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Research Paper

Passenger acceptance of AI-controlled flight operations: Trust and risk perspectives

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Abstract. Aerospace technologies represent some of the most advanced innovations of the modern age. Artificial Intelligence (AI) has become a transformative force in this sector, paving the way for a future where fully autonomous aircraft may carry out air transport. This possibility also brings with it socio-technical challenges, particularly regarding passenger acceptance. This study utilizes a technology acceptance model to examine the intention to fly in AI-controlled aircraft. Data collected from 258 participants were analyzed using structural equation modeling (SEM). The findings show that trust significantly increases perceived usefulness while decreasing perceived risk, playing a central role in the model. Conversely, perceived risk negatively affects perceived usefulness. Perceived usefulness emerges as the strongest predictor of intention to use. Another important finding is that perceived ease of use is not functional in the model. This suggests that in high-risk technologies that have not been directly experienced, evaluations are based more on trust and risk perception than on usability. The proposed model strongly explains both perceived usefulness and intention to use. The findings highlight the critical importance of trust for societal acceptance of AI-based aviation and offer actionable insights for developers, airlines, and policymakers.

Keywords: Technology acceptance, AI-controlled aircraft, trust, perceived risk.

Araştırma Makalesi

Yapay zekâ kontrollü uçuş operasyonlarının yolcular tarafından kabulü: Güven ve risk algısı

Öz. Havacılık ve uzay teknolojileri, modern çağın en ileri yeniliklerinden bazılarını temsil etmektedir. Yapay Zekâ (YZ), bu sektörde dönüştürücü bir güç hâline gelmiş ve gelecekte tamamen otonom uçakların hava taşımacılığını gerçekleştirebileceği bir dönemin yolunu açmıştır. Bu olasılık, özellikle yolcu kabulü gibi sosyo-teknik zorlukları da beraberinde getirmektedir. Bu çalışma, YZ kontrollü uçaklarda uçma niyetini incelemek için teknoloji kabul modelinden yararlanmaktadır. 258 katılımcıdan toplanan veriler yapısal eşitlik modellemesi (YEM) ile analiz edilmiştir. Bulgular, güvenin algılanan faydayı önemli ölçüde artırırken algılanan riski azalttığını ve modelde merkezi bir rol oynadığını göstermektedir. Buna karşılık, algılanan risk algılanan faydayı olumsuz etkilemektedir. Algılanan fayda, kullanım niyetinin en güçlü belirleyicisi olarak ortaya çıkmaktadır. Bir diğer önemli bulgu ise, algılanan kullanım kolaylığının modelde işlevsel olmamasıdır. Bu durum, doğrudan deneyimlenmemiş yüksek riskli teknolojilerde değerlendirmelerin, kullanışlılıktan çok güven ve risk algısına dayandığını göstermektedir. Önerilen model, algılanan kullanışlılık ve kullanma niyetini güçlü biçimde açıklamaktadır. Bulgular, YZ tabanlı havacılığın toplumsal kabulü için güvenin kritik önemini vurgulamakta ve geliştiriciler, havayolu şirketleri ve politika yapıcılar için uygulanabilir içgörüler sunmaktadır.

Anahtar Kelimeler: Teknoloji kabulü, yapay zekâ kontrollü havaaraçları, güven, risk algısı.

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1. INTRODUCTION

Today, the vast majority of aircraft are operated by two pilots in the cockpit. In the not-so-distant past, the cockpit of a commercial aircraft served as a nexus for two pilots, a flight engineer, a navigator, and a radio operator (Gao et al., 2025; Vu et al., 2018). Technological advances have gradually reduced the number of people in the cockpit. If this trend continues, the only people on board aircraft may be passengers. While it is unlikely that cockpits will be unmanned in the near future, single-pilot operations in commercial flights are likely to become commonplace soon. Reaching this conclusion has advantages in terms of efficiency and cost but also requires overcoming many issues, particularly regarding safety (Vu et al., 2018).

Single-pilot operations and subsequently unmanned operations can be achieved by addressing the roles and responsibilities of both air and ground crews (Tokadlı et al., 2021). Single-pilot operations represent an important threshold that must be crossed for the automation system to prove itself and for the cockpit to be entrusted to it. AI-based automation systems are used in the cockpit to assist pilots in their decision-making processes, perform real-time analysis, and contribute to situational awareness (Djartov & Würfel, 2025). These systems are being trained to understand aircraft dynamics and unpredictable conditions, thereby enhancing their knowledge of the real world and their reliability (Menig et al., 2025). Particularly in the context of emergency management, AI-based decision support systems can reduce the workload by assisting the cockpit crew in analyzing information while also increasing decision accuracy. Consequently, a strong foundation is being laid for single-pilot operations and beyond (Djartov & Würfel, 2025; Kirwan, 2024; Piera et al., 2022). There are numerous challenging factors in making AI fully compatible with the cockpit. In particular, pilots question the autonomous decision-making ability of AI in critical situations (Fondevila-Gascón et al., 2025; Holley et al., 2024). This skepticism among pilots is thought to stem from factors such as safety, human factors, and human-machine collaboration. From a safety perspective, the use of AI in risky operations can create legal and ethical issues and necessitate the establishment of standards (Dieter et al., 2024).

The transformation that AI will bring to the aviation sector is not limited to technical infrastructure; it also creates a field encompassing many human-centered factors such as trust, ethical responsibility, law, and passenger acceptance. In this context, passengers' views on fully unmanned operations are also gaining importance as the socio-technical dimension of the situation (Fondevila-Gascón et al., 2025; Holley et al., 2024). AI is used in various areas of the aviation industry, such as safety, security, air traffic control, and airport operations. Therefore, the Technology Acceptance Model (TAM), first developed by Fred D. Davis (1985; 1989), is widely used to explain why users accept or reject new technologies. TAM was first proposed in Davis's doctoral dissertation (1985) and later empirically validated and refined in his groundbreaking work published in MIS Quarterly (1989) In this foundational work, Davis conceptualized technology acceptance as a function of two core cognitive beliefs: perceived usefulness and perceived ease of use. Perceived usefulness is defined as the degree to which an individual believes using a particular system will improve their job performance, while perceived ease of use refers to the degree to which a person believes using the system will not require effort. According to Davis (1989), these beliefs directly influence users' attitudes toward technology use, which in turn shape their behavioral intentions and actual system usage. Furthermore, it is theorized that perceived ease of use has both a direct effect on behavioral intention and an indirect effect through perceived usefulness, highlighting its dual role in the adoption process. TAM is based on the Rational Action Theory (TRA), which assumes that behavior stems from intention, and intention is influenced by attitudes and beliefs. Over time, TAM has been widely validated in various fields and expanded upon with subsequent studies (e.g., TAM2, TAM3, and UTAUT), reinforcing its robustness as a theoretical framework for understanding user adoption of new technologies (Marangunić & Granić, 2015).

The approach of airline passengers to single-pilot and autonomous flight operations is not based solely on technological innovation, but rather on a complex situation shaped by psychological, sociological and trust-related factors. Studies in this field show that passengers take a cautious approach to single-pilot and fully autonomous flights. This cautious approach stems from reasons such as safety, the perception of control, and trust in humans. This is because a pilot is not just an operator for a passenger, but also a symbol of flight safety. In other words, pilots on aircraft are a source of human trust for other people. Therefore, the reduction or complete elimination of human presence in decision-making processes on aircraft leads to an increase in the perceived risk for passengers and questions about trust in AI. Passengers with little flight experience and a high perception of risk may experience greater uncertainty. Consequently, there are serious questions about whether passengers will be able to easily adapt to this new situation, even if they have not yet experienced single-pilot or autonomous flights (Bliss & Wise, 2023; Fondevila-Gascón et al., 2025; Molesworth & Koo, 2016).

