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Modeling the adoption of urban air mobility based on technology acceptance and risk perception theories: A case study on flying cars

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ABSTRACT

Flying cars, a symbol of Urban Air Mobility (UAM), signify a pivotal step in revolutionizing urban transportation and play a pivotal role in shaping future transport systems. To enhance travelers' willingness to accept flying cars and promote the widespread adoption of this novel transportation mode, this study develops a comprehensive model to explore key factors determining the public's acceptance of flying cars by integrating the Technology Acceptance Model, Risk Perception Theory, and Trust Theory. The validity of the model was confirmed through a rigorous structure equation modeling analysis, utilizing 553 sample data collected from a network questionnaire survey across a diverse demographic of the Chinese market. Results revealed significant associations between the intention to use flying cars and various factors, including attitudes towards usage, perceived usefulness, and personal innovativeness. Heterogeneity analysis further uncovered how demographic factors (such as age, gender, education, and possession of a driver's license) impacted perceptions and acceptance. As the study concludes, despite general optimism, public acceptance of flying cars is strongly influenced by factors such as cost, safety, and privacy concerns play crucial roles in public acceptance. The insights from this study provide valuable implications for manufacturers, policymakers, and marketers in strategizing the introduction and promotion of flying cars.

1. Introduction

Urban Air Mobility (UAM), an innovative mode of transportation moving at low or extremely low heights, is gaining more and more interest from both industry and academia, with a projected market worth of $500 billion by 2030 (Reiche et al., 2018; Zheng et al., 2023). The introduction of UAM promises to alleviate congestion in transport networks by offering a safer, more reliable, and environmentally friendly alternative (Airbus, 2017). Flying cars, symbolizing urban air transportation, are novel vehicles capable of traversing both ground and air, and have emerged as a popular research topic in numerous countries, particularly due to their potential in urban low-altitude transportation (Qu et al., 2022; Sasidharan et al., 2023). Statistics indicate that over 200 enterprises and institutions worldwide are actively exploring flying cars. Since 2009, remarkable progress has been made in the field of flying cars, with various prototypes emerging and demonstrating the dynamism and potential of this domain, as shown in Fig. 1.

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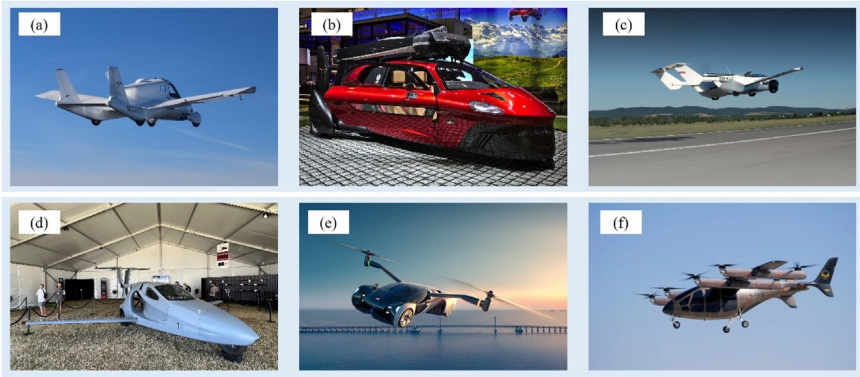

Fig. 1. Application cases of flying cars. (a) Terrafugia transition flight testing (b) the PAL-V liberty (c) Klein vision's air car (d) Roadable aircraft Samson switchblade (e) XPENG AEROHT flying car (f) AEROFUGIA AE200 × 01.

The potential benefits of flying cars to public transportation systems are significant. They offer efficient, convenient travel, especially in congested urban areas, bypassing traffic jams and improving overall efficiency (Postorino and Sarné, 2020). Additionally, flying cars expand transportation networks, enabling access to previously unreachable regions, fostering economic and social inclusivity (Cwerner, 2006; van Arem, 2022). Moreover, their potential to operate on cleaner energy sources and eliminate the demand for extensive infrastructure (e.g., roads and tunnels) could significantly reduce environmental impacts (Pan and Alouini, 2021; Badweeti et al., 2023). Despite the advancements in flying car prototypes and their potential benefits for public transportation systems, the transition to aerial transportation is contingent upon public acceptance and utilization of this novel travel mode (Guo et al., 2020; Cohen et al., 2021; Reiche et al., 2021; Guo et al., 2022; Kim et al., 2023;).

In the academic community, there is a strong interest in the field of UAM. Scholars have conducted research on various aspects of UAM, such as drone logistics, planning and operation of urban aerial systems, and the acceptance of UAM. Wandelt et al. (2024) performed a meta-review on the applications of unmanned aerial vehicles in logistics, transportation, and monitoring, discussing the challenges faced in drone operations. Jin et al. (2024) proposed an integrated optimization approach for strategic planning and service operations in urban air mobility systems. Zhao et al. (2024) investigated the application of UAM in time-sensitive goods transportation, considering the influence of customer preferences, using Chengdu as a case study.

In addition to the aforementioned research directions, public acceptance of UAM is also a crucial research topic. Exploring factors influencing the adoption of flying cars is essential for increasing public approval. Current explorations indicate a growing interest in this field. For instance, Antonio Ariza-Montes et al. (2023) identified performance expectancy, attitudes, and social influence as key factors in enhancing the use intention of Urban Air Autonomous Vehicles (UAAVs), while anxiety diminishes the use intention. Lee et al. (2023) investigated psychological and attitudinal factors, revealing social influence and initial trust as significant predictors of adoption intentions. Al Haddad et al. (2020) focused on quantifying factors affecting UAM adoption, including highlighting trust, safety, comfort with automation, social attitude, data concerns, and socio-demographics. Kim et al. (2023) explored the relationship between trust, service quality and user acceptance. Yavas et al. (2023) proposed a UAM acceptance model, emphasizing UAM conceptual intention, intention to fly, environmental consciousness, affordability, reliability, and perceived usefulness. Eker et al. (2019) found that socio-demographics, behavior, and driving attributes significantly influence views on flying car safety and attitudes towards security measures. Ahmed et al. (2021b) argued that public willingness to use flying taxis and shared flying car services is greatly impacted by socio-demographic factors as well as their perspectives on the advantages and obstacles associated with such services.

Despite the multitude of studies examining the acceptance of flying cars, a prevailing limitation is the myopic focus on isolated or select factors influencing acceptance. Previous research has predominantly concentrated on specific aspects such as technological performance, safety, or privacy risks, rather than providing a holistic perspective. This truncated approach has impeded a thorough grasp of the multifaceted nature of flying car acceptance. Though there exists a substantial body of literature exists on the acceptance of autonomous vehicles (AVs) and connected vehicles (CVs) (Yuen et al., 2020; Kassens-Noor et al., 2020; Ahmed et al., 2021a; Cheng and Lai, 2024), with a particular emphasis on factors like risk perception, safety, and initial trust, it is imperative to recognize that the acceptance of flying cars might be different than that of AVs and CVs because of their intrinsic technological differences and operational environments. Flying cars require advanced propulsion systems for vertical takeoff and flight. However, AVs and CVs use engines or electric motors for horizontal motion on roads. Furthermore, the specific pathways through which these factors influence acceptance, whether direct or indirect, remain obscure for flying cars—a gap that the present study is designed to address.

