Technological Forecasting & Social Change 191 (2023) 122483

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

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

Understanding the behavioral intention to use urban air autonomous vehicles

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ARTICLE INFO

Keywords:
Covariance-based structural equation modeling
Human values
Intention to use
Pro-environmental behavior
Urban air autonomous vehicles

ABSTRACT

In the following years, Urban Air Mobility (UAM) will transform the transport industry. Researching the intention to use air vehicles is not easy, as it is a new mode of transport that has not yet been implemented, so there are no available observed data. This fact is why the many gaps and uncertainties remain unexplored in academic research on this topic. The most critical issues for the successful implementation of a UAM transport system is public acceptance and user adoption. Based on technology adoption theories, this paper investigates critical constructs in generating usage intention to use urban air autonomous vehicles (UAAVs) and the mediator role of pro-environmental behavior and human values in this relationship. Covariance-based structural equation modeling (CB-SEM) was used with a sample from the US and China. The results confirm that attitudes, performance expectancy, and social influence reinforce the intention to use UAAVs, while anxiety reduces it. The UAAV acceptance model is very similar between the Chinese and US populations. The only difference between the two samples is that social influence has a positive and significant effect on intention to use among US people. At the same time, this variable is not essential in the Chinese sample.

1. Introduction: Urban air autonomous vehicles (UAAVs), science fiction or reality?

In an increasingly globalized, uncertain, and hyperconnected world, transport is one business activity whose business model has not matured significantly. However, this situation is set to change radically in the coming years (Richter et al., 2022), causing a technological and logistical revolution of unforeseeable scope in the transport sector that will bring a reordering of the industry (Ghazy et al., 2022; Nikitas et al., 2021).

The use of airspace will soon emerge as a new market. Small, unmanned aerial vehicles (Shamiyeh et al., 2017), typically autonomous vehicles designed for one to five passengers (Straubinger et al., 2020), will provide a service that has rarely been utilized thus far. Flying taxis (piloted) or flying autonomous vehicles (not piloted) form the basis of urban air mobility (UAM), one of the most important revolutions in the transport industry, which is gaining attention from industry leaders and researchers (Tojal et al., 2021). Such companies as Uber and Hyundai are collaborating on a prototype that will be ready in 2025. However, some authors, such as Panetta (2019) or Michelmann et al. (2020), place the starting point later, at around 2030.

The object of the present research concerns UAM, a new transport system designed to fly over densely populated urban areas, which has the potential to revolutionize transportation (Bennaceur et al., 2022). Although UAM was initially conceived with both manned and unmanned vehicles, recent research limits the scope of UAM to unmanned aircraft (Tojal et al., 2021). These vehicles can transport passengers and goods; given the topic investigated in this paper (the acceptance of these vehicles by potential users), the analysis focused exclusively on passenger transport. The development of this new market is generating increasing interest from academia. For example, since 2018, more than two hundred articles indexed in WOS that include the term "urban air

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https://doi.org/10.1016/j.techfore.2023.122483
Received 2 October 2022; Received in revised form 28 February 2023; Accepted 1 March 2023
Available online 8 March 2023

mobility" have been published. The main areas where this topic is being researched are engineering (156 articles), transportation (48), computer science (32), automation control systems (31), mathematics (22), robotics (21), government law (17), and business economics (16). Interestingly, only ten articles (4.8 % of the total) are classified in the area of environmental sciences ecology, suggesting that this topic is under-researched from the point of view of ecological awareness. This fact adds further value to the present study as, among other things, it analyzed the mediating effect of pro-environmental behavior on the intention to use air vehicles.

According to Pukhova et al. (2021), publications on UAM can be classified into four broad categories depending on the research focus: a) technical aspects of the vehicles (e.g., Pavel, 2022; Zhou et al., 2020), b) integration of the vehicles with regular air traffic management (e.g., Thipphavong et al., 2018); c) potential demand for this new transport mode (e.g., Cohen et al., 2021), and d) perceptions of potential users of air vehicles (e.g., Straubinger et al., 2021). The present research falls into the latter category of studies.

Researching the intention to use air vehicles is not easy; as it is a new mode of transport that has not yet been implemented, there are no available observed data. This is why many gaps and uncertainties remain unexplored in academic research on this topic. UAM is an emerging research topic addressed by different disciplines and research areas (Pukhova et al., 2021). One of the most critical issues for developing and implementing this innovative technology will undoubtedly be the degree of acceptance by potential users (Yedavalli and Mooberry, 2019). This fact inevitably leads to the analysis of technology and automation acceptance models and, more specifically, of the factors that influence the acceptance of automation in transport (Al Haddad et al., 2020).

Therefore, the framework for this research adopts the technology acceptance model (TAM) proposed by Davis et al. (1989) as a starting point. The initial proposal of these authors focused on information systems use, a nascent technology at the end of the 1980s, and this model is based on two primary constructs: perceived usefulness and perceived ease of use. From the theory of reasoned action (Fishbein and Ajzen, 1977) and the theory of planned behavior (TPB) (Ajzen, 1985) approach, both factors impact the attitude of potential users toward the technology, which in turn determines their behavioral intention (Al Haddad et al., 2020). The theory of planned behavior is well-established in explaining modal choice and travel behavior founded on attitudes, subjective norms, and perceived behavioral control (Cassar, 2021).

To investigate the intention to use a technology as disruptive as urban air autonomous vehicles, which are not yet in use, it would be necessary to review phenomenologies with similar characteristics. The research object that comes closest to the study of UAAVs is the analysis of the level of acceptance of autonomous cars by users. Recent research on the willingness to use unmanned cars using the Davis et al. (1989) model as a framework can be found in the work of Huang (2021). Despite the undeniable similarities, it is necessary to underline two aspects that differentiate one technology from the other. On the one hand, although autonomous cars are not yet widely available on the market, their implementation in the short term is an indisputable fact that frequently appears in the media. On the other hand, this circumstance means that coming across vehicles without a driver behind the wheel is a closer reality in the public's imagination, which takes away the science fiction component that is undoubtedly present in people's minds when they hear about flying cars for the first time.

Research on the degree of acceptance of autonomous cars by potential passengers has resulted in an extension of the TAM to the car technology acceptance model (CTAM), also known as the extended TAM. This model, developed by Taylor and Todd (1995), arose from the need to study the predictive behavior of potential users in relation to the acceptance of a new technology with which they have no experience of use, such as autonomous cars or urban air vehicles.

Specifically, the present research was based on the theoretical framework proposed by Osswald et al. (2012), which involves an adaptation of the TAM to the CTAM. The proposal of these authors pointed out the significant role that the unified theory of acceptance and use of technology (UTAUT) plays in the CTAM. According to Venkatesh et al. (2003), the UTAUT model is an attempt to bring together into a single consolidated model the different approaches to technology acceptance that exist thus far. Although there are other models for researching the most influential factors in the adoption time horizon of UAM (e.g., the Urban Air Transport Acceptance and Use Model Scale (UAM-AUM) developed by Yavas and Tez, 2023), at present, social scientists still consider the paradigm used by Osswald et al. (2012), which is founded on the TAM-CTAM, the most relevant for analyzing the intention to use new technologies in the initial development stage (Davis et al., 2020). For an in-depth understanding of the different models that exist to explain human technology adoption behavior, we recommend reading the doctoral thesis of Cassar (2021) and the recent work by Yavas and Tez (2023).

The model of Osswald et al. (2012) emphasizes the role of four critical constructs in generating usage intention: performance expectancy, effort expectancy, social influence, and facilitating conditions. The model of Osswald et al. (2012) is an adaptation of the TAM of Davis et al. (1989) and the UTAUT model of Venkatesh et al. (2003) to the acceptance of information technology in an automotive context. Although these authors have investigated technological systems in general, in this research, we refer specifically to autonomous airborne driving systems, i.e., those that are unmanned. The main variables of the model are performance expectancy, effort expectancy, attitude toward using technology, social influence, facilitating conditions, self-efficacy, perceived safety, and anxiety. As facilitating conditions are related to technology use (not intention to use), this construct was removed from our final model, as UAAVs are not yet available. Self-efficacy was not part of the research model; this variable evaluates the users' ability to use new technologies, a circumstance that does not make sense when referring to autonomous, nonuser-piloted vehicles.

The general model developed by Osswald et al. (2012) was extended by considering the mediating effect of two variables on the behavioral intention to use UAAVs: pro-environmental behavior and the human values of potential users. In addition, an exploratory analysis was conducted on whether there is a difference in behavior between the Chinese and US populations, which could indicate the influence of cultural factors on the acceptance of UAAVs.

Based on the theories previously discussed, which were concretized in the adoption of the model of Osswald et al. (2012), a baseline for explaining the behavioral intention to use urban air autonomous vehicles (UAAVs) was developed. The concept of autonomous vehicles was used in this research because although current tests are conducted with a pilot on board or a remote operator, the long-term vision for these vehicles will be to provide their services fully autonomously (Palaia et al., 2021).

