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Abstract

The study applied the Technology Acceptance Model (TAM) to assess trust in artificial intelligence (AI) within the US commercial aviation industry. It found that ease of use and usefulness positively influenced attitudes toward AI, impacting users' intention to use it. However, perceived usefulness did not significantly affect meaning, purpose, and mood positively correlated with trust in AI. In some cases, higher perceived usefulness led to lower trust, indicating the complexity of trust in AI in aviation. This study highlights the importance of trust in AI and suggests the need for further investigation in the aviation context. It also recommends expanding the framework of trustworthy AI to consider factors like algorithm transparency, explainability, and fairness for a more comprehensive understanding.

Keywords: *Artificial Intelligence, Technology Acceptance Model, Trust, Path Analysis, Commercial Aviation*

Introduction

We are living in the fourth industrial revolution, or what is known as "Industry 4.0" (Bécue et al., 2021; i-Scoop, n.d.; Schwab, 2016). Artificial Intelligence (AI) has been evolving for generations and is quickly emerging as a significant applied technology with several applications in numerous fields (Sharda et al., 2020). Global spending on AI solutions is projected to surpass $500 billion by 2027, with significant growth expected in sectors like healthcare, energy, finance, and defense (IDC, 2023).

The global aviation industry's utilization of AI is expected to generate $32.6 billion in revenue by 2027 (Research & Markets, 2022). According to Precedence Research's report from 2023, the estimated market size for AI in aviation worldwide was US$ 653.74 million in 2021. The report projects that the market will exceed US 9,985.85 million by 2030, with a compounded annual growth rate (CAGR) of 35.38% from 2022 to 2030. The newest advances in computing technologies drive AI to other levels and achievements. AI encompasses technologies that can perform tasks that typically require human intelligence, such as speech recognition, visual perception, or decision-making (Riedl, 2022). AI systems referred to in this research include chatbots, robots, and autonomous vehicles, and their significance has become increasingly prominent in the economy and society (Riedl, 2022). Amongst advances, AI is undoubtedly the most disruptive (Chui et al., 2018; Kim et al., 2023).

The United States must take crucial steps to invigorate its aptitude to embrace innovations (Kahn & Candi, 2021) as it develops as the world leader in AI. The aerospace industry is diverse, catering to military, commercial aviation, and space exploration sectors. In aerospace and defense, AI technologies and their underlying rules of engagement center on speed and scale (McKinney, n.d.). The Defense Advanced Research Projects Agency (Defense Advanced Research Projects Agency, n.d.) is directing its investments on the third wave of AI. This project produces machines that comprehend and reason in context and are more than just tools that perform "human-programmed rules or generalize from human-curated data sets" (Defense Advanced Research Projects Agency, n.d.). Air Force AI-driven drone program makes a step into the future (Maucione, 2021). The drones employ sensors to analyze the looming threat, recognize prominent options, and reach resolutions based on recognized rules of engagement via AI (Maucione, 2021).

Integrating AI in aerospace manufacturing processes can aid companies in ensuring safety while optimizing their operations. With the tremendous improvements in the processing power of computers, the promises of AI will increasingly be used in aviation and make autonomous flights, preventive maintenance, and air traffic management (ATM) optimization possible (AltexSoft, 2021). In addition, using AI may simplify and streamline various processes, including analytics, system management, and customer service (International Airport Review, 2021).

Problem Statement

AI is still relatively new, and its emergence as a new technology has created a significant gap in research and insights into its successful development and implementation in aviation (European Union Aviation Safety Agency, 2023). A growing body of research supports the need for further investigation into the use of AI in aviation (Chakraborty et al., 2021; International Airport Review, 2021) and the need to establish a comprehensive trust model in such systems (X. Li et al., 2021). According to Li et al. (2021), users' trust in AI systems is a critical concern affecting adoption and effective utilization. Abraham et al. (2017) suggest that while the airline and aerospace industries are making strides in automating their operations, the successful implementation of these advancements hinges on cultivating trust and fostering more significant demand for these systems. While AI's current and future applications in aviation hold great potential for further enhancing efficiency and achieving better outcomes, the need for established models demonstrating user trust remains a significant challenge. Additionally, user trust in AI systems in aviation must still be adequately addressed in research or modeled with empirical data.

