UNIVERSIDADE CATÓLICA PORTUGUESA

Artificial Intelligence in aviation and airports

Understanding the determinants of adoption and intention to recommend the technology

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Católica Porto Business School

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Abstract

The aviation, an industry usually at the forefront of technological innovation, welcomed Artificial Intelligence (AI) in the last years as a catalyst for transformative change, with several benefits in many domains. Aviation and airports are two sectors of upmost importance in global economy, technology adoption studies in this area involving AI are still scarce and, in some cases, present disperse results, therefore requiring further investigation. In this study we used a mix method approach, combining an initial qualitative analysis with a quantitative analysis with structured equation modelling (SEM). We advance the body of knowledge by designing and using an innovative theoretical research model that combines the strengths of three well-established theories: Artificial Intelligent Device Use Acceptance (AIDUA), the Technology Acceptance Model (TAM), and the Innovation Resistance Theory (IRT), with an Intention to Recommend construct. The research model was empirically tested using one hundred and ninety-six (196) responses mainly collected in a European country. Hedonic motivation, social influence, performance expectancy, value barrier, and behavioural intention were found to influence the adoption of AI. The likelihood of a customer recommending the technology was also confirmed. For researchers, this study may serve as an initial basis for further acceptance models' refinement. For practitioners, understanding the factors that influence AI adoption is crucial to implement and to refine devices, applications, and services in the aviation industry, with increasing the levels of acceptance and recommendation.

Keywords: Artificial Intelligence, aviation, airports, AIDUA, TAM, ITR,
adoption, intention to recommend

Resumo

A aviação, uma indústria geralmente na vanguarda da inovação tecnológica, acolheu a Inteligência Artificial (IA) nos últimos anos como um catalisador de mudança transformadora, com vários benefícios em muitos domínios. A aviação e os aeroportos são dois setores de extrema importância na economia global, estudos de adoção de tecnologia nesta área envolvendo IA ainda são escassos e, em alguns casos, apresentam resultados dispersos, exigindo, portanto, uma investigação adicional. Neste estudo, utilizamos uma abordagem mista, combinando uma análise qualitativa inicial com uma análise quantitativa com modelagem de equações estruturais (SEM). Avançamos o corpo de conhecimento ao projetar e usar um modelo teórico de pesquisa inovador que combina as forças de três teorias bem estabelecidas: Aceitação de Uso de Dispositivos de Inteligência Artificial (AIDUA), o Modelo de Aceitação de Tecnologia (TAM) e a Teoria de Resistência à Inovação (IRT), com um construto de Intenção de Recomendação. O modelo de pesquisa foi testado empiricamente usando cento e noventa e seis (196) respostas coletadas principalmente num país europeu. Motivação hedônica, influência social, expectativa de desempenho, barreira de valor e intenção comportamental foram encontrados para influenciar a adoção de IA. A probabilidade de um cliente recomendar a tecnologia também foi confirmada. Para pesquisadores, este estudo pode servir como uma base inicial para o aperfeiçoamento de modelos de aceitação. Para os praticantes, entender os fatores que influenciam a adoção de IA é crucial para implementar e refinar dispositivos, aplicativos e serviços na indústria da aviação, aumentando os níveis de aceitação e recomendação.

Palavras-chave: Inteligência artificial, aviação, aeroportos, AIDUA, TAM, ITR, adoção, intenção de recomendar

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1. Introduction

Advancements in Artificial Intelligence (AI) have sparked a transformative wave across industries, revolutionizing operational landscapes and redefining the realm of possibility. Within this domain, aviation emerges as a vanguardist industry, not only integrating AI to increase operational efficiency, but also to redefine safety standards, passenger, and airport user experience. AI, fundamentally designed to replicate human intelligence or even to surpass it in some specific domains, has become pivotal in reshaping the core functions of the aviation sector (EASA, 2023; Farzaneh et al., 2021). From its inception in the mid-20th century to its contemporary expertise, the evolution of AI within the aviation industry has been complex and substantial. Over the decades progressed from experimental stages to permeating everyday operations, spanning flight control systems and to customer service (Boucher, 2019; Brynjolfsson et al., 2017). The airport sector welcomed AI as a catalyst for transformative changes in many core areas, evolving from simple traditional airports into modern smart airports with several AI-driven technology showcases (Koroniotis et al., 2020; Serrano & Kazda, 2020). However, the promise of AI-driven advancements also poses some challenges that deserve careful consideration. Cybersecurity, vulnerabilities, potential job displacement, inadequate regulatory frameworks, and ethical dilemmas are among the critical concerns challenging the integration of AI in aviation and in airports (Conde & Twinn, 2019; EASA, 2023). The complexity of all these subjects underscored the industry's measured approach to the adoption of AI, prioritizing safety, reliability, and meticulous planning over rapid assimilation (EASA, 2023). Therefore, this research delves into the core factors behind the adoption and recommendation of AI in the aviation industry.

This study offers a dual contribution to the understanding of the factors driving the adoption of AI within the aviation and airports sectors. Firstly, both direct and indirect factors influencing the acceptance of AI-based technologies were explored. For that reason, an innovative conceptual model was developed, not used in literature until now as far as we know, that combines the strengths of the Artificial Intelligent Device Use Acceptance (AIDUA) (Gursoy et al., 2019), the Technology Acceptance Model (TAM) (Davis, 1989), and the Innovation Resistance Theory (IRT) Click or tap here to enter text.). By integrating these three well-known theories we significantly enhance the predictive power of conventional TAM, contributing to knowledge advancement and at the same time addressing earlier literature failure to explain the absence of AI device adoption behaviours within service-oriented domains, overcoming known limitations. In more detail, first, traditional models underscore ease-of-use, a criterion potentially misaligned with AI service devices, given their design to mimic human interaction. Second, assessing the efficacy of AI devices requires the inclusion of emotional evaluations, reflecting their participatory role in social engagements. Third, the transition from human to AI-driven service yields a spectrum of impacts on the receptivity of individuals towards these services. To navigate the intricacies of AI adoption, the AIDUA framework is introduced, elucidating the progressive and dynamic facets of acceptance and resistance towards AI technology deployment combined. Secondly, a construct of intention to recommend AI technology was also introduced, since prior research predominantly focused on technology usage (Lancelot Miltgen et al., 2013) ,assuming it can add great value to this matter (Moe et al., 2012). This almost unexplored area holds significant promise and relevance to knowledge, especially in a time where users actively shape perceptions through their social networks. Moreover, the aviation and airports sectors hold vital significance in the global economy. Despite this importance, studies on the technology adoption, particularly concerning AI, remain limited in these domains and often hold disparate results, thus necessitating additional research efforts. This evaluation is pivotal as it could influence the trajectory of this technology within aviation and airports, impacting both industry professionals and individuals benefiting from aviation and airports services. Furthermore, our work enables a deeper understanding of the influence exerted by both positive variables (from the AIDUA) and negative variables (from the IRT) on the intention to recommend this technology in the aviation and airports sectors.

The paper is structured across several key sections. It begins by delving into the concept and evolution of Artificial Intelligence, outlining its progression and specific presence in the aviation and airport sectors. This research continues with an in-depth analysis of the associated benefits, risks, and challenges linked to the adoption of AI in these domains. Next, the paper describes the research model employed, the methodology adopted, and the resulting findings. Subsequently, it engages in a discussion centred around the implications of these results, clarifying theoretical contributions and their potential managerial impact. Finally, the paper concludes by presenting various possibilities for future research, providing potential directions for further investigation within the domain of AI in aviation and airports. In our study we used a mix method approach, combining an initial qualitative analysis with a quantitative analysis, described as follow.

