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Fostering trust in artificial intelligence in commercial aviation: an exploratory study

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Abstract

Artificial intelligence (AI) is a transformative force, compelling industries to adapt their operations, management systems, and workforce capabilities. The aviation sector finds itself at the forefront of this transformation, confronted with the imperative to navigate the complex dynamics of trust amidst AI's integration. Through a comprehensive survey involving 310 professionals from across the US commercial aviation sector, the research aims to shed light on the trust construct. The exploratory study provides critical insights for strategic AI adoption within the industry. A crosstabulation explored how employee trust in AI for decision-making differed across various demographic groups. In addition, a one-sample T-test was conducted to determine if the average trust score significantly differed from the hypothesized value of four, corresponding to neutral. Employing a multi-item trust scale allows for a robust investigation into the construct of trust about human-AI interactions in this high-stakes domain.

Keywords: Artificial Intelligence (AI), trust, Commercial Aviation, T-Test, SPSS

Introduction

Artificial Intelligence (AI) developed as our epoch’s utmost transformative high-tech innovations. Its prevalent weight expands amid numerous aspects of individual survival, restructuring how we discern and connect with mass media, converse with one another, and traverse our environments (Agrawal et al., 2019). AI is a compelling power boosting worldwide markets (Agrawal et al., 2019). As businesses quickly embrace and integrate this technology, grasping its capacity to generate value for the economy and society, in general, will play a pivotal role in shaping vital decision-making processes.

Although few organizations rely entirely on AI, many develop characteristics that eventually lead them in that direction. Repetitive tasks are increasingly being automated using AI technology. However, this digital revolution is expected to reduce the number of low-skilled physical and administrative jobs while creating new types of employment that involve handling more complex duties. The aviation sector must adapt by enhancing its operations, management systems, and workforce skills to respond to AI's disruptive effects (EASA, 2023).

Incorporating AI into commercial aviation operations brings up central queries and doubts around trust, automation of human interfaces, and potential or possible replacement. As AI systems assume or handle progressively significant functions and tasks, such as predictive maintenance, knowing how trust is formed and preserved among individual workers and these systems is crucial. This study explored perceptions of AI trust within the aviation industry, which is still in the early stages of development. A one-sample T-test was conducted to evaluate whether the average trust score significantly deviated from the hypothesized neutral value of 4. This statistical analysis assessed the overall trust in AI and its potential adoption within the commercial aviation industry. Additionally, the study recognized the importance of demographic variables in understanding the nuances of trust levels and their implications. Consequently, a comprehensive breakdown of the diverse demographic classifications of respondents is provided, offering insights into the potential factors influencing trust perceptions and AI adoption readiness within this critical sector.

This research begins with an overview of AI in aviation and a brief review of AI in aviation and trust. Next, the study details the methodology and presents the results and analysis. Finally, the conclusion is presented with a summary of the findings.

Artificial Intelligence and Aviation

The evolution made in AI has stimulated a mixture of anticipation and worry. The worries articulated by famous and leading figures, including Elon Musk, Bill Gates, Stephen Hawking, and Steve Wozniak, have grown to substantial hype, rebuking AI's potential to defy humans with shattering costs and effects (Helbing et al., 2017). AI, an area of computer science, is devoted to building smart agents capable of standalone thinking, learning, and decision-making (Dilmegani, 2021; Hodson, 2019; Ostrom et al., 2019). Although AI is still in its nascent stages of evolution, its potential to revolutionize the aviation industry is undeniable (EASA, 2023).

AI involves technologies capable of performing tasks that generally entail human intelligence, such as speech recognition, visual perception, and decision-making (Riedl, 2022). The AI systems discussed in this research include chatbots, robots, and autonomous vehicles, which have gained increasing significance in the economy and society (Riedl, 2022). While AI can potentially enhance lives and economies, it also comes with ethical, legal, social, and technological challenges (Thiebes et al., 2020; Stix, 2022).

Trust

The rapid advancement of artificial intelligence (AI) technologies has sparked a growing interest in exploring their potential applications within the aviation sector. A burgeoning body of research underscores the necessity for further investigation into integrating AI systems into aviation operations and management (Chakraborty et al., 2021; Airport International Review, 2021). These studies highlight the importance of establishing a comprehensive trust model to facilitate AI's successful adoption and effective utilization in this domain (Li et al., 2023). Calnan and Rowe (2007) define trust as an evaluation of risk and benefit, with optimistic expectations about the competence and goodwill of the trustee.

