Journal of Air Transport Management 107 (2023) 102336

Contents lists available at ScienceDirect

Journal of Air Transport Management

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

Consumer intention over upcoming utopia: Urban air mobility

Volkan Yavas [a,*], Özge Yavaş Tez [b]

[a] Ege University - Aviation HVS, İzmir, Turkey
[b] Manisa Celal Bayar University, Turkey

ARTICLE INFO

Keywords:
Urban air mobility
Flying car
Consumer behaviour
Recreation

ABSTRACT

This study investigates the factors affecting users' acceptance of urban air mobility (UAM) systems, constructing a proposed theoretical urban air mobility acceptance and usage model (UAM-AUM). In this context, we posit that intention to fly, UAM conceptual intention, environmental consciousness, UAM affordability, general reliability and perceived usefulness variables are key determinants for behavioural intention to use. Using the UAM-AUM scale we apply structural equation modelling analysis for model validation based on data collected from 348 participants and the results strongly support the proposed model. Perceived usefulness is found to be the strongest determinant of user behavioural intention and mediates the effects of UAM acceptance, influencing the intention to use the system along with other variables. Another critical factor for promoting consumers' positive intentions towards UAM system use is general reliability. The findings provide practical guidance for designing strategic interventions to improve public acceptance of UAM systems.

1. Introduction

The fourth industrial revolution (Industry 4.0) is a new attractive scholarly and professional research consideration for researchers and the sectors and institutions trying to adapt to accelerated technological transformation. Industry 4.0 refers to the accelerated digitalisation and technological transformation process in all sectors, and the transportation sector undoubtedly has the intention and obligation to keep pace with this trend. In the process of the innovative transformation in the transportation sector, electric vehicles will increase dominance in all modes of transportation. Electric vehicles are expected to significantly impact future transportation systems with substantial appeal for reducing energy consumption and emissions through combining high efficiency with low energy use in comparison to traditional methods (Xu et al., 2020, p. 2). Ongoing research and the transformation of road transportation will inevitably reflect other modes and approaches to transport. Given its high energy consumption and emissions, the air transport system, with its existing infrastructure, is not an efficient option compared to other transport modes, particularly for short distances (Liu et al., 2016, p. 280). The new paradigm of UAM has emerged in air transport to address this demand, an innovative concept referencing safe and efficient passenger or cargo transportation activities in urban areas using electric vertical take-off and landing (e-VTOL) aircraft (Kleinbekman et al., 2018, p. 1).

Autonomous and electric vehicles are projected to be an important future transportation choice and will particularly benefit those who have previously been at a disadvantage, such as the disabled and elderly. It is estimated that the demand for UAM systems and autonomous vehicles will increase over time and could achieve use similar to the heavy vehicle traffic experienced on highways today (Wang et al., 2020a, p. 298). Although consumers' acceptance and use of new transportation is thought to be in high demand for road transport, the question of how much or when this transformation will be in the sky remains. The arising queries and uncertainties encountered during this new and exciting advancement towards low-flying air-based transport for both suppliers and passengers are another research interest. Although the economic potential of UAM is revitalising, it faces obstacles for security, safety and community acceptance. From privacy violations to affordability concerns, many elements of public acceptance that need to be addressed also stand out (Thipphavong et al., 2018).

The factors affecting the acceptance of users of urban air mobility (UAM) systems will be presented by creating a theoretical urban air mobility acceptance and use model (UAM-AUM) proposed in the study. The remainder of the study will begin with a literature review, followed by sections on methodology and data, results, discussion and implications.

* Corresponding author.
E-mail addresses: volkan.yavas@ege.edu.tr (V. Yavas), ozgeyavas@hotmail.com.tr (Ö. Yavaş Tez).

https://doi.org/10.1016/j.jairtraman.2022.102336
Received 22 November 2021; Received in revised form 15 November 2022; Accepted 16 November 2022
Available online 7 December 2022
0969-6997/

2. Literature review

Transportation is an important aspect of individuals' daily lives in urban areas. Traditional transportation options primarily include private and public transportation vehicles; however, contemporary transport methods are not fully inclusive. Cultural, generational and consumption behaviour differences have generated new concepts, such as the 'sharing economy'. People are now more willing to rent a bike or share a ride using public transport alternatives and increasingly popular sharing economy apps (Welch et al., 2020, p. 43). Similarly, the on-demand ride-sharing system will inevitably affect air transportation systems, whereas Airbus, Boeing and Uber are working intensively on developing more flexible, environmentally friendly and reliable transportation alternatives using VTOL vehicles in UAM systems (Al Haddad et al., 2020, p. 700).

Developers tailor electronic vehicles' technical features to consumers' varying needs. Considering that consumers' interest in on-demand travel will continue to rise, autonomous vehicles will also be included in future transportation systems (Chen et al., 2016, p. 244). In addition to all economic, technological and legal regulations, the approach of the users who will establish the demand for autonomous systems is also critical. Consumers' interest in autonomous vehicles is heterogeneously distributed among young people living in cities that are overwhelmed by traffic, dislike driving, care about time and have high environmental concerns, whereas well-educated and tech-savvy young people have a more positive perspective (Zhang et al., 2020, p. 1). In contrast, elderly consumers assume a more negative perspective due to a lack of knowledge regarding such systems and safety concerns in general (Zhang et al., 2020, p. 1). As with all emerging technologies, most users (other than early adopters) are not expected to quickly adopt autonomous vehicles over more familiar transportation activities. To reduce these biases and perceived risks, governments and technology developers must strategically develop intensive persuasion processes (Wang et al., 2020a, p. 304). Currently, regulations regarding UAM systems for autonomous or electric vehicles are being followed more comprehensively.

The International Civil Aviation Organization (ICAO) has created a platform, the Electronic and Hybrid Aircraft Platform for Innovation (E-HAPI), simultaneously tracking the evolution of innovative autonomous and electric vehicles, ranging from commercial aviation to UAM system. The projects listed on the platform share the aircraft and technical characteristics intended to enter service between 2020 and 2030 (some of them already making their first flights), and follows the emerging and evolving studies, standards and recommended practices in the field (ICAO, 2021a). The ICAO also hosted a June 2021 event for e-VTOL and UAM systems as a new and sustainable approach to air transport, asserting that development represents a unique opportunity to rebuild air transport systems, particularly from an environmental perspective (ICAO, 2021b). In its document entitled 'Aircraft Technology Roadmap to 2050', the International Air Transportation Association (IATA, 2019) predicted that electric vehicles will be integrated into UAM systems that are expected to be implemented between 2020 and 2025.

With increased studies and significant progress on UAM systems and e-VTOL vehicles, the need to establish air vehicle certification requirements has also emerged. The European Union Aviation Safety Agency (EASA) responded to this need in 2019, establishing certification requirements for this type of aircraft with the 'Special Condition for small-category VTOL aircraft' regulation. It has also determined the beginning of legal regulations (EASA, 2019). Similarly, the Federal Aviation Authority (2019) in the US released its first documentation of operational processes to communicate its vision for an air traffic service to support the first pilot UAM operations.

In addition to the work of these aviation authorities and institutions, many companies, including Uber, Airbus and Boeing, have significantly contributed to the technical development of UAM systems. The potential demand for such systems requires strategic consideration, and researchers should not overlook potential users' opinions. In parallel. Recent studies have measured acceptance and usage intentions.

EASA (2021) published a report on the social acceptance of UAM system in Europe in March 2021, with the following the highlights:

- EU citizens generally have positive attitudes and interest in UAM systems and want to take an active role in the development of the process.
- The primary expectations of UAM are faster, cleaner and increased accessibility.
- Although safety and security are the predominant concerns, ensuring safety at the current aviation standard is acceptable for the majority.
- Noise and environmental concerns are notable priority.
- UAM systems must be designed in a manner that does not harm/disturb existing lifestyle culture, living spaces or cultural heritage.

According to a November 2018 UAM Market study of the US National Aeronautics and Space Administration (NASA), 'safety, privacy, employment, environment, noise and visual distribution' are concerns of UAM public acceptance. Of the 2500 participants in the NASA study, 25% of the respondents had positive intentions towards the system, whereas 25% indicated that they would not use the system until it became wide-ranging (NASA, 2018). The success of UAM systems largely depends on users' acceptance, and the vehicles, flight patterns and circumstances of passengers' flight process and vertiports will have an influence on potential users' assessment (Edwards and Price, 2020).

Research has been undertaken regarding the social, technical, and legal dimensions of UAM systems. For society, studies distinguish the benefits of UAM from public perspectives. The findings of a comprehensive study of UAM systems (Straubinger et al., 2020, p. 10) revealed: (1) UAM can shorten travel times but create energy and cost barriers. (2) UAM can provide high flexibility in vertiport infrastructure only but can lead to high infrastructure costs. (3) Initial UAM will require combined transport (particularly road) connections and will be unable to meet all existing mobility needs. Meanwhile, according to KPMG, one of the world's four giant multinational professional services network companies, about 12 million people worldwide will use UAM systems by the end of 2030, reaching 400 million passengers by 2050, indicating that it UAM systems will service 4% of domestic transportation in the US (Mayor and Anderson, 2019). In parallel, according to a news report, it is estimated that the market will grow 5 times from 2023 to 2030, that the sector will become visible with 4000 vehicles in operation in 2028, and that it will reach widespread use with approximately 23000 vehicles in 2030 (MundoGeo, 2022).