2. Literature Review

2.1 Artificial Intelligence and its evolution

The term "Artificial Intelligence" was first introduced in August 1955 by McCarthy et al. (2006). Their pioneering work suggested that many aspects of learning and intelligence could be described so precisely that a machine could be taught to mimic them (McCarthy et al., 2006). By the late 1990s, AI had made significant steps in reducing decision-making ambiguity, with the advent of statistical learning techniques like Fuzzy Logic (Farzaneh et al., 2021). These AI principles found applications in everyday life, from controlling washing machines to managing high-speed trains, and even in trading stocks (Boucher, 2019; Brynjolfsson et al., 2017). The early 2000s saw a transformative period for AI, driven by the synergy between Machine Learning (ML) and the explosion of Big Data (Reillon, 2018). Enhanced AI capabilities began to foster experience-driven learning, and together with the Internet of Things (IoT) and the vast volume of data generated every second, initiated a revolutionary shift in the application of technology. This profound integration has permeated numerous industries, including finance, healthcare, robotics, education, and transportation (Chen et al., 2020;Virvou et al., 2022).

The swift advancement of AI technology has considerably expanded its potential applications. Even though there is a growing sense of apprehension regarding AI, largely stemming from concerns related to control, the anticipated benefits are immense. It is these benefits that underscore the importance of addressing any reservations and fully exploring the capabilities of AI (Joanna J. Bryson, 2019). Central to the continued development of AI is the overarching goal to amplify the human potential, which remains a guiding light for researchers and innovators (Farzaneh et al., 2021). In this context, we will delve into the AI implications for the aviation and airport sectors, identifying the principal risks and challenges, as follow.

2.2 Artificial Intelligence in the aviation and airport sectors

The transformative power of AI has been felt across various industries, with the aviation and airport sectors being no exception. As a crucial pillar of the global economy and technological landscape, air transportation stands out as one of the most preferred methods for ferrying goods and passengers. It owes its popularity to attributes such as speed, comfort, reliability, and national defence. Historically, the aviation sector has been at the forefront of adopting cutting-edge technologies to enhance operational efficiency, safety, customer experience, and emergency medical assistance; Therefore, the integration of AI into these domains has been revolutionizing traditional operations (Ivanov et al., 2023). From its inception with pioneering flights to the sophisticated operations of today, aviation has witnessed a series of technological metamorphoses that have cumulatively refined the domain of air travel. Among the most transformative advancements is the integration of AI. This infusion offers the capability to engineer intelligent systems that not only furnish unparalleled assistance to human operators, but also increase aircraft performance, refine air traffic coordination, and elevate safety to previously uncharted levels (EASA, 2023).

In the present day, this evolution is made possible through the development and implementation of smart airports (Alansari et al., 2019). The development of airports has been significantly influenced by the emergence of is commonly called as "Industry 4.0", or as the fourth industrial revolution. It has promoted the evolution of the industry by harnessing various technologies, forcing airports to quickly adjust to it (Roblek et al., 2016). Airports have undergone a transformative journey, evolving through four distinct phases: airport 1.0 to airport 4.0 Click or tap here to enter text.. The initial phase, airport 1.0, prioritized fundamental safety operations for aircraft, emphasizing procedures such as take-off, refuelling, and landing. During this phase, passengers were catered to with basic services, primarily focused on boarding and disembarking. Transitioning to the airport 2.0 stage, airports displayed greater adaptability to changing demands. A combined approach emerged with cohesive data exchange via a central network, aligning various airport segments. This approach marked an uplift in operational efficiency and enhanced passenger experiences (Koroniotis et al., 2020). Entering the airport 3.0 era, automation became central to operational controls, with predictive tools and advanced mobility solutions becoming prominent both in terminals and on the airside. The current stage, of a considerable number of airports, airport 4.0, harnesses the power of vast and open datasets to fuel innovation (Rajapaksha & Jayasuriya, 2020). Features like digital biometric identities, sustainable practices, enhanced customer service, integrated security measures, and intelligent service management come to the forefront in this phase (Serrano & Kazda, 2020). Smart Airports use several technologies such as Artificial Intelligence (AI), Machine Learning (ML), machine vision, robotics, natural language processing, the Internet of Things (IoT), advanced aircraft systems, digital twin. It facilitates efficiency by enabling the exchange of real-time information, fostering deep-seated cooperation, and integrating extensive airport processes (Wang et al., 2017). AI applications already cover areas such as predictive maintenance, air traffic management, passenger services, and security, among other areas (Rajapaksha & Jayasuriya, 2020). It also contributes to the making airport services more attractive, ensuring compliance with the rules, norms, and safety standards of the industry (Khadonova et al., 2020).

When analysing the numerous benefits of AI in depth, a feature that stands out significantly is its role in predictive maintenance, both for aircraft and airport infrastructure. Maintenance expenses account for a substantial portion of operating costs for multiple reasons, including but not limited to, the repercussions of flight delays, inventory stock costs, situations of aircraft on the ground (AOG), and the upkeep of critical infrastructures such as runways, taxiways, terminal buildings, security systems, and parking facilities (Kumar, 2022; Lahna et al., 2023). The integration of AI can significantly mitigate these challenges. As the digitization wave progresses, production and maintenance organizations find themselves dealing with vast data volumes. The role of AI in interpreting massive amounts of data and recognizing patterns within it becomes particularly predominant (EASA, 2023). Predictive maintenance powered by AI, enables real-time monitoring of an aircraft's technical status. By utilizing AI technology, a more efficient reporting and analytics process can lead airlines to financial savings, reducing expenses related to expedited component shipping and additional payments for crew members working extended hours (Dalal et al., 2022).

Air Traffic Control (ATC) is another area where AI shows a significant potential, especially when enhancing operations and ensuring most safety becomes crucial. AI has the capability to refine every phase of air travel, from initial flight preparations to trajectory predictions and even automated air traffic oversight, all aimed at amplifying operational efficiency (Kumar, 2022). By meticulously examining data on atmospheric patterns, sector layouts, air traffic congestion, and aiding in swiftly preparing runways for subsequent landings, AI/ML techniques can assist in refining flight routes. This leads to lower flight durations, reduced fuel usage, higher levels of sustainability, and overall cost savings. Such meticulous streamlining subsequently results in an ATC system that is more efficient, cutting delays and amplifying air travel capacity, providing a better traffic management (EASA, 2023; Kumar, 2022).

The transformative capabilities of AI are also prominently seen in its ability to elevate customer service and enhance the overall satisfaction of travellers in the aviation industry. One way to achieved this is connecting AI to the systems and services, refining, and processing real-time feedback from customers. Certain AI algorithms proficiently detect live reactions on social media platforms by searching for relevant keywords, brand associations, geographical tags, and issues relevant to both the company and its competition (Memarzadeh et al., 2020). Other systems emulate human-like interactions with customers, offering better real-time customer service (Kumar, 2022). By combining customer experience and innovation, airports can create a modern and efficient travel environment that prioritizes passenger satisfaction and operational excellence. By utilizing AI technology, airports can enhance services streamline processes, and provide a seamless and enjoyable experience for travellers (Alansari et al., 2019). A case in point is the smart check-in feature. Travelers can use various platforms like websites, mobile apps, personal devices, and computer kiosks to check in (Wittmer, 2011). Another example is the possibility to provide personalized retail and hospitality services to passengers based on their preferences and travel purposes by utilizing data available from the passenger (ChunMin et al., 2016) . By implementing smart airports initiatives, such as IOT applications, data analytics, and automation, it transforms the way airports operate and interact with customers. This customer-centric approach ensures that airports remain competitive, efficient, and responsive to the evolving needs of passengers in the digital age (Alansari et al., 2019).

Another benefit of employing AI technology is the enhanced security it brings to both airports and the broader aviation sector. Compliance with aviation security regulations is crucial to ensure the safety of passengers, aircraft, and all other airport users. Consequently, smart airports are increasing aviation security standards using modern technology in accordance with regulatory requirements, while also aiming to reduce inconvenience for passengers (Rajapaksha & Jayasuriya, 2020). Given that security checks at airports can often be time-consuming and sometimes result in passenger dissatisfaction, the introduction of IoT with AI can be a strategic move to expedite and streamline procedures related to passengers (Jalali & Zeinali, 2018). The potential of AI extends to areas like security assessments and passenger verification, where routine processes are being redefined by the integration of advanced scanners and biometric systems (Kumar, 2022). Furthermore, the area of luggage inspection has seen the development of AI-assisted machinery capable of efficiently scrutinizing luggage across multiple lanes (Puranik & Mavris, 2020).