Thus, the main contribution of this research lies in applying a classical model to a novel research object, such as urban air mobility, providing scientific knowledge about the factors influencing the intention to use flying cars in the future. This topic has yet to be explored in academic research, and is of great interest to those journals focused on analyzing the influence of technology on social change. Additionally, this paper extends the model of Osswald et al. (2012) by analyzing the effect of two variables that mediate the behavior of potential users: pro-environmental behavior and basic human values. The novelty of the research is supported by the following themes:

1) First, the research object itself is novel as it based on the behavioral intention to use urban air autonomous vehicles (UAAVs).
2) Second, the role of pro-environmental behavior is also novel. In autonomous vehicle acceptance models, it has generally been considered that their use will lead to positive environmental and social effects, based on the fact that autonomous cars are linked to electric vehicles (when people think about this kind of car, they imagine electric cars without a driver at the wheel). While electric vehicles are considered environmentally friendly, such an association may not occur in the case of UAAVs. In contrast, the opposite feeling may spring up because these vehicles (such as airplanes) would be considered highly polluting. Nevertheless, our main claim about this issue is that pro-environmental behavior positively affects the behavioral intention to adopt UAAVs.
3) Third, the effect of human values can also be interesting for the scientific community; we propose that people who are more open to change might be more likely to use UAAVs than those who are more conservative.
4) The intention to use UAAVs, the pro-environmental behavior and the human values of Asian versus American citizens could be another exciting and novel research topic regarding the intention to use (or not use) urban air autonomous vehicles. Whether there are cultural factors that influence the intention to use new technology, as proposed by authors such as Kim and Kang (2022) or Goularte and Zilber (2018), was also analyzed on a purely experimental basis.

To achieve the objectives of this research, the other sections of this article are structured as follows. Section 2 reviews the theoretical foundations and sets out the research hypotheses. Section 3 focuses on the research methods. While Section 4 presents the main results of the empirical study. The discussion of the results is presented in Section 5. Finally, the main limitations and some ideas for future research are presented.

2. Theoretical background and hypothesis development

2.1. Factors that influence the behavioral intention to use UAAVs

2.1.1. Performance expectancy and behavioral intention to use UAAVs

This concept refers to the possibility that the subject perceives an improvement in their performance through technology. Different authors, such as Venkatesh et al. (2003) and Raman et al. (2014), considered this construct the strongest predictor of intention to use new technology.

In the specific framework of UAM, several research studies highlight that this form of transport will be faster and cheaper than conventional transport systems (Corwin et al., 2016). Similarly, Al Haddad et al. (2020) conducted research with a sample of 221 people, mainly German, on the factors influencing the adoption and use of urban air vehicles. The results of their study show that travel time and on-time reliability are critical factors for the adoption of UAMs. Hogreve and Janotta (2021) concluded that the main advantages of this technology are the time savings and efficacy of avoiding traffic bottlenecks, although spatial distribution and appropriate placement of vertiports can be influential for demand and travel-time savings (Fu et al., 2022). Straubinger et al. (2020) and Ploetner et al. (2020) found that decreasing the number of stations reduces UAM demand. In his Ph.D. thesis, Boddupalli (2019) surveyed 2500 people across different cities in the United States to estimate the demand for an electric vertical landing and takeoff air taxi service. Using discrete choice modeling as the central methodology, he concluded that traffic congestion, and consequently travel time, are the key elements for estimating potential air taxi demand.

Time savings are also the most critical performance improvement identified by Straubinger et al. (2020), Holden and Goel (2016), and Antcliff et al. (2016) regarding the use of electrically powered air taxis fitted with vertical takeoff and landing (e-VTOL) systems. The value of passenger time was also highlighted in the study by Rothfeld et al. (2019). However, in subsequent research, these authors cautioned that time savings would occur only on journeys of >35 km, a distance that is not common for trips in urban areas (Rothfeld et al., 2021). A similar conclusion was reached in the study by Pukhova et al. (2021); they confirmed that in cities with good highways and public transport networks, the time savings were not significant, especially if the analysis considered the time spent traveling to vertiports, waiting, or boarding.

The previous discussion led to the following research hypothesis:

H1. Performance expectancy has a positive impact on the behavioral intention to use UAAVs.

2.1.2. Effort expectancy and behavioral intention to use UAAVs

According to Venkatesh et al. (2003), effort expectancy is related to the ease of use of the technology. In the case of autonomous aerial vehicles, it seems essential that users quickly and easily understand the different inputs and outputs of the system.

Although it seems obvious to think that ease of use is positively related to intention to use, previous literature on this issue is not as conclusive as one might think; the studies by Kaium et al. (2020) and Srivastava and Raina (2020) found that performance expectancy and effort expectancy directly impact the intention to adopt new technology. However, other research, such as that of Yin et al. (2016), failed to demonstrate the relationship between effort expectancy and adoption intention.

As Garrow et al. (2021) warned, urban air vehicles are not the first to be considered disruptive technology in the transport field. In all likelihood, the findings around the development of electric vehicles and autonomous vehicles may provide a model for UAM to follow. Thus, different studies, such as Wolff and Madlener (2019) and Lee et al. (2019), have confirmed that ease of use is crucial for the acceptance of innovative technologies in the transport field. By conducting a cross-sectional survey at Deutsche Post in Germany, the first of the studies concludes that ease of use helps with the acceptance by commercial drivers of light-duty e-vehicles in place of traditional cars. Moreover, in the second study, Lee et al. (2019) research the factors that influence the adoption of autonomous vehicles by users. These authors pointed out that self-efficacy positively influences the perceived ease of use and intention to use nonpiloted vehicles.

Using a partial least squares (PLS) analysis with a sample of 450 respondents living in South Korea, Kim et al. (2022) noted that perceived usefulness (in a direct way) and ease of use (indirectly, through perceived usefulness) exert a significant influence on the intention to use UAM, although to a lesser extent than trust. According to these authors, safety perception about flying vehicles translates into confidence, making this factor the most influential in the intention to use UAM. However, this relationship has not always been confirmed. A study by Al Haddad et al. (2020) estimated a multinomial logit model that did not find a direct connection between the perceived ease of use and the intention to use urban air vehicles.

Based on the previous arguments, the second hypothesis of this research was proposed as follows:

H2. Effort expectancy has a positive impact on the behavioral intention to use UAAVs.

2.1.3. Attitude toward using technology and behavioral intention to use UAAVs

According to Osswald et al. (2012), this construct reflects the users' beliefs about the use of technology and its effects, i.e., the overall affective reaction to the use of a particular technology. Autonomous air vehicles still seem like madness, a science fiction film, or even a more sophisticated fairground attraction. From this perspective, the affective reaction of potential users can include attitudes such as fun, entertaining, adventurous, or attraction to risk, all of which could be decisive in accepting a technology as disruptive as autonomous air vehicles.

In the context of autonomous cars, a study by Owczarzak and Żak (2015) highlighted comfort as a key element for the acceptance of autonomous cars. Landing on UAAVs, research by Rothfeld et al. (2019) pointed out the need to analyze the effects of aerial vehicles on the well-being of potential consumers. Similarly, a study by Winter et al. (2020), conducted with a sample of half a thousand participants, identified up to six factors related to the willingness to use air taxi services, including attitudes such as fun, fear, and happiness. Similarly, using the willingness to fly scale, Rice et al. (2019) discovered that the predisposition to use autonomous aircraft is determined by fun, wariness toward new technology, happiness, and fear of potential passengers, in addition to other factors of a personal nature, such as age and educational level. In any case, potential customers' attitudes toward flying cars, with or without a pilot, can be considered an emotional reaction to UAM at an early stage of development (Tez et al., 2022).

Therefore, Hypothesis 3 attempted to demonstrate the following:

H3. Positive attitudes toward using technology have a positive impact on the behavioral intention to use UAAVs.

2.1.4. Social influence and behavioral intention to use UAAVs

As Wood (2000) proposed, social influence means that individuals are influenced by the opinion that certain reference groups exert on the degree of acceptance of a specific technology. In the context of autonomous cars, studies by Panagiotopoulos and Dimitrakopoulos (2018), Hein et al. (2018), and Lee et al. (2019) demonstrated that social influence predicts the intention to use this technology.

In the UAM field, Vascik (2017) noted that community acceptance is undoubtedly a key factor in implementing the operations and infrastructures required for developing this technology. Concerning this issue, Goyal et al. (2021) conducted a comprehensive literature review between 2015 and 2021. They examined the potential demand for two types of air transport: airport shuttles and air taxis. Among other factors, these authors found that legal regulations and social ethics were decisive for the future development of this technological innovation. Recently, Hogreve and Janotta (2021) developed a study based on problem-centered interviews, concluding that peer influence could determine their decisions to use UAM.

UAAV travel will probably not be a mass consumer product at first; rather it will be exceptional and expensive, an exclusive product reserved for an elite group of potential consumers. In this scenario, social influence can function as an extrinsic motivator because, as Dečman (2015) pointed out, the use of this technology would provide social recognition to a category of consumers seeking exclusivity in their consumption choices. This reasoning suggests a positive relationship between social influence and the intention to use autonomous aerial vehicles, which led to the following hypothesis:

H4. Social influence has a positive impact on the behavioral intention to use UAAVs.

2.1.5. Perceived safety and behavioral intention to use UAAVs

In a broad sense, perceived safety is the degree to which a person considers that using a particular technology may affect their well-being (Osswald et al., 2012). This construct is another central element in adopting new technologies, especially when they are related to passenger transport (Sonneberg et al., 2019; Straubinger et al., 2020), and even more so when this occurs in urban airspace and in autonomous driving mode. As previous literature indicates, people are reluctant to take autonomous flights due to safety concerns, whether they are commercial or private flights (Kim et al., 2022; Edwards and Price, 2020; Rice and Winter, 2015).

Safety concerns are a recurring theme in the topic of this research, to the point of generating profound ethical debates about the circulation of autonomous vehicles (e.g., Owczarzak and Żak, 2015). Indeed, obstacles of a legislative rather than a technical nature have hindered the pace of transport solutions based on autonomous vehicles (Zöldy, 2018). Fu et al. (2019) examined the transport mode preferences in Munich by evaluating the potential effect of service attributes. The authors pointed out that security is undoubtedly a barrier to wider UAM adoption. They compared four types of transportation (public transportation, private car, autonomous taxi, and autonomous air taxi), concluding that security is one of the essential components affecting UAM's adoption of autonomous transportation modes. Until this issue is fine-tuned, citizens will find it difficult to accept a driverless car pulling up next to them at traffic lights or getting into a taxi without a person at the wheel. Prior research has shown that people prefer to ride in human-controlled vehicles rather than autonomous models (Anania et al., 2018).