The main objective of this study is to examine the intentions of passengers and prospective passengers to fly on AI-controlled aircraft, based on perception, attitude, and trust. The key difference between this study and others in this field is its focus on users' willingness to accept such new technology, rather than on technical and operational contexts. Existing studies in literature examine AI applications in aviation from an engineering, safety, and regulatory perspective. This study, however, aims to reveal how AI-controlled aircraft, potentially used in commercial air transport, are perceived and evaluated by humans. Rather than exploring new assumptions or expert opinions, the study empirically assesses human willingness to adopt these technologies that may emerge in a non-futuristic future. By addressing concepts such as risk perception and trust in automation within a socio-technical context, the study provides airline operators, policymakers, and regulatory bodies with valuable early empirical information on what factors might hinder or facilitate the adoption of AI-controlled aircraft.

The study is designed to consist of six main sections. Following the introduction, the second section addresses the conceptual framework of the study, along with TAM and its application in aviation. The third section, under the heading of methods, includes research design, sampling and data collection process, scales, and measurement techniques. The fourth section contains the analysis of the collected data. In the fifth section, the analyzed data are evaluated in light of the literature, and the findings are discussed. The final section includes the theoretical and practical implications and limitations of the study.

2. LITERATURE AND HYPOTHESIS DEVELOPMENT

2.1. Technology Acceptance Model in Aviation

TAM is a prominent theoretical framework used to explain and predict user adoption behavior. It posits that two primary factors—perceived usefulness (the degree to which a system enhances performance) and perceived ease of use (the degree to which a system is perceived as effortless)—determine an individual's behavioral intention and subsequent usage (Abuhassna et al., 2023; Weerasinghe & Hindagolla, 2017). Rooted in the Theory of Reasoned Action (TRA), TAM suggests that behavior is driven by intention, which is influenced by attitudes and subjective norms. The model has evolved through the integration of additional constructs, such as social influence, cognitive instrumental processes, perceived enjoyment, and trust (Tang & Chen, 2011). Over time, with technological advancements and the increasing complexity of user behavior, TAM has been expanded with various versions. TAM2, developed within this framework, aimed to explain technology acceptance more comprehensively, particularly in an organizational context, by incorporating variables such as social influence and cognitive tools into the model (Bağlıbel et al., 2010). Later, the Unified Technology Acceptance and Use Theory (UTAUT), integrating eight different theories, addressed the effects of performance expectation, effort expectation, social influence, and facilitating conditions on technology use intention; and included individual differences such as age, gender, and experience as moderating variables. UTAUT2, a consumer-oriented version of UTAUT, further enhanced the model's explanatory power by adding hedonic motivation, price value, and habit variables (Venkatesh et al., 2012). This study is grounded in TAM and adopts a context-specific extension by incorporating trust and perceived risk alongside perceived usefulness and perceived ease of use. While retaining the core TAM constructs, the proposed model reflects the safety-critical nature of AI-controlled flight operations by integrating risk- and trust-related beliefs into the acceptance framework.

TAM and its versions have been used in many different sectors and contexts, such as the acceptance of online learning platforms to understand technology acceptance, technology adoption in healthcare, consumer behavior analysis in e-commerce, and digital entrepreneurship (Abuhassna et al., 2023; Dhagarra et al., 2020; Kim, 2024; Mustafa & Garcia, 2021). Technological developments and changes are frequently observed in the aviation industry, as is the case in other sectors. Such alterations may emerge in the service delivery processes for passengers and in the operational processes for operators. Passengers, as customers, experience these changes in both airline and airport operations. Similarly, professional groups such as pilots, air traffic controllers, and maintenance technicians also encounter technologies that are part of their daily professional lives. Hence, the responses of the sides to these technological changes are the subject of studies within the context of TAM.

For instance, Wongyai et al. (2024) conducted a study examining passengers' adoption of self-service and check-in kiosks at airports within the scope of TAM. This study includes the dimensions of perceived usefulness and ease of use in the model, as well as technology self-efficacy, need for human interaction, and perceived enjoyment. In a manner akin to passengers, pilots can similarly serve as test subjects regarding the extent of their adoption of novel technologies. A study examining pilots' willingness to use technology developed to measure fatigue levels found that perceived usefulness and ease of use significantly influence willingness to use the technology (Strong et al., 2025). In the maintenance field, TAM is also used to examine the acceptance levels of aircraft technician candidates towards virtual reality technology in their maintenance training. The research is being expanded to include dimensions such as self-efficacy, perceived enjoyment, perceived health risk, performance expectation, and perceived behavioral control, along with the main dimensions of the model (Carlsson, 2024). Due to the increase in flight numbers and the growing complexity of air traffic, there is a growing need to utilize technology to alleviate the workload of air traffic controllers. In a study conducted by Schon et al. (2025) on the use of AI in air traffic management, TAM and the AI acceptance model are used together.

Recent advancements in unmanned and autonomous aviation technologies, including Unmanned Aerial Vehicles (UAVs), Urban Air Mobility (UAM), and Advanced Air Mobility (AAM), have significantly increased academic interest in societal acceptance and public perception of these systems. The current literature consistently demonstrates that the level of public acceptance of such technologies is primarily shaped by perceived risk, safety concerns, and trust-related factors. Technological advancements in UAVs, Urban Air Transportation (UAM), and Enhanced Air Mobility (AAM) have raised questions about how society views these innovations. Research indicates that risk perception, safety concerns, and a sense of security are key factors in people's adoption of these technologies (Clothier et al., 2015). Initial studies on UAVs revealed that society lacked sufficient information about these vehicles, leading to uncertain or neutral attitudes. The most significant concerns included privacy violations, safety, and the potential misuse of the vehicles (Komasová et al., 2020; Savaş et al., 2025). However, risk perception is a subjective matter. As familiarity with technology increases and vehicles become more common in daily life, concerns tend to decrease. In summary, safety, privacy, and the proper management of risks directly influence people's acceptance of this technology (Yoo et al., 2022). Yılmaz-Halıcı et al. (2025) revealed that individuals' attitudes towards UAVs are related to technology readiness and flight anxiety, and that attitudes towards single-pilot operations are evaluated more positively compared to fully autonomous systems. Similarly, in the Urban Air Transportation Acceptance and Use Model developed by Yavaş & Yavaş Tez (2021), it is stated that trust, intention to use, perceived convenience, and behavioral intention are decisive in UAM acceptance. Lee et al. (2023), in their study based on the UTAUT and initial trust model, found that social influence and initial trust are the strongest determinants of UAM use intention; It is stated that structural assurance, regulations, and institutional security mechanisms, in particular, increase user trust. In the study by Lee et al. (2023), where TAM was expanded with the dimensions of trust and service quality, it was emphasized that trust has a stronger effect on the intention to use than perceived benefit, and that security perception is the most important factor determining the reliability of UAM systems. Johnson et al. (2022) found that early adopters have more trust in technology, a higher risk tolerance, and are more willing to use UAM systems; in contrast, late adopters demand more information, feedback, and pilot presence during flight. Furthermore, Çetin et al. (2022) stated that the public is particularly concerned about safety, privacy, noise, and misuse risks; therefore, regulatory measures, safety mechanisms, and public awareness strategies are necessary to increase societal acceptance. Studies conducted in Türkiye also show that the public views UAM systems as innovative and beneficial; however, they have significant reservations regarding issues such as safety, airspace integration, privacy, and noise (Çınar & Tuncal, 2023b, 2023a). Finally, Chan et al. (2025), in their study conducted in the Greater Bay Area of China, found that trust is the strongest variable explaining the intention to use AAM. The study also revealed that perceived benefit, subjective norms, and perceived behavioral control significantly influence the intention to use. When all these studies are considered together, it is understood that technical capabilities alone are not sufficient for the societal acceptance of AI-controlled and autonomous air transportation systems; individuals' perceptions of safety, risk, loss of control, institutional assurance, and system reliability are the fundamental factors shaping the intention to use.