In addition to the benefits highlighted, other notable advantages emerge from the integration of Artificial Intelligence in the air travel booking systems. First, the introduction of "dynamic pricing" strategies enables the aviation industry to optimize pricing based on a variety of factors, such as departure times, destinations, travel distances, and ticket availability, ensuring maximized profits in alignment with the prevailing market dynamics (Kumar, 2022). In addition, the introduction of aerodrome drones, has allowed a smother introduction to a possible future of a complete autonomous aircraft by using AI and ML systems (EASA, 2023; Ivanov et al., 2023). Finally, the advent of AI-driven flight simulators provides pilots with an immersive and comprehensive training environment. These simulators, equipped with AI capabilities, offer personalized training modules for pilots by assimilating and analysing vast data sets (Kumar, 2022).

2.3 Risks, and challenges associated with Artificial Intelligence

Artificial Intelligence presents numerous opportunities in the aviation sector, however it also introduces a set of risks and challenges that deserve careful consideration. In the subsequent integration of AI in aviation, cyberattacks emerge as the most pressing and significant threat, increasing the need to improve the cybersecurity of the systems. The cybersecurity domain includes three key components: threats that could harm an organization by taking advantage of its vulnerabilities; systems that have vulnerabilities that put it at risk of being exploited, causing operational impacts; and security controls put in place by the defender that reduce one or more security risks (EASA, 2023). Recent studies conducted over the years have shown that the frequency of cyber-attacks is increasing (Geib Alison, 2023). A competent team of hackers can breach airport security systems, accessing and potentially compromising sensitive data, ranging from flight information to personal details (Delain et al., 2016). The stolen data may include crucial information regarding delays or basic information about flights, as well as the names of employers and individual passengers. Additionally, it may result in numerous subsequent attacks that harm IT infrastructures, disrupting airport operations for an extended time (Suciu et al., 2019).

Beyond cybersecurity concerns, another significant risk associated with the increase of AI in aviation is the potential displacement of human jobs. As AI begins to infiltrate sectors traditionally managed by people, there is an observed shift towards a more automated service economy. This change could accelerate the reduction of roles across a spectrum of skills, from basic tasks to specialized ones (Conde & Twinn, 2019). For instance, roles in Data Science might undergo a transformation, especially in areas that involve complex data correlation and analysis (EASA, 2023).

Moreover, the aviation industry is facing operational challenges, emphasized by incomplete regulatory and legal frameworks, gaps in staff competencies, and infrastructural unpreparedness. The introduction of AI also entails significant ethical and social dilemmas. Although the European Union has taken steps towards categorizing AI systems based on risk levels, the industry still lacks a comprehensive set of standards and regulations that address every aspect of its operation (Ivanov et al., 2023).

Addressing these challenges requires holistic industry training to equip everyone with the knowledge to harness AI responsibly and efficiently, from operational staff and flight crews to technical specialists (EASA, 2023). Furthermore, existing airport infrastructures must undergo adaptations to accommodate and optimize AI-driven changes, ensuring a sustained appeal and efficiency for stakeholders and clients alike. A key concern with AI application is data quality. For AI to realize its maximum potential in the aviation sector, it is imperative that the industry use high-quality data. Only with reliable and accurate data can the true benefits of this technology be fully harnessed (Kumar, 2022).

It is evident that the aviation industry continues to take a cautious approach to AI integration given the scope and complexity of these difficulties, especially when compared to other industries. Considering the inherent aviation potential risks and particular operational requirements, it is expected that AI adoption may take longer and be more cautious in this industry. While other industries may rush to adopt AI advancements, the aviation sector, which is constantly concerned with reliability and security, will take longer to ensure that every move forward is well-planned and secure. This measured pace highlights the industry's dedication to striking a balance between innovation and the absolute necessity for passenger safety and system integrity (EASA, 2023).

2.4 Main theoretical models used in literature

Prior literature studied new technologies acceptance as a technical innovation. Six predominant theoretical currents in literature include the innovation diffusion theory (IDT) (Rogers, 1995), theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), theory of planned behaviour (TPB) (Ajzen, 1991), technology acceptance model (TAM) (Davis, 1989), theory of perceived risk (TPR) (Featherman & Pavlou, 2003), and unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). IDT explains factors affecting technology acceptance over time. TRA links beliefs, attitudes, norms, intentions, and behaviours. TPB extend TRA by adding perceived behavioural control. TAM, adapted from TRA, suggests technology use is based on perceived ease of use and usefulness. In 2003, Venkatesh et al. (2003) proposed the UTAU, consolidating eight prominent theories into a comprehensive model for acceptance studied.

The Advanced Intelligent Device Use Acceptance (AIDUA) framework integrates both cognitive and emotional evaluations alongside the acceptance and resistance concerning the utilization of AI-driven devices. The model posits a process supporting the individual’s willingness to engage with AI devices within service transactions. In the preliminary phase, the initial attitudes towards AI-driven devices are formed, which are more likely to have a higher effect on the evaluation of the usage of these devices in specific contexts. Next, the user evaluates the use of AI devices in a more measured and more context-focused manner based on two factors, performance expectancy and effort expectancy (Gursoy et al., 2019).

The Technology Acceptance Model (TAM) has found a widespread application elucidating user behaviour when confronted with novel technological advancements (Davis, 1989). Several scholars have underscored the importance of TAM as a theoretical framework over the years, asserting its reputation over alternative conceptual models. Consequently, TAM has been recognized as a theory possessing significant explanatory efficacy in the context of technology adoption (Porter & Donthu, 2006).

The Innovation Resistance Theory (IRT) was introduced by Ram & Sheth (1989). This model helps understand the resistance-oriented behaviour toward the innovations. Resistance to innovation is characterized by reactions to the acceptance and implementation of new ideas, which lead to upholding existing norms and avoiding changes to prevailing beliefs. (Ma & Lee, 2019). Researchers have noted that user resistance plays a crucial role in deciding the triumph or downfall of new technological advancements (Kaur et al., 2020). Based on the IRT, there are two types of user resistance: active and passive (C. S. Yu & Chantatub, 2016a). Active resistance is tied directly to the features of the innovation, while passive resistance arises mainly due to clashes with individual's current beliefs induced by the innovation. Functional barriers like Usage, Value, and Risk are used to analyse active resistance, which are the variables that are going to be analysed in this model.

3. Research Model

Our research employs an innovative composite model, integrating the Artificial Intelligent Device Use Acceptance (AIDUA) (Gursoy et al., 2019) , the Technology Acceptance Model (TAM) (Davis, 1989), the Innovation Resistance Theory (IRT) (Ram & Sheth, 1989), and the Intention to Recommend construct (Lancelot Miltgen et al., 2013) to meticulously examine the determinants influencing the adoption and recommendation of Artificial Intelligence technology in aviation and airports. The research model is shown in Figure 1.

The combination of these three models fosters a more comprehensive understanding of a user's propensity to adopt and recommend AI technology within the aviation and airports sectors, and therefore is used in our work.