Perspectives regarding the acceptance and use of UAM systems are twofold. (1) The socio-political view of this new technology in the public sphere and (2) potential customers' intention to use UAM systems. Nevertheless, predictions remain difficult because UAM systems are not yet tangible aspects of everyday urban life (Straubinger et al., 2021). Two additional components that may determine UAM system demand include willingness to hire and willingness to pay according to various price scenarios. The factors affecting these measures can be homogeneously distributed based on socio-demographic factors to individual-specific factors. One of the most critical elements is the determination of socially acceptable pricing policies (Ahmed et al., 2021). For instance, in a study of UAM preferences, Fu et al. (2019) find members of generation X to be less interested, whereas millennials and generation Z have a higher level of interest, even when their income levels are low (p. 439). In the same study, no significant difference is found between the sexes in the level of interest in UAM, but education and income level and interest in UAM are found to be parallel. The studies referenced in the previous sentences primarily include evaluations from the perspective of the passenger/consumer in the UAM system, due to the theme of the study. However, it should be noted that the UAM system may be in active use for freight transport, emergency operations, recreation, and other purposes like passenger transport. For this reason, while generalizing the consumer acceptance of the system, aircraft operators should not be excluded from the scope. It should not be overlooked that just as the passengers' access fees to the system are important for the acceptance of the system, the costs for the operators to be included in the system can also have a significant impact. According to a study on the willingness of aircraft operators to pay for low-altitude airspace access, the application of variable fare tariffs according to vehicle type and type of use can create several more fair, efficient, affordable, safe, protective of privacy, satisfaction-enhancing, and promising cumulative positive effects on the development of the system (Merkert et al., 2021).

Ease of use and accessibility are options that often attract consumers. Mola et al. (2020) investigate the advantages of using the mobility-as-a-service option as one of the factors affecting consumer behaviour in this change in the transportation sector, noting that the benefits of such innovations must be conveyed for consumer acceptance or positive intention. Additionally, service and technology manufacturers will continue to share various positive aspects to market UAM and its derivatives, but this new 'thing' must be considered from the consumers' perspective. Although many positive and exciting factors exist, manufacturers, marketers and policymakers must not ignore various consumer concerns. EASA's (2021) report indicates that the top concerns for consumer acceptance are safety and security. In UAM systems and VTOL vehicles, vehicle control (piloted or automated) is at the forefront of consumers' the safety concerns. Apart from safety and security concerns commonly encountered in the adaptation of UAM system, the presence and social media impact of in-car cameras and operators, particularly in autonomous vehicles, are also among the prominent factors of UAM acceptance (Al Haddad et al., 2020).

2.1. Theoretical background and model development

In parallel with the new technology and innovation, researchers have developed many models to explain human technology adoption behaviour. The most well-known of these models is the technology acceptance model (TAM) (Davis, 1989); however, researchers have not limited the factors of adoption to just one model. In addition to the TAM model, planned behaviour theory, the unified technology acceptance and use theory (UTAUT) and the automated tools acceptance model and improved versions thereof are also used in this field (Zhang et al., 2019). These models are based on theoretical constructions to examine the relationship between consumers' attitudes towards new technology and behavioural intention to use it (Zhang et al., 2019).

The TAM includes three variables—perceived ease of use (PEOU), perceived usefulness (PU) and attitude towards using a technology (ATT)—that are considered antecedents to technology acceptance (Davis, 1989), asserting that behavioural intention to use (BIU) a technology is determined by individuals' attitude towards technology use. The construct of attitude includes two primary determinants of attitude, which are PU and PEOU. In addition, PEOU affects PU, and PU has a direct effect on BIU (Zhang et al., 2019). While Swanson (1988) defines system acceptance as consumers' tendency to use a particular system (Szajna, 1996), system acceptance in TAM is determined to be a mediator of BIU (Davis et al., 1989). One TAM study demonstrates a high correlation between intention and behaviour, asserting that users' behaviours can be measured using usage intentions (Mathieson et al., 2001). Consequently, we take BIU as the dependent variable in the study.

BIU refers to the extent to which an individual intends to use a technology. In the original TAM, the BIU mediates the effects of other potential antecedents of actual user behaviour; therefore, when examining the acceptance of technological systems at an early stage, BIU, rather than actual usage, is often a dependent variable (Davis et al., 1989; Holden and Karsh, 2010). The UTAUT TAM was developed to unify acceptance models, combining PU, PEOU, social impact and facilitating conditions as direct determinants of BIU, also suggesting that user characteristics, such as age, gender, experience and willingness to use may moderate the relationships between BIU and its precursors (Zhang et al., 2019).

Another TAM is the automated vehicles (AVs) acceptance model (Zhang et al., 2019). As such vehicles are expected to be available soon, the AVs model represents one of the new models developed to better understand consumers' attitudes and usage intentions regarding the use of automated vehicles. The AVs model is constructed by extending TAM with initial trust and perceived risk variables. In the AVs model, PU refers to the extent to which a person believes using an AV will improve their performance. AVs are expected to offer many benefits for users, such as greater safety, less energy consumption and flexibility to manage travel tasks. These can increase consumers' positive attitude towards and intention to use AVs (Choi and Ji, 2015; Xu et al., 2020; Yousafzai et al., 2007). PEOU refers to the extent to which a person believes using AVs will be effortless. Previous studies acknowledge that PEOU has direct effects on PU and attitude (Yousafzai et al., 2007). PEOU can also affect BIU; however, this effect is found to occur indirectly through PU and attitude structures (Davis et al., 1989; Subramanian, 1994).

According to Lee and See (2004), trust refers to 'the attitude of an agent to help an individual achieve their goals in a situation characterised by uncertainty and vulnerability'. It is identified to be a key element that determines human–automation interactions. While it is possible to eliminate distrust in an automated system, overconfidence can lead to abuse or misuse (Parasuraman and Riley, 1997). Lack of trust in AVs is the most frequently cited reason for not accepting a system (Zmud et al., 2016). Considering that most consumers have not yet interacted with AVs, this form of trust differs from the dynamic trust that is formulated during interaction with a system and is therefore referred to as 'initial trust' (Hoff and Bashir, 2015).

At the initial stage of marketing an emerging technology, potential consumers must build up enough trust to overcome perceptions of risk and develop positive attitudes (McKnight et al., 2002). Therefore, initial trust in AVs is critical for BIU towards AVs (Zhang et al., 2019). Zhang et al. (2019) examine the factors affecting consumers' AV acceptance, proposing a theoretical acceptance model by expanding the TAM with new structures and determining that the construct of initial trust in the model is built on a combination of PU and PEOU. Subsequently, these two variables are considered to be the key determinants and the most critical factors in consumers' AV acceptance. At this point, the region and population density as another important factor in consumer acceptance should also be evaluated. According to a study, AVs were compared with electric cars and gasoline cars; It has been revealed that AVs can provide more environmentally friendly transportation service in the Chicago region of the USA, but it has been emphasized that AVs alone will not make a difference in terms of environmental friendliness due to the high grid emission index in the Dallas region and that their integrated use with electric cars will be more beneficial (Mudumba et al., 2021). What is decisive here is the orientation or persuasion of environmentalist consumers to transportation options that are compatible with the city and lifestyle they live in. Consequently, compatibility affects both PU and PEOU (Yuen et al., 2021). UAM technologies are environmentally friendly vehicles characterised by reduced environmental impact from lower emissions that will offer more efficient travel options (Baptista et al., 2014).

Similarly, the automation acceptance model (AAM) integrates both trust and compliance variables into the model based of the TAM (Ghazizadeh et al., 2012). In AAM, the original TAM construct remains unchanged, while trust and compatibility affect the BIU through PEOU and PU. In addition, the trust variable has a direct effect on the BIU. Although it was one of the first attempts to provide a theoretical framework for the adoption of AAM, the validity of the model has not yet been validated (Zhang et al., 2019). More complex models based on general theories of human behaviour or interview results are also proposed, but their validity is not well documented. Clearly, many models of technology acceptance are presented in the literature to be developed.

Failure to comprehensively investigate the validity of these models following our review of the relevant literature indicates that the development and maturity of contemporary technology acceptance models remains at an early stage (Zhang et al., 2019).

3. Methodology

3.1. Measurements

3.1.1. Urban air mobility acceptance and usage model (UAM-AUM)

The urban air mobility acceptance and usage model (UAM-AUM) determines consumers' attitudes regarding acceptance and use of UAM systems, which have the potential to be an important element of aviation in the near future (Yavaş and Tez, 2021). The UAM-AUM measurement tool combines 30 items in seven dimensions, including intention to fly (IF), UAM affordability (UA), UAM conceptual intention (UCI), environmental consciousness (EC), general reliability (GR), PU and BIU. The measurement tool developed for the UAM-AUM model is a five-point Likert scale.