To bridge this research gap, this study introduces an innovative model for flying car acceptance, expanding the well-established technology acceptance model (TAM) by incorporating social psychological and risk perception factors. The proposed model recognizes the influence of social psychological factors like subjective norms, initial trust, and personal innovativeness, which reflect the interplay between an individual's social environment and psychological traits in the acceptance of new technologies (Schepers and Wetzels, 2007; Wu et al., 2011; Jackson et al., 2013; Nguyen-Phuoc et al., 2022). Moreover, risk perception factors, particularly those

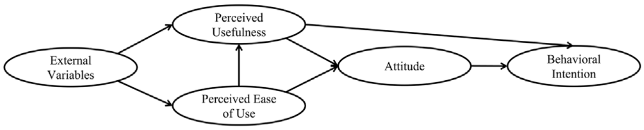

Fig. 2. Original TAM.

pertaining to safety and privacy, are critical in shaping user trust and directly influence acceptance and usage behaviors (Zhang et al., 2019; Ferri et al., 2020). Considering these three dimensions comprehensively is essential for a thorough understanding and accurate prediction of public acceptance of flying cars. This model meticulously examines latent variables—such as perceived usefulness, perceived ease of use, perceived safety risk, perceived privacy risk, initial trust, subjective norms, personal innovativeness, attitudes towards usage, and behavioral intention—to identify the primary factors influencing public acceptance of flying cars. It is expected that this methodology will provide profound insights and lay a solid foundation for guiding future research and policy development in urban air mobility.

Additionally, while some studies have explored the impact of public heterogeneity, the discussion in these areas is not sufficiently in-depth. A significant portion of the studies did not consider the role of public heterogeneity. Those acknowledging individual differences often considered only common factors like age and gender, failing to provide a comprehensive analysis by latent-class or mixed random-parameter modeling of how various demographic factors influence attitudes and intentions towards flying cars. Hence, this study aims to address this deficiency by offering a detailed examination of various elements influencing how the public views and embraces the concept of airborne vehicles.

This study aims to explore the research questions that delve into the complex factors influencing public acceptance of flying cars.

RQ1: Considering factors related to technology acceptance and use, social psychological factors, and risk perception, which elements play a key role in predicting public acceptance of flying cars? How do these factors specifically influence public acceptance?

RQ2: Are there significant differences in the acceptance of flying cars among different demographic groups (such as age, gender, educational background, etc.)? If so, what are the specific manifestations and possible reasons for these differences?

The main contributions of this paper can be summarized as follows: (i) Combining elements and frameworks of the TAM, Risk Perception Theory, and Trust Theory, we establish an influencing factor model of public acceptance of flying cars. Our findings suggest that increasing public exposure, encouraging participation, and fostering trust are essential strategies for reinforcing the usage intention of flying cars. (ii) By conducting a heterogeneity analysis, our study highlights the importance of developing personalized measures tailored to specific demographic segments to improve public acceptance.

The remainder of this paper is structured as follows. Section 2 expounds upon the theoretical framework and delineates the research hypotheses employed in our analysis. Section 3 introduces data sources and provides a comprehensive description of the sample. Model results are presented and discussed in Section 4. Section 5 discusses empirical and policy implications, and points out the limitations of this study and directions of future work. Section 6 concludes the main findings of this paper.

2. Methodology

2.1. Research model and hypothesis

2.1.1. Technology acceptance model

The TAM has proven to be a highly effective framework in studying the acceptance and adoption of various new vehicle technologies, including electric vehicles (Globish et al., 2018; Estriegana et al., 2019; Zhang et al., 2023), autonomous vehicles (AVs) (Xu et al., 2018; Zhang et al., 2019; Acharya and Mekker, 2022) and ride-sharing (Wang et al., 2018). Therefore, this study also adopts TAM as the fundamental framework for exploring acceptance, while extending it to incorporate additional external latent variables. These enhancements aim to provide a more nuanced understanding of the complex factors that influence the acceptance of flying cars. The original TAM is depicted in Fig. 2.

In TAM, Behavioral Intention (BI) signifies a person's plan to utilize a product or service, yet it does not necessarily translate to the actual act of using it. Attitudes toward using (ATT) refers to an individual's attitude when using a product or service, reflecting their level of satisfaction. This attitude can be either positive or negative. In this study, attitudes towards using and use intention are considered as targeted core variables, focusing on how other variables influence these key outcomes. Perceived Usefulness (PU) pertains to individuals' belief in the degree to which flying car technology is beneficial and conducive to fulfilling their flying expectations. Conversely, Perceived Ease of Use (PEU) reflects users' assessment of how straightforward and uncomplicated the utilization of the flying car technology is. These two constructs jointly inform our understanding of how individuals perceive and evaluate this futuristic mode of transportation.

According to TAM, this paper proposes the following hypotheses. According to the trust theory discussed later in the passage, H4 proposes a direct relationship between PU and initial trust in flying cars, as per the idea that perceiving technology as beneficial increases trust (Dikmen and Burns, 2017; Zhang et al., 2019). Similarly, H7 argues that the perception of flying cars as easy to use is expected to strengthen initial trust, since ease of use typically correlates with increased trust in new technologies (Morgan and Hunt, 1994; Wu et al., 2011; Pengnate and Sarathy, 2017).

Hypothesis 1 (H1): Attitudes towards using flying cars significantly positively influence behavioral intention to use them.
Hypothesis 2 (H2): Perceived usefulness significantly positively influences attitudes towards using flying cars.
Hypothesis 3 (H3): Perceived usefulness significantly positively influences the behavioral intention to use flying cars.
Hypothesis 4 (H4): Perceived usefulness significantly positively influences the initial trust in flying cars.
Hypothesis 5 (H5): Perceived ease of use significantly positively influences attitudes towards using flying cars.
Hypothesis 6 (H6): Perceived ease of use significantly positively influences the perceived usefulness of flying cars.
Hypothesis 7 (H7): Perceived ease of use significantly positively influences the initial trust in flying cars.