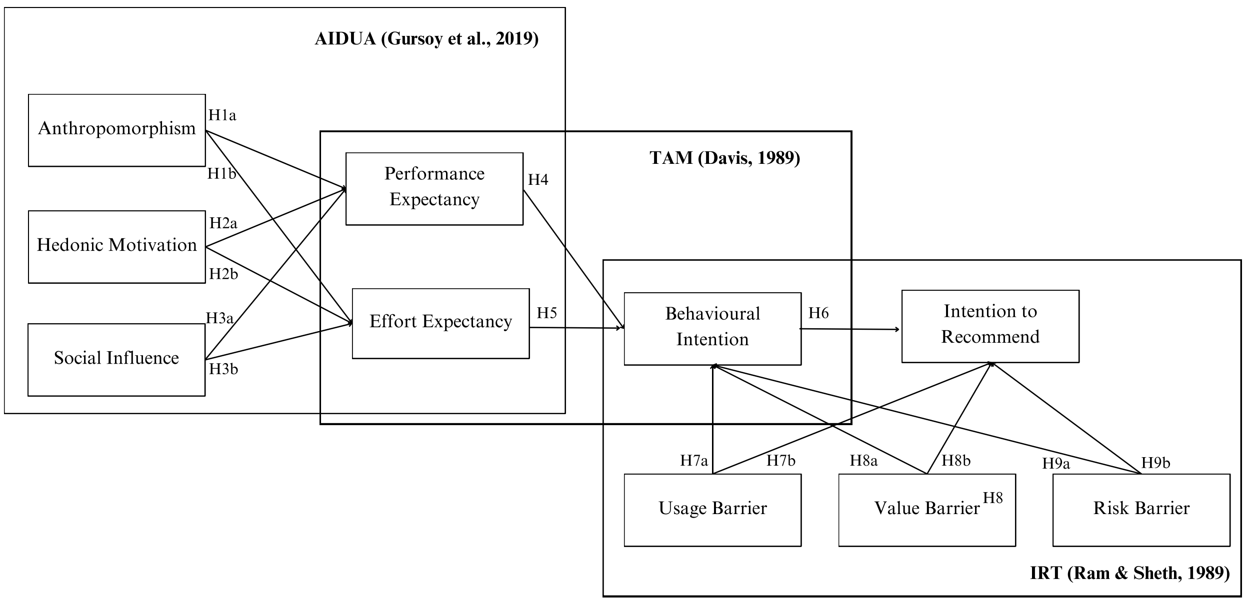


Figure 1 - Research Model

Anthropomorphism refers to the level of an object's humanlike characteristics such as human appearance, self-consciousness, and capacity to express emotions (Hye-Young Kim & Ann. L. Mcgill, 2008). The physical and intellectual similarity of AI devices instantaneously activate consumers initial evaluation of self-relevance, as well as whether such design is aligned to their existing beliefs of technologies used for service interactions. It is an important determinant of how customers behave in terms of AI device use (Lu et al., 2019). Therefore, we hypothesize:

H1a. The impact of anthropomorphism on performance expectancy will be positive.

H1b. The impact of anthropomorphism on effort expectancy will be positive.

Hedonic motivation is related to the perceived fun or pleasure that the user is expected to receive when using AI-driven devices (Gursoy et al., 2019). Hedonic factors usually refer to intrinsic motivation within the consumers (Kim et al., 2016; Law et al., 2018). As a result, customers who have hedonic motivations for using AI devices are more likely to have a positive attitude towards using them (Gursoy et al., 2019). Therefore, we hypothesize:

H2a. The impact of hedonic motivation on performance expectancy will be positive.

H2b. The impact of hedonic motivation on effort expectancy will be positive.

Social influence refers to the degree to which people believe that using AI devices conforms to their group norms (Venkatesh et al., 2003). Theories suggest that individuals are more likely to conform to group norms if the group is important to them. The customer's social network norms and attitude are critical determinants of an individual's behavioural intentions (Gursoy et al., 2019). Therefore, we hypothesize:

H3a. The impact of social influence on performance expectancy will be positive.

H3b. The impact of social influence on effort expectancy will be positive.

Performance expectancy refers to the extent to which people believe that AI devices are likely to perform as well as human beings or even outperform them in terms of accuracy and consistency (Venkatesh et al., 2003). This dimension evaluates the anticipated efficacy and usefulness of the AI service devices, playing a crucial role in influencing individuals' acceptance and adoption decisions concerning these technologies (Gursoy et al., 2019). Therefore, we hypothesize:

H4. The impact of performance expectancy on behavioural intention will be positive.

Effort expectancy is related to the degree of ease associated with the use of AI service devices. It encapsulates the anticipated amount of effort required to engage with and derive benefits from these services transactions (Venkatesh et al., 2003). It is crucial to help understand how the perceived ease or difficulty of using AI devices can impact their acceptance and subsequent use by individuals (Gursoy et al., 2019). Therefore, we hypothesize:

H5. The impact of effort expectancy on behavioural intention will be positive.

Behavioural intention refers to the willingness or intention to engage in a specific behaviour, such as using a particular technology or system (Davis, 1989). It represents the willingness expressed by the users to engage with and endorse AI-driven solutions in the aviation sector. This variable plays a crucial role since it has a substantial influence on technology use (Venkatesh et al., 2003). Therefore, we hypothesize:

H6. The impact of behavioural intention on intention to recommend will be positive.

Usage barrier relates to the resistance stemming from potential changes brought about by innovation. It evaluates the resistance due to the effort required to learn and implement the new system and the changes to the existing routine and habits (Ram & Sheth, 1989). Therefore, we hypothesize:

H7a. The impact of usage barrier on behavioural intention will be positive.

H7b. The impact of usage barrier on intention to recommend will be positive.

Value barrier concerns the resistance arising from misalignment with the current value system. This is especially evident when weighing the costs of adopting and learning the innovation against the benefits it provides (Morar & Dumitrela, 2013). Research indicates that value barriers are linked with user behaviour concerning resistance, adoption, and the utilization of various digital initiatives. Many past studies suggest that value barriers often negatively impact user intentions across different scenarios (Kaur et al., 2020). Therefore, we hypothesize:

H8a. The impact of value barrier on behavioural intention will be positive.

H8b. The impact of value barrier on intention to recommend will be positive.

Risk barrier is related to the resistance arising from the inherent uncertainties linked with any innovation. The acceptance of innovation is influenced by the degree of uncertainty it introduces (Dunphy & Herbig, 1995). As an illustration, innovations with greater uncertainty levels tend to have reduced acceptance. There are four distinct risks related to innovation: physical, economic, functional, and social (Ram & Sheth, 1989). Therefore, we hypothesize:

H9a. The impact of risk barrier on behavioural intention will be positive.

H9b. The impact of risk barrier on intention to recommend will be positive.

4. Methodology and data collection

In our study we used a mix method approach, combining an initial qualitative analysis with a quantitative analysis, described as follow.

4.1 Qualitative analysis

Generalist initial surveys were conducted to explore various facets of the topic to get insights from aviation specialists such as pilots, air traffic control, maintenance engineers, aerospace engineers. A total of seven interviews were performed. The questionnaire used for this purpose can be found in Appendix A. The responses obtained from the interviews were meticulously treated and analysed. This involved an examination of the data collected to identify recurring themes, extract key insights, and recognize patterns within the responses. This stepwise approach ensured a comprehensive and systematic investigation of the research topic. Providing a strong foundation for the next phases of our study.

The responses obtained and the subsequent analysis were helpful in shaping the theoretical framework by providing valuable perspectives and guiding the selection of relevant variables to include. The expert opinions were also used in the discussion of our work' results, adding additional support to this important chapter.

4.2 Quantitative measurement

To test the theoretical constructs, a survey in English was created. The questionnaire was developed from existing literature using constructs and items from the literature (refer Appendix B), targeting adult population with previous experience in airplane travels. Measurement items for anthropomorphism, hedonic motivation, social influence, performance expectancy and effort expectancy, were adapted from Lu et al. (2019) and Venkatesh et al. (2012). The behavioural intention item was adapted from Yuen et al. (2021), while items related to usage, value, and risk barriers were adapted from Laukkanen (2016). Lastly, the intention to recommend item was adapted from Oliveira et al. (2016). Each item was measured on a seven-point Likert scale, ranging from 1 (totally disagree) to 7 (totally agree). The questionnaire also included six demographic questions (age, gender, country, education level, marital status, and employment status), and two control questions.

The questionnaire, originally in English, was translated to Portuguese and validated by an academic from a local university, and then translated back into English, by different people. This process aimed to maintain consistency and accuracy in the survey instruments used for data collection.

4.3 Data Collection

The questionnaire diffusion involved distribution through personal and professional networks and across various social media platforms, between October 2023 to January 2024, using links that could only be used once. The survey was pilot tests amongst a group of 30 respondents, that were not included in final data, to ensure preliminary evidence that the scales were valid. The cumulative responses gathered a total of one hundred and ninety-six (196) completed surveys. First and second respondent groups were compared using the Kolmogorov–Smirnov (K–S) test and verified that they do not differ statistically. The common method bias was also examined using the Harman's single factor test (Podsakoff et al., 2003) and a marker variable (Lindell & Whitney, 2001), confirming their non-existence. The age of the respondents ranged from 18 to over 65 years old, with a predominant representation of people from 18 to 24 years old. The predominant gender representation was female with 62%. Over 95% of the respondents are from Portugal. A significant portion of participants holds a bachelor's degree, while the prevalent marital status reported was single. Moreover, a considerable majority is a full-time worker. Table 1 displays comprehensive descriptive statistics outlining the characteristics of the respondents in detail. In the common method bias (CMB) the SPSS program was used to examine the Harman's single factor, which showed a variance extracted of 34.162% (Podsakoff et al., 2003). Regarding the random dependent variable, the values of the VIF were under the value of 5 by using the CQ1 variable (Hair et al., 2017; Kock & Lynn, 2012), confirming no significant common bias method in the data.