3.2. Participants and sample size

In structural equation modelling (SEM), sample size has a significant role in estimating and interpreting results and potential sampling errors (Hair et al., 2006). At least five respondents is considered the minimum ratio for each predicted parameter, with a ratio of 10 participants per parameter considered optimal, rather than a standard sample size for SEM. A sample size of 100–200 is considered appropriate (Reisinger and Mavondo, 2007; Schreiber et al., 2006; Hair et al., 2006). We should also note that problems may arise in SEM analyses using small samples; thus, sample size should increase as the model complexity increases. The most common estimation procedure in SEM is maximum likelihood estimation (MLE). Both small and large samples may also be insufficient for estimating complex models using the MLE method, as goodness-of-fit values may become weak with increased sensitivity; therefore, sample size should be determined within a range that is consistent with the model (Schreiber et al., 2006).

To create the sample for the UAM-AUM model, 348 participants meeting the minimum requirements were included in the study. We used the criterion sampling method to determine the participants in the research (Patton, 2014). In this context, we invited 'passengers with at least one airline experience' to the study. Since it is not possible to collect data face-to-face due to COVID-19, we created a survey link using online platforms, sending the link to all stakeholders, universities and institutions related to the aviation industry on various social media platforms in Turkey, collecting data between 1 April and May 15, 2021. Table 1 summarises the participants' demographic characteristics.

Participants' demographic information is presented in Table 1. Accordingly, the age of the participants varies from 20 to 71 years, and employment areas range from businesspersons to academics, and health sector workers to finance sector workers. Of the 348 participants, there are 196 males and 152 females. The participants are from 38 cities in Turkey, particularly concentrated in Izmir, Istanbul and Ankara, with a small number from abroad. Moreover, the participants primarily listed fun/travel, work and leisure experience as the 'purpose of flight'. In addition, 54, 195 and 99 participants completed their undergraduate, master's and doctoral education, respectively. Participants' monthly household incomes of the participants vary between 1 and 700 USD and 701–1400 USD. Air travel frequency of 'at least once a year' was the most common response. Moreover, for the participants that chose 'other' regarding the frequency of flights, reasons included 'it has decreased due to the pandemic', 'it is uncertain', 'it changes according to the situation' and 'it increases or decreases when necessary'.

Table 1
Demographic characteristics of participants.

Demographics	Category	Frequency	Percentage %
Gender	Male	196	56,3
	Female	152	43,7
Age	20–25 years	164	47,1
	26–30 years	32	9,2
	31–35 years	54	15,5
	36–40 years	36	10,3
	Above 41	62	17,8
Education Level	BS	54	15,5
	MS	195	56,0
	PhD	99	28,4
Travel Frequency	At least once a week	8	2,3
	At least once a month	23	6,6
	At least once every three months	26	7,5
	At least once in six months	51	14,7
	At least once per year	165	47,4
	Other	75	21,6
Monthly Income	1–700 USD	226	64,9
	701–1400 USD	92	26,4
	1401–2100 USD	18	5,2
	2101–2800 USD	6	1,7
	2801 USD and above	6	1,7
Flight Purpose	Entertainment/travel	218	62,6
	Business	78	22,4
	Leisure Experience-Recreation	52	14,9

3.3. Data collection method and analysis

We conducted a pre-SEM technical analysis stage before SEM. In this stage, analyses related to model determination and testing of the determined measurement model are performed. Confirmatory factor analysis was executed during measurement model testing. Cronbach's alpha and split-half tests were performed for reliability analysis. For convergent and divergent validity, mean explained variance (AVE), average variance extracted square root ($\sqrt{AVE}$) and structural reliability (CR) values were calculated. The established SEM based on the theoretical infrastructure was then tested. This testing phase examined direct and indirect effects. The bootstrapping method was used to examine the mediating role of the model. We used SPSS, AMOS, Excel and PROCESS programmes for the entire analyses process conducted, presenting the results below.

3.4. Research model and research hypotheses

For this study, the SEM was constructed based on previous research and theoretical proposals. The graphical representation of the research model is presented in Fig. 1.

Fig. 1 presents the research model, in which the dependent variable is BIU, independent variables are IF, UA, UCI, EC and GR and the mediating variable is PU. IF refers to the intention to fly in the UAM system and is defined as consumers' willingness to use the system. UA refers to the perceived affordability of the UAM system and the price consumers may be willing to pay for the UAM system. UCI is related to conceptual intent and is defined as individuals' psychological tendency towards using the UAM system. EC refers to participants' environmental awareness in terms of the UAM system and is defined as individuals' tendency to use the UAM system to support environmental sustainability. Finally, GR refers to the overall safety and security of the system and includes considerations of trust in the manufacturers of the UAM system and safety precautions during use. The dependent variable in the study, BIU, is related to behavioural intention. After the production of the UAM system, consumers prefer these tools and their attitudes towards their use. The mediating variable of PU is related to the use of the system, defined as the perceived convenience of the UAM system, which is related to the convenience, change and benefits that a UAM will provide to consumers when using the system. In this context, we propose the

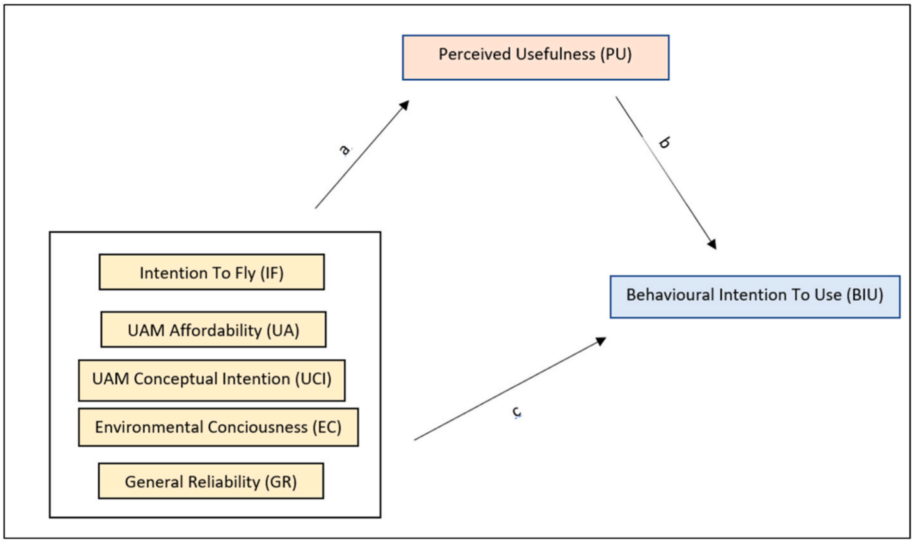

Fig. 1. Research model.

following hypotheses:

H1. A, B, C, D, E: IF-UA-UCI-EC-GR have a positive effect on PU.

H2. A, B, C, D, E: IF-UA-UCI-EC-GR have a positive effect on BIU.

H3. PU has a positive effect on BIU.

H4. A, B, C, D, E: PU has a mediating effect on IF-UA-UCI-EC-GR on BIU.

4. Data analysis

4.1. Pre-structural equation model technical analysis

SEM is one of the multivariate techniques that simultaneously predicts a set of hypothetically linked relationships among a set of latent constructs (Reisinger and Mavondo, 2007). In this respect, SEM is applied to examine the nature and magnitude of putative relationships and to evaluate direct and indirect effects (Schumacker and Lomax, 2004; Reisinger and Mavondo, 2007). SEM is considered to be a more advanced method compared to other multivariate techniques, as it can simultaneously predict several interrelated dependency relationships (Byrne, 1998). The choice and preference of a particular statistical technique are subject to the data availability; however, once this decision has been made, the researcher must have basic knowledge of the technique in question. In general, before using an SEM, it is necessary to determine the model in a pre-SEM technical analysis to validate the measurement model. Researchers must fulfil conditions such as preliminary SEM analysis, examining data characteristics and fulfilment of basic statistical assumptions prior to conducting SEM analysis. In addition, researchers must determine the appropriate model prior to the analysis. Researchers are usually guided by a combination of theory and empirical results from previous research in determining this model (Hox and Bechger, 1998).

4.2. Determining the urban air mobility model

In the process of constructing the UAM model, we scanned national and international databases. Searching the Web of Science (WOS) database with the keywords 'urban air mobility', 'VTOL' and 'flying car' yielded a total of 96 studies; the oldest study was in 2018. In contrast, the Scopus database yielded 4965 results with the same keywords, and the oldest study was related to the VTOL keyword in 1956–1957. When we examined the related studies in detail, it became clear that the word VTOL had a different meaning than is known today (i.e. electric, digital, intelligent), and our search continued using the words 'urban air mobility' and 'flying car', eliciting 502 studies. Among these studies, we found a study by Crow (1990) regarding the theme of 'personal aviation' to be the oldest; however, studies close to the current UAM construct started in 2003–2004. Finally, a Google Scholar database search determined the oldest study on the subject to be by Nneji et al. (2017) and is in the NASA archive. We evaluated the details of approximately 700 studies from WOS, Scopus and Google Scholar databases, determining approximately 95% of the studies to be related to technical, technological and engineering fields. Among the limited number of studies on UAM systems, very few measured consumer behaviours or intentions (Yavaş and Tez, 2021). These conditions were considered, in the development of UAM-AUM to determine consumers' attitudes towards acceptance and use of UAM systems (Yavaş and Tez, 2021). Previous studies were referenced (Chen and Lu, 2016; Chancey, 2020; Davis, 1989; Davis et al., 1989; Zhang et al., 2019; Al Haddad, Chaniotakis, Straubinger, Plötner and Antoniou, 2020; Yuen et al., 2020; Yuen et al., 2021) when developing the model. In addition to the sample items and approaches, new items deemed suitable for the subject were also added.