This concern increases exponentially with vehicles that can fly overhead, with the threat that this poses in the event of an accident. For this reason, manufacturers and regulators should guarantee high levels of security for flying cars (Kalakou et al., 2023). Several studies have analyzed the importance of safety for accepting aerial vehicles. For example, Corwin et al. (2016) were convinced that the safest forms of transport will be those that prevail over the transport systems we know today. In 2018, NASA conducted a study to explore the potential market for three types of UAM (airport shuttle, air taxi, and air ambulance). Combining quantitative (surveys) and qualitative (focus groups and interviews) methodologies, the study's authors found that among the key factors for adopting autonomous transportation modes, safety plays a main role. A recent publication used structural equation modeling with a sample of 450 respondents, concluding that trust is critical for UAM acceptance, and safety perception is the most crucial factor in promoting UAM's trustworthiness (Kim et al., 2022).

Similarly, a study by Al Haddad et al. (2020) identified safety as the most important factor in the intention to use air vehicles. Specifically, more than half the respondents said this was the essential element, ahead of such others as cost, journey time, or on-time reliability. A similar conclusion was reached by Palaia et al. (2021), highlighting that safety and reliability are substantial for potential passengers to recognize and value the benefits of using air vehicles. Recently, Çetin et al. (2022) developed a qualitative study to analyze the impact that the implementation of air vehicles would have on society, as well as possible strategies to mitigate the adverse effects. Using word clouds to process and display the results of their study, these authors identified two broad categories of public concern: environmental and safety concerns, with the latter related to the potential risks and hazards associated with the development of air vehicles. Among the possible safety measures, a study by Ward et al. (2021) conducted with two different samples from the US and India concluded that automatic airframe parachute availability increases the acceptance of aerial vehicles.

Based on the previous arguments, Hypothesis 5 stated the following:

H5. Perceived safety has a positive impact on the behavioral intention to use UAAVs.

2.1.6. Anxiety and behavioral intention to use UAAVs

Anxiety linked to the use of new technology is a state of mind that results in feelings of fear, excitement, or discomfort, among others (Osswald et al., 2012). Closely related to the issue of safety, a model by Osswald et al. (2012) highlights anxiety as an antecedent to the intention to use UAAVs. This effect is likely to be even stronger in the case of this research, because if it is already anxiety-provoking to see (or ride in) a self-driving car, it will be even more stressful to do the same in an aerial vehicle.

As an example of the study of unmanned ground vehicles, the work of Tan et al. (2022) used a sample of 1582 respondents to conclude that anxiety is one of the psychological elements behind consumers' acceptance. Moving up to the UAM space, the results of Winter et al.'s (2020) research identified six significant predictors of willingness to fly in autonomous air taxis, most notably the fear and anxiety of potential passengers. Desai et al. (2021) highlighted that autonomous systems are not well accepted in the transport industry. The anxiety of not having a pilot on board reduces the acceptance of UAM, as highlighted in the studies of Dunn (2018) and Chancey and Politowicz (2020). The preference for piloted aircraft was also noted in a NASA (2018) study. Finally, Ward et al. (2021) observed that anxiety is reduced and the desire to use air vehicles increases with the presence of automatic parachute systems.

Consequently, Hypothesis 6 aimed to demonstrate the following:

H6. Anxiety has a negative impact on the behavioral intention to use UAAVs.

2.2. Mediating role of pro-environmental behavior and human values

As indicated at the beginning of this section, the above factors proposed in the model of Osswald et al. (2012) may influence the decision of whether to board an air vehicle. However, the explanatory capacity of the model may be conditioned by other elements that, as Sun and Zhang (2006) note, are critical in technology acceptance models.

This paper considers that the behavioral intention to use UAAVs can be influenced, directly or indirectly, by two fundamental variables: pro-environmental behavior and human values, specifically the users' openness to change. Incorporating these variables represents an extension of the general model of Osswald et al. (2012) that provides novelty and a theoretical contribution to the scientific community.

2.2.1. Pro-environmental behavior and behavioral intention to use UAAVs

Pro-environmental behavior is defined by Krajhanzl (2010) as the behavior in which individuals take actions aimed at protecting the environment. Those with deep environmental feelings will preferably use environmentally friendly products, avoiding buying products that harm the environment (Nekmahmud et al., 2022). These environmentally conscious consumers prefer the more ecologically friendly alternative whenever a choice is available. Corwin et al. (2016) used this argument to ensure that potential users choose transport modes that are cleaner than other options available today. Similarly, Cassar (2021) stated that individuals' pro-environmental attitude is one of the most common factors in deciding the travel mode. In fact, an analysis of word clouds by Çetin et al. (2022) pointed out that the management of environmental issues is one of the leading public concerns to be solved to make the use of this technology more widespread. According to Papadopoulos et al. (2018), the increase in mobility requires more efficient solutions that use fewer fossil energy sources and are oriented to preserve the environment. Thus, a study by Owczarzak and Żak (2015) showed that environmental friendliness is a pivotal element for developing and implementing innovative public transport solutions based on autonomous vehicles. Focusing on UAM, the structural equation modeling (SEM) developed by Yavas and Tez (2023) with a sample of 348 Turkish participants found that environmental consciousness was a leading factor in the behavioral intention to use flying cars ($\beta = 0.684$, $t = 10.612$, $p < 0.001$).

Different authors have highlighted noise (acoustic pollution) and gas emissions into the atmosphere (environmental pollution) as the main environmental problems in implementing autonomous vehicles (Palaia et al., 2021; Eißfeldt, 2020; Vascik and Hansman, 2018; NASA, 2018). Using a sensitivity analysis applied to a case study of the Tampa Bay region, Zhao et al. (2022) verified that public acceptance of UAM depends on how environmental impact concerns will be addressed, basically noise and emissions. Given that UAAVs will travel over urban areas, reducing the sound of these devices so that they generate as little noise pollution as possible is a challenge that must be met (Jeong et al., 2021). Studies such as Yedavalli and Mooberry (2019) and Kalakou et al. (2023) warned of the importance of mimicking the sound of air vehicles with the ambient noise of cities.

It is necessary to convince citizens of the benefits of these vehicles in regard to gas emissions. For example, Straubinger et al. (2020) concluded that air vehicles pollute less when transporting three or more passengers than combustion cars and even electric cars. The advantages of shorter and therefore less polluting travel times should also be considered. Moreover, the future of UAAVs is firmly linked to the development of electric mobility, which is expected to be energy efficient and nonpolluting (Lineberger et al., 2018). The qualitative research approach of Hogreve and Janotta (2021) highlighted environmental protection as a critical component in the decision to use UAM due to the electrical propulsion of these vehicles. Despite this, Pukhova (2018) advised that electrically propelled aerial vehicles will benefit the environment only when the electricity they use is generated from renewable energy sources.

Several studies have tested the direct and mediating effects of pro-environmental behavior in relation to technology acceptance patterns (e.g., Zhang and Liu, 2022; Whittle et al., 2020; Yoon, 2018; Lee and Jan, 2018). However, to our knowledge, no previous study has investigated this effect in the UAM context.

Using the framework of Osswald et al. (2012), we assumed that the variables in their model will ultimately promote the behavioral intention to use UAAVs through pro-environmental behavior. Therefore, Hypothesis 7 stated the following:

H7. Pro-environmental behavior positively mediates the relationships of previous factors (performance expectancy, effort expectancy, attitude, social influence, perceived safety, and anxiety) with the behavioral intention to use UAAVs.

2.2.2. Human values and behavioral intention to use UAAVs

The study of human values is dominated by two major theories: the theory of basic human values by Schwartz and the postmaterialist theory by Ronald Inglehart. In the present research, Schwartz's theory is adopted as a frame of reference. Based on the previous work of Rokeach (1973), Schwartz (1992) considered that human values are desirable, transcendent, and significant objectives to the point of establishing the principles that orient and guide the life of any individual. In other words, values drive the actions of individuals, developing attitudes and behavior rules to be applied in the face of certain objects and situations.

Schwartz (1992)'s theory of human values groups ten basic tenets (conformity, tradition, benevolence, universalism, self-direction, stimulation, hedonism, achievement, power, and security) around two bipolar axes representing change versus continuity on the one hand and collectivism versus individualism on the other. For the purposes of this research, we were mainly interested in the openness to change–conservation axis. Each dimension proposed by Schwartz (2012) reflects different motivational goals. Openness to change is based on self-direction and stimulation values, focusing on freedom of thought and action. In contrast, the values of tradition, conformity, and security build on the axis of conservation, characterized by resistance to change and an emphasis on order, tradition, and preservation of the past.

The importance of this axis for this research lies in the direct and indirect effects of human values on the intention to use UAAVs. On the one hand, it is expected that the influence of the different factors of the Osswald et al. (2012) model on the intention to use UAAVs will be lower among more conservative subjects; on the other, it will intensify among people who are more open to change, that is, those who seek enjoyment, stimulation, and pleasure. The latter subjects are characterized by audacity, freedom, curiosity, and creativity and are expected to be more inclined to use technological innovations. As Yavas and Tez (2023) noted, technology needs to fit with society's culture to establish a place in that society.