2.2. Hypothesis Development

The development of AI technologies and their applications in aviation have gained significant momentum in recent years, paving the way for fundamental transformations in the sector. In particular, the increasing level of automation in flight operations, coupled with the advent of single-pilot and fully autonomous flight systems, has begun to redefine aviation's traditional human-centric structure. Parallel to this rapid technological advancement, there has been a noticeable increase in academic literature examining the effects of AI on aviation safety, operational efficiency, ethical decision-making, and passenger acceptance. In this context, the existing literature reveals that AI-based flight systems constitute a multidisciplinary field of research that focuses not only on technical adequacy but also on human-machine interaction, trust, and technology acceptance.

Technological developments can give rise to uncertainty and risks that are difficult to predict. This situation can cause individuals to approach new technologies cautiously and reduce their trust in that technology (Clarke & Beck, 1994). AI-supported autonomous systems can also be evaluated in this category. In fact, it may be one of the key factors that reduces user trust along with risk perception (Schwesig et al., 2023; Shao et al., 2025). Furthermore, high risk perception can reduce trust and thus decrease the desire to use technology (Zhu et al., 2025). Winter et al. (2020) found that individuals' willingness to fly in autonomous air taxis was reduced by fear and wariness of new technology. Avetisyan et al. (2025) found that trust in autonomous vehicles is not only cognitive but also influenced by emotions, and that perceived risk has an indirect effect on trust. The study by Zhang & Yu (2025)shows that trust in AI increases the intention to use it, while risk perception has the opposite effect. We propose following hypotheses based on existing literature.

H_1: Trust in the AI system negatively impacts perceived risk of AI-controlled aircraft.

H_2: The perceived risk of AI-controlled aircraft negatively impacts perceived usefulness.

Bliss and Wise (2023) conducted semi-structured interviews to gain insights into how pilots perceive and evaluate the idea of an unmanned cockpit, focusing on their attitudes, concerns, and expectations regarding such technology. The pilots participating in the study assessed that during flight, the pilot's role would evolve from directly flying the aircraft to that of an observer. Furthermore, autonomous systems have the potential to create psychological effects in pilots, such as loss of control, job security concerns, skepticism towards technology, and the need for adaptation. Although there are some fundamental differences, it can be argued that unmanned flights have similar effects on passengers (Fondevila-Gascón et al., 2025). An additional investigation, which attempted to assess air passengers' perspectives on aircraft being piloted from the ground by human aviators instead of completely by computerized systems, determined that passengers favored conventional piloted flights over remotely controlled flights. Nevertheless, concerns such as seat cost, in-flight amenities, and innovative technology might modify perceptions.

Gao et al. (2025) conducted a study on the social acceptability of two-pilot and AI-assisted single-pilot flights, showing that two-pilot flights are preferred over single-pilot and AI-assisted flights. This difference is found to stem from low trust, high risk, and negative attitudes. Another qualitative study examining individuals' approach to new technologies explores people's attitudes towards autonomous flights based on cultural and political contexts. The negative attitude towards autonomous flights is assessed as stemming from potential technological failures, distrust of companies and governments, and the possibility of a climate crisis (Belton & Dillon, 2021).

Vance & Malik (2015) examine the factors influencing technology and aviation professionals' decision to board unmanned aircraft. In the study, which utilizes the Bayesian method, the airline's reputation and integrity emerge as positive influences, while life insurance and compensation are highlighted as negative influences. Other findings of the study reveal that participants still prefer to trust a human rather than technology, that cost is secondary, that younger passengers and those who fly less frequently are more willing, and that those with a bachelor's degree or higher are more skeptical. Rice et al. (2019), in their study examining passengers' intention to fly in autonomous aircraft, found that familiarity with the concept of autonomous flight, finding autonomous flights enjoyable, happiness levels, and having a postgraduate education create positive attitudes, while anxiety about new technologies, fear, and older age support negative attitudes. Thus, this study emphasizes that individual characteristics are important in the acceptance of new technologies.

Halawi et al. (2024) examined airline passengers' intentions to fly on aircraft controlled entirely by AI using TAM. Their study shows that perceived ease of use and usefulness positively influences flight intentions, but that usefulness has an indirect rather than a direct effect on flight intentions. From the earliest studies in this field (Macsween-George, 2003) to the present day, it is evident that people have hesitations about the automation of the cockpit and continue to have these hesitations. We propose following hypotheses based on existing literature.

H_3: Trust in AI system positively impacts perceived ease of use of AI-controlled aircraft.

H_4: Trust in AI system positively impacts perceived usefulness of AI-controlled aircraft.

H_5: Perceived risk of AI-controlled aircraft negatively impacts perceived ease of use.

H_6: Perceived ease of use of AI-controlled aircraft positively impacts perceived usefulness.

H_7: Perceived usefulness of AI-controlled aircraft positively impacts intention to use.

H_8: Perceived ease of use of AI-controlled aircraft positively impacts intention to use.

TAM is used to understand technology acceptance in many areas, from online learning platforms to e-commerce, and from the healthcare sector to digital entrepreneurship (Abuhassna et al., 2023; Dhagarra et al., 2020; Kim, 2024; Mustafa & Garcia, 2021). The aviation sector is no exception in this regard; increasing levels of automation are reshaping the way both passengers and professionals interact with technology. From the passengers' perspective, research conducted by Wongyai et al. (2024) has shown that perceived usefulness, ease of use, and self-efficacy towards technology are decisive factors in the adoption of self-service and kiosk technologies at airports. Similarly, studies conducted on pilots (Strong et al., 2025) and maintenance technicians (Carlsson, 2024) have revealed that perceived usefulness is a fundamental motivating factor in the acceptance of new technologies. Furthermore, Schon et al. (2025) examined AI applications in air traffic management and determined that trust and emotional factors significantly influence the intention to use technology.

Based on the TAM, we assume that the model shown in Figure 1 will be useful in determining individuals' intentions to fly in aircraft controlled by AI.

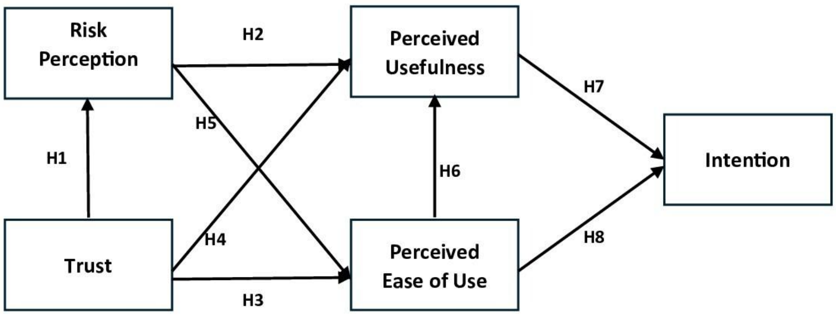

Figure 1. Research Model

3. METHOD

3.1. Data Collection and Sampling

The study sample consisted of adult individuals aged 18 and over residing in Hatay province, Türkiye, who are potential future users of AI-controlled aircrafts. Data were collected through a web-based survey distributed via social media platforms. A non-probability sampling approach, specifically convenience sampling, was used. Participation was voluntary, and participants were self-selected. Therefore, although efforts were made to reach diverse participant groups, the sample may not fully represent the target population. The data collection process was carried out online via a structured questionnaire distributed through social media channels between November 2025 and December 2025. Participants were provided with information regarding the purpose of the study, the confidentiality of their responses, and their right to withdraw at any stage. Informed consent was obtained from all participants before their involvement in the study. A total of 258 participants were included in the final sample.

