Supported
χ^2:459.154; df:173; $p < 0.001$						
χ^2/df: 2.658						
CFI: 0.934						
RMSEA: 0.067						
SRMR: 0.055						
Autonomous Passenger Drone Acceptability Model						
H7	APD_PE	APD_BI	0.211	3.059	0.002	Supported
H8	APD_EE	APD_BI	0.144	1.892	0.058	Supported
H9	APD_SI	APD_BI	0.242	3.739	<.001	Supported
H10	APD_HM	APD_BI	0.240	3.898	<.001	Supported
H11	APD_PS	APD_BI	0.107	1.899	0.058	Supported
H12a	PI	APD_PE	0.780	6.710	<.001	Supported
H12b	PI	APD_EE	0.826	6.930	<.001	Supported
χ^2:461.729; df:173; $p < 0.001$						
χ^2/df: 2.669						
CFI: 0.942						
RMSEA: 0.067						
SRMR: 0.052						

AV: autonomous vehicle, APD: autonomous passenger drone, PE: performance expectancy, EE: effort expectancy, SI: social influence, HM: hedonic motivation, PS: perceived safety, PI: personal innovativeness, BI: behavioral intention.
$^{\dagger}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
The std. path coefficients and R^2 values of AV and APD models are separated by a slash. The former shows the std. path coefficients and R^2 values of the AV model, and the latter shows the std. path coefficients and R^2 values of the APD model.

intention at the 0.01 significance level, while social influence and hedonic motivation had a significant and positive effect on behavioral intention at the 0.001 significance level. In addition, personal innovativeness was significantly associated with performance expectancy and effort expectancy at the 0.001 significance level. Thus, all the hypotheses (H7-H12) were supported by the APD acceptability model.

Fig. 2 presents standardized path coefficients and explained variances (R^2) of endogenous variables. The overall R^2 values indicate that



†p<0.1, *p<0.05, **p<0.01, ***p<0.001
The std. path coefficients and R^2 values of AV and APD models are separated by a slash. The former shows the std. path coefficients and R^2 values of the AV model, and the latter shows the std. path coefficients and R^2 values of the APD model.

Fig. 2. Results of the structural model.

both models could explain 60 % of the variance related to behavioral intention to use AVs and APDs by university students.

6. Discussion

This study tested the assumptions of the proposed extended UTAUT model for AV/APD acceptability. Findings revealed that both proposed extended UTAUT models explain a 60 % variance of behavioral intention to use AVs and APDs. The explanatory power of the proposed models is more than the average explanatory power ($R^2 = 0.46$) of previous autonomous vehicle acceptability studies (Keszey, 2020).

6.1. Theoretical implications

First, looking at the AV acceptability model revealed that perceived safety and performance expectancy had the strongest effects on behavioral intention. According to Moody et al. (2020), respondents in Türkiye have low perceptions of current AV safety. Nevertheless, they believe that AVs will be safe enough to use shortly. This finding supports the respondents' concerns about the importance of safety. In line with previous studies (Choi and Ji, 2015; Buckley et al., 2018; Panagiotopoulos and Dimitrakopoulos, 2018; Lee et al., 2019; Morrison and Van Belle, 2020; Farzin et al., 2022), the strong effect of performance expectancy on behavioral intention to use AVs was also verified in this study. Contrary to previous studies (Madigan et al., 2017; Garidis et al., 2020; Morrison and Van Belle, 2020), the effect of hedonic motivation on behavioral intention was found relatively weak. In the Turkish context, Korkmaz et al. (2021) found that the effect of hedonic motivation on behavioral intention to use automated public transport was non-significant. Nevertheless, this study found a marginally significant association between hedonic motivation and use intention. The weak effect of hedonic motivation in AV acceptability may be due to the fact that AVs are primarily marketed for their traffic-reducing and time-saving features, emphasizing their performance. As a result, usefulness and safety issues take precedence over hedonic motivation, which is less emphasized. Additionally, the lack of hedonic experience in conditional vehicles and the inability to experience a fully autonomous vehicle may contribute to the weak effect of hedonic motivation. Finally, cultural norms and demographics may also lead to differences between hedonic and practical perceptions. Further research is needed to explore the reason behind the weak effect of hedonic motivation on behavioral intention.