The SEM approach limits the path diagram to structures, and researchers must determine the variables for measuring each structure in a diagram. In the models developed, a single structure may have a variable which may cause a problem with estimation reliability if it does not adequately represent the intended measure. For a superior approach, researchers have demonstrated that each construct should have at least two variables, but the preferred minimum number of indicators is reportedly three (Reisinger and Mavondo, 2007; Hair et al., 2006). Hair et al. (2006) suggest that although there is no limit to the number of indicators for each structure, using five to seven variables is an ideal structure. During the development of the UAM-AUM model, 10 variables (IF, UA, UCI, EC, GR, PU, BIU, PEOU, image/subjective norm and compatibility) and a pool of 58 items were initially created. Following construct validity testing, the number of validated variables was seven. We used SPSS 23 exploratory factor analysis (EFA) to reveal the latent structures of the model. At this stage, we considered the suggestions arising from the problems related to scale development in the literature, selecting principal axis factoring and the direct oblimin method (Cox et al., 2003; Cattell, 1978; Comrey et al., 1992; Tabachnick and Fidell, 2001; Hair et al., 2009; Preacher and MacCallum, 2002; McDonald, 1985). Following EFA, we validated structural features using confirmatory factor analysis (CFA), a verification method that allows more precise analyses with a focus on theory. It is important to reduce the effect of consistency and chance factors after confirming the structure revealed with one sample on a different sample (Cox et al., 2003). Therefore, we conducted CFA using a different sample group. In addition, after the verification of the structure, we performed additional validity and reliability analyses. Following psychometric analysis, the validity and reliability of the 30-item and seven-factor structure of the UAM-AUM were proven. The results of the development process of the measurement tool are provided in detail in the previous study (Yavaş and Tez, 2021).

4.3. Measurement model

SEM is a modelling tool that provides a powerful, enduring data analysis and causal modelling, presenting an extremely useful methodology for a particular type of model (Barrett, 2007). The first step in SEM is to develop a theoretical model and transform the theoretical model into a path diagram representing the causal relationships between variables. At this point, the model setting process consists of all the steps necessary to identify the relationships between the latent structures and to determine how to measure the latent structures. This step is the most critical, difficult and vital, as the next steps can occur following this step. Analysis of a measurement model means investigating the relationship between (latent and observed) variables. The measurement model must be validated prior to testing hypothetical relationships between the model's constructs (Cheng, 2001; Anderson and Gerbing, 1988). There are two different approaches to assessing the validity of a measurement model, including each measure of a construct being tested individually, or all measures being tested together. The second of these two ways, namely the 'second measurement model evaluation method' is most used (Cheng, 2001). We adopted the second measurement model to test the fit of the UAM-AUM model with the data, using AMOS software to estimate the correlations of models and structures. We employed the widely used MLE procedure for model estimation, which provides valid results even if the sample size is small (Reisinger and Mavondo, 2007; Hair et al., 2006). We conducted a CFA of the combined measurement model to examine the measurements of hidden structures. Our analyses considered the suitability of the measurement model to the data by looking at the fit indices. There are important discussions in the literature regarding fit indices. Some researchers assert that fit indices do not add anything to an analysis and only emphasise the need for chi-squared (x^2) interpretation. The argument of this view is that fit indices allow researchers to argue that an incorrectly defined model is not a bad model (Barrett, 2007).

The debate regarding the adequacy of fit indices emphasises the inherent limitations of any index and the need to complement one index using others (Singh, 2009). General structural model fit is also known as the evaluation of fit criteria of structural models. Goodness-of-fit measures determine whether the researcher should reject or accept the structural model being tested (Hair et al., 2006; Reisinger and Mavondo, 2007). Consequently, in evaluating the UAM-AUM measurement model, we used four main goodness-of-fit measures, including incremental, parsimonious, absolute and noncentrality-based measures. Many researchers, including Hair et al. (2006), are of the opinion that it is not necessary to use multiple measures; however, different indices from each type of goodness-of-fit measure are appropriate for evaluating our model.

Our evaluation of the current UAM-AUM measurement model, four types of goodness-of-fit measurements, chi-squared ($\chi 2$) and the ratio of degrees of freedom, and GFI, CFI, NFI, TLI, RFI, IFI and RMSEA values were used. As the critical values that will describe the acceptance point; $\chi 2/sd \leq 5$; GFI, CFI, NFI and TLI ≥ 0.90; RMSEA ≤ 0.80 are accepted (Hu and Bentler, 1999; Kline, 2015; MacCallum et al., 1996; Tabachnick and Fidell, 2001). Examining the results of the fit indices for the four types of goodness-of-fit measurements of the current UAM-AUM measurement model, the model was determined to be structurally compatible with the data set, and the model fit indices were at sufficient levels ($\chi 2/sd = 1.70$, GFI = 0.91; CFI = 0.96; IFI = 0.96; TLI = 0.95; NFI = 0.92; RFI = 0.90, RMSEA = 0.04). The fit indices of the model support our SEM (Maruyama, 1197). We also performed discriminant and convergent validity and reliability analyses to examine measurement reliability (Hair et al., 2009).

A previous study asserts that the composite reliability (CR) value should be 0.70 and above (Straub et al., 2004), and we determined the CR value for each factor of the UAM-AUM to be 0.70 and above the threshold value defining the strength of the reliability (CR values were PU = 0.93, IF = 0.91, UA = 0.81, EC = 0.89, UCI = 0.90, BI = 0.90, GR = 0.86). While Hair et al. (2009) asserted that the threshold value for factor loading and AVE values should be 0.50; Fornell and Larcker (1981) indicated that although AVE value may be below 0.50, such values can be accepted when the CR value is 0.70 and above. We determined the AVE values of the UAM-AUM to be above the threshold value, excluding the GR factor. Since the CR values of the GR factors were 0.70 and above, reference values were considered and the AVE value was also accepted (factor loading and AVE values were PU = 0.70, IF = 0.67, UA = 0.54, EC = 0.68, UCI = 0.69, BI = 0.70, GR = 0.46). We evaluated discriminant validity by calculating the square root of the $\sqrt{\text{AVE}}$. Researchers assert that for discriminant validity, the value obtained by calculating the $\sqrt{\text{AVE}}$ of a dimension should be greater than the correlation value with other dimensions but should be below the limit value of 0.90 (Fornell and Larcker, 1981; Kline, 2005). The fact that the $\sqrt{\text{AVE}}$ value calculated for the discriminant validity of the UAM-AUM is below the limit value and is greater than the correlation value for the other dimensions indicates that each dimension in the measurement model measures a separate structure, confirming discriminant validity. We also measured the reliability of UAM-AUM with a cut-off value of 0.70 with the help of Cronbach's alpha, as suggested by Nunnally et al. (1967). Accordingly, the Cronbach's alpha reliability values of our model were determined to be PU = 0.92, IF = 0.91, UA = 0.82, EC = 0.90, UCI = 0.90, BI = 0.90 and GR = 0.71, further confirming reliability.

4.4. Structural equation model

Kline (2005) proposed a two-stage method for SEM analysis. The first of these stages is testing the measurement model, and the second is testing the SEM established based on the verified theoretical infrastructure. In the previous stage, the UAM-AUM measurement model was validated, and the second stage conducted the SEM testing phase. In this stage, paths are established to reveal the cause–effect relationships between the variables in a statistical context to examine the significance of the paths and the compatibility of the model. The bootstrapping method, which is frequently used, was also used to test the direct and indirect effects in examining the mediating role of the established structural model (Inoue et al., 2017; Preacher and Hayes, 2008; Pandey and Shrivastava, 2017). Bootstrapping is an intensive computational method that involves estimating the indirect effect using a resampling process that is assumed to represent a larger characterisation of the original sample (Preacher and Hayes, 2008; Byrne, 2010). The bootstrapping method is preferred because it is more powerful than the Sobel test, it is superior in reducing the Type 1 error rate and it provides the opportunity to control the variables (Hayes, 2012; Preacher and Hayes, 2008). If the bootstrap confidence intervals of 95% that are calculated to determine the significance of the direct and indirect effects established in the model, do not contain zero this indicates that the mediating effect is significant Hayes (2012). In this context, the mediating effect in the study was examined using 5000 bootstrap samples. To validate the mediating effect, the model must meet three conditions. The first is the effect of IF, UA, UCI, EC and GR on PU (path a), the second is the effect of PU on BIU (path b) and the third is the effect of IF, UA, UCI, EC, GR on BIU (path c). In addition, when the mediating variable (PU) and independent variables (IF, UA, UCI, EC, GR) are included in the model together, path c should become meaningless, or the effect should decrease. To determine this, path c must be examined. If this path is meaningless, a full mediating effect can be asserted, whereas if this effect decreases but remains significant, it indicates a partial mediating effect (Montoya and Hayes, 2017). Analysis results are presented in Table 2 indicating the direct effect results obtained with the SEM analysis.