In this regard, a study by Ghazizadeh et al. (2012) analyzed the role of human–automation interaction in explaining behavioral intentions to adopt automation innovations. The results of their study underline the importance that users' values play in the model, such that consistency with personal values and beliefs is a critical factor for the successful implementation and acceptance of new technology. Similarly, Al Haddad et al. (2020) noted that an affinity to automation, an attitude that can be considered close to openness to change, is vital for accepting urban air mobility. Moreover, qualitative research by Hogreve and Janotta (2021) found that people who were more enthusiastic about technology and more open-minded were more likely to use flying autonomous vehicles. In contrast, Winter et al. (2020) found that 3/4 of the variance in willingness to fly could be explained by only six components, one of which was wariness toward new technology. This circumstance is likely to be more pronounced among conservative individuals than among subjects with a greater propensity to change.

Consequently, Hypothesis 8 stated that:

H8. Openness to change positively mediates the relationships of previous factors (performance expectancy, effort expectancy, social influence, etc.) with the behavioral intention to use UAAVs.

2.3. Potential cultural differences between China and the US

Cultural differences in the use of technology have been recognized in previous academic publications. For example, regarding in-vehicle technology design, a study by Young and Rudin-Brown (2014) highlighted the main cultural factors influencing user acceptance of technology. Sabino et al. (2022) also pointed out these cultural differences in the public citizens' acceptance of drones. Likewise, Sun et al. (2022) found that perceived usefulness and subjective norms could be cross-cultural factors that may serve to understand passenger acceptance of driverless buses in China.

Regarding autonomous air vehicles, studies by Anania et al. (2018a) and Ragbir et al. (2018) found a greater desire to fly in these vehicles among an Indian population than among that in the United States. They attribute this result to cultural factors; namely, the predominantly collectivist cultural orientation of India compared to the more individualistic perspective of Americans. However, Ward et al. (2021) observed that cultural orientation is a weak predictor of willingness to fly. Furthermore, Rice et al. (2014)'s study found that American passengers considered the piloted UAM design more positively than Indian passengers but reacted more negatively to non-pilot vehicles.

Undoubtedly, certain cultural factors about the adoption of technological innovations, environmental awareness, or human values prevalent among the Chinese and US populations may influence the intention to use (or not to use) urban air autonomous vehicles. For this reason, in this research, we will conduct a purely exploratory analysis aimed at examining whether the behaviors of the Chinese sample and the US sample are similar or different and can be attributed to factors of a cultural nature.

Fig. 1 highlights the main theoretical model and research hypotheses of the current study. The core of this design (dependent variables that influence the behavioral intention to use UAAVs, the independent variable of this research) is based on Osswald et al. (2012)'s research model. This theoretical approach, founded on the TAM, has been extended by considering that this relationship could be mediated by pro-environmental behavior and human values.

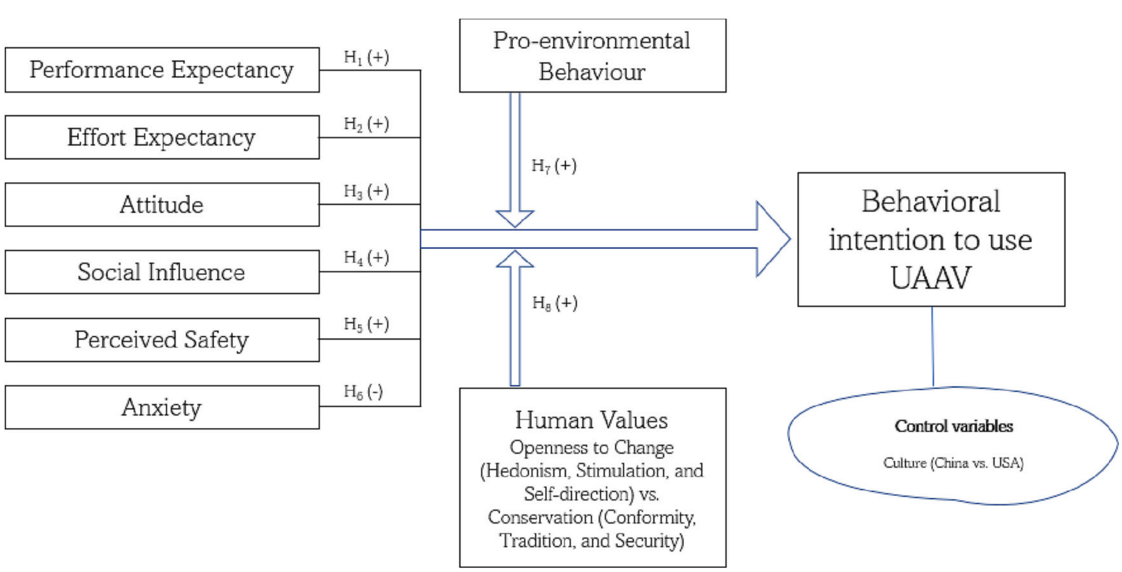

Fig. 1. Proposed theoretical model.

3. Material and methods

3.1. Data collection and sample

The present study sampled participants from China (400 participants) and the United States (411 participants), the world's two largest and most technologically developed economies.

The original questionnaire was developed in English. To improve the comprehension of Chinese participants, we invited professional translators to translate the original English version into Chinese through the back-to-back translation method with a full understanding of the study content. The questionnaires were collected through online surveys in April 2022 through professional questionnaire agencies in the U.S. and China. Prior to participating in the survey, the potential participants were asked to indicate their willingness to participate in the survey and their understanding of the study's research questions. The qualified participants were requested to complete the questionnaire with a full understanding of the study content and purpose. The participants were required to complete all questions; that process would take approximately 10–15 min. Through this procedure, we ended up with 411 and 400 usable US and Chinese samples, after removing the responses that contained missing values and incompleteness. Data analysis was performed on these samples.

The 411 US samples contained 57.4 % responses from males and 42.6 % from females. The average age was 40.78 years old. The educational attainment of the participants was categorized as less than a high school degree (1.5 %), high school degree (16.5 %), or more than a high school degree (82.0 %). Frequency analysis of annual income showed that the 41.8 % of participants with an annual income of $100,000 or more earned the highest proportion. The participants earning $55,000–$99,999 amounted to 30.3 % of the total. The annual income of $25,000–$54,999 was represented by 20.4 % of the sample. Last, participants with an income of less than $25,000 annually accounted for the smallest percentage, at 7.5 %.

The 400 Chinese samples contained 26.8 % responses from males and 73.3 % from females. The mean age of the respondents was 33.84 years. The educational level of the Chinese sample was significantly higher, with 99 % of the participants having more than a high school degree. No participant had less than a high school degree, and 1.0 % had finished only a high school degree. Frequency analysis of annual income showed that 48.0 % of the participants had an annual income of $100,000 or more, which was the largest share. The participants earning $55,000–$99,999 amounted to 40.6 % of the total, and 11.1 % of the participants declared earnings of $25,000–$54,999. Last, those earning less than $25,000 annually accounted for the smallest percentage, at 0.3 %.

3.2. Measurements

The dependent variable of this research, the behavioral intention to use UAAVs, was measured using a 3-item scale extracted from the model proposed by Osswald et al. (2012), adopting the unified theory of acceptance and use of technology (UTAUT) as a reference domain. Specifically, the respondents were presented with the following statements: (1) I intend to use UAM vehicles in my city commuting, (2) I plan to use UAM vehicles when they become available, and (3) I predict that I will use UAM vehicles in the near future to avoid traffic congestion. The response scale for these items was 1–7, from strongly disagree to strongly agree.

As research by Osswald et al. (2012) was the focus of this research, the independent variables of our model were based on it. The respondents were asked to indicate their level of agreement with some statements using a scale ranging from a value of 1 (extremely low) to a value of 7 (extremely high). Some examples of items for each variable are the following: (1) performance expectancy (using UAM vehicles would enable me to travel across cities more quickly), (2) effort expectancy (I would find UAM vehicles easy to use), (3) attitude (using UAM vehicles for city travel would be fun), (4) social influence (people who are important to me would think that I should use UAM vehicles for city travel), (5) perceived safety (I would feel safe while using UAM vehicles), and (6) anxiety (UAM vehicles would be somewhat frightening to me).

Last, the two mediating variables were measured as explained below.

The scale of pro-environmental behavior was measured using Sudbury-Riley and Kohlbacher (2016)'s ethically mindful consumer behavior (EMCB) scale. Some examples of items are the following: I do not buy household products that harm the environment, I have paid more for environmentally friendly products when there is a cheaper alternative, or I will not buy a product if I know that the company that sells it is socially irresponsible. These items were answered on a scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Human values were measured with Schwartz's 21-item portrait values questionnaire. Each item describes the personal values of one subject. The openness to change dimension was measured using items as follows: (1) She/he likes surprises and is always looking for new things to do. She/he thinks it is important to do lots of different things in life; (2) She/he looks for adventures and likes to take risks. She/he wants to have an exciting life; and (3) Thinking up new ideas and being creative is important to her/him. She/he likes to do things in her/his own original way. The respondents should answer whether they identify more or less identified with each of these statements. For this purpose, a scale ranging from 1 (in no way fits the description of me) to 7 (the description closely resembles me) was administered.

3.3. Research methodology

This study primarily used a structural equation modeling (SEM) methodology to confirm the proposed objectives due to its high efficiency in assessing measurements and building structural models. Despite the notable increase in recent years in the use of diverse methodologies in the social sciences, SEM has become a relatively important statistical concept in the research field (Hair et al., 2017; Dash and Paul, 2021).

Particularly, we used a covariance-based structural equation modeling (CB-SEM) because our proposed theoretical framework needed to be confirmed and evaluated rather than tested for conceptual development and predictive purposes (Dash and Paul, 2021). Furthermore, the use of CB-SEM is particularly prominent in the field of tourism research, fully enriching the statistical base of the study (Nunkoo et al., 2013). Therefore, CB-SEM was used in this study to further evaluate the theoretical framework by constructing a structural equation model based on the research model through the Amos 26.0 program.