Purpose Statement

This study was conducted to explore the perceptions of AI use and trust within the US commercial aviation industry, which is still in its nascent stage of development. This research is a condensed version of a thesis (Halawi, 2023). This research applies the technology acceptance model (TAM) to explain the aviation industry's intention to embrace AI technology and the level of trust it engenders regarding prospective applications and future improvements. Consequently, this research offers actionable insights into the determinants of AI adoption within the aviation industry.

Theoretical Foundation

TAM and its Components

Davis (1989) proposed technology acceptance (TAM) as a modification of the theory of reasoned action (TRA) by Fishbein and Ajzen (1991). TAM seeks to explain the behavioral inclination of potential users toward adopting technological innovation (Davis et al., 1989). TAM is based on TRA, a social psychology theory that explains intention based on general human behavior (Chau & Jen-Hwa Hu, 2001). TAM adopts the TRA model and provides insight into user acceptance or rejection of information technology. The TAM model suggests that the intention to use a system is determined by the user's attitude toward the system, which is influenced by the user's perception of the system's usefulness and ease of use (Agarwal & Prasad, 1999; Chau & Jen-Hwa Hu, 2001; Dadayan & Ferro, 2005; Mathieson, 1991; Pires & Halawi, 2019, 2020; Taylor & Todd, 1995). The relationship between perceived ease of use and intention to use the system is fully mediated by user attitude, while the relationship between perceived usefulness and intention to use the system is partially mediated by user attitude (Agarwal & Prasad, 1999; Chau & Jen-Hwa Hu, 2001; Dadayan & Ferro, 2005; Mathieson, 1991; Pires & Halawi, 2019, 2020; Taylor & Todd, 1995).

Richardson et al. (2019) used TAM to study pilot acceptance of AGCAS in F-16 fighter aircraft, finding that ease of use, and perceived usefulness, influenced usage and proposing a model for autonomous collision avoidance systems. Techau (2018) applied UTAUT2 to investigate GA pilot acceptance of EFBs, highlighting factors like social influence, effort expectation, and price value, with EFB experience playing a significant role. Pan and Truong (2018) extended TPB to understand factors affecting the intention to use LCCs in China, revealing that price and service quality were critical determinants, offering insights for LCCs to improve services. Lee et al. (2018) explored how pre-flight safety communication influenced passengers' attitudes, subjective norms, and intentions, finding that personal criteria significantly impacted passengers' intent to receive safety briefings. Nugroho et al. (2017) emphasized the importance of perceived ease of use and utility in users' motivation to use technology, focusing on Traveloka's app adoption in the travel industry.

AI Trustworthiness as a Key Driver

In the aviation industry, trust plays a critical role in relationships and is utilized by airlines and aerospace manufacturers to make decisions when there is a shortage of information. According to Calnan and Rowe (2007), trust involves a cognitive-affective evaluation of risk and benefit, wherein the trustor holds optimistic expectations about the trustee's competence and goodwill in the future has much potential to enhance people's lives and economies, but it also comes with many new ethical, legal, social, and technological challenges (Stix, 2022; Thiebes et al., 2020). Trustworthy AI (TAI) is founded on the belief that trust is the foundation of all communities, economies, and long-term success. People, companies, and society will only be able to realize AI's full potential if confidence in its development, implementation, and use can be established. According to the notion of TAI, individuals, companies, and society can only ever attain the full potential of AI if trust can be developed robustly at the deployment and development stage. This will assist the use case in maximizing the advantages of AI while minimizing or even avoiding associated risks and hazards (Thiebes et al., 2020). Ground-breaking developments in machine learning and deep learning subfields have spurred people's thoughts of a reality that has helped businesses grow since the early 2010s (Thiebes et al., 2020). However, it is becoming evident that AI is not the magic bullet that some would like to believe it is. AI will spawn new ethical, legal, and social concerns like any other technology.

TAI is built on the premise that trust is the bedrock of communities, economies, and long-term growth and that the full potential of AI can only be realized if trust can be developed in it. On the other hand, TAI is a multidisciplinary and active topic of study, with several research streams and debates spanning disciplines (Thiebes et al., 2020). Preconditions, including ethical and legal criteria that must be met, are unequally prioritized worldwide, while knowledge of technological and non-technical tools to actualize TAI is ever-increasing. Given that trust is a complex issue that has inspired multiple academic debates in recent decades, it is natural that the conceptualization of AI trust, and what makes AI trustworthy, remains ambiguous and intensely discussed in study and application today (Thiebes et al., 2020).