In this study, gender, age, education level, digital literacy level, travel frequency, and autonomous vehicle experience were used as control variables. These demographic control variables were examined using frequency analysis. The results showed that most participants were women (69.4%, n=179). The majority of participants were young people (18-24) (n=169). Participation is considered valuable given that young people are likely to experience AI-controlled aircraft in the future, and that their technological perspectives are generally more moderate than those of older age groups. A large proportion of participants (82.6%) had an education above high school level. Only a small group had high school education or less (1.6%). A large proportion of participants considered themselves experienced in digital literacy (78.7%). The fact that the majority of participants were young people may be a factor reducing the number of air travel experiences. Approximately one-third of the participants reported never having traveled by plane before. This could potentially explain some of the sensitivity regarding safety. More than half of the participants (57.4%) reported having no prior experience with autonomous vehicles.

3.2. Measures

The study utilized a survey method, adapting and applying scales developed for autonomous vehicle experience. A 5-point Likert scale was used for measurement. Participants responded on a scale of 1 (strongly disagree), 2 (disagree), 3 (neutral), 4 (agree), and 5 (strongly agree).

The scales created regarding perceived usefulness, perceived ease of use, trust, perceived risk, and intention to use were adapted from the studies by Chalermpong et al. (2024), T. Zhang et al. (2019), and Kenesei et al. (2022). The perceived usefulness scale aimed to identify an individual's assumptions about the potential usefulness of a flight in an AI-controlled aircraft. In this context, participants were asked questions about how they could affect the quality and efficiency of the flight in a fully autonomous system. For example: "Traveling in AI-controlled aircraft can make flight time more efficient (e.g., faster check-in, baggage management)", "AI-controlled aircraft can improve passenger comfort by better managing situations such as turbulence".

The perceived ease of use scale was used to determine the degree to which individuals would find it easy to travel in an AI-controlled aircraft. In short, the aim was to determine how much effort would be required to travel in an AI-controlled aircraft. Participants were asked questions such as, "I believe that special training or preparation will be required to travel in a fully autonomous aircraft," "I imagine that if a problem occurs during the flight, the AI will be able to explain the situation to us (the passengers) in an understandable way," and "I don't think that finding the locations of basic necessities like digital screens, emergency exits, and restrooms in AI aircraft will be more difficult than in traditional aircraft."

The trust scale aimed to determine the level of trust individuals might have in AI-controlled aircraft, even if they haven't experienced such a journey themselves, given the current technology. Trust was assessed based on trust in AI itself, trust in AI's decision-making abilities, and trust in the airlines using AI. Participants were asked questions such as, "I believe that AI-controlled aircraft will get me to my destination safely," "I believe that the software on AI-controlled aircraft will function flawlessly," and "I believe that the airlines using AI-controlled aircraft will manage their AI systems correctly."

The perceived risk scale addresses individuals' perceptions of the risks associated with AI-controlled aircraft. Based on perceptions of uncertainty, safety concerns, assumptions and anxieties about the robustness of the technology, participants were asked questions such as, "The idea that an AI-controlled aircraft could crash due to a technical malfunction worries me," "The risk of AI-controlled aircraft being hijacked bothers me," and "In piloted aircraft, I trust that the pilot will resolve any potential problems. However, I don't think I would feel the same trust in a fully AI-controlled aircraft."

This scale was developed to clarify the level of intention participants have to use the technology or how widely it might be accepted. Participants were asked whether they would use such technology if it existed. Statements such as, "I would consider traveling on AI-controlled planes within the next 10 years," "I wouldn't hesitate to travel on an AI-controlled plane with my family," and "Traveling on AI-controlled planes will become commonplace and ordinary for everyone in the future," were used to measure intention to use the technology."

Since the measurement scales were initially developed in different cultural contexts, a rigorous adaptation process was undertaken to ensure linguistic clarity and contextual appropriateness. The scale items were translated into Turkish by the author, taking into account the terminology and conceptual framework in the aviation and technology acceptance literature. Following the translation, the items were informally reviewed for clarity and consistency. A pilot study was conducted with a small sample (n = 30), and minor revisions were made to improve wording and eliminate ambiguities based on participant feedback. This process ensured that the adapted scale items were understandable and contextually appropriate for the target audience.

Table 1. Measurement Items

Constructs	Variable	Item (Turkish Version)	References
Perceived Usefulness	PU1	YZ kontrollü uçaklar, insan pilotlu uçaklara göre daha güvenli bir seyahat deneyimi sunabilir.	T. Zhang et al. (2019); Chalermpong et al. (2024)
	PU2	YZ kontrollü uçaklar, daha az gecikmeyle zamanında kalkış ve iniş yapabilir.	Chalermpong et al. (2024)
	PU3	YZ kontrollü uçaklarda seyahat etmek, uçuş süresini daha verimli hale getirebilir.	T. Zhang et al. (2019)
	PU4	YZ kontrollü uçaklar, türbülans gibi durumları daha iyi yöneterek yolcu konforunu artırabilir.	K. Zhang (2021); Kenesei et al. (2022)
	PU5	YZ kontrollü uçaklarda acil durum protokolleri daha etkili olabilir.	Kenesei et al. (2022)
	PU6	YZ kontrollü uçaklarda seyahat etmek genel olarak daha sorunsuz bir yolculuk deneyimi sağlayabilir.	Chalermpong et al. (2024)
Perceived Ease of Use	PEU1	Tamamen YZ tarafından uçurulan bir uçakta kendimi daha stresli hissedeceğimi düşünüyorum.	T. Zhang et al. (2019)
	PEU2	YZ uçakta acil durum talimatlarını anlamanın ve uygulamanın zor olacağını düşünüyorum.	T. Zhang et al. (2019)
	PEU3	Otonom uçakta yolculuk etmek için özel bir eğitim veya ön hazırlık gerektiğine inanıyorum.	T. Zhang et al. (2019)
	PEU4	İnsan pilotlu uçakta olduğu kadar rahat hissedeceğimi düşünüyorum.	Chalermpong et al. (2024)
	PEU5	YZ'nın uçuş sırasında durumu yolculara anlaşılır şekilde açıklayabileceğini düşünüyorum.	Chalermpong et al. (2024)
	PEU6	YZ uçaklarda yön bulmanın zor olmayacağını düşünüyorum.	Kenesei et al. (2022)
Trust	TR1	YZ kontrollü uçakların beni güvenli bir şekilde varış noktasına ulaştıracağına inanıyorum.	T. Zhang et al. (2019); Kenesei et al. (2022)
	TR2	YZ kontrollü uçakların yazılımının hatasız çalışacağına inanıyorum.	Kenesei et al. (2022)
	TR3	YZ kontrollü uçakların acil durumlarda doğru kararlar alacağına inanıyorum.	T. Zhang et al. (2019)
	TR4	YZ sistemlerini kullanan havayolu şirketlerinin bu sistemleri doğru yöneteceğine inanıyorum.	Kenesei et al. (2022)
	TR5	YZ kontrollü uçakların yolcu güvenliğini her şeyin üzerinde tutacağına inanıyorum.	Chalermpong et al. (2024)
Risk Perception	RP1	YZ kontrollü uçakların teknik arıza nedeniyle kaza yapabileceği fikri beni endişelendirir.	Kenesei et al. (2022); T. Zhang et al. (2019)
	RP2	YZ kontrollü uçakların kontrolünün ele geçirilme riski beni rahatsız eder.	Kenesei et al. (2022)
	RP3	YZ'nın beklenmedik durumlarda nasıl tepki vereceğini bilmemek endişe vericidir.	T. Zhang et al. (2019)
	RP4	Pilotlu uçakta hissedilen güveni YZ uçakta hissetmeyeceğimi düşünüyorum.	Chalermpong et al. (2024)
	RP5	YZ kontrollü uçakta seyahat eden ilk yolculardan biri olmak istemem.	T. Zhang et al. (2019); Chalermpong et al. (2024)
Intention to Use	IN1	Önümüzdeki 10 yıl içinde YZ kontrollü uçaklarda seyahat etmeyi düşünürüm.	T. Zhang et al. (2019); Chalermpong et al. (2024)
	IN2	YZ uçakların biletleri daha ucuz olursa bunları tercih ederim.	Chalermpong et al. (2024)
	IN3	Ailemle birlikte YZ kontrollü uçakta seyahat etmekten çekinmem.	Chalermpong et al. (2024)
	IN4	YZ uçak kullanımı yaygınlaştıkça ben de kullanırım.	T. Zhang et al. (2019)
	IN5	YZ kontrollü uçaklarla seyahat etmek gelecekte yaygın hale gelecektir.	Chalermpong et al. (2024)

3.3. Statistical Analysis

In this study, a two-stage analytical procedure, Anderson & Gerbing (1988), was applied in the analysis of the data, the evaluation of the measurement model, and hypothesis testing. In the first stage, confirmatory factor analysis (CFA) was used to evaluate the adequacy of the scales. Convergent validity, discriminant validity, and composite reliability of the constructs were performed considering the studies of Fornell & Larcker (1981) and Bagozzi & Yi (1988). In the second stage, hypotheses developed based on literature and the relationships between variables were investigated using structural equation modeling (SEM). SPSS AMOS 24.0 and SPSS 24.0 software packages were used to perform these statistical analyses.