4. Results

4.1. Data quality testing by confirmatory factor analysis

An examination of the quality of the data sample was performed by the statistical programs SPSS and Amos 26.0. We assessed the measurement model by confirmatory factor analysis (CFA) to ensure its reliability and validity. The results are summarized in Tables 1 and 2, with the measurement model reflecting satisfactory model goodness-of-fit statistics (whole sample: 1481.428, df = 524, $\chi2/df = 2.827$, $p < 0.01$, IFI = 0.942, TLI = 0.935, CFI = 0.941, RMSEA = 0.048; US sample: $\chi2 = 1315.630$, df = 524, $\chi2/df = 2.511$, $p < 0.01$, IFI = 0.919, TLI = 0.907, CFI = 0.918, RMSEA = 0.061; Chinese sample: $\chi2 = 102.981$, df = 524, $\chi2/df = 1.948$, $p < 0.01$, IFI = 0.943, TLI = 0.935, CFI = 0.942, RMSEA = 0.049).

The variable loadings for all measures in the three sample groups ranged from 0.648 to 0.893, which is greater than the recommended metric of 0.500 suggested by Hair et al. (2017). Therefore, all measurement items were retained. In addition, the average variance

Table 1
Assessment of correlations.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Whole sample									
[1] PEE	*0.770*								
[2] EE	0.767**	*0.772*							
[3] AT	0.724**	0.764**	*0.803*						
[4] SI	0.674**	0.676**	0.755**	*0.789*					
[5] PS	0.718**	0.769**	0.772**	0.780**	*0.803*				
[6] ANX	0.124**	0.149**	0.091*	0.273**	0.138**	*0.822*			
[7] INT	0.697**	0.737**	0.799**	0.749**	0.730**	0.069	*0.832*		
[8] PROE	0.711**	0.686**	0.744**	0.669**	0.642**	0.167**	0.732**	*0.743*	
[9] OTC	0.696**	0.706**	0.699**	0.687**	0.647**	0.191**	0.700**	0.703**	*0.718*
CR	0.853	0.855	0.845	0.831	0.784	0.862	0.871	0.917	0.809
AVE	0.593	0.596	0.645	0.622	0.644	0.675	0.692	0.552	0.515
Mean	5.74	5.65	5.75	5.43	5.70	4.58	5.76	5.51	5.57
SD	1.248	1.264	1.103	1.326	1.351	1.767	1.116	1.103	0.989
US sample									
[1] PEE	*0.789*								
[2] EE	0.609**	*0.792*							
[3] AT	0.753**	0.773**	*0.827*						
[4] SI	0.756**	0.649**	0.726**	*0.808*					
[5] PS	0.697**	0.750**	0.768**	0.755**	*0.825*				
[6] ANX	0.287**	0.278**	0.149*	0.460**	0.271**	*0.778*			
[7] INT	0.699**	0.747**	0.726**	0.734**	0.729**	0.179**	*0.831*		
[8] PROE	0.703**	0.687**	0.710**	0.637**	0.605**	0.291**	0.688**	*0.732*	
[9] OTC	0.708**	0.743**	0.663**	0.693**	0.631**	0.324**	0.662**	0.803**	*0.769*
CR	0.868	0.871	0.866	0.850	0.810	0.820	0.870	0.912	0.852
AVE	0.622	0.627	0.683	0.653	0.681	0.605	0.691	0.536	0.591
Mean	5.60	5.51	5.69	5.23	5.52	4.73	5.65	5.40	5.52
SD	1.389	1.418	1.277	1.485	1.494	1.668	1.228	1.223	1.071
CN sample									
[1] PEE	*0.734*								
[2] EE	0.641**	*0.734*							
[3] AT	0.712**	0.724**	*0.756*						
[4] SI	0.709**	0.721**	0.711**	*0.744*					
[5] PS	0.640**	0.730**	0.743**	0.716**	*0.755*				
[6] ANX	−0.037	0.025	0.036	0.104	0.023	*0.863*			
[7] INT	0.680**	0.710**	0.660**	0.665**	0.725**	−0.024	*0.830*		
[8] PROE	0.710**	0.678**	0.708**	0.720**	0.700**	0.058	0.735**	*0.759*	
[9] OTC	0.668**	0.677**	0.662**	0.701**	0.675**	0.157**	0.706**	0.628**	*0.712*
CR	0.823	0.824	0.800	0.788	0.726	0.898	0.869	0.924	0.805
AVE	0.538	0.539	0.572	0.554	0.570	0.745	0.689	0.576	0.507
Mean	5.89	5.79	5.82	5.63	5.89	4.42	5.88	5.63	5.63
SD	1.067	1.068	0.886	1.108	1.16	1.851	0.976	0.952	0.895

Note 1. PEE: performance expectancy, EE: effort expectancy, AT: attitude, SI: social influence, PS: perceived safety, ANX: anxiety, INT: intention to use, PROE: pro-environmental behavior, OTC: openness to change.
AVE: Average variance extracted, CR: Composite reliability, SD: Std. Deviation.
Note 2. CN: Chinese sample.
Coefficient in Italic: $\sqrt{AVE}$.
* $p < 0.05$.
** $p < 0.01$.

extracted (AVE) values for all constructs ranged from 0.507 to 0.692, and the composite reliability values (CR) ranged from 0.784 to 0.924. These values exceed the recommended critical values of 0.500 and 0.700 (Hair et al., 2017). Consequently, the measurement model would be considered to have excellent internal consistency and convergence. The square root of AVE values calculated from the average variance extracted values were applied to assess the discriminant validity. That is, the positive square root of AVE of each latent variable (0.712 to 0.863) is higher than the highest correlation with any other latent variable. Hence, the scale in this study provided favorable discriminant validity (Fornell and Larcker, 1981).

4.2. *Structural model, hypotheses, and indirect effects assessment*

Structural equation modeling was developed for the research model proposed in this study by the maximum likelihood method, and the hypotheses and the goodness-of-fit indicators of the structural equation model were tested. All three samples of the structural equation model demonstrated a sufficient goodness-of-fit of the data (whole sample: $\chi2 = 1285.179$, df = 498, $\chi2/df = 2.581$, $p < 0.01$, IFI = 0.946, TLI = 0.936, CFI = 0.945, RMSEA = 0.049; US sample: $\chi2 = 1207.324$, df = 498, $\chi2/df = 2.424$, $p < 0.01$, IFI = 0.928, TLI = 0.913, CFI = 0.927, RMSEA = 0.059; Chinese sample: $\chi2 = 1094.806$, df = 498, $\chi2/df = 2.198$, $p < 0.01$, IFI = 0.932, TLI = 0.918, CFI = 0.932, RMSEA = 0.055).

As shown in Table 3, the results of the whole sample reveal that performance expectancy, attitude, and social influence exhibit a significant positive effect on intention to use ($\beta_{performance\ expectancy} = 0.192^{**}$, $\beta_{attitude} = 0.823^{**}$, $\beta_{social\ influence} = 0.176^{**}$), while anxiety shows a negative positive effect ($\beta_{anxiety} = -0.060^{*}$). Moreover, effort expectancy and perceived safety ($\beta_{effort\ expectancy} = 0.059^{n.s.}$, $\beta_{safety} = -0.009$

Table 2
Evaluation of confirmatory factor analysis.

	Measurement items	β (W)	β (US)	β (CN)
PEE1	UAM vehicles would be useful in my city travel.	0.759	0.818	0.648
PEE2	Using UAM vehicles would improve my chances of achieving city travel experiences that are important to me.	0.736	0.735	0.730
PEE3	Using UAM vehicles would enable me to travel across cities more quickly.	0.794	0.811	0.767
PEE4	Using UAM vehicles would increase the quality of my city travel decision-making.	0.789	0.789	0.783
EE1	My interaction with UAM vehicles would be clear and understandable.	0.765	0.781	0.729
EE2	It would be easy for me to become skillful at using UAM vehicles for city travel.	0.771	0.794	0.729
EE3	I would find UAM vehicles easy to use.	0.773	0.791	0.739
EE4	Learning how to use UAM vehicles for city travel would be easy for me.	0.778	0.802	0.737
AT1	I would prefer to use UAM (urban air mobility) - flying cars rather than other payment methods.	0.815	0.830	0.780
AT2	For me, UAM (urban air mobility) - flying cars are a great way to commute.	0.830	0.873	0.747
AT3	For me, using UAM (urban air mobility) - flying cars will be satisfying.	0.763	0.774	0.741
SI1	People who influence my behavior would think that I should use UAM vehicles for city travel.	0.784	0.799	0.738
SI2	People who are important to me would think that I should use UAM vehicles for city travel.	0.800	0.821	0.766
SI3	People whose opinions that I value would prefer that I use UAM vehicles for city travel.	0.782	0.805	0.727
PS1	I would feel safe while using UAM vehicles.	0.820	0.846	0.762
PS2	I would trust UAM vehicles.	0.786	0.804	0.748
ANX1	I would have concerns about using UAM vehicles.	0.791	0.728	0.860
ANX2	UAM vehicles would be somewhat frightening to me.	0.889	0.876	0.893
ANX3	I am afraid that I would not understand UAM vehicles.	0.781	0.720	0.835
PROE1	When there is a choice, I always choose the product that contributes to the least amount of environmental damage.	0.818	0.838	0.778
PROE2	I have switched products for environmental reasons.	0.848	0.846	0.845
PROE3	If I understand the potential damage to the environment that some products can cause, I do not purchase those products.	0.830	0.809	0.864
PROE4	I do not buy household products that harm the environment.	0.722	0.717	0.731
PROE5	I make every effort to buy paper products (toilet paper, tissues, etc.) made from recycled paper.	0.755	0.762	0.741
PROE6	I will not buy a product if I know that the company that sells it is socially irresponsible.	0.715	0.671	0.767
PROE7	I will not buy products from companies I know use sweatshop labor, child labor, or other poor working conditions.	0.727	0.691	0.780
PROE8	I have paid more for environmentally friendly products when there is a cheaper alternative.	0.773	0.772	0.769
PROE9	I have paid more for socially responsible products when there is a cheaper alternative.	0.759	0.726	0.808
OTC1	She/he likes surprises and is always looking for new things to do. She/he thinks it is important to do lots of different things in life.	0.754	0.742	0.747
OTC2	She/he looks for adventures and likes to take risks. She/he wants to have an exciting life.	0.699	0.736	0.741
OTC3	Thinking up new ideas and being creative is important to her/him. She/he likes to do things in her/his own original way.	0.700	0.765	0.744
OTC4	It is important to her/him to make her/his own decisions about what she/he does. She/he likes to be free and not depend on others.	0.716	0.786	0.728
INT1	I intend to use UAM (urban air mobility) - Flying cars in my city commuting.	0.693	0.732	0.724
INT2	I plan to use UAM (urban air mobility) - Flying cars in when they become available.	0.752	0.803	0.694
INT3	I predict that I will use UAM (urban air mobility) - Flying cars to avoid traffic congestion in near future.	0.702	0.751	0.702