On the other hand, many modern AI systems have been proven open to undetectable assaults, prejudiced towards underrepresented groups, deficient in user privacy protection, and so on, which affects user experience and erodes society's faith in all AI systems. Li et al. (2023) provide AI practitioners with a complete roadmap for developing reliable AI systems. The researchers begin by laying out the theoretical foundations for critical features of AI trustworthiness before looking at some of the industry's most innovative remedies to these issues. The researchers presented a systematic strategy that examines the entire lifetime of AI systems, from data collecting through model generation, development, deployment, and ongoing monitoring and governance, to integrate the existing fragmented approaches toward trustworthy AI. They also provide practitioners and societal stakeholders with tangible action items to promote AI trustworthiness in this framework. Finally, they highlight significant potential and obstacles in developing trustworthy AI systems in the future, including the need for a paradigm change toward completely reliable AI systems (B. Li et al., 2023).

Dobrin (2021) highlights four critical elements of a trustworthy AI: (1) assessment, audit, and risk mitigation; (2) end-to-end AI lifecycle; (3) AI governance frameworks; and (4) guidance and education. First, companies will need direction and tools to analyze, audit, and manage risk to make AI solutions dependable. Second, as they move toward AI, most companies form data science teams of experts in machine learning and deep learning algorithms, frameworks, and approaches. However, many of these businesses need help to make their AI initiatives relevant to their operations, failing to put them into total production and integrate them with current apps and procedures. Only a few AI initiatives are considered real successes by many line-of-business stakeholders. Finally, with AI governance frameworks to regulate the data and model lifecycles, guardrails can be created to ensure that recruiting procedures, as in our example use case, are free of bias, reducing the risk of negative litigation publicity. Finally, AI is a cutting-edge technology that requires a high level of competence. Building AI solutions with less understanding might jeopardize the company's bottom line and reputation. The aviation sector must know the best practices for developing reliable AI solutions and educate data scientists, developers, and decision-makers.

Methodology

Participants

The study used a diverse sample representing different aviation industry backgrounds and geographic locations in the United States. The final sample is not purely random because of the non-probability filtering based on the citizenship question and profession (working in the sector). From May to August 2023, we distributed the survey through Survey Monkey and social media, particularly LinkedIn, targeting individuals within the US commercial aviation industry. This approach aimed for transparency and comprehensive respondent representation. We received 310 responses, with 15 not granting consent and 22 incomplete, resulting in a final sample of 273 participants for analysis.

Materials

An online survey was utilized as the data collection method in this study. The study used items adapted from the determinants of the Technology Acceptance Model (TAM), namely Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). In addition, behavioral intentions to use (BIU) and Attitude Toward Using (AU) were derived from previous studies that had already established their reliability and validity. These studies include those conducted by Davis (1989), Mathieson (1991), Moore and Benbasat (1991), Taylor and Todd (1995), and Venkatesh and Davis (1996). The trust construct was derived from the study conducted by McKnight et al. (2002). The survey consisted of anonymous demographic and screening inquiries and 33 closed-ended statements evaluated on a coded 7-point Likert scale aligned with TAM.

This research seeks to answer the following question: Is there a relationship between the aviation industry's perceptions of perceived usefulness, perceived ease of use, perceived usage, attitude to use, behavioral intention to use, trust, and actual usage in AI?

Hypotheses

The following hypotheses were tested:

- **H1:** Perceived ease of use (PEOU) positively impacts Attitude to use (AU).
- **H2:** Perceived usefulness (PU) positively impacts attitude to use (AU).
- **H3:** Attitude to use (AU) positively impacts behavioral intention to use (BIU).
- **H4:** Perceived usefulness (PU) positively impacts behavioral intention to use (BIU).
- **H5:** Behavioral intention to use (BIU) positively impacts trust (TU).
- **H6:** Attitude to use (AU) positively impacts trust (TU).
- **H7:** Perceived ease of use (PEOU) positively impacts trust (TU).
- **H8:** Perceived usefulness (PU) impacts trust (TU).

Procedure

King and He (2006) emphasized that SEM and path analysis are commonly used analysis techniques in studies that apply the TAM model. The study used path analysis, a simplified form of Structural Equation Modeling (SEM), with single indicators for each variable in the causal model. Path analysis is suitable for smaller datasets due to its reduced computational demands. IBM AMOS v.25 software assessed the model fit and tested the hypotheses within the Technology Acceptance Model (TAM) framework.