2.1.2. *Risk perception*

Perceived risk was pioneered by Bauer at Harvard, who stressed that consumers face uncertainty when using products, leading to satisfaction or disappointment (Bauer, 2001). This uncertainty constitutes the initial definition of risk. The unique performance of flying cars, which combine car and aircraft features, may raise consumer concerns about overall safety (Eker, 2020). These concerns encompass potential safety risks from system or equipment failures. Additionally, privacy risk poses a noteworthy concern for the public (Kyriakidis et al., 2015; Bansal et al., 2016). The implementation of flying cars may necessitate the collection and processing of travel and behavioral data. If such information is transmitted to governments, vehicle developers, and insurance companies without the explicit consent of users, or if it falls into the hands of hackers, it could pose serious threats to privacy and security concerns. In studies on the acceptance of AVs, Zhang et al. (2019) divided perceived risk into Perceived Safety Risk (PSR) and Perceived Privacy Risk (PPR), exploring their impact on user trust. Their findings indicate that perceived safety risk has a more significant effect on user trust than perceived privacy risk. Although there are differences between flying cars and autonomous vehicles, we can still draw from the research hypothesis paths of autonomous driving while retaining the factor of perceived privacy risk. Hence, the following hypotheses are proposed. H8 posits that a higher perceived safety risk is likely to negatively impact initial trust in flying cars, grounded in the idea that safety concerns can erode trust in new technologies. H9 suggests that perceived privacy risks are inversely related to initial trust, as concerns about privacy breaches typically lower trust in technological innovations (Ortega Egea and Roman Gonzalez, 2011; Yang et al., 2015).

Hypothesis 8 (H8): Perceived safety risk significantly negatively affects initial trust.
Hypothesis 9 (H9): Perceived privacy risk significantly negatively affects initial trust.

2.1.3. *Socio-psychological factors*

Socio-psychological factors often mirror an individual's positioning within their social and cultural contexts, revealing how these backgrounds influence attitudes and receptiveness towards new technologies. In this study, we delve into three pivotal dimensions of socio-psychological factors: subjective norms, initial trust, and personal innovativeness. Each of these dimensions plays a critical role in shaping how individuals perceive and embrace the concept of flying cars. Subjective norms reflect the impact of societal norms and peer perceptions, initial trust addresses the foundational confidence in the technology and its providers, while personal innovativeness highlights the inclination of individuals to adopt novel advancements. By examining these aspects, the study aims to comprehensively understand the nuanced interplay of social and psychological elements in the public acceptance of flying cars.

2.1.4. *Trust theory*

Originally rooted in psychology and sociology, trust theory primarily examined the formation of trust in interpersonal relationships, later extending to organizational and societal trust (Morgan and Hunt, 1994). It has been pinpointed as a crucial factor that shapes the interaction between humans and automation systems (Lee and See, 2004). Trust theory is extensively applied in areas such as e-commerce, online transactions, artificial intelligence, and the acceptance of emerging technologies (e.g., AVs, Zhang et al., 2019). It should be noted though, as the flying cars have not yet been commercially available and lack interaction with consumers, the trust herein is more precisely referred to as Initial Trust (IT). Trust theory provides a crucial theoretical framework for understanding and explaining public acceptance of the innovative technology of flying cars. Studying the development, upkeep, and determinants of trust can lead to a deeper comprehension of how the public perceives and intends to use flying car technology. Thus, we suggested incorporating initial trust into the original TAM and put forth the hypothesis H10.

Hypothesis 10 (H10): Initial trust significantly positively affects attitudes towards using flying cars.

2.1.5. *Subjective norms*

Subjective Norms (SN), derived from the Theory of Planned Behavior (Ajzen, 1991), refer to the social pressure individuals perceive from significant others or groups, influencing their decisions to perform specific actions. Certain research efforts have been directed toward comprehending the acceptance of novel technologies, revealing that potential novel mobility behaviors are shaped by social influences (Guo et al., 2022). Subjective norms can shape individuals' perceptions of flying cars based on the opinions and attitudes of their social environments, i.e., individual's families, relatives, friends, and colleagues (Dong et al., 2015; Maes et al.,2014; Paul et al., 2016). Positive societal attitudes can lead to positive opinions, whereas worries about safety or privacy can increase perceived dangers. For this reason, we put forward the following hypotheses:

Hypothesis 11 (H11): Subjective norms significantly positively affect perceived usefulness.
Hypothesis 12 (H12): Subjective norms significantly positively affect perceived ease of use.
Hypothesis 13 (H13): Subjective norms significantly positively affect perceived safety risk.
Hypothesis 14 (H14): Subjective norms significantly positively affect perceived privacy risk.
Hypothesis 15 (H15): Subjective norms significantly positively affect initial trust.

2.1.6. Personal innovativeness

Personal Innovativeness (PI) is defined as an individual's proclivity towards experimentation with novel entities, highlighting the distinct personal traits exhibited in response to technological advancements (Agarwal and Prasad, 1998). Incorporating PI, originating from the information technology domain, into the TAM explains how variations in individual innovativeness influence the willingness to adopt new technologies. Additionally, prior research has consistently acknowledged the direct impact of personal innovativeness on both attitude and behavioral intention (Chen and Chen, 2011). Flying cars are a relatively novel form of transportation with a strong sense of technology. Therefore, in studying the acceptance of flying cars, this paper also considers the individual differences of users when faced with technological innovation, adding personal innovativeness as a variable and hypothesizing that:

Hypothesis 16 (H16): Personal innovativeness significantly positively affects attitudes towards using flying cars.
Hypothesis 17 (H17): Personal innovativeness significantly positively affects the behavioral intention to use flying cars.

2.2. Structural equation modeling approach

To validate the framework of our proposed model, we utilize an approach based on structural equation modeling (SEM). We chose to employ SEM in our study due to its ability to simultaneously examine the complex relationships among multiple variables, including latent constructs. SEM allows us to test the hypothesized relationships between the factors influencing the adoption of flying cars, as outlined in our conceptual model. By using SEM, we can assess the direct and indirect effects of various factors on the intention to use flying cars, while accounting for measurement errors and providing a comprehensive understanding of the interplay between these factors. An SEM encompasses two fundamental components: a structural model and a measurement model. The structural model meticulously outlines the intricate relationships among latent variables and their associations with observable variables. The formalization of the structural model construction is outlined in the following manner.

$$\eta = \mathrm{B}\eta + \Gamma X + e$$

where η represents a vector of latent variables. X is a vector of observed variables. B represents parameters that qualify the relationships among latent variables. Γ is a matrix of parameters corresponding to the connections between latent variables η and observed variables X. e is a vector of error terms.

The measurement model specifies the relationship between latent variables and their corresponding indicators, elucidating how these indicators operationalize and represent the latent variables under investigation. The formulation of the measurement model is presented as:

$$y = \Lambda\eta + K\mathrm{X} + \varepsilon$$

where y is the vector of categorical variables representing the indicators of the latent variables. Λ is a factor loading matrix. K represents the relationship between y and X. ε stands for a vector of error terms. The SEM was estimated based on the maximum likelihood methods.

The Multiple Indicators Multiple Causes (MIMIC) approach, a variant of SEM, merges factor analysis with a linear regression framework. This model excels in elucidating how various observed variables (or indicators) represent a latent variable, and how external factors, termed as causes or covariates, can exert influence on this latent construct.

The research framework (shown in Fig. 3) consists of nine latent variables and seventeen hypotheses, and we employ SEM to examine the hypotheses.