Li et al. (2023) emphasize that cultivating users' trust in AI systems is a prerequisite for widespread acceptance and realizing their full potential benefits. This assertion is echoed by Abraham et al. (2017), who note that while the airline and aerospace industries are automating various operations, successfully implementing these technologies hinges significantly on nurturing trust among stakeholders and increasing demand for AI-powered solutions.

Despite the promising potential of AI to enhance operational efficiency, improve decision-making processes, and ultimately achieve better outcomes in aviation, the absence of well-established trust models that demonstrate and foster user trust remains a significant barrier to widespread adoption. Moreover, the issue of user trust in AI systems within the specific context of the aviation sector needs to be adequately addressed in prior research or empirically modeled, posing a challenge to the broader integration of these transformative technologies.

In a forthcoming article to be featured in a special issue on AI in aviation, Halawi, Miller, and Holley (2024) apply the technology acceptance model (TAM) to explore the aviation industry's perceptions of AI's usefulness, ease of use, attitude towards usage, behavioral intention to use, trust level, and actual usage of AI. Surprisingly, higher perceived usefulness was sometimes associated with lower levels of trust, highlighting the intricate and nuanced nature of trust formation in the context of AI integration within the aviation domain. The study's findings emphasize the pivotal significance of trust in facilitating the successful adoption and integration of AI technologies within the aviation sector.

Methodology

Using Survey Monkey and social media, particularly LinkedIn, a comprehensive online survey targeted a diverse pool of 360 aviation professionals spanning multiple roles within the industry. The sample was filtered based on citizenship and profession to ensure relevant representation. The sample exhibited a gender distribution, with 61.2% being males, 35.2% being females, 1.5% being intersex disclosed, and 2.2% preferred not to disclose. The survey captured perspectives from professionals with varying experience levels, ranging from 1 to 30 years, distributed across junior, mid-career, and senior levels. This strategic sampling approach facilitated a comprehensive understanding of the industry's perspectives, capturing insights from individuals at different career stages and roles within the aviation sector,

This research aims to investigate how different demographic groups within the commercial aviation industry perceive and trust the use of AI, considering its early stages of development. To answer this question, “How do different demographic groups within the commercial aviation industry perceive and trust the use of AI?” a crosstab analysis was conducted to examine the relationship between employees' trust in AI applications for decision-making and various demographic factors. Additionally, a one-sample t-test was performed to assess if the average trust score among these groups significantly deviated from a hypothesized value of 4, representing a neutral stance toward AI. This hypothesis is based on the premise that individuals' trust in emerging AI technologies may vary depending on age, gender, education level, job role, and experience within the aviation industry.

The trust construct consisted of eight questions derived from the study conducted by McKnight et al. (2002). Factor analysis using principal component analysis with varimax rotation was conducted in SPSS to assess the construct validity of the measurement scale. The analysis followed an iterative approach to ensure a robust and valid factor structure (Hair et al., 2017; Kerlinger, 1986; Cooper & Schindler, 2011). Initially, the 9-item scale did not load onto a single factor as expected. Instead, the items are loaded onto two separate factors. Per the guidelines of Hair et al. (2017), items with factor loadings below 0.5 and cross-loadings on multiple factors were systematically eliminated. Specifically, one item was dropped due to its failure to meet the 0.5 loading cutoff criterion. The remaining eight items were subjected to another round of factor analysis. This iterative process of running factor analysis, evaluating loadings, removing problematic items, and re-running continued until a clear factor structure emerged. Factor loadings exceeding 0.5 were considered highly significant indicators of construct validity. Ultimately, the iterative factor analysis approach yielded a coherent and interpretable factor solution, ensuring the construct validity of the measurement scale. This study assessed the construct using Cronbach's Alpha to ensure consistent reliability. The trust construct exhibited an (α) value above 0.934. Additionally, SPSS version 28 was employed to generate other data necessary for the research analysis.

Results and Discussion

A cross-tabulation analysis explored the relationship between the trust component and various demographic variables to understand the factors influencing trust perceptions and AI adoption readiness within the commercial aviation industry. This analysis provided valuable insights into how demographic groups perceive and trust AI technologies. This section presents the results of examining the relationship between trust and demographic variables. Using a crosstabulation, we begin by exploring the distribution of trust scores across different demographic groups.