Measures

The study used items adapted from the determinants of the Technology Acceptance Model (TAM), namely Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). In addition, behavioral intentions to use (BIU) and Attitude Toward Using (AU) were derived from previous studies that had already established their reliability and validity (Ajzen, 1991). These studies include those conducted by Davis (1989), Mathieson (1991), Moore and Benbasat (1991), Taylor and Todd (1995), and Venkatesh and Davis (1996). The trust construct was derived from the study conducted by McKnight et al. (2002). Additionally, SPSS version 28, IBM AMOS v.25, and Excel were employed to generate other data necessary for the research analysis.

Results

Respondent Demographics

It is essential to highlight that the participants in our survey comprise individuals from all hierarchical levels within these organizations. Responses indicated that 61.2% were males, 35.2% percent were females, 1.5% were intersex, and 2.2% preferred not to disclose. Thirteen percent were employed less than one year, 20.9% were employed between one to three years, 11.4% were employed between 3 to 5 years, 18.7% were employed between 5 and 10 years, and 35.9% were employed more than ten years. The usage duration of AI among respondents varied significantly, with 54.6% reporting using AI for less than one year, 22% for one to two years, 10.6% for two to three years, and 4.8% for three to five years.

Instrument Validity & Reliability Analysis

An iterative approach was adopted for factor analysis, wherein items failing to meet the loading cutoff criterion and displaying cross-loadings on multiple factors were systematically eliminated. Reliability pertains to measurement accuracy without errors. To ensure consistent reliability, this study employed the TAM's core determinants, which were tailored for AI, and assessed the constructs using Cronbach's Alpha. All items from the survey exhibited an (α) value above 0.65, as provided in Table 1.

Table 1

Reliability Statistics

Variable	N of Items	Cronbach's Alpha
Perceived Usefulness	6	.933
Perceived Ease of Use	7	.905
Attitude Toward Use	4	.903
Behavioral Intention Toward Use	4	.908
Trust	8	.934

Path Analysis

The path analysis model was estimated by simultaneous process and a maximum likelihood (ML) method using AMOS 25 (Arbuckle, 2008; Bollen, 1989). This study involved executing two distinct path analyses: the initial analysis used a testing data set to predict AI Use, while the subsequent analysis used a validation data set. Utilizing a testing data set and a validation sample in path analysis using AMOS offers several advantages, making it a preferred approach in empirical research. We used the standard approach to create the testing data set and validation sample, which involved a random division of the original sample (about 67% for testing and 33% for validation). This ensured an unbiased representation of data across both subsets. Also, incorporating reliability into a path analysis can help control measurement errors in the observed variables. The evaluation of model fit with the observed data was initially performed using the goodness-of-fit chi-square statistic. In line with standard practices in studies utilizing structural equation modeling (SEM), a range of indices was employed to gauge the model fit. Among these fit indices, the goodness of fit (GFI), the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean residual (SRMR) are commonly recommended for assessing model fit.

Table 2 presents the results of the fit indices for our proposed research model with the testing data set in this study.

Table 2

Optimized Model Fit Statistics – Testing Sample

Statistic	Model Value	Acceptable
CMIN/DF (Normed Chi-square)	3.962	2.0 - 5.0
RMSEA	.129	$<$.080
CFI	.996	$\geq$ .900
SRMR	.01447	$<$.080

While most values met the recommended acceptable criteria, the RMSEA value (.0144) indicates an acceptable (though not 'close') model fit. Similarly, the 90% CI indicates an acceptable (but not close) fit. The result for the chi-square goodness of fit test indicates that we should reject the null of an exact-fitting model $\mathcal{X}^2(1)$ = 3.962, p$<$ .001 (0.047). Achieving optimal model fit requires an iterative examination and adjusting the model fit statistics. Using the validation data set helped address any misspecification and lack of it. It also offered evidence for the generalization of the model. Our optimized fitted model is presented in Figure 1.

Path coefficient values provide a means to assess hypothesized relationships between constructs. By examining path coefficients derived from analyzing relationships between constructs, the researcher determined the strength of relationships amongst variables. Path coefficients range between -1 and +1. Coefficients closer to +1 indicate a stronger positive relationship, while coefficients closer to -1 indicate a stronger negative relationship (Hair et al., 2017). The results of the fit indices for our proposed research model with the validation data set in this study are presented in Table 3.