Table 1 - Descriptive statistics of respondents' characteristics

Measure	Value	Frequency	%
Age	Between 18 - 24	83	42.3%
	Between 25 - 64	110	56.1%
	Over 65	3	1.5%
Gender	Feminine	122	62.2%
	Masculine	72	36.7%
	Other	2	1%
Country	Portugal	187	95.4%
	Other European Country	7	3.6%
	Other	2	1%
Education Level	Lower than Bachelor	34	17.3%
	Bachelor's degree	90	45.9%
	Master's degree or higher	68	34.7%
	Other	4	2%
Marital Status	Married	68	34.7%
	Widowed	1	0.5%
	Divorced	14	7.1%
	Single	93	47.4%
	Other	20	10.30%
	Full-time	103	52.6%

Measure	Value	Frequency	%
Employment Status	Part-time	4	2%
	Contract	15	7.7%
	Retired	6	3.1%
	Unemployed	2	1%
	Student	60	30.6%
	Other	6	3%

5. Data Analysis and Results

Structural Equation Modelling (SEM) method commonly employed to establish causal relationships through a blend of statistical data and qualitative hypotheses, has garnered attention from researcher due to its capacity to differentiate between measurement and structural models while factoring in measurement error (Henseler et al., 2009). Within SEM, there are two primary techniques: covariance-based and variance-based approaches. In the context of this study, the variance-based method utilizing partial least squares (PLS) is preferred due to several reasons: first, not all items in the dataset conform to a normal distribution ($p<0.01$) based on the Kolmogorov-Smirnov test; second, the research model was not yet tested in existing literature; third, the research model is considered complex. To analyse the research model, Smart PLS 4 software (Ringle et al., 2022) is employed. The analysis begins with an assessment of the measurement model to assess its reliability and validity, followed by the structural model testing.

5.1 Measurement model

The measurement model was progressively assessed for items reliability, internal consistency, convergent validity, and discriminant validity. Table 2 lists the average variance extracted (AVE), composite reliability (CR), Cronbach's alpha values, loadings, and t-values. Starting with the item's reliability, all loadings presented values above 0.7, confirming their reliability.

The items' reliability was evaluated based on the criteria that the loadings should be greater than 0.7 (Straub, 1989), and that every loading under this value should be eliminated (Henseler et al., 2009). Indicators A1, EE1, EE2, EE3, VB3, and VB4 were eliminated due to low factor loading (Yi et al., 2006). In what concerns to internal consistency, all constructs have composite reliability above the 0.7 threshold, and all constructs except intention to recommend show Cronbach's alpha values above 0.7. Following Taan & Hajjar (2018) suggestion, if a Cronbach's alpha falls between 0.6 and 0.8, the scale used to measure the construct should also be consider consistent, confirming a good indicator reliability of the instrument. Convergent validity was assessed using the Average Variance Extracted (AVE) as a criterion. For adequate validity, the AVE should exceed 0.5 (Fornell & Larcker, 1981). As seen in Table 2 all constructs surpass the AVE minimum acceptable value, fulfilling this criterion.

Table 2- Quality Criterion and Factor Loadings

Construct	Item	AVE	Composite Reliability	Cronbach's Alpha	Loadings	t-value
Anthropomorphism	A2	0.755	0.90	0.84	0.91	6.33
	A3				0.88	7.17
	A4				0.82	5.84
Hedonic Motivation	HM1	0.863	0.95	0.92	0.89	89.14
	HM3				0.88	42.53
	HM5				0.92	59.35
Social Influence	SI1	0.756	0.95	0.94	0.83	23.87
	SI2				1.00	41.72
	SI3				0.94	42.60
	SI4				0.93	64.89
	SI5				0.92	55.89
	SI6				0.91	37.35
Performance Expectancy	PE1	0.829	0.95	0.93	0.82	47.09
	PE2				0.89	34.50
	PE3				0.91	66.28
	PE4				0.92	73.52
Effort Expectancy	EE4	-	-	-	0.92	n/a
Behavioural Intention	BI1	0.779	0.93	0.91	0.83	56.23
	BI2				0.90	41.74
	BI3				0.90	62.08
	BI4				0.83	20.91
Usage Barrier	UB1	0.727	0.89	0.81	0.80	27.38
	UB3				0.88	24.29
	UB4				0.88	28.60
Value Barrier	VB1	0.849	0.92	0.82	0.91	41.01
	VB2				0.89	54.79
Risk Barrier	RB1	0.752	0.92	0.89	0.85	13.80

Construct	Item	AVE	Composite Reliability	Cronbach's Alpha	Loadings	t-value
	RB2				0.86	26.18
	RB3				0.86	21.01
	RB4				0.83	16.27
Intention to Recommend	ITR1	0.755	0.86	0.68	0.92	75.74
	ITR2				0.92	20.86

Discriminant validity involved the realization of three key tests: cross-loadings, the Fornell-Larcker, and HTMT (heterotrait-monotrait ratio of correlations). The cross-loadings, criteria stipulate that each indicator's loading should be higher than any cross-loadings (Gotz et al., 2009). All loadings exceed their corresponding cross-loadings, as seen in Appendix C. According to the Fornell-Larcker criteria, it is crucial that the square root of the Average Variance Extracted (AVE) exceeds the correlations between each pair of constructs (Fornell & Larcker, 1981). Table 3 illustrates that all diagonal values (representing the square root of AVE) surpass the off-diagonal values, supporting discriminant validity.

Table 3- Fornell-Larcker

	A	BI	EE	HM	ITR	PE	RB	SI	UB	VB
A	**0.869**									
BI	0.176	**0.883**								
EE	0.114	0.425	**1.000**							
HM	0.133	0.642	0.436	**0.929**						
ITR	0.028	0.726	0.376	0.514	**0.869**					
PE	0.069	0.702	0.325	0.480	0.517	**0.911**				
RB	-0.144	-0.282	-0.181	-0.115	-0.250	-0.112	**0.867**			
SI	0.258	0.588	0.315	0.467	0.429	0.483	-0.149	**0.869**		
UB	0.212	0.610	0.426	0.441	0.534	0.537	-0.245	0.403	**0.852**	
VB	0.146	0.715	0.305	0.466	0.592	0.584	-0.270	0.450	0.658	**0.922**

Third, the Heterotrait-Monotrait ratio (HTMT) of correlations criteria should be lower than 0.9 (Henseler et al., 2015), presented in Table 4.