Question: *I would trust an AI agent or tool to avoid a mistake without my intervention." by the number of years employed (figure 1)*

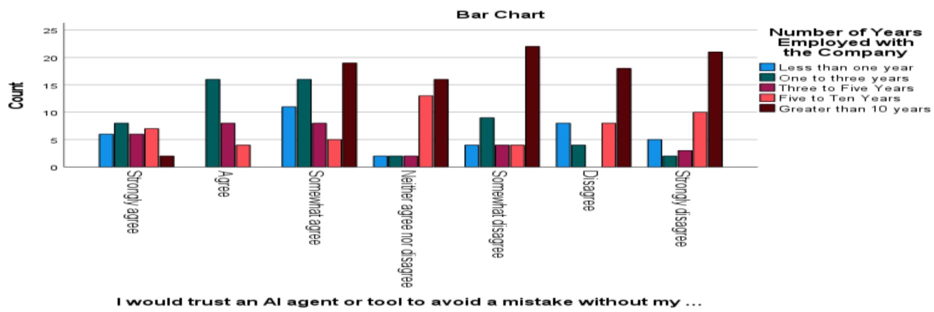

Figure 1: Trust and Number of Years Employed

Figure 1 shows some notable patterns: For shorter employment durations (less than one year and 1-5 years), there is a higher percentage expressing some level of agreement (strongly/somewhat agree) than disagreement. For longer employment durations (5-10 years and over 15 years), there is a higher percentage expressing disagreement than agreement. The "Neutral or not sure" response has a relatively consistent percentage across employment durations.

Question 2: *I trust AI applications to make decisions in my best interest."and educational level (figure 2)*

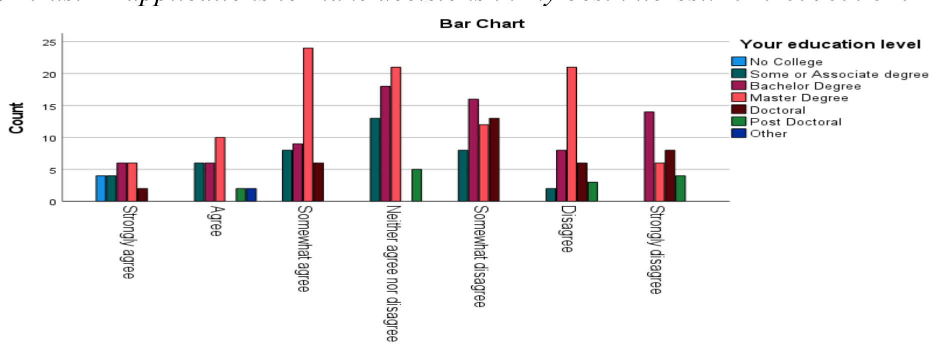

Figure 2: Trust and Educational Level

Figure 2 shows a few notable patterns. Among those with lower education levels (No College, Some/Associate degrees), there seems to be a higher proportion who either strongly agree or agree that they trust AI applications to make decisions aligned with their interests. For groups with higher education levels (Bachelor's, Master's, Doctoral, Post Doctoral), there is a more mixed response, with sizable percentages expressing disagreement or being neutral/unsure. The "Neither agree nor disagree" response has a relatively consistent percentage across most education levels. The "Strongly disagree" response shows a notable pattern, with a higher percentage among the Post Doctoral and Doctoral education levels than others. The "Strongly agree" percentage is highest for the "No College" group but lower and more varied across other education levels. These patterns suggest that education level may influence individuals' trust in AI decision-making applications, with those with higher education levels expressing more skepticism or uncertainty.

Question 3: *"I would trust an AI agent's decision more than a human decision." by the position in the company (figure 3)*