Table 3

Optimized Model Fit Statistics – Validation Sample

Statistic	Model Value	Acceptable
CMIN/DF (Normed Chi-square)	.028	2.0 - 5.0
RMSEA	.000	$<$.080
CFI	1.000	$\geq$ .900
SRMR	.0017	$<$.080

Standardized path models are presented in Table 4 and were used to evaluate hypothesized direct effects in the model. Significant effects were identified in keeping with the hypotheses of the proposed fitted model.

Table 4

Hypotheses

Hypotheses				Estimate	SE.	CR.	P	Result
H1	L_AU	<—	L_PEOU	.309	.145	2.127	.033	Accepted
H2	L_AU	<—	L_PU	.765	.139	5.499	***	Accepted
H3	L_BIU	<—	L_AU	.805	.252	3.198	.001	Accepted
H4	L_BIU	<—	L_PU	.084	.277	.303	.762	Rejected
H5	L_TU	<—	L_BIU	.726	.247	2.944	.003	Accepted
H6	L_TU	<—	L_AU	1.197	.459	2.609	.009	Accepted
H7	L_TU	<—	L_PEOU	.113	.241	.469	.639	Rejected
H8	L_TU	<—	L_PU	-1.335	.380	-3.508	***	Accepted

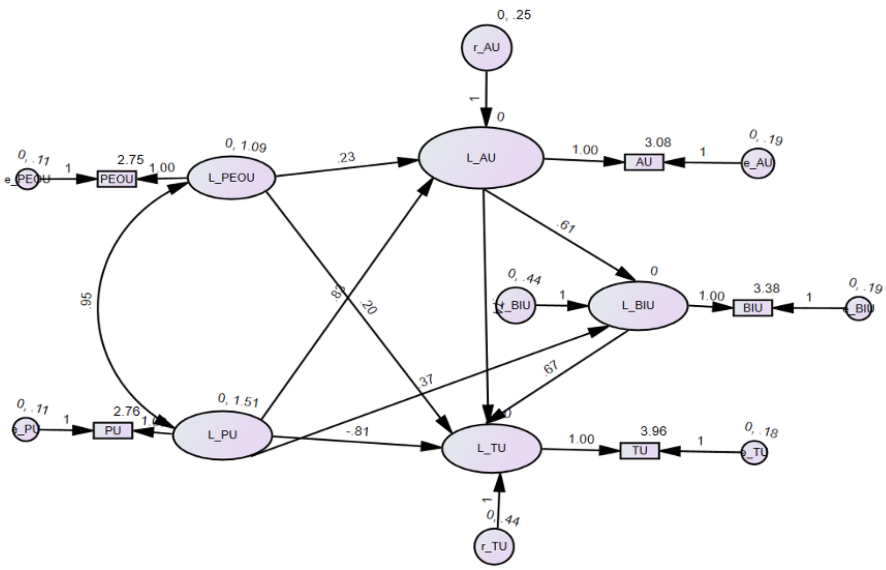
Discussion and Conclusion

The study used the Technology Acceptance Model (TAM) with trust in AI for the commercial aviation industry in the US. Two path analyses were conducted, one with a training set and one with a validation test. The chi-square goodness-of-fit test was used to evaluate the goodness-of-fit of the proposed models with the data. However, considering the sensitivity of chi-square to sample size and the risk of making a type II error (i.e., rejecting a well-fitting or acceptable model), additional indices of good fit were utilized. These indices included the comparative fit index (CFI), the non-normed fit index (NNFI), the standardized root mean squared residuals (SRMSR), and the root mean square error of approximation (RMSEA). An acceptable model was indicated by CFI and NNFI values of .90 or above, with a value greater than .95 considered preferable. For SRMSR and RMSEA, values approaching .08 or lower were deemed satisfactory for a well-fitting model (Browne & Cudeck, 1993).

The present study aimed to test the TAM model with an added trust component related to AI use among users in the commercial aviation industry in the USA. Path analytics models supported the hypotheses of the proposed model. Firstly, the literature review emphasizes the significance of trust in the aviation industry and the need for trustworthy AI (TAI) to unlock AI's full potential (Stix, 2022; Thiebes et al., 2020). Trust is essential for establishing confidence in AI's development, imple-

Figure 1

Path Model – Optimized Validation Set



mentation, and use (Thiebes et al., 2020). Dobrin (2021) highlights critical elements of trustworthy AI, including assessment, audit, risk mitigation, end-to-end AI lifecycle management, AI governance frameworks, and guidance and education. These elements align with the aviation industry's need to ensure AI systems' reliability and safe utilization. The results of the AMOS path analysis provide valuable insights into the relationships between perceived ease of use (PEOU), perceived usefulness (PU), attitude towards using (AU), behavioral intention to use (BIU), and trust (TU) in the context of AI adoption in the aviation industry. These findings align with the literature review, which emphasized the significance of trust in AI systems and the multidimensional nature of trustworthy AI.