Goodness-of-fit statistics for the baseline model (Whole sample, n = 811): $\chi 2 = 1481.428$, df = 524, $\chi 2/\mathrm{df} = 2.827$, $p < 0.01$, IFI = 0.942, TLI = 0.935, CFI = 0.941, RMSEA = 0.048.
Goodness-of-fit statistics for the baseline model (US sample, n = 411): $\chi 2 = 1315.630$, df = 524, $\chi 2/\mathrm{df} = 2.511$, $p < 0.01$, IFI = 0.919, TLI = 0.907, CFI = 0.918, RMSEA = 0.061.
Goodness-of-fit statistics for the baseline model (Chinese sample, n = 400): $\chi 2 = 102.981$, df = 524, $\chi 2/\mathrm{df} = 1.948$, p < 0.01, IFI = 0.943, TLI = 0.935, CFI = 0.942, RMSEA = 0.049.
Note 1. PEE: performance expectancy, EE: effort expectancy, AT: attitude, SI: social influence, PS: perceived safety, ANX: anxiety, INT: intention to use, PROE: pro-environmental behavior, OTC: openness to change.
Note 2. W: whole sample, US: US sample, CN: Chinese sample.

$^{n.s.}$) have no significant effect. Therefore, Hypotheses 1, 3, 4, and 6 were supported, whereas Hypotheses 2 and 5 were not supported.

The inclusion of two mediating variables in the Osswald et al. (2012) model shows, first, that neither pro-environmental behavior ($\beta_{\text{pro-environmental behavior}} = 0.013$) nor openness to change ($\beta_{\text{openness to change}} = 0.055$) exhibit a direct effect on the intention to use UAAVs. However, when the indirect effects are analyzed, some significant results can be seen in relation to the mediating role of these two variables (see Table 3). Therefore, the outcomes of testing for indirect effects revealed that only the entire samples of social influence → pro-environmental behavior → intention to use (β = 0.068*); perceived safety → pro-environmental behavior → intention to use (β = 0.044*); social influence → openness to change → intention to use (β = 0.080*); and perceived safety → openness to change → intention to use (β = 0.044*) have significant indirect effects. These results partially confirm Hypotheses 7 and 8.

Finally, Tables 4 and 5 present the results segmented into two samples of the 400 Chinese citizens and the 411 participants from the US. The results obtained on the direct effects of the US sample, the results obtained show that attitude (β = 0.846**), performance expectancy (β = 0.113**), and social influence (β = 0.203**) exhibit a significant positive effect on the intention to use UAAVs. The other variables in the US sample had no significant effects on the intention to use these air vehicles. In the Chinese sample, the results showed a significant effect for attitude (β = 0.847**) and performance expectancy (β = 0.278**). As with the US sample, both factors are vital in the intention to use UAAVs. However, among Chinese people, social influence does not have a significant effect (β = $0.033^{n.s.}$), as happens with the rest of the variables considered by the Osswald et al. (2012) model.

Regarding indirect effects, Tables 4 and 5 show that no variable has a significant indirect impact on the intention to use through the pro-environmental behavior and/or the openness to change value.

Table 3
Evaluation of structural models and indirect effects for the whole sample (n = 811).

Direct paths			β	t-Values	Results
Performance expectancy	→	Intention to use	0.192	6.042**	H1 Supported
Effort expectancy	→	Intention to use	0.059	1.694	H2 Not supported
Attitude	→	Intention to use	0.823	15.239**	H3 Supported
Social influence	→	Intention to use	0.176	5.771**	H4 Supported
Perceived safety	→	Intention to use	−0.009	−0.139	H5 Not supported
Anxiety	→	Intention to use	−0.060	−2.161*	H6 Supported
Pro-environmental behavior	→	Intention to use	0.013	0.321	
Openness to change	→	Intention to use	0.055	1.298	
Performance expectancy	→	Pro-environmental behavior	0.234	6.616**	
Effort expectancy	→	Pro-environmental behavior	0.255	7.187**	
Attitude	→	Pro-environmental behavior	0.539	12.942**	
Social influence	→	Pro-environmental behavior	0.124	3.623**	
Perceived safety	→	Pro-environmental behavior	−0.015	−0.139	
Anxiety	→	Pro-environmental behavior	0.083	2.494*	
Performance expectancy	→	Openness to change	0.166	4.280**	
Effort expectancy	→	Openness to change	0.375	8.931**	
Attitude	→	Openness to change	0.420	9.922**	
Social influence	→	Openness to change	0.172	4.361**	
Perceived safety	→	Openness to change	−0.008	−0.138	
Anxiety	→	Openness to change	0.083	2.192*	

Indirect path	β (t-values)	Lower	Upper
PE → PROE → INT	0.095	0.010	0.142
PE → OTC → INT	0.107	0.013	0.147
EE → PROE → INT	−0.001	−0.035	0.034
EE → OTC → INT	0.026	−0.027	0.068
AT → PROE → INT	−0.001	−0.076	0.049
AT → OTC → INT	0.024	−0.039	0.058
SI → PROE → INT	0.068*	0.011	0.091
SI → OTC → INT	0.080*	0.008	0.106
PS → PROE → INT	0.044*	0.008	0.066
PS → OTC → INT	0.044*	0.004	0.075
ANX → PROE → INT	0.003	−0.002	0.007
ANX → OTC → INT	0.003	−0.003	0.009

Variance explained of pro-environment behavior, openness to change and intention to use:
R^2 for pro-environmental behavior = 0.381, R^2 for openness to change = 0.433, R^2 for intention to use = 0.817.
Total effect on intention to use: $\beta_{\text{performance}}$ = 0.195**, β_{effort} = 0.055, β_{attitude} = 0.849**, β_{social} = 0.181**, β_{safety} = −0.008, β_{anxiety} = −0.065, $\beta_{\text{pro-environmental behavior}}$ = 0.013, $\beta_{\text{openness to change}}$ = 0.055.
Goodness-of-fit statistics for the baseline model: $\chi2$ = 1285.179, df = 498, $\chi2$/df = 2.581, $p < 0.01$, IFI = 0.946, TLI = 0.936, CFI = 0.945, RMSEA = 0.049.
Note. PEE: performance expectancy, EE: effort expectancy, AT: attitude, SI: social influence, PS: perceived safety, ANX: anxiety, INT: intention to use, PROE: pro-environmental behavior, OTC: openness to change.
*$p < 0.05$ and **$p < 0.01$.

4.3. Invariance test by comparing chi-square differences

Finally, we analyzed the variability between American and Chinese individuals by using the whole sample as the data sample (see Table 6). A baseline model was constructed for this purpose, and the variability was compared with the chi-square values of the constrained nested model. As a result of the analysis, the baseline model demonstrated satisfactory model goodness-of-fit statistics ($\chi2$ = 2223.938, df = 1050, $\chi2$/df = 2.118, $p < 0.01$, IFI = 0.937, TLI = 0.928, CFI = 0.936, RMSEA = 0.037). Moreover, we only found significant differences in some of the paths in the proposed hypotheses. In particular, there were significant differences between the American and Chinese samples for performance expectancy ($\Delta\chi2[1]$ = 3.622, $p <$. 05) and social influence ($\Delta\chi2[1]$ = 3.151, p <. 05) in the relationship with the intention to use UAAVs.

5. Discussion and implications

5.1. Discussion of results

The disruptive innovation that UAM development will bring and the social impact it will have on transport and urban mobility have led to increased academic interest in its theoretical research and practical application (Tojal et al., 2021). Thus, researchers are analyzing the technical aspects of the vehicles, the necessary infrastructure, legislative barriers, market viability, and other elements indispensable for the successful adoption of this technology.

One of these basic pillars is undoubtedly society's unquestioning acceptance of potentially dangerous devices flying over citizens' heads, with the risk that this entails in the event of an accident (Straubinger et al., 2020). Despite the importance of public acceptance for the industry's success, to date, few studies have investigated the issue in

Table 4
Evaluation of structural models and indirect effects for the US sample ($n = 411$).