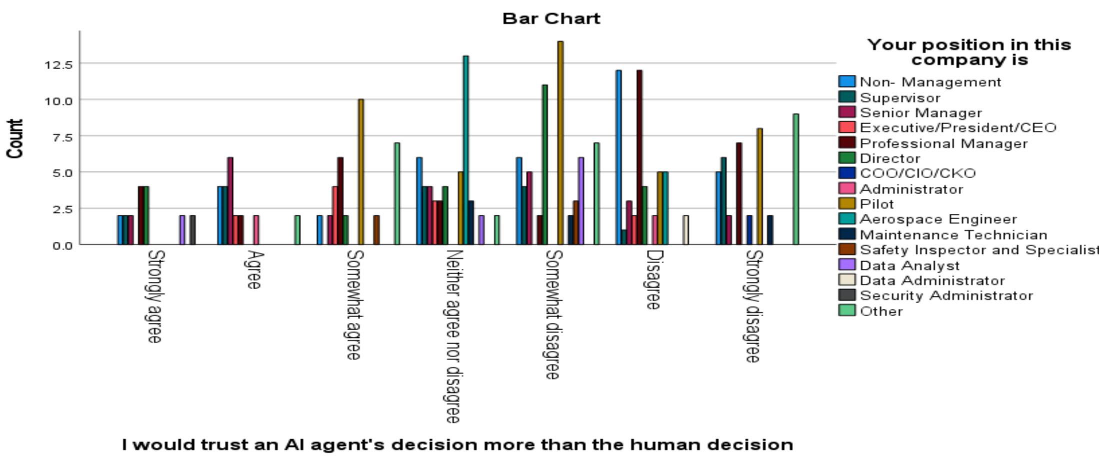

Figure 3: Trust and Position in Company

Figure 3 shows noticeable differences in response patterns across various role categories. Some roles tend to have a higher proportion of respondents who disagreed or strongly disagreed with the statement. In contrast, others show a more evenly distributed or even a leaning towards agreement. These variations could indicate differences in perceptions, attitudes, or experiences with AI decision-making across different organizational roles or levels. However, drawing definitive conclusions would require further context and analysis, considering factors such as job responsibilities, exposure to AI systems, and organizational culture.

Question 4*: "Commercials and advertising would increase my trust in AI agents and tools." by gender assigned at birth (figure 4).*

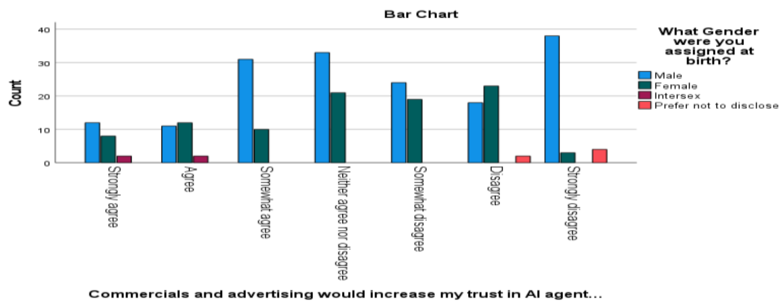

Figure 4: Trust and Gender Assigned at Birth

According to Figure 4, overall, the chart suggests that commercials and advertising influence trust in AI tools, with males showing a broader distribution of opinions and females generally more skeptical or undecided.

Question 5: *I am comfortable relying on AI applications for important decisions," by educational level (figure 5)*

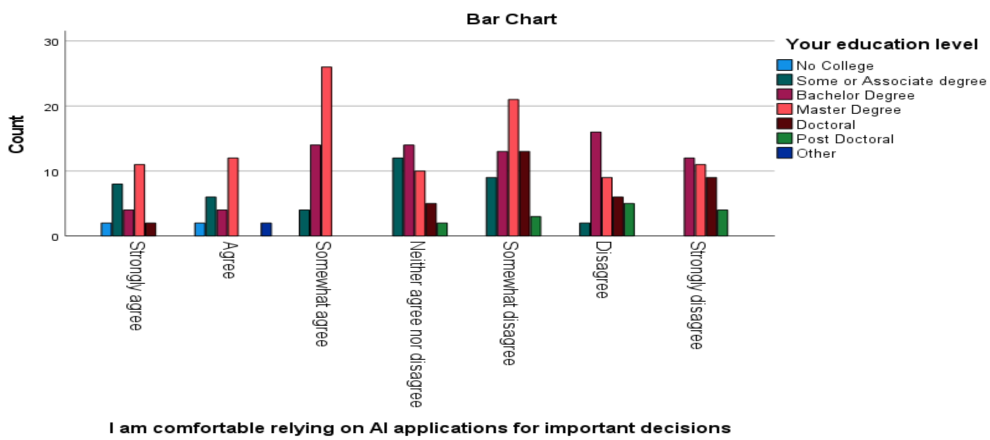

Figure 5: Trust and Educational Level

According to Figure 5, as the education level increases from some/associate degree to bachelor's to master's to doctoral, there is a general trend of decreasing agreement (strongly agree + agree) with relying on AI for important decisions. The data suggests that higher education levels correspond with more hesitancy or disagreement about relying heavily on AI for important decisions. At the same time, those with bachelor's degrees exhibit the highest comfort level.

Question 6: I believe AI applications can provide reliable results based on the organization's position (figure 6).