2.3. Model evaluation

To test the measurement models, exploratory factor analysis (EFA) and confirmatory factor analyses (CFA) were performed, accompanied by reliability and validity checks to ensure the consistency and validity of the instruments. Reliability tests, assessing the stability of the measurement model, used Cronbach's alpha to gauge internal consistency. A Cronbach's alpha above 0.7 is considered reliable (Fornell and Larcker, 1981). Observed variables failing reliability tests due to issues like unclear questions or low factor loadings (cutoff of 0.6 used here) were excluded. Internal consistency was further ensured using Cronbach's alpha (>0.70), composite reliability (CR>0.70), and average variance extracted (AVE>0.50) (Fornell and Larcker, 1989; Zhang et al., 2019).

Model performance was assessed through fit indices such as chi-square/degree of freedom (x^2/df), CFI, TLI, and RMSEA. Acceptable model fit is indicated by, CFI and TLI > 0.80, and RMSEA < 0.08 (Hu and Bentler, 1999).

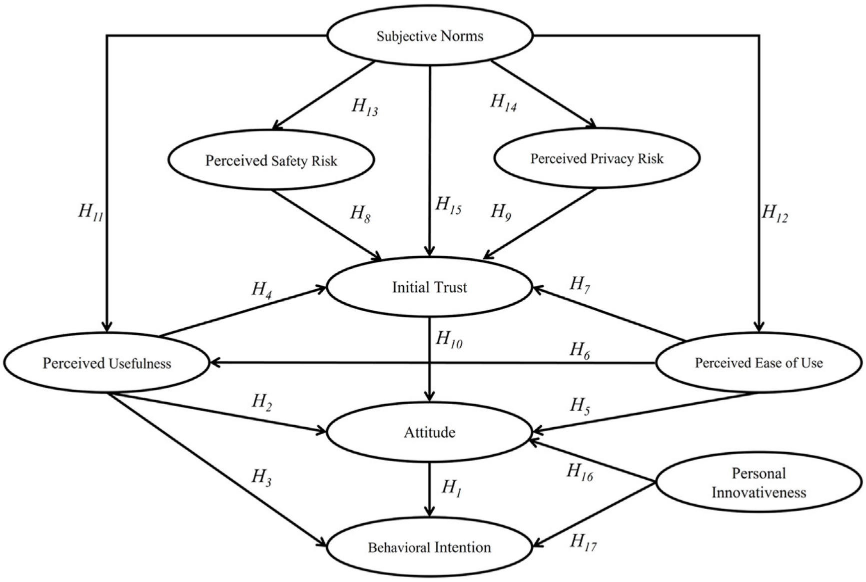

Fig. 3. Research framework.

3. Data source and sample description

3.1. Data source

The empirical data used in this study were collected from a comprehensive survey conducted between March and June 2023, focusing on the acceptance of flying cars. This study initiative focused on the Guangdong province, chosen for its diverse demographic and socio-economic profile, thereby offering a rich and varied sample for the study.

The questionnaire comprised three parts. The first part provided a brief introduction, including detailed explanations of the concept and functionality of flying cars. This guaranteed that participants possessed the essential comprehension of flying cars, leading to more precise and perceptive answers. The following section collected fundamental personal details such as age, gender, educational background, job status, ownership of a driving license, and driving experience. This part comprised a total of 10 questions. The third part contained questions to measure the influencing factors, including nine latent variables, which are described in detail in the preceding subsections. There were 31 questions in this part, shown in a Likert scale format with 5 points (Strongly Disagree; Disagree; Neutral; Agree; Strongly Agree), and scores from 1 to 5. A total of 669 questionnaires were collected in this survey. After data screening, 553 valid questionnaires were retained, with a validity rate of 82.7 %. The questionnaire scale is shown in Table 1.

3.2. Sample description

The demographics is shown in Table 2. 58.20 % of respondents (322 individuals) were male. This gender distribution ensures a balanced representation of perspectives. The age distribution was notably focused on younger individuals, with 53.50 % aged 18–22 years and 44.10 % falling within the 23–44 years group. This skewed distribution towards younger respondents may introduce a bias in the sample. However, younger generations tend to be more open to adopting new technologies and may have different risk perceptions compared to older age groups. Considering that younger people are the primary early adopters of this emerging technology, the sample distribution is justifiable in the context of our study, which aims to promote the acceptance of flying cars. The majority of respondents, comprising 85.50 %, owned a bachelor's or associate's degree. Postgraduates and those with higher education accounted for 8.50 %. This prevalence of higher education among respondents enhances the credibility and depth of insights into technological adoption. Over half of the respondents were students (59.90 %, 331 respondents), underscoring the study's emphasis on a younger, potentially more tech-savvy demographic. Furthermore, 71.80 % of respondents have driving licenses, suggesting a familiarity with transport technology. This diverse demographic profile forms a robust basis for analyzing varied perspectives on urban air mobility and the acceptance of flying cars.

4. Model results

4.1. Reliability and validity test

Using exploratory factor analysis, the Cronbach's α and KMO values were evaluated. The Cronbach's α coefficients for each variable were all greater than 0.7, indicating good internal consistency in the questionnaire data. The KMO values for each variable were all

Table 1
Questionnaire question and sources.

Variables	Items	Statement	Sources
Perceived Usefulness (PU)	PU1	Using a flying car will help meet my travel needs.	Davis (1989) and Rahman et al. (2017)
	PU2	Operating a flying car will make driving easier for me.	
	PU3	Using a flying car will reduce my risk of being involved in traffic accidents.	
	PU4	A flying car will improve my travel efficiency and save time.	
	PU5	A flying car will make my travel more convenient.	
	PU6	Overall, I find flying cars to be very useful.	
Perceived Ease of Use (PEU)	PEU1	For me, learning how to use a flying car would be easy.	Davis (1989) and Rahman et al. (2017)
	PEU2	For me, using a flying car to do what I want would be easy.	
	PEU3	For me, becoming proficient in using a flying car would also be easy.	
	PEU4	Overall, I think flying cars would be easy to use.	
Perceived Safety Risk (PSR)	PSR1	I am concerned about the overall safety of flying car technology.	Zmud et al. (2016)
	PSR2	I am worried about the driving risks that may arise from improper operation of a flying car.	
	PSR3	I am concerned about the safety of my travel being affected due to potential issues like system hacking or malfunctions in the flying car, leading to errors in personal, vehicle, and travel data.	
Perceived Privacy Risk (PPR)	PPR1	I am concerned that flying cars might collect too much personal information about me.	Kyriakidis et al. (2015)
	PPR2	I am worried that flying cars might share my personal information for other purposes without my authorization.	
	PPR3	I am apprehensive about flying cars sharing my information with other systems without my consent.	
Initial Trust (IT)	IT1	I believe that flying cars are reliable.	Choi and Ji (2015)
	IT2	I think that flying cars are safe.	
	IT3	I am confident in the technology behind flying cars.	
Subjective Norms (SN)	SN1	The attitudes of my family and friends would influence my use of flying cars.	Venkatesh and Davis (2000)
	SN2	The attitudes of people around me would affect my decision to use flying cars.	
	SN3	Guidance from the government and media promotion would impact my use of flying cars.	
Personal Innovativeness (PI)	PI1	I am willing to embrace changes brought about by high-tech products like flying cars.	Agarwal and Prasad (1998)
	PI2	I often keep up with the latest developments in flying car technology.	
	PI3	Compared to people around me, I usually adopt new technologies earlier.	
Attitude (ATT)	ATT1	Using flying cars is a good idea.	Davis (1989)
	ATT2	Using flying cars would be enjoyable.	
	ATT3	For me, the use of flying cars is attractive.	
Behavioral Intention (BI)	BI1	I anticipate using flying cars in the future.	Venkatesh and Davis (2000)
	BI2	If the price is right, I will consider purchasing a flying car in the future.	
	BI3	Given the opportunity, I would like to try using a flying car now.	