4. RESULTS

4.1. Measurement Model

The construct was tested using CFA, and the goodness-of-fit values of the two different models were compared. Initially, a construct consisting of 27 items was tested. As a result of confirmatory factor analyses, the entire perceived ease of use (PEU) dimension and items 2, 3, 4, and 5 of the perceived usefulness (PU) dimension were excluded from the analysis due to structural bias and low factor loadings. Consequently, the perceived usefulness construct was represented by two items (PU1 and PU6), which demonstrated acceptable reliability and validity values. While three or more items are generally recommended for latent constructs, the use of two-item constructs is considered acceptable in SEM when supported by sufficient reliability (CR ≥ 0.70) and convergent validity (AVE ≥ 0.50). The analysis was subsequently continued with a 17-item and 4-factor model structure. They are risk perception (RP), trust (TR), perceived usefulness (PU) and intention (IN). When examining the model fit indices, it was observed that the proposed model was consistent with the data. The fact that the comparative fit indices (CFI = 0.94, TLI = 0.93) and absolute fit indices (GFI = 0.90) were above acceptable threshold values supports the validation of the model structure. Furthermore, the fact that error-based indices such as RMSEA (0.06) and SRMR (0.06) remain within good fit limits indicates that the model represents the data at a reasonable level ($\chi2$= 237.248, df = 117, $\chi2$/df = 2.028, CFI = 0.94, PCFI = 0.81, GFI=0.90, RMSEA = 0.06, IFI = 0.94, TLI = 0.93, SRMR=0.06). Reliability tests were performed on the structure that emerged following CFA analyses (Table 1).

Table 2. Reliability and Validity Analysis

Dimension	Item	AVE	CR	Cronbach Alfa
RP	5	0.52	0.84	0.84
TR	5	0.53	0.85	0.84
PU	2	0.54	0.70	0.70
IN	5	0.53	0.85	0.84

AVE values above the threshold of 0.50 for each dimension (between 0.52 and 0.54) indicate convergent validity. The fact that the CR values (between 0.70 and 0.85) and Cronbach's alpha coefficients (between 0.70 and 0.84) are above 0.70 in all dimensions indicates that the scale has a high level of internal consistency and provides reliable measurements. Although the PU dimension consists of only two items, the fact that the AVE (0.54), CR (0.70) and Cronbach's alpha (0.70) values meet acceptable thresholds supports the adequate reliability of this short subscale (Fornell & Larcker, 1981). In the study, Harman's single-factor test was applied to assess the possibility of common method bias. The analysis identified a total of three factors with eigenvalues greater than 1 (according to the Initial Eigenvalues section), and the total variance explained by the model forced into a single factor was calculated as 35.57%. The fact that this value is below the 50% threshold indicates that common method bias does not pose a serious problem in the data set.

Correlation analysis examines the relationships between demographic variables, RP, TR, PU, and IN (Table 2).

Table 3. Correlations

	1	2	3	4	5	6	7	8	9	10
Gender (1)	1									
Age (2)	-0.157*	1								
Education (3)	-0.293**	0.451**	1							

Digital literacy (4)	-0.156*	0.113	0.148*	1						
Travel Frequency (5)	-0.163**	0.221**	0.188**	0.196**	1					
AV Experience (6)	0.141*	-0.042	-0.064	-0.202**	-0.205**	1				
PU (7)	-0.060	0.034	-0.005	-0.020	0.077	0.138*	1			
TR (8)	-0.049	0.048	-0.036	0.030	0.061	0.140*	0.629**	1		
RP (9)	0.182**	-0.084	0.020	0.046	-0.069	0.027	-0.386**	-0.362**	1	
IN (10)	-0.085	-0.025	0.012	-0.043	0.122	0.005	0.511**	0.612**	-0.353**	1

* Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

The analysis results indicate a positive relationship between gender and RP, and a negative relationship with age and education. There is a moderate correlation between age and educational level ($r = 0.45$, $p < 0.01$) and a weak correlation between age and travel frequency ($r = 0.22$, $p < 0.01$). An interesting, albeit weak, negative and significant relationship ($r = -0.20$, $p < 0.01$) was observed between digital literacy and AV experience. However, there is also a weak but significant relationship ($r = 0.14$, $p < 0.05$) between digital literacy and educational level. AV experience shows a positive and significant relationship with PU and TR. However, it has a negative and significant relationship with travel frequency. A strong positive relationship was determined between PU and TR ($r = 0.63$, $p < 0.01$). Furthermore, it was observed that RP had significant negative relationships with both PU and TR. The strong relationship between IN and TR and PU is another noteworthy finding. The direction of the relationship is positive, indicating a relationship above the medium level. As expected, there is a negative and significant relationship between RP and IN. Significant relationships between IN and demographic variables could not be observed. The results of the correlation analysis suggest that psychological factors may play a more defining role than demographic characteristics in the acceptance process of AI-controlled aircraft.

4.2. Hypothesized Model

The model's fit indices are at a good level of fit, indicating that the structural model is appropriate for the data ($\chi2=411.126$, df=215, $\chi2/df=1.912$, CFI = 0.91, PCFI = 0.77, GFI=0.88, RMSEA=0.06, IFI=0.91, TLI=0.89, SRMR=0.06). The analysis results (Table 3) revealed that trust in AI-controlled aircraft significantly reduced RP ($\beta = -0.42$, $p < 0.001$) and that trust also strongly increased PU ($\beta=0.85$, $p < 0.001$). However, the negative effect of RP on PU was also found to be significant ($\beta =-0.17$, $p=0.005$). Finally, the positive effect of PU on IN is quite strong ($\beta=0.78$, $p < 0.001$). The model's explanatory power is notable: Squared Multiple Correlations results indicate that TR variable explains 17.8% of the variance in RP; TR and RP together explain 88.3% of PU; and PU explains 64.3% of IN. These results demonstrate that the model has a conceptually robust and consistent structure.

Table 4. Regression Results

Dependent	Predictor	p	S.E.	C.R. (t)	B	β
RP	TR	***	0.068	-5.754	-0.39	-0.42
PU	TR	***	0.068	11.718	0.79	0.85
PU	RP	0.005	0.061	-2.840	-0.17	-0.17
IN	PU	***	0.083	10.844	0.89	0.78
IN	DigLit.	0.123	0.053	-1.544	-0.08	-0.08
IN	FlgFrq.	0.086	0.043	1.715	0.07	0.09
IN	AVexp.	0.138	0.078	-1.485	-0.11	-0.07
IN	Education	0.310	0.110	1.015	0.11	0.05
IN	Age	0.051	0.042	-1.951	-0.08	-0.11
IN	Gender	0.763	0.086	-0.301	-0.02	-0.01

Preliminary examinations conducted using CFA revealed that the 'PEU' variable did not meet the expected factor loadings and was excluded from the hypothesis tests; hypotheses based on this variable (H3, H5, H6, and H8) could not be tested. The results demonstrate that the other hypotheses (H1, H2, H4, and H7) were confirmed.