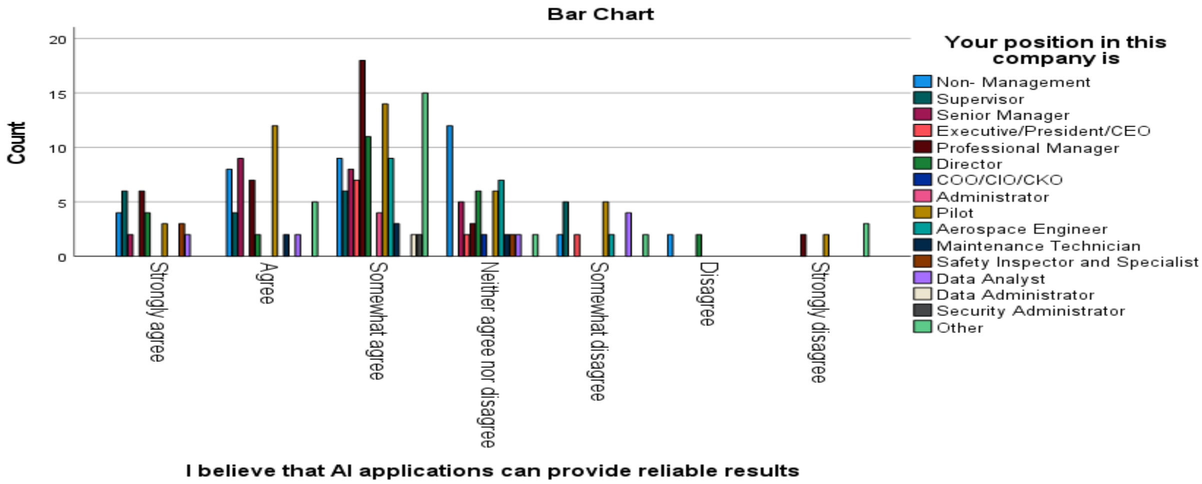

Figure 6: Trust by Position

We investigate the distribution between an individual's belief that AI applications can provide reliable results and their position in the organization. The bar chart shows that a higher percentage of people in senior management positions believe that AI applications can provide reliable results than those in lower-level positions.

Question 7: *"I have confidence in the accuracy of AI applications." by organization type (Figure 7).*

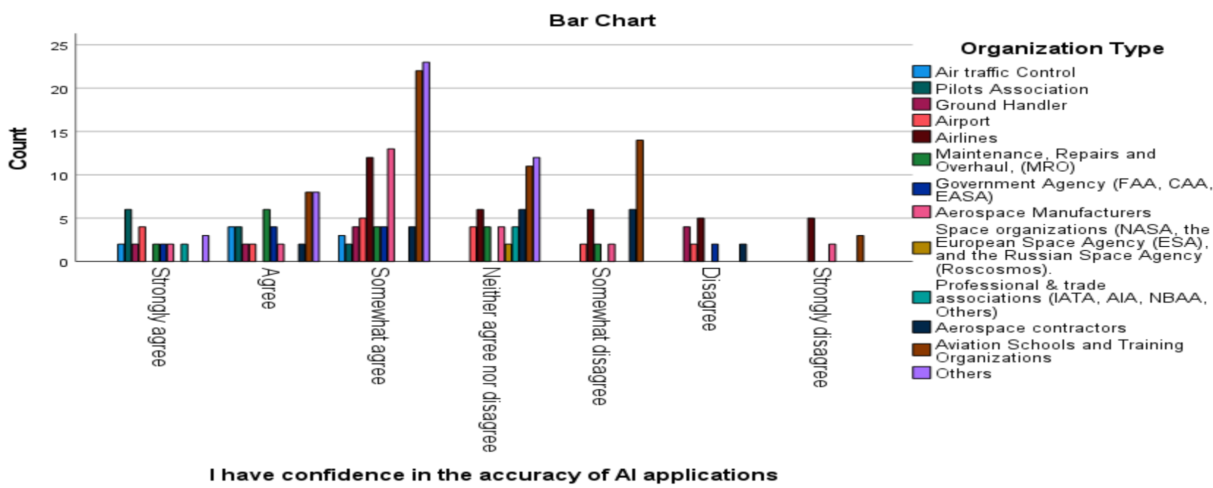

Figure 7: Trust by Organization Type

Figure 7 portrays the distribution by organization type, suggesting that the highest percentage expressing confidence in AI accuracy was from the Academic organization type, while the lowest was from the other categories. However, the differences across types do not appear extremely large.