Direct paths			β	t-Values	Results
Performance expectancy	→	Intention to use	0.113	2.806**	H1 Supported
Effort expectancy	→	Intention to use	0.099	1.702	H2 Not supported
Attitude	→	Intention to use	0.846	11.992**	H3 Supported
Social influence	→	Intention to use	0.203	4.811**	H4 Supported
Perceived safety	→	Intention to use	0.021	0.538	H5 Not supported
Anxiety	→	Intention to use	−0.024	−0.593	H6 Not supported
Pro-environmental behavior	→	Intention to use	0.024	0.424	
Openness to change	→	Intention to use	−0.024	−0.377	
Performance expectancy	→	Pro-environmental behavior	0.067	1.450	
Effort expectancy	→	Pro-environmental behavior	−0.086	−1.598	
Attitude	→	Pro-environmental behavior	0.155	3.262**	
Social influence	→	Pro-environmental behavior	0.148	3.167**	
Perceived safety	→	Pro-environmental behavior	0.495	9.098**	
Anxiety	→	Pro-environmental behavior	0.511	8.709**	
Performance expectancy	→	Openness to change	0.160	3.102**	
Effort expectancy	→	Openness to change	−0.084	−1.466	
Attitude	→	Openness to change	0.110	2.129*	
Social influence	→	Openness to change	0.367	7.147**	
Perceived safety	→	Openness to change	0.046	0.920	
Anxiety	→	Openness to change	0.362	6.714**	

Indirect path	B (t-values)	Lower	Upper
PE → PROE → INT	0.002	−0.009	0.023
PE → OTC → INT	−0.004	−0.044	0.014
EE → PROE → INT	−0.002	−0.023	0.01
EE → OTC → INT	0.002	−0.016	0.031
AT → PROE → INT	0.004	−0.014	0.018
AT → OTC → INT	−0.003	−0.023	0.007
SI → PROE → INT	0.004	−0.011	0.035
SI → OTC → INT	−0.001	−0.03	0.01
PS → PROE → INT	0.009	−0.036	0.051
PS → OTC → INT	−0.012	−0.081	0.058
ANX → PROE → INT	0.012	−0.07	0.059
ANX → OTC → INT	−0.009	−0.105	0.028

Variance explained of pro-environment behavior, openness to change and intention to use:
R^2 for pro-environmental behavior = 0.440, R^2 for openness to change = 0.438, R^2 for intention to use = 0.787.
Total effect on intention to use: $\beta_{\text{performance}} = 0.116$, $\beta_{\text{effort}} = 0.096$, $\beta_{\text{attitude}} = 0.850$**, $\beta_{\text{social}} = 0.201$**, $\beta_{\text{safety}} = 0.021$, $\beta_{\text{anxiety}} = -0.023$, $\beta_{\text{pro-environmental behavior}} = 0.024$, $\beta_{\text{openness to change}} = -0.024$.
Goodness-of-fit statistics for the baseline model: $\chi2 = 1207.324$, df = 498, $\chi2/df = 2.424$, $p < 0.01$, IFI = 0.928, TLI = 0.913, CFI = 0.927, RMSEA = 0.059.
Note. PEE: performance expectancy, EE: effort expectancy, AT: attitude, SI: social influence, PS: perceived safety, ANX: anxiety, INT: intention to use, PROE: pro-environmental behavior, OTC: openness to change.
*$p < 0.05$ and **$p < 0.01$.

depth, which calls for more research on the topic (Al Haddad et al., 2020; Yedavalli and Mooberry, 2019).

In response to the call of these researchers, the current study aimed to analyze the factors that explain the behavioral intention to use UAAVs among potential users of a new technology that is not yet available on the market. The theoretical basis of this paper was built by adopting technology adoption theories as a reference framework and, more specifically, the proposal of Osswald et al. (2012). The model of these authors was extended by introducing two variables that could act as mediators in the behavior of potential consumers: pro-environmental behavior and openness to change. Regarding the environmental topic, it is surprising that of the total number of scientific articles published since 2018 in WOS journals about UAM, only 10 (4.8 % of the total) are classified in the area of environmental sciences ecology, suggesting that this topic is under-researched from the point of view of ecological awareness.

In addition, for purely exploratory purposes, the aim was also to analyze whether the behavior of the Chinese and US samples was similar or whether there were differences that could point to the existence of cultural factors in the intention to use UAAVs.

Structural equation modeling was developed for the research model proposed in this study. Adopting the model of Osswald et al. (2012) as a starting point, the results confirm that only four of the six variables in the model influence the intention to use UAAVs. Three variables, including attitudes, performance expectancy, and social influence, reinforce the intention to use, while another variable, anxiety, reduces it. Thus, Hypotheses 1, 3, 4, and 6 are supported. Finally, two variables that in the Osswald et al. (2012) model determined the intention to use a new technology do not exert a significant influence in the case of UAAVs: effort expectancy and perceived safety. Therefore, Hypothesis 2 and Hypothesis 5 are not supported.

These results partially converge with those obtained in previous research in the framework of intention to use new technologies. Different authors, such as Venkatesh et al. (2003) and Raman et al.

Table 5
Evaluation of structural models and indirect effects for the Chinese sample ($n = 400$).

Direct paths			β	*t*-Values	Results
Performance expectancy	→	Intention to use	0.278	4.803**	H1 Supported
Effort expectancy	→	Intention to use	0.016	0.391	H2 Not supported
Attitude	→	Intention to use	0.847	8.232**	H3 Supported
Social influence	→	Intention to use	0.033	0.858	H4 Not supported
Perceived safety	→	Intention to use	0.059	1.602	H5 Not supported
Anxiety	→	Intention to use	−0.060	−1.631	H6 Not supported
Pro-environmental behavior	→	Intention to use	−0.034	−0.470	
Openness to change	→	Intention to use	0.122	1.825	
Performance expectancy	→	Pro-environmental behavior	0.060	1.311	
Effort expectancy	→	Pro-environmental behavior	0.115	2.685**	
Attitude	→	Pro-environmental behavior	0.048	1.126	
Social influence	→	Pro-environmental behavior	0.310	5.920**	
Perceived safety	→	Pro-environmental behavior	0.668	1.202**	
Anxiety	→	Pro-environmental behavior	0.170	3.107**	
Performance expectancy	→	Openness to change	0.051	0.926	
Effort expectancy	→	Openness to change	0.105	2.084*	
Attitude	→	Openness to change	0.065	1.269	
Social influence	→	Openness to change	0.095	2.095*	
Perceived safety	→	Openness to change	0.342	5.59**	
Anxiety	→	Openness to change	0.570	8.510**	

Indirect Path	B (*t*-values)	Lower	Upper
PE → PROE → INT	−0.002	−0.041	0.008
PE → OTC → INT	0.006	−0.014	0.047
EE → PROE → INT	−0.004	−0.039	0.020
EE → OTC → INT	0.013	−0.012	0.053
AT → PROE → INT	−0.002	−0.009	0.002
AT → OTC → INT	0.008	−0.001	0.014
SI → PROE → INT	−0.011	−0.068	0.034
SI → OTC → INT	0.042	−0.004	0.116
PS → PROE → INT	−0.003	−0.035	0.006
PS → OTC → INT	0.021	−0.003	0.062
ANX → PROE → INT	−0.023	−0.150	0.069
ANX → OTC → INT	0.070	−0.015	0.140

Variance explained of pro-environment behavior, openness to change and intention to use:
R^2 for pro-environmental behavior = 0.488, R^2 for openness to change = 0.571, R^2 for intention to use = 0.913.
Total effect on intention to use: $\beta_{\text{performance}} = 0.309^{**}$, $\beta_{\text{effort}} = 0.033$, $\beta_{\text{attitude}} = 0.894^{**}$, $\beta_{\text{social}} = 0.037$, $\beta_{\text{safety}} = 0.068$, $\beta_{\text{anxiety}} = -0.053$, $\beta_{\text{pro-environmental behavior}} = -0.034$, $\beta_{\text{openness to change}} = 0.122$.
Goodness-of-fit statistics for the baseline model: $\chi2 = 1094.806$, df = 498, $\chi2/\text{df} = 2.198$, $p < 0.01$, IFI = 0.932, TLI = 0.918, CFI = 0.932, RMSEA = 0.055.
Note. PEE: performance expectancy, EE: effort expectancy, AT: attitude, SI: social influence, PS: perceived safety, ANX: anxiety, INT: intention to use, PROE: pro-environmental behavior, OTC: openness to change.
*$p < 0.05$ and **$p < 0.01$.

(2014), claimed that performance expectancy and effort expectancy should be the most decisive predictors of whether to accept a new technological innovation. In this study, the possibility of improving performance with air vehicles (performance expectancy) is not the most robust predictor, but rather the affective attitude of the potential consumer toward the technology is. In the same way, the ease of use of UAAVs (effort expectancy), which a priori should be an essential element for user acceptance, does not show statistically significant results in this research.

These results may be explained by a starting point that should not be ignored. UAAVs are not operational, nor can they be expected to fly over our heads in the short term. Several obstacles still exist to be overcome, such as community acceptance, UAM traffic management, landing infrastructures, privacy, cybersecurity, and charging stations (Desai et al., 2021; Straubinger et al., 2020; Fu et al., 2019). Attitudes such as fun, adventure, or the attraction to risk are the strongest predictors of acceptance of air vehicles and may be motivated by this point. UAAVs sound like fantasy, a pipe dream. Potential users may not believe this fancy can become a reality; if it does, it will be in a distant future that they will not inhabit. From this perspective, it is much easier to think about the fun, risk, or social status that riding in one of these vehicles confers (similar to driving a Tesla) than about critical factors such as ease of use or the potential safety issues highlighted in another study (Winter et al., 2020; Rice et al., 2019). These elements undoubtedly become more prominent when the technology is at a more advanced stage of market introduction, such as in the case of autonomous cars.

However, potential passengers value performance improvement as an essential factor to be considered for the acceptance and use of UAAVs. This result is in line with other research that considers time savings (Hogreve and Janotta, 2021) and traffic flow decongestion (Boddupalli, 2019) as critical factors for the acceptance or nonacceptance of technological innovations.