According to Table 2; IF–PU ($\beta = 0.285$, $t = 4.965$, $p < 0.001$), UCI–PU ($\beta = 0.646$, $t = 10.525$, $p < 0.001$), EC–PU ($\beta = 0.558$, $t = 8.600$, $p < 0.001$), UA–PU ($\beta = 0.217$, $t = 3.635$, $p < 0.001$) and GR–PU ($\beta = 0.187$, $t = 2.861$, $p < 0.001$) have positive and significant effects. When this situation is evaluated, it can be said that all variables (IF, UCI, EC, UA, GR) have a positive effect on the perceived ease/usefulness (PU) of the acceptance and use of the UAM system.

Similarly, IF–BIU ($\beta = 0.380$, $t = 6.597$, $p < 0.001$), UCI–BIU ($\beta = 0.736$, $t = 13.389$, $p < 0.001$), EC–BIU ($\beta = 0.684$, $t = 10.612$, $p < 0.001$), UA–BIU ($\beta = 0.247$, $t = 4.056$, $p < 0.001$) and GR–BIU ($\beta = 0.202$, $t = 3.011$, $p < 0.001$) also have positive and significant effects. Finally, PU positively and significantly affects BIU ($\beta = 0.660$, $t = 11.092$, $p < 0.001$). When this situation is evaluated, it can be said that all variables (IF, UCI, EC, UA, GR, PU) have a positive effect on the behavioural intention (BIU) towards the acceptance and use of the UAM system.

To test the mediating effects in the study, five different models in which PU was the mediating variable were established. Table 3 presents the results of the structural models with mediating variables.

Consequently, Table 3 indicates that the indirect effect of IF on BIU via PU is significant (indirect effect = 0.172, 95% CI [0.095,.251]). When we included the mediating variable in the analysis, the decrease in the effect of IF on BIU ($\beta = 0.380$, $p < 0.001$; $\beta = 0.209$, $p < 0.001$) reveals a partial mediating effect. Accordingly, the mediating variable PU explains only a part of the observed relationship between the independent variable (IF) and the dependent variable (BIU).

The indirect effect of UCI on BIU through PU is significant (indirect effect = 0.202, 95% CI [0.109,.270]). When we included the mediating variable in the analysis, the decrease in the effect of UCI on BIU ($\beta = 0.736$, $p < 0.001$; $\beta = 0.537$, $p < 0.001$) reveals a partial mediating effect. Accordingly, the mediating variable PU explains only a part of the observed relationship between the independent variable (UCI) and the dependent variable (BIU).

The indirect effect of EC on BIU via PU is significant (indirect effect = 0.226, 95% CI [0.160,.303]). When we included the mediating variable in the analysis, the decrease in the effect of EC on BIU ($\beta = 0.684$, $p < 0.001$; $\beta = 0.458$, $p < 0.001$) reveals a partial mediating effect. Accordingly, the mediating variable PU explains only a part of the observed relationship between the independent variable (EC) and the dependent variable (BIU).

The indirect effect of UA on BIU through PU is significant (indirect effect = 0.148, 95% CI [0.066,.207]). When we include the mediating variable in the analysis, the decrease in the effect of UA on the BIU ($\beta = 0.247$, $p < 0.001$; $\beta = 0.109$, $p < 0.05$) and the decrease in the level of significance reveal a partial mediating effect. Accordingly, the mediating variable PU explains only a part of the observed relationship between the independent variable (UA) and the dependent variable (BIU).

The indirect effect of GR on BIU via PU is significant (indirect effect = 0.121, 95% CI [0.030,.206]). When we included the mediating variable in the analysis, the disappearance of the effect of GR on the BIU ($\beta = 0.202$, $p = 0.003$; $\beta = 0.081$, $p = 0.130$) and the disappearance of the statistical significance level reveals the existence of a full mediating effect. Accordingly, the mediating variable PU explains the entire observed relationship between the independent variable (GR) and the dependent variable (BIU).

For the models established in the mediating effect analysis using the bootstrapping method to be accepted, the lower and upper limits of the values in the 95% confidence interval obtained as a result of the analysis should not cover the zero (0.000) value. The analysis results determined that the lower and upper confidence intervals obtained using percentile bootstrap confidence intervals from the bootstrapping analysis did not include a zero (0.000) value, indicating that there is a mediating (partial and full) effect. Finally, Table 4 presents the model fit indices related to the mediating models.

Table 4 presents the model fit indices related to the mediating models ($\chi2/sd \leq 5$; GFI, CFI, NFI, TLI $\geq$0.90; RMSEA $\leq$0.80), indicating that the fit indices of the path analysis are within the acceptable threshold values established in the literature (Hu and Bentler, 1999; Kline, 2015; MacCallum et al., 1996; Tabachnick and Fidell, 2001), indicating that the established models are compatible with the data and are acceptable.

4.5. Theoretical and practical implications

General Reliability (GR) refers to the overall safety and security of the system. General safety and security with the UAM system includes considerations of individuals' trust in UAM manufacturers and the safety precautions applied during use. In other words, GR affects the intention to use the UAM system (BIU) through advantages and perceived ease (PU). PU has a key role, as it relates to perceived ease, change and gains regarding the use of the system. If a user can eliminate general security concerns about the system with perceived ease, their intention to use the system and reliability will increase. Theoretically, this finding suggests that GR is a significant avenue for factors influencing consumers' adoption of technology involving uncertainty regarding system security. These findings provide practical guidance for designing interventions to improve public acceptance of the UAM system. While it is known that various factors affect consumers' behaviour towards UAM use, one of the most prominent issues here is the negative and uncertain perception of safety and security (Gillis et al., 2021). In this sense, the first test projects known as emergency service applications will be promising to positively affect the behaviour and acceptance of consumers towards the UAM system. According to another study, safety is the first thing that comes to mind rather than comfort and convenience, and all safety-related elements (seat belts, air quality, cabin indicators, etc.) are a very good choice to positively affect consumers' usage behaviors and intentions. The importance of transferring it to the consumer is mentioned (Johnson et al., 2022). According to another research, timesaving, intramodality, convenience, environment friendly, silence and safe& reliability are shown as key promises of the UAM system, and it is emphasized that in parallel with the results of our study, it will create a very high level of ease of use and be highly safe compared to all flight systems (Hader, 2022). It is claimed that with the system, the wish of "have a safe flight" will be replaced by "have a nice flight" and safety may turn out to be hesitation (Hader, 2022). All this is a sign that safety & security, which is the biggest theoretical concern, is the feature that should be highlighted in practice and marketing strategies. On the other hand, the cost will continue to be one of the first options that come to mind. In this context, in addition to the consumer/passenger-oriented approach for UAM affordability (UA), the costs of system operators

Table 2
Direct effect results.

Variables	β	Standard β	S.E	t value	p value
IF–PU	0.292	0.285	0.059	4.965	***
UCI–PU	0.500	0.646	0.047	10.525	***
EC–PU	0.657	0.558	0.076	8.600	***
UA–PU	0.200	0.217	0.055	3.635	***
GR–PU	0.247	0.187	0.086	2.861	***
IF–BIU	0.450	0.380	0.068	6.597	***
UCI–BIU	0.665	0.736	0.050	13.389	***
EC–BIU	0.935	0.684	0.088	10.612	***
UA–BIU	0.263	0.247	0.065	4.056	***
GR–BIU	0.307	0.202	0.102	3.011	***
PU–BIU	0.762	0.660	0.069	11.092	***

Note: *0.05, **0.01, ***0.001.

Table 3
Mediating variables and bootstrap values.