Question 8: *"I think AI applications are trustworthy by age (figure 8)*

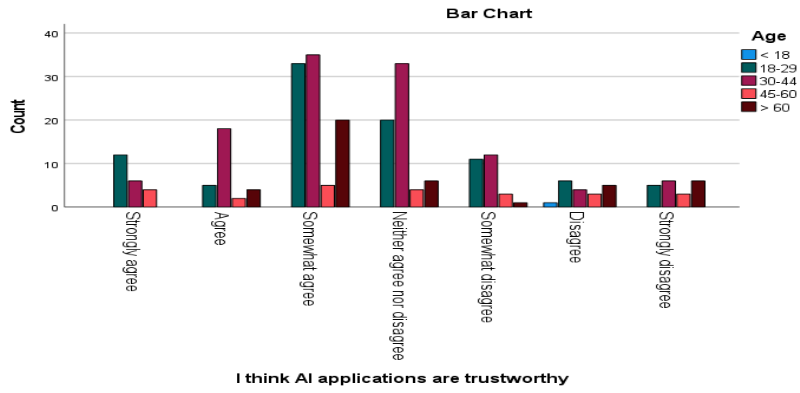

Figure 8: Trust and Age

The bar chart illustrates the responses to the statement "I think AI applications are trustworthy" across different age groups. Younger individuals (<18): More likely to strongly trust AI applications. Young adults (18-29): Have a significant spread across all responses, with a notable number in "somewhat agree" and "neither agree nor disagree," indicating mixed feelings. Middle-aged adults (30-44): Show more skepticism, with higher counts in "somewhat disagree" and "disagree. "Older adults (45-60 and >60): Generally, more skeptical or undecided about AI trustworthiness, with fewer showing solid opinions either way. This graph indicates that trust in AI applications varies widely across age groups, with younger individuals tending to trust more and middle-aged to older adults showing more skepticism.

T-test

To further investigate the overall trust score, we conducted a one-sample t-test to determine if the average trust score significantly differed from the hypothesized value of four, representing a neutral position on the trust scale."

> ***The null Hypothesis (H_0):*** The average (mean) of the population is equal to 4.
> ***Alternative Hypothesis (H_1):*** The average (mean) of the population is not equal to 4.

The results of the one-sample t-test suggest a rejection of the null hypothesis (Figure 9). The null hypothesis typically assumes no difference between the population mean and the hypothesized value of 4 (neutral trust). However, the two-sided p-value of less than .001 indicates a statistically significant difference, implying that there is strong evidence to suggest that the population mean trust score deviates from the neutral value of 4.

Specifically, the observed sample mean of 3.96 indicates a slightly lower level of trust than the hypothesized neutral value. However, it is crucial to acknowledge the limitations of this test. While it provides insights based on the sample data, the results may not be generalizable to the entire population within the commercial aviation industry. Sample size, sampling methods, and potential biases should be considered when interpreting and extrapolating these findings.

One-Sample Test

	Test Value = 0						
			Significance			95% Confidence Interval of the Difference	
	t	df	One-Sided p	Two-Sided p	Mean Difference	Lower	Upper
TU	47.020	272	<.001	<.001	3.96108	3.7952	4.1269

Figure 9: One Sample T-Test

Conclusion

By examining the variations in trust levels across diverse demographics, the study uncovered potential factors influencing the acceptance and adoption of AI technologies within the commercial aviation sector, where trust and confidence in emerging technologies are paramount for successful implementation. The one-sample t-test determined if the overall trust level significantly deviates from neutrality, indicating either heightened trust or distrust toward AI among commercial aviation personnel. Concurrently, the crosstab analysis revealed patterns in how different demographic segments perceive the trustworthiness of AI applications for decision-making. Concurrently, the one-sample t-test determined if the overall trust level significantly deviates from neutrality, indicating either heightened trust or distrust toward AI among commercial aviation personnel.

There is a persistent need for wide-ranging research investigating the complex issues affecting trust in AI within the aviation domain. By analytically examining the sophisticated interactions among system types, human factors, organizational effects, and trust formation, such a study may offer constructive perceptions to inform the advancement and implementation of trusted AI systems designed for the aviation industry's exceptional necessities. This research encourages continuous and intensive efforts to highlight the intricate factors affecting trust in AI within the aviation industry's exclusive context. Future research should prioritize building and maintaining trust in AI-powered aviation systems. This includes exploring ethical considerations, legal frameworks, and governance structures for developing and deploying AI in aviation.

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