The general model of Osswald et al. (2012) was extended by including two potentially mediating variables (pro-environmental behavior and openness to change), which is a further contribution of this work in the field of theoretical implications. The results suggest that no direct effects show a positive relationship between these two variables and the intention to use UAAVs. However, indirect effects of pro-environmental behavior and openness to change with intention to use are observed for the variables of social influence and perceived safety. This fact confirms the proposed mediating role of personal values (concern for the environment and proactivity toward change), so it can be stated that Hypotheses 7 and 8 are supported.

A final goal of the present study was to analyze in an exploratory way the behavior of the research model in two culturally very different samples of individuals, Chinese society versus American society. As

Table 6
Comparison of differences between nationalities by invariance test.

Paths			US participants (n = 411)		Chinese participants (n = 400)		Baseline model	Nested model	$\Delta\chi2(1)$	p-Value	Results
			β	t-Values	β	t-Values					
PEE	→	PROE	0.148	3.167**	0.310	5.920**	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2226.367$	2.429	$p > 0.05$	Not supported
PEE	→	OTC	0.046	0.920	0.342	5.590**	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2229.755$	5.817	$p < 0.05$	Supported
EE	→	PROE	0.367	7.147**	0.095	2.095*	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2226.854$	2.916	$p < 0.05$	Supported
EE	→	OTC	0.511	8.709**	0.170	3.107**	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2228.396$	4.458	$p < 0.05$	Supported
AT	→	PROE	0.495	9.098**	0.668	1.202**	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2232.045$	8.107	$p < 0.01$	Supported
AT	→	OTC	0.362	6.713**	0.570	8.510**	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2229.643$	5.705	$p < 0.05$	Supported
SI	→	PROE	0.067	1.450	0.060	1.311	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2223.944$	0.006	$p > 0.05$	Not supported
SI	→	OTC	0.160	3.102**	0.051	0.926	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2224.359$	0.421	$p > 0.05$	Not supported
PS	→	PROE	−0.086	−1.598	0.115	2.685**	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2228.166$	4.228	$p < 0.05$	Supported
PS	→	OTC	−0.084	−1.466	0.105	2.084*	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2227.860$	3.922	$p < 0.05$	Supported
ANX	→	PROE	0.155	3.262**	0.048	1.126	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2228.494$	4.556	$p < 0.05$	Supported
ANX	→	OTC	0.110	2.129*	0.065	1.269	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2225.080$	1.142	$p > 0.05$	Not supported
PEE	→	INT	0.113	2.806**	0.278	4.803**	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2227.560$	3.622	$p < 0.05$	Supported
EE	→	INT	0.099	1.702	0.016	0.391	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2224.580$	0.642	$p > 0.05$	Not supported
AT	→	INT	0.846	11.992**	0.847	8.232**	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2224.380$	0.442	$p > 0.05$	Not supported
SI	→	INT	0.203	4.811**	0.033	0.858	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2227.089$	3.151	$p < 0.05$	Supported
PS	→	INT	0.021	0.538	0.059	1.602	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2224.419$	0.481	$p > 0.05$	Not supported
ANX	→	INT	−0.024	−0.593	−0.060	−1.631	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2223.991$	0.053	$p > 0.05$	Not supported
PROE	→	INT	0.024	0.424	−0.034	−0.470	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2224.298$	0.360	$p > 0.05$	Not supported
OTC	→	INT	−0.024	−0.377	0.122	1.825	$\chi2(1050) = 2223.938$	$\chi2(1051) = 2226.203$	2.265	$p > 0.05$	Not supported

Goodness-of-fit statistics for the baseline model: $\chi2 = 2223.938$, df = 1050, $\chi2/df = 2.118$, $p < 0.01$, IFI = 0.937, TLI = 0.928, CFI = 0.936, RMSEA = 0.037.
Note. PEE: performance expectancy, EE: effort expectancy, AT: attitude, SI: social influence, PS: perceived safety, ANX: anxiety, INT: intention to use, PROE: pro-environmental behavior, OTC: openness to change.
* $p < 0.05$.
** $p < 0.01$.

noted in the systematic review by Masimba et al. (2019), several authors argued that certain cultural factors may favor or hinder potential users' acceptance of the technology. A close look at the results shows that the UAAV acceptance model is very similar between the Chinese and US populations. In particular, there is a common stem, as two variables in the Osswald et al. (2012) model directly affect attitudes and performance expectancy. Attitude toward technological innovations is the most influential factor for the Chinese and US samples. The only difference between the two samples is that social influence has a positive and significant effect on the intention to use among Americans. At the same time, this variable is not important in the Chinese sample. This result is surprising, given that Asian societies tend to be more collectivist (Parker et al., 2009), we expected social influence to exert a more potent effect among the Chinese than among Americans, who tend to show a heavy emphasis on individualistic values and, therefore, are less influenced by other people's opinions. Future research should verify whether these contradictory findings are anecdotal or whether some cultural change is taking place in the Chinese economy and society.

The results of the empirical study highlight that, unlike in the general model, no variable has an indirect impact on the intention to use air vehicles, neither through the pro-environmental behavior nor the openness to change values. Further studies should investigate this issue to confirm whether any cultural factor actually differentiates the pattern of technology acceptance between Chinese and US citizens as applied to the case of UAAVs.

5.2. Theoretical contributions

Both theoretical and practical implications can be drawn from this work. At the theoretical level, the results of our research help validate the applicability of the Osswald et al. (2012) model to the context of UAAVs. Furthermore, this paper considers that the behavioral intention to use UAAVs can be directly or indirectly influenced by two fundamental variables: pro-environmental behavior and human values, specifically the openness to change of future users. Some literature has tested the direct and mediating effects of pro-environmental behavior on technology acceptance patterns (e.g., Zhang and Liu, 2022; Whittle et al., 2020; Yoon, 2018; Lee and Jan, 2018). However, to the best of our knowledge, no previous study has investigated this effect in the UAM context. Consequently, incorporating these variables is an extension of the general model of Osswald et al. (2012). Finally, the present research suggests no major cultural differences in the intention to use UAAVs, except for the incidence of social influence among US citizens. Future research should investigate this issue further to confirm whether the impact of reference groups has a significant effect on the acceptance degree of UAAVs.

5.3. Managerial contributions

Companies wishing to succeed in this emerging market must understand the concerns of their customers and adapt their marketing strategy accordingly. Therefore, from a practical point of view, the industry should highlight positive messages and refute the presumed adverse effects of implementing UAM. In particular, public opinion should be made aware that the model proposed in this research is environmentally friendly, as it is based on air vehicles powered by electricity. These vehicles pollute less noise and greenhouse gas emissions into the atmosphere. Although not explicitly addressed, the visual impact is another issue that should concern the industry (Al Haddad et al., 2020). Policymakers must regulate the height at which such vehicles can fly, which will undoubtedly influence acceptance by the community, both users and nonusers. Another important issue is safety, a critical element determined by different components, such as automation reliability, vehicle safety, and locus of control. For example, Ward et al. (2021) found that the desire to fly in autonomous air taxis increased among potential passengers when parachute systems were available. Any progress on these issues and a good communication policy with society will increase trust and reduce the anxiety associated with this technology. Intervention by the authorities would also help by establishing rigorous regulations that reaffirm trust and alleviate negative perceptions.

Another question for the industry is whether the penetration of UAAVs will become a mass-market product or remain a niche mode for special purposes. Our research has shown that performance expectancy is crucial for the acceptance of air vehicles, mainly travel-time savings. However, authors such as Pukhova et al. (2021) warned that the time savings associated with UAM are limited, especially in cities with a robust infrastructure network and a good public transport network. Expressly, these authors pointed out that in addition to the time lost for recharging air vehicles powered by electricity, the points of origin and destination must be equipped with infrastructures that allow these vehicles to take off and land. This fact results in other time losses associated with traveling to these points and aircraft boarding times. Therefore, Wu and Zhang (2021) argued that the potential market for air vehicles will be limited to special purposes, such as medical emergencies, VIPs, tourism, inspections, surveys, or goods delivery. Other possible uses are fire brigade transport, organ transport, transport to remote locations (e.g., exploration bases in polar areas or oil platforms), or just as a fun and adventurous experience.

Finally, we believe that a marketing strategy should be designed to focus explicitly on promoting word of mouth due to the importance of social influence highlighted in this research, mainly among US citizens.

5.4. Conclusion

This study's main contribution is identifying the main factors influencing the intention to use flying cars in the future. Additionally, this article extends the model of Osswald et al. (2012), pointing out the role of human values and pro-environmental behavior in the intention to adopt UAAVs. Finally, an exploratory study analyzed the cultural factors determining the intention to use new technology among Asians and Americans.

5.5. Limitations and future research

This research exhibits four primary limitations. The first is that there are no observed data. Therefore, the scenarios presented to respondents are hypothetical. Second, the design of this research is cross-sectional. Therefore, causality should be understood with caution. Third, the sample included only Chinese and Americans. Consequently, the results might not be easily generalized to other countries and cultures. Last, the sample shows an uneven gender distribution, with a higher proportion of female respondents, especially in the Chinese sample.

Proposals for future research are oriented toward overcoming previous limitations. Another interesting research should contrast the hypothetical data of intention to use with real data of use once flying cars are available in our cities in the near future. New research should consider using alternative methodological approaches, e.g., heuristic analysis, the study of comparable modes of transport, or simulations. To address the problem of cross-sectional data, we suggest developing other studies with longitudinal designs. Other research should collect data from countries with different cultures. Finally, we believe that more research is needed on the influence of sociodemographic factors (gender, age, education, marital status, or income level) on the behavioral intention to use air vehicles in the future.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Author statements

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Data availability

Data will be made available on request.

Acknowledgements

The authors are grateful for the constructive comments and feedback from the Editor of TFSC and the anonymous referees.

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