Table 4 - Heterotrait-Monotrait

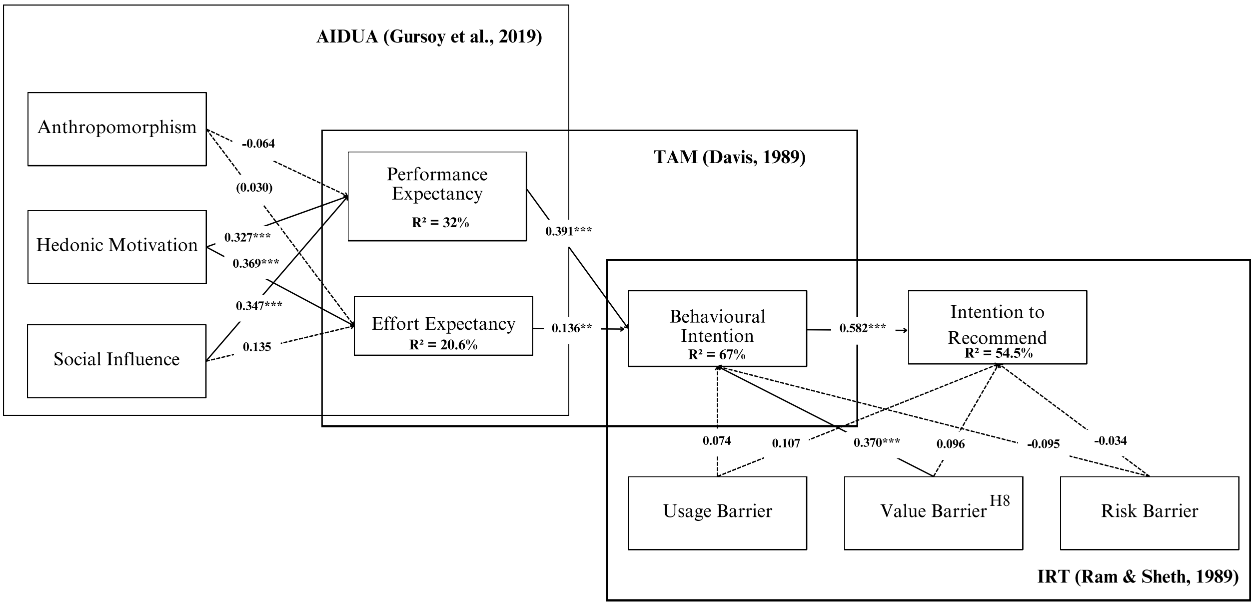
	A	BI	EE	HM	ITR	PE	RB	SI	UB	VB
A										
BI	0.202									
EE	0.125	0.446								
HM	0.151	0.696	0.452							
ITR	0.053	0.899	0.432	0.612						
PE	0.075	0.764	0.338	0.512	0.623					
RB	0.166	0.304	0.186	0.127	0.319	0.117				
SI	0.291	0.638	0.322	0.499	0.521	0.511	0.172			
UB	0.257	0.705	0.471	0.505	0.698	0.614	0.283	0.452		
VB	0.176	0.827	0.334	0.534	0.770	0.666	0.310	0.510	0.798	

Consequently, both sets of criteria have been met, providing compelling evidence supporting the discrimination validity of the scales. The results of the measurement model reveal strong construct reliability, indicator reliability, convergence validity, and discriminant validity. These findings assure that the constructs are statistically distinct and suitable for assessing the structural model.

5.2 Structural Model

Collinearity was analysed comparing all the items Variance Inflation Factor (VIF) against the maximum value of 5, according to the best practices (Hair et al., 2017) revealing no collinearity problems, as seen in Appendix D. The variables HM2, HM4 and UB2 were removed since they don't avoid collinearity (Hair et al., 2017).

The evaluation of hypotheses and relationships among constructs relied on assessing standardized paths. Path significance levels were determined by the bootstrap resampling method (Henseler et al., 2009), involving 5000 resampling iterations. The results are presented in Figure 2.



Note: (*p<0.10; **p<0.05; ***p<0.01)

Figure 2 - Paths coefficients

The model explains 32% of performance expectancy, 20.6% of effort expectancy, 67% of behavioural intention, and 54.5% of intention to recommend. Hedonic motivation and social influence were found statistically significant in explaining performance expectancy, as did hedonic motivation in elucidating effort expectancy, all at a significance level of $p < 0.01$, supporting hypotheses H2a, H2b and H3a. In opposition, anthropomorphism, and social influence (H3b) are not statistically significant, not supporting hypotheses H1a, H1b, and H3b. performance expectancy, value barrier (H8a) and effort expectancy were found statistically significant in explaining behavioural intention, at a significance level of $p < 0.01$ and $p < 0.05$ correspondingly. In the opposite situation hypotheses H7a and H9a were not found statistically significant in explaining behavioural intention. Behavioural intention was found to be statistically significant in explaining intention to recommend, with a level of significance of $p < 0.01$. In contrary, the hypotheses H7b, H8b and H9b were not found statistically significant in explaining intention to recommend.

Overall, of the fifteen-hypothesis formulated, seven were supported by the data collected. The following step in the analysis was to evaluate the total effects. Similar to the link between the direct effect of behavioural intention and the intention to recommend, the total effect also shows that hedonic motivation ($\hat{\beta}$ = 0.104; $p < 0.01$), social influence ($\hat{\beta}$ = 0.090; $p < 0.01$), performance expectancy($\hat{\beta}$ = 0.228; $p < 0.01$), effort expectancy ($\hat{\beta}$ = 0.079; $p < 0.05$), and value barrier ($\hat{\beta}$ = 0.312; $p < 0.01$) were found to be statistically significant in explaining the intention to recommend of the user to recommend AI-based devices, applications, and services in aviation and airports to other individuals.

Table 5 - Hypotheses results

Path	Hypotheses	Result
HM -> PE	H2a	Supported
SI -> PE	H3a	Supported
HM -> EE	H2b	X
PE -> BI	H4	Supported
EE -> BI	H5	X
VB -> BI	H8a	X

X – Not Supported

6. Discussion

Prior studies related to AI in aviation and airports have not yet fully understood the various factors that influence the willingness to adopt and recommend this technology in the aviation sector.

The research model explains 67% of behavioural intention to engage with AI-driven solutions even if the percentage is lower than other studies mentioned, 67% to 75% of Yuen et al. (2021). This variance can be attributed to the relatively limited research conducted in this specific area. The research model also explains 54.5% of variation in intention to recommend AI-based devices, applications and services in aviation and airports, that can be considered a solid result and an equivalent value to others obtained in similar studies, namely 58.6% in Kaur et al. (2020) study. The factors that positively influence acceptance are hedonic motivation (explains both PE and EE), social influence (explains PE), performance expectancy (explains BI), effort expectancy (explains BI), value barrier (explains BI), and behavioural intention (explains ITR). These and other findings are described below.

The research model confirmed two connections with performance expectancy, specifically, with hedonic motivation (H2a) and social influence (H3a). These findings are aligned with earlier research (Gursoy et al., 2019). Customers who perceive AI device usage as enjoyable are inclined to expect higher performance from these activities (Van Der Heijden, 2004; Wei et al., 2016) . Their evaluation of AI devices benefits and drawbacks is significantly influenced by prevailing social norms and attitudes (Gursoy et al., 2019). The research model also confirmed one connection with effort expectancy, exclusively, with hedonic motivation (H2b). This result is not consistent with former research, customers driven by high hedonic motivation tend to perceive superior device performance and reduced effort, influenced by a bias in their assessment of benefits and costs associated with AI device usage (Van Der Heijden, 2004; Wei et al., 2016). Furthermore, the model confirmed a connection between performance expectancy (H4) and behavioural intention (H6) validating previous research (Gursoy et al., 2019), since customers who perceive AI devices as having high performance expectancy are more likely to be willing to use them. It also confirmed two connections of effort expectancy (H5) and value barrier (H8a) with behavioural intention (H6), which contradicts previous earlier research (Gursoy et al., 2019; Kaur et al., 2020), it can be explained since increased levels of effort expectancy reduce the acceptance of AI device usage and raised objections through emotional influence, even after controlling for performance expectancy effects, which aligns with the idea that if users perceive the costs of using the technology to be higher than the benefits, their willingness to use it reduces. The research model also validates one connection between behavioural intention and intention to recommend that is consistent with prior research (Gursoy et al., 2019; Davis, 1989). Anthropomorphism, usage barrier, and risk barrier were not statistically significant in the context of this study.

The qualitative analysis shows that the specialist perspectives are aligned with the work main findings, emphasizing the importance of hedonic motivation and social norms in shaping user acceptance of AI technology. Their positive point views underscored the potential leveraging enjoyment and entertainment factors, as well as harnessing social networks to positively influence attitude towards AI devices. Moreover, it highlighted the importance of addressing performance expectancy and value barriers in managerial strategies. Specialist's identified AI's superior capabilities in aviation, aligning with confirmed quantitative connections between performance expectancy and behavioural intention. Additionally, concerns about value barriers highlight the managerial imperative to reduce obstacles and emphasize AI's value in aviation. This highlights the importance of considering both analyses to achieve a more comprehensive understanding of the dynamics involved in adopting AI. The specialist' viewpoints also emphasized AI's potential to increase security, save costs, enable statistical and predictive analysis, and improve overall efficiency. Several concerns were raised by the specialists, such as job loss, higher operational costs, varying approaches to data treatment among airlines, and the industry's resistance to change.