H1 and H2 both received support from the analysis, affirming that perceived ease of use and usefulness positively impact the attitude toward using AI. This is consistent with previous studies highlighting the role of user experience and utility in shaping attitudes toward adopting new technologies (Nugroho et al., 2017; Techau, 2018). The positive relationship between perceived usefulness and attitude towards using AI suggests that users' perception of the AI system's value significantly influences their attitude toward its adoption.

Furthermore, H3 received strong support, indicating that attitude towards using AI positively influences behavioral intention to use it. This aligns with the findings of Richardson et al. (2019), who reported that pilots' positive attitudes toward highly automated systems correlated with their behavioral intention to accept and utilize those systems. The implication is that cultivating a favorable attitude towards AI adoption is crucial for encouraging users to engage in the intended behaviors associated with AI utilization.

However, H4 did not receive significant support from the analysis, indicating that perceived usefulness does not significantly impact behavioral intention to use AI. This finding contrasts with previous research on technology acceptance, which often highlights the importance of perceived usefulness as a predictor of behavioral intention (Pan & Truong, 2018). This suggests that, in the context of AI in the aviation industry, other factors might play a more dominant role in shaping users' behavioral intentions.

On the other hand, H5 received strong support, indicating that behavioral intention to use AI positively influences trust. This finding aligns with the literature review, highlighting trust's fundamental role in AI systems (Dobrin, 2021; Thiebes et al., 2020). It suggests that users with a solid intention to use AI systems are more likely to trust the technology and its capabilities, emphasizing the role of perceived value in fostering trust.

Additionally, H6 received support from the analysis, revealing that attitude towards using AI positively impacts trust. This finding underscores the importance of users' positive attitudes towards AI adoption in building trust in the technology. It aligns with the notion that trust is intricately linked to users' perceptions of the usefulness and relevance of AI in their tasks and operations (Thiebes et al., 2020).

Finally, H7 and H8 did not receive significant support from the analysis. H7 indicated that perceived ease of use does not significantly impact trust, while H8 showed a strong negative relationship between perceived usefulness and trust. These results imply that perceived ease of use might not play a significant role in shaping users' trust in AI systems, and surprisingly, higher perceived usefulness might be associated with lower trust in specific contexts. These findings call for further exploration and understanding of the factors influencing trust in AI systems in the aviation industry.

In summary, perceived ease of use and usefulness positively affected attitudes towards AI, influencing users' intention to use it. However, perceived usefulness did not significantly impact intention. Intention and attitude positively influenced trust in AI. In some cases, higher perceived usefulness was associated with lower trust, highlighting the complexity of trust in AI in aviation. The study aligns with the importance of trust in AI and suggests the need for further exploration in the aviation context. One limitation of this study is that it restricted the population and sample to only US-based individuals within the commercial aviation space. A larger sample size increases statistical power and reduces the risk of type II errors, leading to more robust and reliable findings.

To enrich the conceptual framework for trustworthy AI, it is essential to consider the multidimensional nature of trust in AI systems. While the proposed framework encompasses critical dimensions identified in the literature review, further research could explore additional factors that influence trust. For instance, factors related to AI algorithms' transparency, interpretability, and fairness play a crucial role in building user trust. Integrating these aspects into the framework would provide a more comprehensive view of trustworthy AI and its impact on user perceptions and behaviors.

Practical Contributions

The findings of this study hold crucial practical implications for the aviation industry's adoption and integration of AI systems. The positive relationship between perceived ease of use and attitudes towards using AI underscores the importance of prioritizing user-centric design principles in developing AI technologies. Aviation companies should strongly emphasize creating intuitive and user-friendly AI interfaces to enhance user acceptance and foster a positive attitude toward AI adoption. Conducting thorough usability tests and seeking end-user feedback during the design phase can ensure that AI systems align with users' needs and preferences. This will lead to heightened user satisfaction and increased utilization of AI technology in aviation operations.

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