Models		β	Stand. β	S.E	t value	P value	Stand. Total Effects	Stand. Direct Effects
Model 1	**IF–PU**	0.294	0.286	0.059	4.978	***	0.286	0.286
IF–PU–BIU	**PU–BIU**	0.692	0.601	0.067	10.363	***	0.683	0.683
	IF–BIU	0.247	0.209	0.056	4.372	***	0.380	0.209
	Standardised Indirect Effect: 0.172							
	Bootstrap (LLCI):.095							
	Bootstrap (ULCI):.251							
Model 2	UCI–PU	0.499	0.649	0.047	10.657	***	0.649	0.649
UCI–PU–BIU	PU–BIU	0.363	0.312	0.067	5.399	***	0.312	0.312
	UCI–BIU	0.481	0.537	0.055	8.772	***	0.740	0.537
	Standardised Indirect Effect: 0.202							
	Bootstrap (LLCI):.109							
	Bootstrap (ULCI):.270							
Model 3	EC–PU	0.668	0.559	0.078	8.585	***	0.559	0.559
EC–PU–BIU	PU–BIU	0.463	0.405	0.063	7.300	***	0.405	0.405
	EC–BIU	0.627	0.458	0.081	7.732	***	0.685	0.458
	Standardised Indirect Effect: 0.226							
	Bootstrap (LLCI):.160							
	Bootstrap (ULCI):.303							
Model 4	UA–PU	0.201	0.219	0.055	3.666	***	0.219	0.219
UA–PU–BIU	PU–BIU	0.735	0.637	0.069	10.721	***	0.637	0.637
	UA–BIU	0.116	0.109	0.052	2.246	0.02	0.249	0.109
	Standardised Indirect Effect: 0.139							
	Bootstrap (LLCI):.066							
	Bootstrap (ULCI):.207							
Model 5	GR–PU	0.248	0.187	0.086	2.863	0.004	0.187	0.187
GR–PU–BIU	PU–BIU	0.744	0.645	0.069	10.802	***	0.645	0.645
	GR–BIU	0.123	0.081	0.081	1.512	0.130	0.202	0.081
	Standardised Indirect Effect: —							
	Bootstrap (LLCI): —							
	Bootstrap (ULCI): —							

Note: *0.05, **0.01, ***0.001.

Table 4
Model fit indices.

	x2/sd	CFI	GFI	NFI	TLI	RMSEA
Model 1 **IF–PU–BIU**	2.50	0.97	0.92	0.95	0.96	0.06
Model 2 **UCI–PU–BIU**	3.88	0.95	0.90	0.93	0.93	0.07
Model 3 **EC–PU–BIU**	3.13	0.96	0.91	0.94	0.95	0.08
Model 4 **UA–PU–BIU**	3.38	0.95	0.90	0.93	0.94	0.08
Model 5 **GR–PU–BIU**	2.44	0.97	0.93	0.95	0.96	0.06

Note: χ^2/sd, CFI = comparative fit index, GFI = goodness-of-fit index, NFI = normed fit index, TLI = Tucker–Lewis index and RMSEA = root mean square error of approximation.

(Merkert et al., 2021) should also be taken into consideration as it will be an important element in the general pricing criteria.

The study provides an opportunity to understand the perceptions and behaviours of potential users regarding UAM systems. Although consumers' adaptation to rapidly transforming technological innovations vary, this process was conducted to make sense of considerations for UAM systems. The findings of the study provide significant insights into consumer acceptance for stakeholders developing UAM systems.

5. Discussion and conclusion

Previous studies have demonstrated that the role of trust in AV acceptance is insignificant or that it is mediated by other factors such as PU (Kaur and Rampersad, 2018; Buckley et al., 2018). Zhang et al. (2019) asserted that the role of initial trust is important for the acceptance AVs, and this trust is key to predicting user behaviour. In addition, researchers consider trust to be as a tool for reducing cognitive complexity, which helps to simplify and facilitate the decision-making process, particularly in risky and uncertain situations (Earle and Cvetkovich, 1995; Kim et al., 2008; Zsifkovits and Günther, 2015). Emphasising the importance of establishing trust first and considering to be a key factor for system use, Zhang et al. (2019) approached this finding from a critical perspective, based on the limitations of proposed models or survey population. Consequently, Zhang et al.'s (2019) findings regarding trust are consistent with the results of our study demonstrating that trust affects system usage through PU, but not alone. The second contribution of this study is the conclusion that other factors IF, UA, UCI and EC also influence BIU via PU, with a partial mediating effect, and not full mediation as with the trust factor. This indicates the potential existence of other variables with multiple mediating effects between IF, UCI, EC, UA and BIU.

Some studies also support our findings. PU of ease of use in a study of bike sharing; behaviours that are developed positively regarding the system also positively affect usage intention (Yu et al., 2018). A study on green transport demonstrated that environmental awareness and PEOU had a positive effect on intention to use (Chen and Lu, 2016). Wang et al.'s (2020b) study on ride-sharing service revealed that PU had the greatest influence on BIU among all other factors. A study of online transportation revealed that perceived convenience, subjective norms, and innovative features were effective on BIU (Septiani et al., 2017). It has been emphasized that the PU regarding AVs has the most important effect on BIU and is a characteristic feature of the perception towards AVs (Lee et al., 2019). In a similar study on autonomous driving, Panagiotopoulos and Dimitrakopoulos (2018) determined that PEOU, PU, trust and social factors affect BIU. In a study on technological systems, Wadud and Huda (2020) reported that PU influences BIU. Another study assumed that a person familiar with a particular technology was more likely to use technology than one that is less interested, but the research result did not confirm this general view (Keller et al., 2021). Notably, multiple studies have reported that older users tend to rate AVs as less reliable and less useful, indicating less interest and willingness to purchase (Schoettle and Sivak, 2014; Bansal et al., 2016; Menon et al., 2016; Hohenberger et al., 2016; Nees, 2016; Abraham et al., 2017).

The critical point is that no matter how much technology develops, it cannot change the culture inherent in societies at the same rate. For this reason, customs and traditions that are important in a society and to the target audience have a significant influence in the adoption of technology. It is important that developing technology serve culture-based lifestyles. This suggests that technological development alone is insufficient, and technology must continuously correspond with cultural norms and changes; otherwise, a technology that cannot keep pace with the culture of the society will not be able to establish a place in that society. Technology's adaptation to culture is one of the factors that technology developers, marketers and researchers should focus on. These considerations should be consistently reviewed at all stages of project development. In this process, the project team should fully understand the culture, customs, and traditions of the target society to which the technology will be presented. Technology and culture affect one another and the change and evolution of both is inevitable over time. For this reason, whether the UAM system is compatible with the cultural structure of a country and whether it corresponds to their expectations must be closely monitored.

We propose a theoretical TAM of UAM-AUM, identifying the factors that may directly and indirectly affect whether users will accept UAM. The results provide strong support for the proposed model. PU is identified as the strongest determinant of user behaviour and mediates the effects on UAM acceptance. IF, UCI, EC, UA and GR together with PU determine the intention to use the UAM system (BIU) and the critical factor for promoting an accepting attitude towards the UAM system is GR.

Specifically, our results determine that IF, UCI, EC, UA and GR have a direct effect on BIU. However, although the variable PU has a key role, it partially mediates the relationship between IF, UCI, EC, UA and BIU. PU is also determined to fully mediate the relationship between GR and BIU.

6. Limitations and further studies

The results of our study must be interpreted considering various limitations. First, due to COVID-19 pandemic restrictions, we conducted data collection online. Another limitation is that no participants have real UAM experience, and the variables discussed in this study represent information built from knowledge that our participants acquired from social media, various trade shows, the internet or TV. In this respect, some users could consider a UAM system to be a speculative future concept. Assuming that future users will have a deeper understanding of what UAM technologies are and how they work as systems become available, more interesting results are likely to emerge. In addition, further results can be obtained from a repeat study sharing examples of the system and limited usage information globally and face-to-face interviews and discussions. For further research, future studies can be conducted in accordance with the AUM-AUM scale in different countries, cultures and geographies to expand and contribute to the field. In addition, studies conducted after the technical and commercial details of UAM systems are clarified will be interesting in terms of tracking consumer intent. In this context, the adoption and use of the AUM-AUM model in technologically developing countries will increase knowledge regarding perceptions of UAM technologies and provide both practical and theoretical results. The findings of this study can guide the acceptance and use of UAM technologies and contribute to the development of UAM technology.

Authorship contributions

Please indicate the specific contributions made by each author (list the authors' initials followed by their surnames, e.g., Y.L. Cheung). The name of each author must appear at least once in each of the three categories below.

Category 1.

Conception and design of study: Volkan YAVAS, Ozge YAVAS TEZ

Acquisition of data: Ozge YAVAS TEZ, Volkan YAVAS

Analysis and/or interpretation of data: Ozge YAVAS TEZ, Volkan YAVAS.

Category 2.

Drafting the manuscript: Volkan YAVAS, Ozge YAVAS TEZ

Revising the manuscript critically for important intellectual content: Volkan YAVAS, Ozge YAVAS TEZ.

Category 3.

Approval of the version of the manuscript to be published (the names of all authors must be listed): **Volkan YAVAS, Ozge YAVAS TEZ**.

Data availability

Data will be made available on request.

Acknowledgements

We are grateful to Ege University Planning and Monitoring Coordination of Organizational Development and Directorate of Library and Documentation for their support in editing and proofreading service of this study.

References

Abraham, H., Lee, C., Brady, S., Fitzgerald, C., Mehler, B., Reimer, B., Coughlin, J.F., 2017. Autonomous vehicles and alternatives to driving: trust, preferences, and effects of age. In: Paper Presented at the Proceedings of the Transportation Research Board 96th Annual Meeting (TRB'17).

Ahmed, S.S., Fountas, G., Eker, U., Still, S.E., Anastasopoulos, P.C., 2021. An exploratory empirical analysis of willingness to hire and pay for flying taxis and shared flying car services. J. Air Transport. Manag. 90, 101963.