5. DISCUSSION

In this study, the ‘perceived ease of use’ (PEU) dimension within TAM framework, which was developed to explain the intention to fly with AI-controlled aircraft, was removed from the model because of the exploratory and confirmatory factor analyses conducted. The analysis findings showed that the factor loadings for this dimension were low, and the composite reliability (CR) and average variance explained (AVE) values were below acceptable levels. This suggests that participants may not have developed a clear perception of ease of use during the evaluation process. Similar findings have been reported in literature, particularly in the context of technologies that are still untested or newly emerging. The use of new technology involves uncertainty, lack of knowledge, and cognitive complexity for users. Venkatesh et al. (2012) noted that individuals with low levels of experience cannot base ease of use on actual experience, and therefore the reliability of measurements of this dimension may be weakened. Similarly, Martins et al. (2014) showed that users base ease of use in new technologies on cognitive predictions rather than concrete performance experience, resulting in weak factor loadings in the model. Sagnier et al. (2020) reported that in augmented reality (AR) technologies, users base their decisions regarding the technology on more intuitive and perceptual factors such as ‘trust’ and “usability” rather than ‘ease of use’. This situation demonstrates that, trust’ precedes cognitive evaluations in users' interactions with new technologies (T. Zhang et al., 2019). Users generally attempt to reduce their risk perceptions by developing initial trust in untested systems (Hoff & Bashir, 2015; McKnight et al., 2002). In this context, as AI-controlled flight systems have not yet been directly experienced by users, participants may not have formed consistent judgements regarding the concept of “ease of use”. Instead, they are likely to have based their assessments on more distinct concepts such as “trust”, “risk” and “usability”. Therefore, removing this dimension from the model is a consistent decision both for measurement reasons (weak factor loadings and validity issues) and theoretical grounds (lack of experience, cognitive uncertainty, and the dominant role of initial trust).

The current study validates TAM-based relationships within a model developed to explain individuals’ intentions to fly with AI-controlled aircraft. The findings indicate that trust in AI has a significant negative effect on perceived risk, which is in line with Clarke & Beck (1994) risk society perspective, suggesting that diminished trust in technological innovations amplifies individuals’ risk perceptions. Studies show that increased risk perception weakens trust and makes it more difficult for individuals to accept new technology (Schwesig et al., 2023; Shao et al., 2025; Zhu et al., 2025). Furthermore, a significant and negative correlation between perceived risk and perceived usefulness is clearly observed in our study. Therefore, this finding supports the study of Gao et al. (2025) and Belton & Dillon (2021), who argue that an increase in perceived risk contributes to negative perceptions of technology. Thus, a high level of perceived risk can reduce an individual's trust in the usefulness of technology, making it more difficult to accept it. The studies by G. Zhang & Yu (2025) and Avetisyan et al. (2025) emphasize the concept of emotional trust, reporting that individuals' trust is not only based on cognitive foundations but also on establishing an emotional connection with technology, and that they find technology more functional as a result of this emotional connection. From this perspective, it shows that building trust in artificial intelligence systems cannot be achieved solely through technical reliability, but that transparency and communication strategies that can increase psychological safety can contribute to the creation of this emotional connection.

In this study, perceived usefulness stands out as the strongest predictor of intention to use. This result partially supports the findings of Halawi et al. (2024). While Halawi et al. (2024) emphasized the effect of perceived usefulness more indirectly, this effect is more direct in this study. The difference between the two studies is thought to stem from the sample and context. In the aforementioned study, the sample was selected directly from employees working in the aviation industry in the United States, whereas in current study, it was done randomly. When all the findings of the study are considered together, it can be argued that the fundamental assumptions of TAM are supported. In particular, while perceived usefulness is a strong predictor of technology adoption in technologies such as AI-controlled aircraft that are not yet operational, trust and risk perception stand out as important predictors of perceived usefulness. This situation has the potential to become even more significant in the future as these technologies become operational.

6. CONCLUSIONS AND IMPLICATIONS

6.1. Conclusions

This study examined the intention to fly with AI-controlled aircraft within the framework of the TAM, revealing the decisive role of trust and perceived risk in technology acceptance. The findings show that trust reduces perceived risk, increases perceived usefulness, and consequently strengthens individuals' intention to fly. The exclusion of the "perceived ease of use" dimension from the model due to lack of experience highlights the measurable reflections of cognitive uncertainties in early-stage technologies. The study demonstrates that trust in AI-based aviation technologies is not merely a psychological factor but also a structural element that guides adoption intentions. These findings provide a strong foundation for developing trust-centered approaches in future research and sectoral strategies.

6.2. Theoretical and Practical Implications

This study tested the assumptions of TAM in the context of the adoption of ai-controlled aircraft. The findings showed that previously unexperienced technologies weakened the model, particularly in the "perceived ease of use" dimension. Therefore, it may limit the model's use in the adoption of previously unexperienced technologies. In this respect, the study provides a theoretical contribution to the field. Another theoretical contribution of the model is the critical role that trust plays in the adoption of unexperienced technologies. Trust can shape the intention to use both directly and indirectly, because trust strongly influences both risk perception and perceived usefulness. Including the trust dimension in research on the adoption of futuristic technologies such as artificial intelligence and autonomous vehicles is one of the recommendations of this study.

Examining the historical development of technology shows that applications in the military field have gradually opened up to civilian applications. Technologies such as unmanned aerial vehicles (UAVs) and AI-controlled drones, which are heavily used in the military field, have the potential to follow a similar pattern. Trust can be an important tool in preparing the aviation industry for such a transformation. Organizations such as ICAO (International Civil Aviation Organization), EASA (European Union Aviation Safety Agency), and FAA (Federal Aviation Administration) can facilitate the acceptance of technology by conducting certification processes for AI-controlled aircraft with transparency in a way that reduces public risk perception and minimizes uncertainty. Similarly, AI developers and airlines could inform the public about how the system works, how human control is maintained, and what safety and security systems are in place. Based on perceived usefulness, AI-controlled aircraft may need to be positioned not only as a new technology but also in terms of their functional benefits. Highlighting functional benefits such as reducing or eliminating human error and fuel efficiency can facilitate acceptance. Finally, to reduce uncertainty and promote technology adoption, simulation and phased exposure programs can be used as experience-enhancing tools.

6.3. Limitations

Several limitations must be considered when interpreting the findings of this study. First, AI-controlled flight is a technology that has not yet been directly experienced by users. Therefore, the participants' responses are based largely on assumption and cognitive inference, rather than on real-world experience. This may have had a limiting effect on the measurement reliability of key variables such as perceived benefit, risk, and safety (Sun & Zhang, 2006; Venkatesh & Bala, 2008). From a sample perspective, the research is limited to a specific demographic and cultural structure. This raises questions about the extent to which the results can be transferred to different social contexts. Testing the proposed relationships on other cultural and professional groups will strengthen the generalizability of the model (Tarhini et al., 2016). Furthermore, the cross-sectional nature of the study does not allow for the interpretation of relationships between variables within a causal framework. The use of a self-report data collection method also carries the risk of methodological bias (Podsakoff et al., 2003). While theoretically, TAM is a well-established model that addresses technology acceptance through cognitive processes, it may be insufficient to fully explain the emotional, ethical, and social dimensions that artificial intelligence systems bring with them (Bagozzi, 2007). Including variables such as fear, curiosity, or ethical risk perception in future models could help bridge this gap. The formal back-translation procedure, commonly recommended in the scale adaptation process, was not applied. Although the scale items were evaluated in line with the opinions of field experts and reviewed for linguistic appropriateness, the absence of a formal back-translation process can be considered a limitation in terms of the conceptual equivalence of the expressions. Therefore, it is recommended that more comprehensive translation and cultural adaptation procedures be used in future studies. Finally, given the rapid advancements in AI-powered aviation technologies, it is clear that users' perceptions of trust and safety will not remain static. Longitudinal research designs and realistic simulation environments can offer a much more suitable ground for understanding how these perceptions transform as experience is gained.