6.1 Theoretical and practical implications

By examining both direct and indirect influences on the acceptance of AI-based devices, applications, and services within the aviation industry, this research sheds lights on significant factors affecting the behavioural intention and the intention to recommend this technology. The results of this study have implications for researchers and practitioners. For researchers this study provides a basis for further refinement acceptance models in their respective fields, laying a foundation for future research. For practitioners, they can benefit from a deeper understanding of the key constructs outlined in the research model. This understanding is crucial for designing, refining, and implementing AI-based technology that gathers high levels of acceptance.

The quantitative research provides five important practical implications related to the integration of AI-based devices within aviation. First, the study underscores the influential roles of hedonic motivations and social norms. It shows that hedonic motivations, such as enjoyment and entertainment, can significantly impact users' acceptance of technology. Simultaneously, recognizing the influence of social networks on user perceptions emphasizes the need to leverage these networks to influence and shape positive attitudes towards AI devices. Furthermore, the research highlights the supreme importance of performance expectancy. Users exhibit a greater willingness to engage with AI devices when these technologies are perceived as high performing. This marks the necessity to show the superior capabilities of AI within aviation contexts, emphasizing their efficiency and functionality to drive acceptance and adoption. Also, unexpectedly, it highlights effort expectancy relevance on the willingness to use this technology, explained since most participants are young adults who are more familiarized with technology and more open to use it. This analysis also shows that value barriers significantly influence user intentions, requiring strategies that reduce these barriers and accentuate the inherent value proposition of AI-based aviation technologies.

By understanding the main factors influencing the intention to recommend and use of AI-based technology, as well as considering constraints and nuances, particularly hedonic motivation, social influence, performance expectancy, value barrier, and behavioural intention, the aviation industry will be able to evolve, and practitioners can tailor their strategies effectively to meet consumer needs and preferences to raise acceptance. The aviation and airports sectors should continue to implement AI-based devices, applications, and services to show users the usefulness and benefits of this technology. Moreover, efforts should be made to enhance overall user experience. By focusing on these elements, it can positively influence the individual's perception and adoption of the technology in this industry.

6.2 Limitations and future research

This study identifies some limitations requiring further investigation. We decided not to include the traditional barriers and image barriers from the IRT model (Ram & Sheth, 1989) in our study due to the dimension of the theoretical model, but they may also be perceived as important for the adoption and recommendation of AI in the aviation sector. Considering the expanding presence of AI technology, integrating these variables into the research framework may become a relevant aspect to pursue. Another limitation of this research pertains to the demographic of the questionnaire respondents, with 95% of respondents from Portugal and only 5% from different countries. Future studies should explore other countries and cultural differences that might influence the adoption of AI in aviation.

Regarding the qualitative analysis with aviation specialists, it emphasized the multifaceted nature of challenges associated with the adoption of this technology. Since this research focuses primarily on the intention to adopt and to recommend the AI technology at individual level, it would be interesting to consider a future study solely with industry professionals, at firm level. Future research could identify specific areas, such as the usability of this technology only within professionals of the aviation industry. This could involve assessing usage patterns in activities directly related to flight operations, examining the significance of AI integration. Secondly, another aspect to explore is ethical considerations, delving into the ethical dilemmas linked to adopting and recommending AI in this sector. Exploring questions surrounding the ethical implications of AI implementation is crucial for a future comprehensive analysis. Lastly, outcome measurement also needs to be considered, examining outcome measures such as safety and security levels, cost reductions, efficiency in flight operations, and data management. This could provide valuable insights into the practical impacts of AI adoption.

Given that AI technology in aviation is still in its early stage due to the industry's conservative nature (EASA, 2023), a longitudinal study might better capture the evolving dynamics of this phenomenon. Additionally, considering the complex nature of security concerns associated with AI implementation, encompassing technological aspects, trustworthiness of involved parties, data storage location, regulatory culture, and privacy legislation, conducting focused studies on these individual or interconnected issues could also be a valuable to pursuit.

7. Conclusion

Artificial Intelligence technology is experiencing an unprecedent surge on a global scale, with the aviation industry progressively incorporating it across various functions. This integration spans from industry professionals to everyday users availing themselves of aviation related services. However, a comprehensive assessment of the factors shaping the adoption and future recommendation of this technology remains incomplete. As far as we know, this is one of the first AI technology studies within airport and aviation context. To complete this gap, we employed a mixed (qualitative and quantitative) methods approach in our study, known to produce excellent results, combined with an innovative and cohesive research model combining three established theories, AIDUA, TAM and IRT, with the intention to recommend construct. The outcome emphasized the robustness of the proposed model, demonstrating its ability to effectively predict the intention regarding the adoption and recommendation of AI-based devices, applications, and services in the aviation and airports sectors. Our result demonstrated convergences and divergences with previous studies. To explain the expectation efficacy and usefulness of AI-based services hedonic motivation and social influence were found to be the most significant antecedents of performance expectancy. Regarding the anticipated amount of effort required to engage with these devices hedonic motivation was found to be the most significant precursor of effort expectancy. To explain the willingness or intention to engage in a specific behaviour performance expectancy, effort expectancy, and value barrier were found significant antecedents of behavioural intention. Finally, behavioural intention was found to be a significant antecedent of intention to recommend construct on the adoption and recommendation of AI within the sector. For researchers, this study serves as a foundational theoretical support for refining acceptance models paving the way for future investigations. For practitioners, the research highlights the importance of prioritizing user-friendly approaches and seamlessly integrate AI-based technologies. This emphasis aims to improve user experiences, leading to widespread acceptance and adoption of AI technology in aviation and airport sectors.

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Appendices

Appendix A – Survey

Topic	Question
General	What kind of responsibilities do you have and how long have you been on this position?
Artificial Intelligence	Regarding the AI, could you tell me in which areas of aviation is it already being used?
	What were the main factors that led aviation to start to use AI assistance?
	On your point of view, what kind of consequences (positive or negative) has AI brought to your functions, to the company, and, from a passenger's point of view?
	Do you believe that, on a global scale, the industry is still somewhat hesitant towards this change?
Challenges and Concerns	In your opinion, what are the main critical success factors to consider when implementing AI initiatives?
Clients	In your opinion, how are passengers perceiving the importance of AI in the industry?
	How do you think the integration of AI is influencing their perception of safety and efficiency in aviation?
Future	How do you expect the evolution of AI in the aviation industry will be in the next decade?
	Could aviation industry potentially be carried out only by using AI?
Conclusion	Is there any additional point regarding AI in the aviation industry that you would like to add?

Appendix B – Questionnaire

Construct	Items	Source
Anthropomorphism (A)	A1:AI-based devices, applications, and services have a mind of their own.	(Lu et al., 2019)
	A2: AI-based devices, applications, and services have consciousness.	
	A3: AI-based devices, applications, and services have their own free will.	
	A4: AI-based devices, applications, and services can experience emotions.	
Hedonic Motivation (HM)	HM1: I have fun interacting with AI-based devices, applications, and services in airports and air travels.	
	HM2: Interacting with AI-based devices, applications, and services in airports and air travels is fun.	(Venkatesh et al., 2012)
	HM3: Interacting with AI-based devices, applications, and services in airports and air travels is entertaining.	
	HM4: Interaction with AI-based devices, applications, and services in airports and air travels is enjoyable.	
	HM5: The actual process of interacting with AI-based devices, applications, and services in airports and air travels is pleasant.	(Lu et al., 2019)
Social Influence (SI)	SI1: Using AI-based devices, applications, and services reflects status in my social network (e.g., friends, family, and co-workers).	