Table 2
Statistics of demographics.

Variables	Items	Frequency	Percentage
Gender	Male	322	58.20 %
	Female	231	41.80 %
Age	18–22 years	296	53.50 %
	23–44 years	244	44.10 %
	>45 years	13	2.40 %
Education	Junior high school and below	6	1.10 %
	High school	27	4.90 %
	Bachelor's/Associate's degree	473	85.50 %
	Postgraduate and above	47	8.50 %
Employment status	Student	331	59.90 %
	Government employee or public institution staff	52	9.40 %
	Enterprise employee	95	17.20 %
	Freelancer	50	9.00 %
	Other	25	4.50 %
Do you have a driving license?	Yes	397	71.80 %
	No	156	28.20 %

Table 3
Results of the discriminant validity test.

	PU	PEU	IT	SN	PI	ATT	BI	PSR	PPR
Perceived Usefulness	0.749								
Perceived Ease of Use	0.580	0.850							
Perceived Safety Risk	0.576	0.688	0.819						
Perceived Privacy Risk	0.295	0.274	0.335	0.886					
Initial Trust	0.525	0.615	0.664	0.300	0.868				
Subjective Norms	0.684	0.631	0.651	0.292	0.682	0.779			
Personal Innovativeness	0.560	0.552	0.551	0.260	0.619	0.772	0.715		
Attitude	−0.066	0.008	0.093	−0.312	−0.007	−0.028	−0.068	0.824	
Behavioral Intention	−0.106	−0.166	−0.019	−0.270	−0.168	−0.071	−0.140	0.572	0.802

Table 4
Reliability and validity test result of each variable.

Constructs	Items	Cronbach's α	KMO	FL	AVE	CR
Perceived Usefulness	PU1	0.882	0.875	0.758	0.561	0.884
	PU2			0.765		
	PU3			0.713		
	PU4			0.656		
	PU5			0.761		
	PU6			0.829		
Perceived Ease of Use	PEU1	0.910	0.847	0.843	0.722	0.912
	PEU2			0.780		
	PEU3			0.869		
	PEU4			0.902		
Perceived Safety Risk	PSR1	0.858	0.732	0.788	0.671	0.860
	PSR2			0.833		
	PSR3			0.836		
Perceived Privacy Risk	PPR1	0.916	0.756	0.860	0.785	0.916
	PPR2			0.882		
	PPR3			0.915		
Initial Trust	T1	0.900	0.744	0.829	0.753	0.901
	T2			0.868		
	T3			0.905		
Subjective Norms	SN1	0.816	0.694	0.817	0.608	0.821
	SN2			0.845		
	SN3			0.664		
Personal Innovativeness	PI1	0.744	0.616	0.638	0.511	0.757
	PI2			0.748		
	PI3			0.752		
Attitude	ATT1	0.865	0.738	0.845	0.678	0.863
	ATT2			0.804		
	ATT3			0.821		
Behavioral Intention	BI1	0.833	0.693	0.864	0.6430	0.842
	BI2			0.826		
	BI3			0.707		

greater than 0.6, suggesting that the questionnaire had good construct validity. Using confirmatory factor analysis, the composite reliability (CR), average variance extracted (AVE), and factor loadings (FL) were evaluated. The calculations showed that the CR values of each variable were greater than 0.7, and the square root of the AVE values was greater than the correlation coefficients between the variables. The FL values of each variable were all greater than 0.5, indicating good convergent and discriminant validity of the questionnaire. The correlation coefficients between variables are presented in Table 3, and the test results are shown in Table 4.

4.2. Structural equation model results

The structural equation model for this study was constructed utilizing AMOS 24.0 software. To assess the model's goodness-of-fit, several indices were employed: chi-square to degrees of freedom ratio (CMIN/DF), root mean square error of approximation (RMSEA), goodness of fit index (GFI), comparative fit index (CFI), and Tucker-Lewis index (TLI).

After assessing the model's fit, we examined the path coefficients using the maximum likelihood approach. This analysis aimed to validate the hypothesized relationships between various influencing factors and assess their significance. The initial model estimation shows that the majority of path coefficients are statistically significant, supporting the hypothesized relationships. However, H5 and H17 have critical ratios (C.R.) with absolute values lower than 1.96 and p > 0.05(H5: p = 0.26>0.05; H17: p = 0.17>0.05), falling to meet the standard criteria. This indicates the necessity for modifications to the hypothesized paths.

Table 5
Revised models' Goodness-of-fit Measurements.

Measure		CMIN/DF	RMSEA	GFI	TLI	CFI
Threshold		<5	<0.08	>0.8	>0.8	>0.8
Result	Before Revision	4.482	0.079	0.823	0.864	0.878
	After Revision	3.939	0.073	0.840	0.885	0.897

Table 6
Revised model estimation result.

Hypothesis	Paths	Estimate	S.E.	C.R.	P	Test result
H1	ATT→BI	0.982	0.078	11.537	***	Supported
H2	PU→ATT	0.581	0.043	10.829	***	Supported
H3	PU→BI	−0.183	0.046	−2.928	**	Supported
H4	PU→IT	0.268	0.042	5.709	***	Supported
H6	PEU→PU	0.621	0.041	13.632	***	Supported
H7	PEU→IT	0.549	0.040	11.175	***	Supported
H8	PSR→IT	−0.123	0.042	−2.653	**	Supported
H9	PPR→IT	−0.086	0.033	−1.971	*	Supported
H10	IT→ATT	0.215	0.042	4.597	***	Supported
H11	SN→PU	0.132	0.043	3.188	**	Supported
H12	SN→PEU	0.285	0.056	5.902	***	Supported
H13	SN→PSR	0.380	0.052	7.536	***	Supported
H14	SN→PPR	0.336	0.060	6.976	***	Supported
H15	SN→IT	0.182	0.037	4.648	***	Supported
H16	PI→ATT	0.401	0.084	8.331	***	Supported