ETHICAL STATEMENT & GENERAL STATEMENTS

This study has been found to be in compliance with research and publication ethics by the İskenderun Technical University Scientific Research and Publication Ethics Board's decision with number 10, dated 03.11.2025. This article meets the standards of research and publication ethics.

ARTIFICIAL INTELLIGENCE USE DISCLOSURE

During the preparation of this manuscript, ChatGPT (Open AI) was used for translation purposes, and to improve grammar, spelling, punctuation, and/or linguistic fluency. AI was not used to generate the scientific content of the study. All AI-assisted suggestions were reviewed and verified by the author(s).

AUTHORS' CONTRIBUTIONS

The author has read and approved the final manuscript.

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Not applicable.

COMPETING INTERESTS

The authors declare that they have no competing interests.

REFERENCES

Abuhassna, H., Yahaya, N., Zakaria, M. A. Z. M., Zaid, N. M., Samah, N. A., Awae, F., Nee, C. K., & Alsharif, A. H. (2023). Trends on using the technology acceptance model (TAM) for online learning: A bibliometric and content analysis. *International Journal of Information and Education Technology*, *13*(1), 131–142. https://doi.org/10.18178/ijiet.2023.13.1.1788

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Avetisyan, L., Abolarin, E., Zakarian, V., Yang, X. J., & Zhou, F. (2025). The mediating effects of emotions on trust through risk perception and system performance in automated driving. *International Journal of Human-Computer Studies*, *205*. https://doi.org/10.1016/j.ijhcs.2025.103642

Bağlıbel, M., Samancıoğlu, M., & Summak, M. S. (2010). Okul yöneticileri tarafından e-okul uygulamasının genişletilmiş teknoloji kabul modeline göre değerlendirilmesi. *Mustafa Kemal Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, *7*(13), 331–348.

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems*, *8*(4). https://doi.org/10.17705/1jais.00122

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94. https://doi.org/10.1007/BF02723327

Belton, O., & Dillon, S. (2021). Futures of autonomous flight: Using a collaborative storytelling game to assess anticipatory assumptions. *Futures*, *128*. https://doi.org/10.1016/j.futures.2020.102688

Bliss, T. J., & Wise, A. J. (2023). Examining the future of automation in commercialized flight and its impact on airline pilots. *The Collegiate Aviation Review*, *41*(2). https://doi.org/10.22488/okstate.24.100205

Carlsson, L. (2024). *Technology acceptance of virtual reality for aircraft maintenance training.* Embry-Riddle Aeronautical University.

Çetin, E., Cano, A., Deransy, R., Tres, S., & Barrado, C. (2022). Implementing mitigations for improving societal acceptance of urban air mobility. *Drones*, *6*(2). https://doi.org/10.3390/drones6020028

Chalermpong, S., Thaithatkul, P., & Ratanawaraha, A. (2024). Trust and intention to use autonomous vehicles in Bangkok, Thailand. *Case Studies on Transport Policy*, *16*. https://doi.org/10.1016/j.cstp.2024.101185

Chan, E. T. H., Li, T. E., & Schwanen, T. (2025). Societal acceptance of advanced aerial mobility in China's Greater Bay Area among young- and middle-aged adults. *Transportation Research Part F: Traffic Psychology and Behaviour*, *110*. https://doi.org/10.1016/j.trf.2025.02.008

Çınar, E., & Tuncal, A. (2023a). A comprehensive analysis of society's perspective on urban air mobility. *Journal of Aviation*, *7*(3), 317–328. https://doi.org/10.30518/jav.1324997

Çınar, E., & Tuncal, A. (2023b). The future of UAVs in urban air mobility: Public perception and concerns. *Türkiye İnsansız Hava Araçları Dergisi*, *5*(2), 50–58. https://doi.org/10.51534/tiha.1381175

Clarke, L., & Beck, U. (1994). Risk society: Towards a new modernity. *Social Forces*, *73*(1). https://doi.org/10.2307/2579937

Clothier, R. A., Greer, D. A., Greer, D. G., & Mehta, A. M. (2015). Risk perception and the public acceptance of drones. *Risk Analysis*, *35*(6). https://doi.org/10.1111/risa.12330

Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results. *Management*, *Ph.D.* https://doi.org/oclc/56932490

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–340. https://doi.org/10.2307/249008

Dhagarra, D., Goswami, M., & Kumar, G. (2020). Impact of trust and privacy concerns on technology acceptance in healthcare: An Indian perspective. *International Journal of Medical Informatics*, *141*. https://doi.org/10.1016/j.ijmedinf.2020.104164

Dieter, M., Sprenger, E., Pasnicu, O., Staudt, J., & Ellenrieder, N. (2024). Virtual flight deck crew assistance utilizing artificial intelligence methods to interpret NOTAMs: a user acceptance study. *CEAS Aeronautical Journal*, *15*(4). https://doi.org/10.1007/s13272-024-00767-1

Djartov, B., & Würfel, J. (2025). Navigating decisions in the cockpit: The intelligent pilot advisory system. In *Progress in IS: Part F820, 305–325*. https://doi.org/10.1007/978-3-031-83512-4_18

Fondevila-Gascón, J. F., Gutiérrez-Aragón, Ó., Lopez-Lopez, D., Curiel-Barrios, G., & Alabart-Algueró, J. (2025). Passenger perceptions of artificial intelligence in airline operations: Implications for air transport management. *Journal of Air Transport Management*, *129*. https://doi.org/10.1016/j.jairtraman.2025.102874

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Gao, S., Lu, Z., Luan, H., Yin, M., & Wang, L. (2025). AI pilot in the cockpit: An investigation of public acceptance. *International Journal of Human-Computer Interaction*, *41*(1). https://doi.org/10.1080/10447318.2024.2301856

Halawi, L., Miller, M. D., & Holley, S. J. (2024). Artificial intelligence in aviation: A path analysis. *Journal of Aviation/Aerospace Education & Research*, *33*(4). https://doi.org/10.58940/2329-258x.2061

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors*, *57*(3). https://doi.org/10.1177/0018720814547570

Holley, S., Miller, M., & Halawi, L. (2024). Artificial intelligence on the digital flight deck: A continuum with parallel trajectories. *Proceedings of the Human Factors and Ergonomics Society*, *68*(1), 1260–1264. https://doi.org/10.1177/10711813241260403

Johnson, R. A., Miller, E. E., & Conrad, S. (2022). Technology adoption and acceptance of urban air mobility systems: Identifying public perceptions and integration factors. *International Journal of Aerospace Psychology*, *32*(4). https://doi.org/10.1080/24721840.2022.2100394

Kenesei, Z., Ásványi, K., Kökény, L., Jászberényi, M., Miskolczi, M., Gyulavári, T., & Syahrivar, J. (2022). Trust and perceived risk: How different manifestations affect the adoption of autonomous vehicles. *Transportation Research Part A: Policy and Practice*, *164*. https://doi.org/10.1016/j.tra.2022.08.022

Kim, S. D. (2024). Application and challenges of the technology acceptance model in elderly healthcare: Insights from ChatGPT. *Technologies*, *12*(5). https://doi.org/10.3390/technologies12050068

Kirwan, B. (2024). The impact of artificial intelligence on future aviation safety culture. *Future Transportation*, *4*(2). https://doi.org/10.3390/futuretransp4020018

Komasová, S., Tesař, J., & Soukup, P. (2020). Perception of drone related risks in Czech society. *Technology in Society*, *61*. https://doi.org/10.1016/j.techsoc.2020.101252