Second, the APD acceptability model suggested that social influence had the strongest effect on behavioral intention among all constructs. Rohlik and Stasch (2019) also presented the strong effect of social influence in this context. One possible reason for this outcome may be the collectivist culture in Türkiye. As presented by Im et al. (2011), collectivist and individualist cultures differ in terms of technology acceptance. They found that although it was non-significant, the coefficient of social influence was stronger in the Korean population than in the US population. It can be deduced that potential users in Türkiye are sensitive to trends in their social environment in the context of APD acceptability. Contrary to the AV acceptability model, hedonic motivation was a strong determinant of APD acceptability. This finding is in line with Venkatesh et al. (2012), as well as Winter et al. (2020). The acceptability of APDs is closely related to how enjoyable it is. On the other hand, perceived safety did not appear to be at the forefront as a predictor of APD's use intention. This finding is in line with Rohlik and Stasch (2019) however, contrary to Kim et al. (2022). The weaker effect of perceived safety in APD model may arise from the fact that safety is not the primary expectation in a new and unfamiliar mode of transportation. However, users might prioritize safety in AVs because they are more familiar with the concept. Furthermore, the ability of users to directly control AVs or engage in interactions with the environment and the vehicle may emphasize safety perception more prominently compared to the more straightforward nature of safety concerns in APDs. In conclusion, the closer conceptual familiarity of users with AVs and the perceived controlled and reliable nature of aviation might contribute to this outcome. Future studies should delve into the effect of perceived safety on behavioral intention to use UAM.

Third, the role of personal innovativeness was proposed as a new exogenous mechanism in both models (Venkatesh et al., 2016). In line with previous studies (Leicht et al., 2018; Winter et al., 2019), the significant and positive effect of personal innovativeness on performance expectancy and effort expectancy was proved empirically. Personal innovativeness is a strong factor when estimating utilitarian value in the context of AV and APD acceptability. These findings suggest that tech-savvies expect high performance from AVs/APDs and believe that these vehicles can be used with little effort.

Fourth, both models revealed a marginally significant association between effort expectancy and behavioral intention. Several studies have found a weak significant effect of effort expectancy on behavioral intention to use AVs (Choi and Ji, 2015; Panagiotopoulos and Dimitrakopoulos, 2018; Dirsehan and Can, 2020; Garidis et al., 2020), some even found that this effect was non-significant (Madigan et al., 2017; Buckley et al., 2018; Lee et al., 2019; Nordhoff et al., 2021). A review study reported that effort expectancy is less likely to be found significant among other baseline UTAUT constructs (Williams et al., 2015). The results of this study are in line with those findings. The fact that AVs/APDs have not yet been released to the market and, therefore, they have not been experienced, may have caused this result. Yet, the effect of effort expectancy on behavioral intention has remained controversial in the context of AV acceptability.

When examining the two models, it is evident that perceived safety and performance expectancy are prominent for AV model, while social influence and hedonic motivation stand out in the APD model. Therefore, the two models diverge. However, personal innovativeness and effort expectancy variables show similarities in both models in terms of impact and importance. Overall, all hypotheses in both models are supported at a significance level of at least 0.10.