Note: N = 553. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

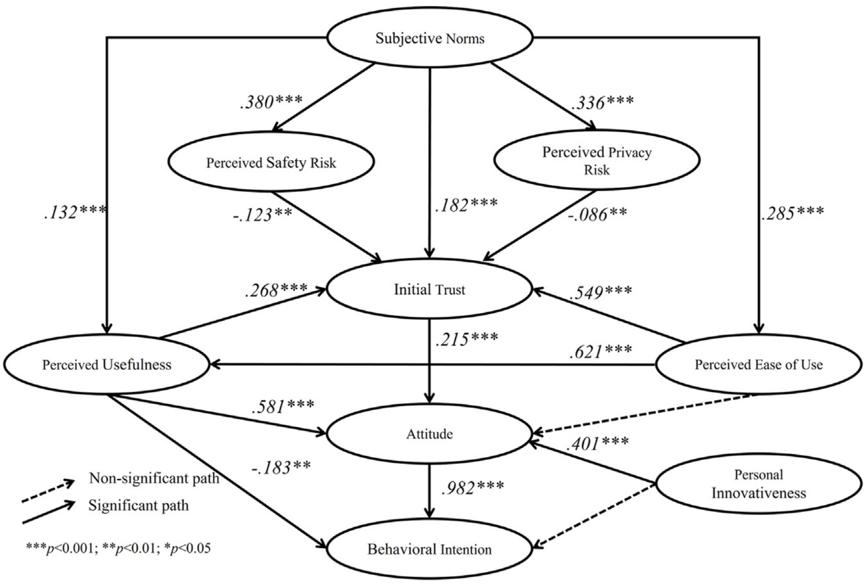

Fig. 4. Modified model results.

4.3. Model modification

Since the path coefficients of H5 and H17 do not meet the standard criteria in terms of C.R. values and *P* values, the hypothesized paths H5 and H17 were removed to further improve the model's fit. The results of the modified fit and the analysis of the path coefficients are shown in Table 5 and Table 6, respectively. The final model results are depicted in Fig. 4.

To further explore the causal relationships and pathways among the variables, the Bootstrap method was used to investigate the mediating effects in the model (Efron and Tibshirani,1994; Awang et al., 2015). Based on the principle that "total effect = direct effect + indirect effect", the results of the mediation effect tests are presented in Table 7.

Table 7
Test results of mediating effects.

Paths	Direct effect	Indirect effect	Total effect
PU→BI	−0.183	0.627	0.444
PEU→BI		0.392	0.392
PSR→BI		−0.026	−0.026
PPR→BI		−0.018	−0.018
IT→BI		0.211	0.211
SN→BI		0.193	0.193
PI→BI		0.394	0.394
ATT→BI	0.982		0.982

Table 8
Results of heterogeneity analysis.

Constructs	Sociodemographic				
	Gender	Age	Education	Occupation	Driving license
Perceived Usefulness	0.234	0.019 **	0.001 **	<0.001 ***	0.339
Perceived Ease of Use	0.090	<0.001 ***	0.020 *	<0.001 ***	<0.001 ***
Perceived Safety Risk	0.796	0.013 *	0.562	<0.001 ***	0.116
Perceived Privacy Risk	0.691	0.803	0.953	0.003 **	0.366
Initial Trust	0.319	<0.001 ***	0.001 **	<0.001 ***	0.057
Subjective Norms	0.907	0.010 *	0.216	0.043 *	0.966
Personal Innovativeness	0.012**	0.006 **	0.027 *	<0.001 ***	0.033 *
Attitude	0.201	0.054	0.026 *	<0.001 ***	0.238
Behavioral Intention	0.071	0.087	0.097	<0.001 ***	0.055

Note: N = 553. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

4.4. Heterogeneity analysis

To further explore the preference heterogeneity in the acceptance of flying cars among different individuals, this study conducted a heterogeneity analysis based on personal attributes such as gender, age, occupation, and education. A multi-causal multi-indicator model (MIMIC) analysis (as shown in Table 8) was first conducted to identify individual attribute variables with significant differences in latent variables. Subsequently, an in-depth exploration was carried out into how different classifications of individual attribute variables correspond to the average values of specific items related to these latent variables.

4.4.1. Gender-based differences in latent variables

The gender categories, "male" and "female", were analyzed using an independent samples T-test, and processed with SPSS software. As shown in Tables 8–9, gender significantly influences only the variable of personal innovativeness, with men scoring higher than women. This suggests that men might be more interested in high-tech information and more enthusiastic about using new high-tech products.

4.4.2. Age-based differences in latent variables

This study utilized a one-way ANOVA method (St and Wold, 1989) to compare various age groups and determine if there were any notable distinctions among them, acknowledging the diverse nature of age categories. We use SPSS to conducte the one-way ANOVA tests. Table 9 reveals significant differences in perceived usefulness, perceived ease of use, perceived safety risk, initial trust, subjective norms, and personal innovativeness among different age groups. For the age groups "18–22 years", "23–44 years", ">45 years", the data show a trend of increasing scores with age in all variables except for perceived safety risk and subjective norms. For example, perceived usefulness peaks in the ">45 years" group, followed by "23–44 years", with "18–22 years" being the lowest. This trend indicates that as people age and accumulate driving experience, they are more inclined to recognize the practical value inherent in high-tech products. Similarly, older individuals, due to their experience, more easily recognize the convenience of new technologies and thus show higher initial trust. As for subjective norms, it is relatively low in the "23–44 years" age group, aligning with the social norm that teenagers and older adults are more likely to be influenced by their peers, and their decisions often involve strong emotional factors.

4.4.3. Occupation-based differences in latent variables

Regarding different occupations, employment situations were categorized into students, government employees, enterprise employees, freelancers, and others. A one-way ANOVA test was conducted using SPSS software. As presented in Table 9, a distinct pattern is evident in the perceived risk scores across various occupational categories. Specifically, government employees demonstrate relatively lower scores in perceived risk, followed by enterprise employees and students. This trend suggests that individuals with more stable employment and income streams tend to perceive fewer risks. Conversely, freelancers tend to score higher in terms of perceived risk, potentially attributed to their frequent social interactions, which may enhance their awareness and sensitivity towards potential

Table 9
Results of T-tests and ANOVA tests.

Gender-based differences in latent variables					Differences in education			
Personal Innovativeness	Male	Female			Junior high school and below	High school	Bachelor's/Associate's degree	Postgraduate and above
	3.759	3.609		Perceived Usefulness	4.194	3.889	3.769	3.387
Differences in age	Perceived Ease of Use	4.083	3.759	3.462	3.239			
	18–22 years	23–44 years	>45 years	Initial Trust	4.000	3.790	3.529	3.156
Perceived Usefulness	3.721	3.751	4.389	Personal Innovativeness	4.000	3.963	3.697	3.495
Perceived Ease of Use	3.315	3.613	4.063	Attitude	4.444	3.988	3.838	3.617
Perceived Safety Risk	4.038	3.803	4.111	Differences in driving license				
Initial Trust	3.370	3.664	4.000		with a driver's license		without a driver's license	
Subjective Norms	3.676	3.652	4.139	Perceived Ease of Use	3.543		3.264	
Personal Innovativeness	3.607	3.796	4.021	Personal Innovativeness	3.736		3.596	