Lee, C., Bae, B., Lee, Y. L., & Pak, T. Y. (2023). Societal acceptance of urban air mobility based on the technology adoption framework. *Technological Forecasting and Social Change*, *196*. https://doi.org/10.1016/j.techfore.2023.122807

Macsween-George, S. L. (2003). Will the public accept UAVs for cargo and passenger transportation? *IEEE Aerospace Conference Proceedings*, *1*. https://doi.org/10.1109/AERO.2003.1235066

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1). https://doi.org/10.1007/s10209-014-0348-1

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management*, *34*(1). https://doi.org/10.1016/j.ijinfomgt.2013.06.002

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, *13*(3). https://doi.org/10.1287/isre.13.3.334.81

Menig, A., Becker, N., & Kleudgen, J. P. (2025). Investigating the role of an AI-based assistance system for the decision-making process of pilots- an interview study. *Transportation Research Procedia*, *88*. https://doi.org/10.1016/j.trpro.2025.05.021

Molesworth, B. R. C., & Koo, T. T. R. (2016). The influence of attitude towards individuals' choice for a remotely piloted commercial flight: A latent class logit approach. *Transportation Research Part C: Emerging Technologies*, *71*. https://doi.org/10.1016/j.trc.2016.06.017

Mustafa, A. S., & Garcia, M. B. (2021). Theories integrated with technology acceptance model (TAM) in Online learning acceptance and continuance intention: A systematic review. *2021 1st Conference on Online Teaching for Mobile Education, OT4ME 2021*. https://doi.org/10.1109/OT4ME53559.2021.9638934

Piera, M. A., Munoz, J. L., Gil, D., Martin, G., & Manzano, J. (2022). A socio-technical simulation model for the design of the future single pilot cockpit: An opportunity to improve pilot performance. *IEEE Access*, *10*. https://doi.org/10.1109/ACCESS.2022.3153490

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. In *Journal of Applied Psychology* (Vol. 88, Number 5). https://doi.org/10.1037/0021-9010.88.5.879

Rice, S., Winter, S. R., Mehta, R., & Ragbir, N. K. (2019). What factors predict the type of person who is willing to fly in an autonomous commercial airplane? *Journal of Air Transport Management*, *75*. https://doi.org/10.1016/j.jairtraman.2018.12.008

Sagnier, C., Loup-Escande, E., Lourdeaux, D., Thouvenin, I., & Valléry, G. (2020). User acceptance of virtual reality: An extended technology acceptance model. *International Journal of Human-Computer Interaction*, *36*(11). https://doi.org/10.1080/10447318.2019.1708612

Savaş, T., On, M., & Özdemir, U. (2025). A systematic literature analysis of the public perception of UAVs. *Türkiye İnsansız Hava Araçları Dergisi*, *7*(1). https://doi.org/10.51534/tiha.1623582

Schon, J., Bruder, C., Liebherr, M., & Theis, S. (2025). Cleared for takeoff - artificial intelligence acceptance in air traffic control. *CHIWORK 2025 - Proceedings of the 4th Annual Symposium on Human-Computer Interaction for Work*. https://doi.org/10.1145/3729176.3729185

Schwesig, R., Brich, I., Buder, J., Huff, M., & Said, N. (2023). Using artificial intelligence (AI)? Risk and opportunity perception of AI predict people's willingness to use AI. *Journal of Risk Research*, *26*(10). https://doi.org/10.1080/13669877.2023.2249927

Shao, C., Nah, S., Makady, H., & McNealy, J. (2025). Understanding user attitudes towards ai-enabled technologies: An integrated model of self-efficacy, TAM, and AI ethics. *International Journal of Human-Computer Interaction*, *41*(5). https://doi.org/10.1080/10447318.2024.2331858

Strong, R., Samu, J., Pan, B. D., & Liu, D. (2025). Pilot Acceptance of wearable fatigue monitoring technology using extended technology acceptance model. *Journal of Air Transportation*. https://doi.org/10.2514/1.d0462

Sun, H., & Zhang, P. (2006). The role of moderating factors in user technology acceptance. *International Journal of Human Computer Studies*, *64*(2). https://doi.org/10.1016/j.ijhcs.2005.04.013

Tang, D., & Chen, L. (2011). A review of the evolution of research on information technology acceptance model. *BMEI 2011 - Proceedings 2011 International Conference on Business Management and Electronic Information*, *2*. https://doi.org/10.1109/ICBMEI.2011.5917980

Tarhini, A., Elyas, T., Akour, M. A., & Al-Salti, Z. (2016). Technology, demographic characteristics and e-learning acceptance: A conceptual model based on extended technology acceptance model. *Higher Education Studies*, *6*(3). https://doi.org/10.5539/hes.v6n3p72

Tokadlı, G., Dorneich, M. C., & Matessa, M. (2021). Toward human–autonomy teaming in single-pilot operations: Domain analysis and requirements. *Journal of Air Transportation*, *29*(4). https://doi.org/10.2514/1.D0240

Vance, S. M., & Malik, A. S. (2015). Analysis of factors that may be essential in the decision to fly on fully autonomous passenger airliners. *Journal of Advanced Transportation*, *49*(7). https://doi.org/10.1002/atr.1308

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2). https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly: Management Information Systems*, *36*(1). https://doi.org/10.2307/41410412

Vu, K. P. L., Lachter, J., Battiste, V., & Strybel, T. Z. (2018). Single pilot operations in domestic commercial aviation. *Human Factors*, *60*(6). https://doi.org/10.1177/0018720818791372

Weerasinghe, S., & Hindagolla, M. (2017). Technology acceptance model in the domains of LIS and education: A review of selected literature. *Library Philosophy and Practice*, *2017*.

Winter, S. R., Rice, S., & Lamb, T. L. (2020). A prediction model of consumer's willingness to fly in autonomous air taxis. *Journal of Air Transport Management*, *89*. https://doi.org/10.1016/j.jairtraman.2020.101926

Wongyai, P. H., Suwannawong, K., Wannakul, P., Thepchalerm, T., & Arreras, T. (2024). The adoption of self-service check-in kiosks among commercial airline passengers. *Heliyon*, *10*(19). https://doi.org/10.1016/j.heliyon.2024.e38676

Yavaş, V., & Yavaş Tez, Ö. (2021). Kentsel hava taşımacılığı kabul ve kullanım modeli: Bir ölçek geliştirme çalışması. *Journal of Aviation Research*, *3*(2). https://doi.org/10.51785/jar.962735

Yılmaz-Halıcı, Ö., Yıldız, E., Çeken, S., Beyhan-Acar, A., & Özveren, C. G. (2025). Understanding Public perceptions of unmanned aerial vehicles in Türkiye. *Aviation Psychology and Applied Human Factors*. https://doi.org/10.1027/2192-0923/a000303

Yoo, J., Choe, Y., & Rim, S. I. (2022). Risk perceptions using urban and advanced air mobility (UAM/AAM) by applying a mixed method approach. *Sustainability (Switzerland)*, *14*(24). https://doi.org/10.3390/su142416338

Zhang, G., & Yu, T. (2025). Association between generative AI self-efficacy and generative AI acceptance: The mediating role of generative AI trust and the moderating role of generative AI risk perception. *Acta Psychologica*, *261*. https://doi.org/10.1016/j.actpsy.2025.105791

Zhang, K. (2021). Application of data mining based on machine learning in automobile power prediction. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3501409.3501532

Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., & Zhang, W. (2019). The roles of initial trust and perceived risk in public's acceptance of automated vehicles. *Transportation Research Part C: Emerging Technologies*, *98*. https://doi.org/10.1016/j.trc.2018.11.018

Zhu, W., Huang, L., Zhou, X., Li, X., Shi, G., Ying, J., & Wang, C. (2025). Could AI Ethical anxiety, perceived ethical risks and ethical awareness about AI influence university students' use of generative AI products? An ethical perspective. *International Journal of Human-Computer Interaction*, *41*(1). https://doi.org/10.1080/10447318.2024.2323277