6.2. Practical implications

The study's prominent results indicate that perceived safety and performance expectancy are crucial factors in the adoption of AVs. Therefore, organizing education and marketing campaigns focused on the safety aspects of AVs would be beneficial for vehicle manufacturers and policymakers. Informative initiatives aimed at convincing people about the safety of these vehicles can accelerate the adoption process. In addition to theoretical explanations, it is important to organize practical events where users can directly experience AVs. This will help convey the utilitarian value that AVs offer to users in daily use. Through such activities, concerns related to both performance expectancy and perceived safety can be addressed, providing concrete answers to potential concerns, and fostering a more positive attitude towards AVs. On the other hand, vehicle designers can increase the appeal of AVs by prioritizing designs that provide in-vehicle entertainment and comfort features. Marketing campaigns can also be developed to emphasize and promote these aspects of AVs.

In the case of APD adoption, social influence and hedonic motivation are key factors. Therefore, it is crucial to develop marketing strategies that dwell on positive endorsements and experiences from influential figures or social networks. Furthermore, using hedonic attractions like panoramic vistas or entertainment alternatives as part of the promotional and marketing plan can raise passenger satisfaction levels overall. On the other hand, promoting the safety of the system through social influence can be effective in facilitating the adoption process. For example, statements from high social influencers about safety, and the transparency and clarity of vehicle manufacturers in their technical explanations can increase the perceived safety of APDs.

Finally, it can be concluded that both modes of transportation are likely to be used by individuals with a high level of personal innovativeness. To facilitate the adoption process, pilot trials should be conducted in areas with a high level of technological proficiency, and focus groups for marketing campaigns should be selected from these areas. In other respects, to enhance the weak impact of effort expectancy, user-friendly designs by vehicle designers and user-friendly interfaces and controls in operational practices can accelerate the adoption process for both transportation modes.

6.3. Limitations

Online surveys are cost-effective and practical for many studies, especially during the pandemic period. However, bias in the population is one of the limitations of this approach. The results may have not fully represented the whole university student population in Türkiye. Apart from that, most of the respondents have low levels of knowledge about AVs and APDs. Furthermore, the models were assessed without moderator and mediator effects. Lastly, previous international studies proved that public opinions about AVs (and possibly APDs) are changing across countries (Schoettle and Sivak, 2014; Nordhoff et al., 2018; Moody et al., 2020). The result of this study therefore may not be generalizable. Future studies could focus on different target groups in different cultures, different exploratory factors, and their moderation/mediation effects.

7. Conclusion

The primary objective of the present study was to find the antecedents that explain behavioral intention to use two emerging transport technologies and thereby provide an early insight. In this regard, an extended UTAUT model was proposed with additional hedonic motivation, perceived safety, and personal innovativeness constructs to estimate behavioral intention to use AV/APD. The target group was defined as university students. Then, a sample (N = 369) was drawn from this target group. The analysis was made by using CB-SEM and the findings revealed that all the hypotheses (H1-H12) were supported by the AV/APD acceptability models. The study adds to the existing body of knowledge as an early investigation of the antecedents of behavioral intention to use AVs and APDs comparatively. In addition, the study yields important insights from a developing country in the field of automated transportation technologies.

In the AV acceptability model, perceived safety and performance expectancy were the strongest determinants of university students' behavioral intention to use AVs. The ones who believe that AVs would increase their performance and ensure safe travel, are the potential early adopters. On the other hand, social influence and hedonic motivation were the main drivers of university students' APD acceptability. The findings suggest that university students would use APDs because they related to this means of transport as an entertainment instrument. In addition, those who define themselves as innovative expect high performance from AVs/APDs and believe that these vehicles can be used with little effort.

Although performance and safety are the most important factors in AV acceptability, it was revealed that the importance of safety lags behind hedonic motivation and social influence in the APD acceptability model. It can be deduced that university students perceive using AVs as more realistic, and hence consider the performance and safety factors. On the other hand, they perceive APDs as a means of entertainment and status symbol beyond their performance and safety. These salient findings could guide the politicians, scholars, and stakeholders of AV and the UAM market.

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Yigit Can Yavuz: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The author declares no conflict of interest regarding the publication of this paper.

Data availability

Data will be made available on request.

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