Differences in occupation

	Student	Government	Enterprise	Freelancer	Other
Perceived Usefulness	3.659	3.981	3.779	4.117	3.560
Perceived Ease of Use	3.285	3.760	3.590	4.250	3.180
Perceived Safety Risk	4.023	3.436	3.712	4.187	4.040
Perceived Privacy Risk	3.688	3.410	3.533	4.100	3.680
Initial Trust	3.349	3.853	3.618	4.120	3.413
Subjective Norms	3.645	3.712	3.611	3.953	3.507
Personal Innovativeness	3.570	3.914	3.826	4.155	3.510
Attitude	3.716	3.974	3.856	4.447	3.773
Behavioral Intention	3.741	3.923	3.853	4.467	3.813

hazards. This observation underscores the influence of occupational characteristics and social engagement patterns on individuals' risk perception. Freelancers, government workers, and corporate employees are rated higher in terms of perceived usefulness and ease of use, while students fall behind in comparison. One possible explanation is that students are less inclined to have private vehicles, leading to a reduced level of exposure to the conveniences that come with car ownership in comparison to those who are employed. Students primarily depend on non-motorized transportation, resulting in lower ratings for perceived usefulness and ease of use. Freelancers have the most positive attitude and intention to adopt flying cars, with government employees, enterprise employees, and students following behind. This trend may correlate with the nature of their work; freelancers often need to visit diverse and non-fixed destinations, leading to a deeper awareness of current traffic conditions and a desire to improve travel efficiency.

4.4.4. Educational level-based differences in latent variables

Regarding the educational level of individuals, the classifications were "Junior high school and below", "High school", "Bachelor's/Associate's degree", and "Postgraduate and above". A one-way ANOVA test was analyzed.

The data analysis in Table 9 reveals notable variances in latent factors like perceived usefulness, perceived ease of use, initial trust, personal innovativeness, and attitude towards using. Additionally, the mean values of these variables decrease as education level increases. This phenomenon could be linked to the limited prevalence of flying cars, and the public maintains a cautious attitude towards such new technologies. Across different levels of educational attainment, individual's attitudes towards new technologies seem more rational, reflecting a general increase in public knowledge and a more reasoned evaluation of new things. For instance, in terms of attitude towards using, the average value for the group with junior high school education and below is 4.444, while for high school, bachelor's/associate's degree, and postgraduate and above, these figures are 3.988, 3.838, and 3.617, respectively. This indicates that individuals with higher education exhibit more caution towards new technologies, resulting in more conservative evaluations in their attitudes towards use.

4.4.5. Analysis of differences in latent variables based on possession of a driver's license

For survey respondents with and without a driver's license, an independent samples T-test method was used to analyze the differences.

Table 9 shows that having a driver's license has a significant impact on two latent factors: perceived ease of use and personal innovativeness. Respondents with a driver's license generally scored higher on these variables compared to those without a license. Specifically, respondents with a driver's license rated perceived ease of use at 3.543, while those without a license rated it at 3.264. Individuals with driving experience are more comfortable and confident in operating flying cars and perceive them as easy to master because they have a deeper understanding of vehicle operations and internal devices. Regarding personal innovativeness, those with a driver's license scored 3.736, compared to 3.596 for those without a license. This may suggest that individuals with extensive driving experience have a greater interest in new devices and technologies for improving car performance. They are more attentive and willing to explore and accept high-tech products.

5. Discussions

5.1. Empirical implications

This study integrated the original TAM, risk perception theory, and trust theory to examine public acceptance of flying cars. $R^2 = 0.62$, indicating that the model's good applicability to understanding the acceptance of flying cars. This study examined how other variables affect attitudes towards using and behavioral intention. As shown in Table 7, among the influencing factors investigated, attitudes towards using have the most significant impact on behavioral intention to use flying cars, with a total effect of 0.982. This is consistent with most studies where user attitudes positively influence usage, suggesting that correctly guiding public attitudes is crucial to developing the flying car market (Chen, 2019; Chen et al., 2019; Ro and Ha, 2019). The impacts of other factors are discussed as follows

5.1.1. Perceived usefulness and perceived ease of use

Our research reveals the relationship between perceived ease of use and attitudes towards the adoption of flying cars. Contrary to common expectations, we found that perceived ease of use does not directly influence attitudes, a finding consistent with prior studies by Daştan and Gürler (2016) and Hu et al. (2024). This suggests that while individuals may value the user-friendliness of flying cars, it does not necessarily translate into a more positive attitude towards their adoption.

However, our study validates the significant impacts of both perceived usefulness and perceived ease of use on behavioral intention, with total effects of 0.444 and 0.392, respectively. These findings underscore the pivotal role of public perception in the acceptance of flying cars. Individuals are more likely to consider using flying cars if they believe they will provide tangible benefits and are easy to operate.

Concerning behavioral intention, our study shows that the perceived usefulness has a direct negative impact of −0.183 and an indirect positive impact of 0.627, whereas the perceived ease of use has an indirect impact of 0.392. Flying cars, combining the advantages of traditional cars and aircraft, offer rapid ground travel and utilize new energy technologies. Furthermore, their ability to operate in low-altitude airspace can alleviate urban road traffic congestion. They meet travel demands efficiently, reduce urban noise, and improve comfort, convenience, and safety, while addressing environmental concerns associated with automotive energy use. Moreover, flying cars are more likely to be accepted by the public due to their simplicity of operation. Thus, the perceived usefulness and ease of use both have a positive impact on the willingness to adopt flying cars.

The inverse correlation between perceived usefulness and behavioral intention to use flying cars may be due to two reasons. First, people may view flying cars as cutting-edge technology but not necessarily practical for their everyday routines. This could be due to a mismatch between the features of flying cars and the specific needs or preferences of individuals. Secondly, the significant cost concerns related to flying cars, both in terms of purchase price[1] and ride cost,[2] can outweigh the perceived usefulness, despite a positive evaluation of their potential utility. Compared to other transportation modes, the cost of flying cars may lead to negative behavioral intention, as individuals may hesitate to adopt this technology due to its high cost. Most existing studies have provided empirical results regarding the cost as being crucial in determining consumer adoption of flying cars (e.g., Peeta et al., 2008; Kreimeier and Stumpf, 2017).

Considering that flying cars utilize autonomous flying, they pose an inherent safety risk as an emerging transportation mode not yet fully integrated into public life. The perceived risk, especially before firsthand experience with new technology, can significantly overshadow the perceived usefulness, contributing to the negative direct effect observed in the model. The total effect of 0.444 from perceived usefulness on usage intention, aligning with Davis's classical model, further validates the positive correlation between perceived usefulness and usage intention, reinforcing the model's accuracy.

5.1.2. Risk perception factors

Perceived safety risk and perceived privacy risk had negative impacts of −0.026 and −0.018, respectively, on the intention to use flying cars. However, their total effects are relatively small, which differs from the study on autonomous vehicles by Zhang et al. (2019). This study suggests that the influence of perceived safety risk and perceived privacy risk on usage intention

[1] Xpeng Motors unveiled the concept of its sixth-generation flying car, stating its ambition to achieve mass production by 2024 while keeping the price under 1 million yuan (https://www.feiauto.com/news/202203/20538.html).