Al Haddad, C., Chaniotakis, E., Straubinger, A., Plötner, K., Antoniou, C., 2020. Factors affecting the adoption and use of urban air mobility. Transport. Res. Pol. Pract. 132, 696–712.

Anderson, J.C., Gerbing, D.W., 1988. Structural equation modeling in practice: a review and recommended two-step approach. Psychol. Bull. 103 (3), 411.

Bansal, P., Kockelman, K.M., Singh, A., 2016. Assessing public opinions of and interest in new vehicle technologies: an Austin perspective. Transport. Res. C Emerg. Technol. 67, 1–14.

Baptista, P., Melo, S., Rolim, C., 2014. Energy, environmental and mobility impacts of car-sharing systems. Empirical results from Lisbon, Portugal. Procedia-Social and Behavioral Sciences 111, 28–37.

Barrett, P., 2007. Structural equation modelling: adjudging model fit. Pers. Indiv. Differ. 42, 815–824.

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. https://doi.org/10.1016/j.aap.2018.03.021.

Byrne, B.M., 1998. Structural Equation Modelling with LISREL, PRELIS, and SIMPLIS.

Byrne, B.M., 2010. Structural equation modeling with AMOS: basic concepts, applications, and programming (multivariate applications series). Taylor & Francis Group 396 (1), 7384. New York.

Cattell, R.B., 1978. Fixing the number of factors: the most practicable psychometric procedures. In: The Scientific Use of Factor Analysis in Behavioral and Life Sciences. Springer, Boston, MA, pp. 72–91.

Chancey, E.T., 2020. Effects of Concepts of Operation Factors on Public Acceptance and Intention to Use Urban Air Mobility (UA0//M)—trust and Technology Acceptance Modelling. https://ntrs.nasa.gov/api/citations/20205003359/downloads/NASA-TM-20205003359.pdf. (Accessed 4 June 2022).

Chen, S.Y., Lu, C.C., 2016. Exploring the relationships of green perceived value, the diffusion of innovations, and the technology acceptance model of green transportation. Transport. J. 55 (1), 51–77.

Chen, T.D., Kockelman, K.M., Hanna, J.P., 2016. Operations of a shared, autonomous, electric vehicle fleet: implications of vehicle & charging infrastructure decisions. Transport. Res. Pol. Pract. 94, 243–254.

Cheng, E.W., 2001. SEM being more effective than multiple regression in parsimonious model testing for management development research. J. Manag. Dev. 20 (7), 650–667.

Choi, J.K., Ji, Y.G., 2015. Investigating the importance of trust on adopting an autonomous vehicle. Int. J. Hum. Comput. Interact. 31 (10), 692–702.

Comrey, A.L., Lee, H.B., 1992. Interpretation and application of factor analytic results. Comrey AL, Lee HB. A first course in factor analysis 2, 1992.

Cox, R.H., Martens, M.P., Russell, W.D., 2003. Measuring anxiety in athletics: the revised competitive state anxiety inventory–2. J. Sport Exerc. Psychol. 25 (4), 519–533.

Crow, S.C., 1990. Back to the future of personal aviation. SAE Trans. 2150–2176.

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 319–340.