Construct	Items	Source
	SI2: People who influence my behaviour would want me to utilize AI-based devices, applications, and services.	(Venkatesh et al., 2012)tal., 2019)
Social Influence (SI)	SI1: Using AI-based devices, applications, and services reflects status in my social network (e.g., friends, family, and co-workers).	
	SI2: People who influence my behaviour would want me to utilize AI-based devices, applications, and services.	(Venkatesh et al., 2012)
	SI3: People in my social networks who would utilize AI devices have more prestige than those who don't.	(Lu et al., 2019)
	SI4: People whose opinions that I value would prefer that I utilize AI-based devices, applications, and services.	(Venkatesh et al., 2012)
	SI5: People who are important to me would encourage me to utilize AI-based devices, applications, and services.	
	SI6: People in my social networks who would utilize artificially intelligent have a high profile.	(Lu et al., 2019)
Performance Expectancy (PE)	PE1: AI-based devices, applications, and services in airports and air travels are more accurate than human beings.	
	PE2: AI-based devices, applications, and services in airports and air travels are more accurate with less human errors.	
	PE3: AI-based devices, applications, and services in airports and air travels provide more consistent service than human beings.	
	PE4: Information provided by AI-based devices, applications, and services in airports and air travels are more consistent.	

Construct	Items	Source
Effort Expectancy (EE)	EE1: Using AI-based devices, applications, and services in airports and air travels takes too much of my time.	
	EE2: Working with AI-based devices, applications, and services in airports and air travels is so difficult to understand and use in services.	
	EE3: It takes me too long to learn how to interact with AI-based devices, applications, and services.	
	EE4: It is easy for me to become skilful at using AI-based devices, applications, and services in airports and air travels.	(Venkatesh et al., 2012)
Behavioural Intention (BI)	BI1: I intend to use AI-based devices, application, and services in airports and air travels in the future.	(Yuen et al., 2021)
	BI2: I have positive things to say about AI-based devices, application, and services in airports and air travels.	
	BI3: I would encourage others to use AI-based devices, application, and services in airports and air travels.	
	BI4: I would choose airports and air travels that uses AI technology.	(J.-H. Kim & Park, 2019)
Usage Barrier (UB)	UB1: AI-based devices, applications, and services in airports and air travels are convenient because I can access them by mobile phone that is always with me.	(Laukkanen, 2016)
	UB2: AI-based devices, applications, and services in airports and air travels are convenient because I can use them anytime.	
	UB3: AI-based devices, applications, and services in airports and air travels are convenient because I can use them in any situation.	
	UB4: AI-based devices, applications, and services are convenient because they are not complex.	

Construct	Items	Source
Value Barrier (VB)	VB1: AI-based devices, applications, and services in airports and air travels offers many advantages compared with handling my travel matters all by myself.	
	VB2: AI-based devices, applications, and services in airports and air travels increases my ability to control my travel matters all by myself.	
	VB3: I will wait to utilize an AI-based devices, applications, and services in airports and air travels until it proved to be beneficial for me.	
	VB4: Using an AI-based devices, applications, and services in airports and air travels maybe wastage of money.	
Risk Barrier (RB)	RB1: I fear that while I am using AI-based devices, applications, and services in airports and air travels, I might type my information incorrectly.	
	RB2: I fear that while I am using AI-based devices, applications, and services in airports and air travels, I may pay more money.	
	RB3: I fear that while I am using AI-based devices, applications, and services in airports and air travels I pay money to the wrong vendor.	
	RB4: I fear that while I am using AI-based devices, applications, and services in airports and air travels someone may hack my account.	
Intention to Recommend (ITR)	ITR1: I will recommend to my friends to use AI-enabled devices, applications and services in airports and air travels, if they are available.	(Oliveira et al., 2016)
	ITR2: If I have a good experience with AI-enabled devices, applications and services in airports and air travels I will recommend to my friends to use them.	

Appendix C – Cross Loadings

	A	BI	EE	HM	ITR	PE	RB	SI	UB	VB
A2	**0.906**	0.191	0.094	0.157	0.035	0.094	-0.15	0.292	0.184	0.135
A3	**0.877**	0.14	0.111	0.058	0.049	0.039	-0.17	0.202	0.21	0.14
A4	**0.822**	0.118	0.093	0.127	-0.019	0.039	-0.044	0.165	0.156	0.103
BI1	0.06	**0.893**	0.392	0.63	0.653	0.676	-0.245	0.465	0.586	0.677
BI2	0.215	**0.881**	0.42	0.521	0.589	0.584	-0.259	0.511	0.508	0.605
BI3	0.156	**0.923**	0.397	0.614	0.733	0.61	-0.288	0.557	0.535	0.656
BI4	0.202	**0.831**	0.288	0.49	0.576	0.61	-0.201	0.546	0.523	0.581
EE4	0.114	0.425	**1**	0.436	0.376	0.325	-0.181	0.315	0.426	0.305
HM1	0.108	0.642	0.431	**0.936**	0.504	0.524	-0.096	0.45	0.428	0.453
HM3	0.132	0.548	0.385	**0.93**	0.44	0.413	-0.066	0.392	0.414	0.401
HM5	0.132	0.591	0.393	**0.921**	0.484	0.385	-0.162	0.457	0.382	0.442
ITR1	0.027	0.719	0.423	0.578	**0.912**	0.548	-0.183	0.422	0.537	0.598
ITR2	0.02	0.518	0.199	0.271	**0.823**	0.321	-0.269	0.312	0.369	0.407
PE1	0.091	0.596	0.338	0.443	0.416	**0.891**	-0.052	0.444	0.47	0.46
PE2	0.026	0.616	0.322	0.436	0.467	**0.907**	-0.159	0.408	0.546	0.584
PE3	0.072	0.653	0.27	0.401	0.482	**0.923**	-0.103	0.448	0.465	0.551
PE4	0.061	0.689	0.258	0.469	0.514	**0.921**	-0.095	0.457	0.478	0.531
RB1	-0.115	-0.208	-0.153	-0.097	-0.158	-0.084	**0.834**	-0.127	-0.242	-0.224
RB2	-0.109	-0.306	-0.199	-0.1	-0.286	-0.183	**0.898**	-0.082	-0.264	-0.272
RB3	-0.155	-0.208	-0.128	-0.06	-0.188	-0.025	**0.903**	-0.096	-0.159	-0.2
RB4	-0.131	-0.229	-0.131	-0.139	-0.203	-0.059	**0.832**	-0.228	-0.171	-0.225
SI1	0.295	0.482	0.211	0.39	0.3	0.366	-0.161	**0.8**	0.309	0.359
SI2	0.224	0.494	0.279	0.383	0.36	0.351	-0.161	**0.882**	0.322	0.371
SI3	0.254	0.471	0.225	0.347	0.324	0.399	-0.134	**0.875**	0.288	0.359
SI4	0.263	0.532	0.303	0.439	0.396	0.433	-0.173	**0.912**	0.388	0.403
SI5	0.19	0.542	0.303	0.466	0.431	0.488	-0.078	**0.893**	0.417	0.43
SI6	0.146	0.531	0.301	0.395	0.402	0.455	-0.091	**0.85**	0.354	0.412
UB1	0.174	0.527	0.32	0.415	0.45	0.463	-0.262	0.372	**0.864**	0.549
UB3	0.204	0.444	0.351	0.325	0.451	0.403	-0.197	0.263	**0.863**	0.491
UB4	0.166	0.576	0.414	0.381	0.461	0.498	-0.169	0.384	**0.829**	0.631
VB1	0.19	0.635	0.197	0.434	0.552	0.488	-0.275	0.424	0.549	**0.919**
VB2	0.081	0.682	0.361	0.425	0.539	0.586	-0.223	0.406	0.663	**0.924**

Appendix D – Outer model - List

	VIF
A2	2.273
A3	2.095
A4	1.741
BI1	2.795
BI2	2.844
BI3	3.679
BI4	2.079
EE4	1.000
HM1	3.280
HM3	3.593
HM5	3.351
ITR1	1.367
ITR2	1.367
PE1	2.916
PE2	3.354
PE3	3.911
PE4	3.677
RB1	2.180
RB2	2.621
RB3	3.313
RB4	2.173
SI1	2.367
SI2	3.883
SI3	3.390
SI4	4.751
SI5	3.557
SI6	2.908
UB1	2.010
UB3	2.087
UB4	1.539
VB1	1.955
VB2	1.955