[2] The maiden flight of a flying taxi in China has been a success, but its ticket price of 41.6 dollars for a 20-minute trip from Shenzhen to Zhuhai, which is significantly higher than the price of a high-speed railway ticket, which costs only 20 dollars for the same route. (https://www.163.com/dy/article/IT0FVCVE0519D4UH.html)

is not significant. This may be attributed to the limited exposure of flying cars to the public, and there have been no incidents involving flying cars, contributing to a general perception of trust in the overall safety of flying cars.

5.1.3. Socio-psychological factors

The total effect of initial trust on the intention to use is 0.211, which is relatively small compared to the impact found by Gillath et al. (2021) on public acceptance of artificial intelligence. This may stem from the public's limited comprehension of flying cars and the scarcity of opportunities for interaction. As flying cars evolve and their social impact expands, the relationship between initial trust and usage intention is anticipated to become increasingly strengthened.

Personal innovativeness reflects a desire to explore new things, a willingness to accept new things or technologies, and a readiness to try them out. The study clearly shows that personal innovativeness has a direct impact on attitudes towards using (Agarwal and Prasad, 1998), which then indirectly affects intention to use, leading to a total effect of 0.394. Personal innovativeness has a significant impact on usage intention, coming in second only to perceived usefulness.

People are always influenced by external factors, referred to as subjective norms. In considering specific actions, they are often swayed by public opinions or the opinions of others. Table 7 displays that subjective norms greatly influence the usage intention, resulting in a total effect of 0.193. Subjective norms play a crucial role in determining the public's readiness to embrace flying cars, ultimately impacting their willingness to utilize this mode of transportation. This finding aligns with previous research findings. Specifically, Herrenkind et al. (2019) observed that the perspectives of individuals' family members, friends, and colleagues regarding automated buses play a significant role in their acceptance of the technology.

5.2. Policy implications

Attitude towards using exhibited the greatest effects on users' behavioral intention to use flying cars, and mediated the effects of the perceived usefulness, initial trust, and personal innovativeness. This implies that improving users' attitudes towards using is the most important measurement in enhancing the public's acceptance of flying cars. Based on the model results, one possible strategy is to increase the public's perception of the usefulness. Manufacturers may need to consider how to make flying cars easier to operate by designing control systems, and to increase public exposure whenever possible. Offering users opportunities to experience flying cars in person improves perceived usefulness in terms of comfort, convenience, and safety. Another potential strategy to bolster trust involves enhancing trust by improving users' attitudes towards using by decreasing perceived safety and privacy risks. Manufacturers may also consider offering safety test reports of flying cars issued by professional organizations. These reports should clearly communicate the extensive testing and fail-safe mechanisms employed to ensure the safety of flying cars, even in the rare event of component malfunctions. Providing accessible and transparent information about the rigorous safety standards and backup systems in place can help build public trust in the technology. Moreover, manufacturers and policymakers should not ignore individual innovation differences among users. Individuals with strong innovation may be the first to experience flying cars, creating a driving effect for broader acceptance.

The heterogeneity analysis, particularly regarding educational levels, suggests that individuals with higher education levels tend to have a more rational and cautious attitude towards flying cars. This suggests that policymakers and manufacturers should tailor their communication strategies to address the concerns and information needs of this demographic. Providing detailed technical information, safety reports, and transparent cost-benefit analyses may be particularly important for highly educated individuals.

5.3. Limitations and future work

While this study provides valuable insights, several limitations several limitations should be acknowledged and pave the way for future research: First, the questionnaire samples were primarily concentrated among the younger population from Guangzhou, China, potentially introducing a bias in the sample distribution. Although this younger demographic is a key target audience for flying cars, this limitation restricts the generalizability of our findings to the broader population, as well as the geographical and cultural universality. Future research should therefore strive to incorporate a more diverse sample population, encompassing a wide range of ages, genders, educational backgrounds, and geographical locations.

Second, due to data limitations, property ownership and the urban environment are not considered in this study, even though they are likely to have significant impacts on public perceptions of flying cars. For instance, individuals who own property might have different perspectives on the integration of flying cars into their neighborhoods compared to those who do not. Similarly, city size can influence the perceived need for flying cars, with residents in larger metropolitan areas potentially viewing them as a more viable solution to traffic congestion.

Third, this study predominantly relies on self-reported data, which may be susceptible to biases stemming from factors such as social desirability or inaccurate self-perception. Future research could benefit from integrating objective data sources or observational methods to validate and complement the findings. Furthermore, as flying car technology and regulations evolve, continuous research is essential to track changes in public perception and acceptance.

Fourth, while the survey instrument's conciseness was advantageous for respondent engagement, it may have constrained the depth of our exploration into the various dimensions of flying car acceptance. This brevity could introduce potential biases in interpretation, impacting the reliability and validity of our measures. To address this limitation and strengthen future research, it is recommended that multiple items be used to assess behavioral intentions.

6. Conclusion

This study combines the original TAM model with Risk Perception Theory and Trust Theory to examine the different elements that impact the public's willingness to accept flying vehicles. By an empirical approach and subsequent analysis utilizing Structural Equation Modeling (SEM), this study arrives at several noteworthy conclusions:

(1). Various underlying factors significantly impact the intention to use flying cars: Attitudes (0.982), Perceived Usefulness (0.444), Personal Innovativeness (0.394), Perceived Ease of Use (0.392), Initial Trust (0.211), Subjective Norms (0.193), Perceived Privacy Risk (−0.018), and Perceived Safety Risk (−0.026). Perceived usefulness and attitudes directly influence the usage intention, while other factors have an indirect impact.

(2). Using the above integrated model framework, this study examines the public acceptance of flying cars and provides suggestions for business decision-making and government policy formulation. To enhance public acceptance of flying cars, it is imperative to amplify public exposure, encourage participation and interaction to cultivate impressions and trust. These efforts are crucial for reinforcing the usage intention of flying cars, ultimately contributing to the widespread adoption of flying cars.

(3). The heterogeneity analysis shows that individuals with different genders, age groups, education levels, occupations, and possession statuses of driving licenses have different attitudes toward using and behavioral intentions of flying cars. Males, the older, and individuals with driving licenses are more likely to have positive attitudes and usage intention of flying cars. Higher education correlates with a more rational and cautious attitude towards flying cars. Personalized measurements may be implemented to improve the public acceptance of flying cars. In conclusion, realizing the potential of flying cars as a revolutionary technology requires a comprehensive and multidimensional effort to enhance their popularity and acceptance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Sangen Hu: Formal analysis, Data curation, Conceptualization. **Zikang Huang:** Writing – review & editing, Writing – original draft, Methodology, Data curation. **Ke Wang:** Writing – review & editing, Methodology, Conceptualization. **Haiyuan Lin:** Methodology, Data curation. **Mingyang Pei:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

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