Davis, F.D., Bagozzi, R.P., Warshaw, P.R., 1989. User acceptance of computer technology: a comparison of two theoretical models. Manag. Sci. 35 (8), 982–1003.
Earle, T.C., Cvetkovich, G., 1995. Social Trust: toward a Cosmopolitan Society. Greenwood Publishing Group.
EASA, 2019. SPECIAL CONDITION Vertical Take-Off and Landing (VTOL) Aircraft. https://www.easa.europa.eu/sites/default/files/dfu/SC-VTOL-01.pdf. (Accessed 22 May 2021).
EASA, 2021. Study on the Societal Acceptance of Urban Air Mobility in Europe. https://www.easa.europa.eu/full-report-study-societal-acceptance-urban-air-mobility-europe. (Accessed 22 May 2021).
Edwards, T., Price, G., 2020. eVTOL Passenger Acceptance. https://core.ac.uk/download/pdf/286816773.pdf. (Accessed 23 May 2021).
FAA, 2019. Urban Air Mobility—Concept of Operations. https://assets.evtol.com/wp-content/uploads/2020/07/UAM_ConOps_v1.0.pdf. (Accessed 22 May 2021).
Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Market. Res. 18 (1), 39. https://doi.org/10.2307/3151312.
Fu, M., Rothfeld, R., Antoniou, C., 2019. Exploring preferences for transportation modes in an urban air mobility environment: munich case study. Transport. Res. Rec. 2673 (10), 427–442.
Ghazizadeh, M., Lee, J.D., Boyle, L.N., 2012. Extending the technology acceptance model to assess automation. Cognit. Technol. Work 14 (1), 39–49. https://doi.org/10.1007/s10111-011-0194-3.
Gillis, D., Petri, M., Pratelli, A., Semanjski, I., Semanjski, S., 2021. Urban air mobility: a state of art analysis. In: International Conference on Computational Science and its Applications. Springer, Cham, pp. 411–425.
Hader, M., 2022. Advanced Air Mobility: Market Study for APAC. Access. https://www.rolls-royce.com/~/media/Files/R/Rolls-Royce/documents/news/press-releases/rre-apac-aam-study-16-02-2022-v2.pdf. (Accessed 20 October 2022).
Hair, J.F., et al., 2006. SEM: confirmatory factor analysis. Multivariate Data Anal. 6, 770–842.
Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2009. Advanced Diagnostics for Multiple Regression: A Supplement to Multivariate Data Analysis. Prentice Hall, Upper Saddle River, NJ.
Hayes, J.R., 2012. Modeling and remodeling writing. Writ. Commun. 29 (3), 369–388.
Hoff, K.A., Bashir, M., 2015. Trust in automation: integrating empirical evidence on factors that influence trust. Hum. Factors 57 (3), 407–434.
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.: Pol. Pract. 94, 374–385.
Holden, R.J., Karsh, B.T., 2010. The technology acceptance model: its past and its future in health care. J. Biomed. Inf. 43 (1), 159–172.
Hox, J.J., Bechger, T.M., 1998. An Introduction to Structural Equation Modeling.
Hu, L.T., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct. Equ. Model.: A Multidiscip. J. 6 (1), 1–55.
IATA, 2019. Aircraft Technology Roadmap to 2050. https://www.iata.org/contentassets/8d19e716636a47c184e7221c77563c93/technology20roadm ap20to20205020no20foreword.pdf. (Accessed 22 May 2021). Accessed.
ICAO, 2021a. Electric and Hybrid Aircraft Platform for Innovation (E-HAPI). https://www.icao.int/environmental-protection/Pages/electric-aircraft.aspx. (Accessed 22 May 2021).
ICAO, 2021b. E-VTOL and Urban Air Mobility—A New Systemic and Sustainable Approach for Air Travel. https://www.icao.int/Meetings/Stocktaking2021/Pages/prest4.aspx. (Accessed 22 May 2021).
Inoue, Y., Funk, D.C., McDonald, H., 2017. Predicting behavioral loyalty through corporate social responsibility: the mediating role of involvement and commitment. J. Bus. Res. 75, 46–56.
Johnson, R.A., Miller, E.E., Conrad, S., 2022. Technology adoption and acceptance of urban air mobility systems: identifying public perceptions and integration factors. The International Journal of Aerospace Psychology 32 (4), 240–253.
Kaur, K., Rampersad, G., 2018. Trust in driverless cars: investigating key factors influencing the adoption of driverless cars. J. Eng. Technol. Manag. https://doi.org/10.1016/j.jengtecman.2018.04.006.
Keller, M., Hulínská, Š., Kraus, J., 2021. Integration of UAM into cities—the public view. Transport. Res. Procedia 59, 137–143.
Kim, D.J., et al., 2008. A trust-based consumer decision-making model in electronic commerce: the role of trust, perceived risk, and their antecedents. Decis. Support Syst. 44 (2), 544–564.
Kleinbekman, I.C., Mitici, M.A., Wei, P., 2018. eVTOL arrival sequencing and scheduling for on-demand urban air mobility. In: 2018 IEEE/AIAA 37th Digital Avionics Systems Conference (DASC). IEEE, pp. 1–7.
Kline, T., 2005. Psychological Testing: A Practical Approach to Design and Evaluation. Sage.
Lee, J.D., See, K.A., 2004. Trust in automation: designing for appropriate reliance. Hum. Factors 46 (1), 50–80.
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.
Liu, H., Stockwell, N., Rodgers, M.O., Guensler, R., 2016. A comparative life-cycle energy and emissions analysis for intercity passenger transportation in the US by aviation, intercity bus, and automobile. Transport. Res. Transport Environ. 48, 267–283.
MacCallum, R.C., Browne, M.W., Sugawara, H.M., 1996. Power analysis and determination of sample size for covariance structure modeling. Psychol. Methods 1 (2), 130.
Maruyama, G., 1197. Basics of Structural Equation Modeling. Sage.
Mathieson, K., Peacock, E., Chin, W.W., 2001. Extending the technology acceptance model: the influence of perceived user resources. ACM SIGMIS - Data Base 32 (3), 86–112.
Mayor, Anderson, 2019. KPMG: Getting Mobility of the Ground. https://assets.kpmg/content/dam/kpmg/ie/pdf/2019/10/ie-urban-air-mobility.pdf. (Accessed 23 May 2021).
McDonald, R.P., 1985. Comments on DJ Bartholomew," Foundations of Factor Analysis: Some Practical Implications.". British Psychological Society.
McKnight, D.H., Choudhury, V., Kacmar, C., 2002. The impact of initial consumer trust on intentions to transact with a web site: a trust building model. J. Strat. Inf. Syst. 11 (3–4), 297–323.
Menon, N., Pinjari, A.R., Zhang, Y., Zou, L., 2016. Consumer perception and intended adoption of autonomous vehicle technology – findings from a university population survey. In: Paper Presented at the Meeting of the Transportation Research Board.
Merkert, R., Beck, M.J., Bushell, J., 2021. Will It Fly? Adoption of the road pricing framework to manage drone use of airspace. Transport. Res. Pol. Pract. 150, 156–170.
Mola, L., Berger, Q., Haavisto, K., Soscia, I., 2020. Mobility as a service: an exploratory study of consumer mobility behaviour. Sustainability 12 (19), 8210.
Montoya, A.K., Hayes, A.F., 2017. Two-condition within-participant statistical mediation analysis: a path-analytic framework. Psychol. Methods 22 (1), 6.
Mudumba, S.V., Chao, H., Maheshwari, A., DeLaurentis, D.A., Crossley, W.A., 2021. Modeling CO2 emissions from trips using urban air mobility and emerging automobile technologies. Transport. Res. Rec. 2675 (9), 1224–1237.
MundoGeo, 2022. Urban Air Mobility Market Expected to Reach USD 15.54. Billion by 2030. https://mundogeo.com/en/2022/03/15/urban-air-mobility-market-expected-to-reach-usd-15-54-billion-by-2030/#:~:text=The%20Urban%20Air%20Mobility%20(UAM,market%20research%20Reports%20And%20Data. (Accessed 20 October 2022).
NASA, 2018. NASA Urban Air Mobility (UAM) Market Study. https://www.nasa.gov/sites/default/files/atoms/files/uam-market-study-executive-summary-v2.pdf. (Accessed 23 May 2021).
Nees, M.A., 2016. Acceptance of self-driving cars: an examination of idealized versus realistic portrayals with a self-driving car acceptance scale. In: Paper Presented at the Proceedings of the Human Factors and Ergonomics Society Annual Meeting.
Nneji, V.C., Stimpson, A., Cummings, M., Goodrich, K.H., 2017. Exploring concepts of operations for on-demand passenger air transportation. In: 17th AIAA Aviation Technology, Integration, and Operations Conference, p. 3085.
Nunnally, J.C., Bernstein, I.H., Berge, J.M.F., 1967. Psychometric Theory. McGraw Hill, New York.
Panagiotopoulos, I., Dimitrakopoulos, G., 2018. An empirical investigation on consumers' intentions towards autonomous driving. Transport. Res. C Emerg. Technol. 95, 773–784.
Pandey, D., Shrivastava, P., 2017. Mediation effect of social support on the association between hardiness and immune response. Asian Journal of Psychiatry 26, 52–55.
Parasuraman, R., Riley, V., 1997. Humans and automation: use, misuse, disuse, abuse. Hum. Factors 39 (2), 230–253.
Patton, M.Q., 2014. Nitel Çalışma Ve Değerlendirme Yöntemleri, (Üçüncü Baskıdan Çeviri). Pegem Yayıncılık, Ankara.
Preacher, K.J., Hayes, A.F., 2008. Assessing mediation in communication research. In: The Sage Sourcebook of Advanced Data Analysis Methods for Communication Research, pp. 13–54. London.
Preacher, K.J., MacCallum, R.C., 2002. Exploratory factor analysis in behavior genetics research: factor recovery with small sample sizes. Behav. Genet. 32 (2), 153–161.
Reisinger, Y., Mavondo, F., 2007. Structural equation modeling: critical issues and new developments. J. Trav. Tourism Market. 21 (4), 41–71.
Schoettle, B., Sivak, M., 2014. A Survey of Public Opinion about Autonomous and Self-Driving Vehicles in the US, the UK, and Australia (UMTRI-2014-21). University of Michigan Ann Arbor Transportation Research Institute.
Schreiber, J.B., Nora, A., Stage, F.K., Barlow, E.A., King, J., 2006. Reporting structural equation modelling and Confirmatory factor analysis results: a review. J. Educ. Res. 99 (6), 323–337.
Schumacker, R.E., Lomax, R.G., 2004. A Beginner's Guide to Structural Equation Modeling. psychology press.
Septiani, R., Handayani, P.W., Azzahro, F., 2017. Factors that affecting behavioral intention in online transportation service: case study of GO-JEK. Procedia Comput. Sci. 124, 504–512.
Singh, R., 2009. Does my structural model represent the real phenomenon?: a review of the appropriate use of Structural Equation Modelling (SEM) model fit indices. Market. Rev. 9 (3), 199–212.
Straub, D., Boudreau, D., Gefen, D., 2004. Validation guidelines for IS positivist research. Commun. Assoc. Inf. Syst. 13 (1), 1–20.
Straubinger, A., Rothfeld, R., Shamiyeh, M., Büchter, K.D., Kaiser, J., Plötner, K.O., 2020. An overview of current research and developments in urban air mobility—setting the scene for UAM introduction. J. Air Transport. Manag. 87, 101852.
Straubinger, A., Michelmann, J., Biehle, T., 2021. Business model options for passenger urban air mobility. CEAS Aeronautical Journal 12 (2), 361–380.
Subramanian, G.H., 1994. A replication of perceived usefulness and perceived ease of use measurement. Decis. Sci. J. 25 (5-6), 863–874.
Swanson, E.B., 1988. Information System Implementation: Bridging the Gap between Design and Utilization. McGraw-Hill, Irwin.
Szajna, B., 1996. Empirical evaluation of the revised technology acceptance model. Manag. Sci. 42 (1), 85–92. https://doi.org/10.1287/mnsc.42.1.85.
Tabachnick, B.G., Fidell, L.S., 2001. Using Multivariate Statistics, fourth ed. Allyn & Bacon, Boston.

Thipphavong, D.P., Apaza, R., Barmore, B., Battiste, V., Burian, B., Dao, Q., Verma, S.A., 2018. Urban air mobility airspace integration concepts and considerations. In: 2018 Aviation Technology, Integration, and Operations Conference, p. 3676.
Wadud, Z., Huda, F.Y., 2020. Fully automated vehicles: the use of travel time and its association with intention to use. In: Proceedings of the Institution of Civil Engineers- Transport. Thomas Telford Ltd, pp. 1–15.
Wang, S., Jiang, Z., Noland, R.B., Mondschein, A.S., 2020a. Attitudes towards privately-owned and shared autonomous vehicles. Transport. Res. F Traffic Psychol. Behav. 72, 297–306.
Wang, Y., Wang, S., Wang, J., Wei, J., Wang, C., 2020b. An empirical study of consumers' intention to use ride-sharing services: using an extended technology acceptance model. Transportation 47 (1), 397–415.
Welch, T.F., Gehrke, S.R., Widita, A., 2020. Shared-use mobility competition: a trip-level analysis of taxi, bikeshare, and transit mode choice in Washington, DC. Transportmetrica: Transport. Sci. 16 (1), 43–55.
Xu, X., Aziz, H.M.A., Liu, H., Rodgers, M.O., Guensler, R., 2020. A scalable energy modeling framework for electric vehicles in regional transportation networks. Appl. Energy 269, 115095.
Yavaş, V., Tez, Ö.Y., 2021. Kentsel Hava Taşımacılığı Kabul ve Kullanım modeli: Bir Ölçek Geliştirme Çalışması. Havacılık Araştırmaları Dergisi 3 (2), 279–298.
Yousafzai, S.Y., Foxall, G.R., Pallister, J.G., 2007. Technology acceptance: a meta-analysis of the TAM: Part 1. J. Model. Manag.
Yu, Y., Yi, W., Feng, Y., Liu, J., 2018. Understanding the intention to use commercial bike-sharing systems: an integration of TAM and TPB. In: Proceedings of the 51st Hawaii International Conference on System Sciences.
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.
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 (5), 505–519.
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, W., Wang, K., Wang, S., Jiang, Z., Mondschein, A., Noland, R.B., 2020. Synthesizing neighborhood preferences for automated vehicles. Transport. Res. C Emerg. Technol. 120, 102774.
Zmud, J., Sener, I.N., Wagner, J., 2016. Consumer Acceptance and Travel Behavior: Impacts of Automated Vehicles (No. PRC 15-49 F). Texas A&M Transportation Institute.
Zsifkovits, M., Günther, M., 2015. Simulating resistances in innovation diffusion over multiple generations: an agent-based approach for fuel-cell vehicles. CEJOR 23 (2), 501–522.