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Araştırma Makalesi

EXAMINING THE AI ANXIETY LEVELS OF AVIATION EMPLOYEES BASED ON DEMOGRAPHIC VARIABLES

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Abstract[1]

The accelerated advancements in Artificial Intelligence (AI) give rise to anxieties regarding workplace tasks, job security, privacy, and ethics, which significantly impact employees in the technology-intensive aviation sector. The aim of the study was to examine the level of AI anxiety among professionals in the aviation sector and to investigate whether it varies based on factors such as gender, education, age, experience, and sub-sector. A survey methodology was employed. An online questionnaire was used to collect data from 345 aviation sector employees. The AI Anxiety Scale, a 5-point Likert-based instrument, was used as the measurement tool. The analysis results indicated that AI anxiety levels among aviation sector employees were moderate (M=2.8047). AI anxiety levels were highest in the sociotechnical/blindness sub-dimension (M=3.3775) and lowest in the AI learning sub-dimension (M=2.1055). No statistically significant differences in anxiety levels were found based on age, experience, or sub-sector, whereas education level showed significant differences. Although general AI anxiety did not significantly vary by gender, a notable difference was observed in AI configuration. As AI evolves in the aviation sector, addressing employee anxieties across sub-dimensions is essential for effective integration. Given the rapid advancements in AI technology, future studies should adopt a more detailed approach, focusing on sector-specific variations and analyzing the unique structures and requirements of each aviation sub-sector.

Keywords: *Artificial Intelligence, Artificial Intelligence Anxiety, Aviation, Employment, Technology.*

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HAVACILIK ÇALIŞANLARININ YAPAY ZEKA KAYGI DÜZEYLERİNİN DEMOGRAFİK DEĞİŞKENLERE GÖRE İNCELENMESİ

Öz

Yapay zekanın (YZ) hızlı gelişimi işyerindeki görevler, iş devamlılığı, gizlilik ve etik sorunlar gibi konularda kaygılara yol açmaktadır. Yoğun teknolojinin kullanıldığı havacılık sektöründeki çalışanlar da bu kaygılardan etkilenebilir. Bu çalışmanın amacı, havacılık sektöründeki YZ kaygı düzeylerini incelemek ve bu durumun cinsiyet, eğitim, yaş, tecrübe ve alt sektör gibi faktörlere göre değişip değişmediğini araştırmaktır. Çalışmada tarama yöntemi kullanılmış ve çevrimiçi anket yoluyla havacılık sektöründe çalışan 345 katılımcıdan veri toplanmıştır. Ölçme aracı olarak 5'li Likert derecelendirmesine dayalı YZ kaygı ölçeği kullanılmıştır. Bulgular havacılık sektörü çalışanları arasında orta düzeyde bir kaygı olduğunu (M=2.8047) göstermiştir. YZ sosyoteknik/körlük alt boyutunda kaygı seviyesi (M=3.3775) daha yüksek iken, YZ öğrenme alt boyutunda kaygı seviyesi (M=2.1055) daha düşüktür. Yaş, tecrübe ve alt sektörler arasında kaygı seviyelerinde anlamlı bir istatistiksel farklılık bulunmamıştır; ancak eğitim düzeyine bağlı farklılıklar tespit edilmiştir. Cinsiyet açısından genel olarak YZ kaygısında anlamlı bir farklılık bulunmamakla birlikte, YZ yapılandırma boyutunda anlamlı bir fark gözlemlenmiştir. Havacılık sektöründe YZ'nin gelişimiyle birlikte, çalışanların farklı boyutlardaki kaygılarının ele alınması etkin entegrasyon için önem taşımaktadır. Hızla gelişen YZ teknolojisi göz önüne alındığında, gelecekteki araştırmaların daha detaylı bir yaklaşım benimsemesi ve sektöre özgü varyasyonlar ile her bir havacılık alt sektörünün benzersiz yapı ve ihtiyaçlarını incelemesi önerilmektedir.

Anahtar kelimeler: *Havacılık, İstihdam, Teknoloji, Yapay Zeka, Yapay Zeka Kaygısı.*

INTRODUCTION

Artificial intelligence (AI) has emerged as an indispensable element of modern society, significantly influencing diverse sectors such as healthcare, transportation, and public administration. Since its initial conceptualization at the Dartmouth Conference in 1956, AI has undergone significant evolution, leading to sophisticated systems capable of replicating human cognitive functions, such as learning and decision-making (Zhang & Lu, 2021). Recent advancements in computational capabilities, particularly in neural networks and deep learning, have greatly expanded AI's utility. These advancements have driven substantial global investments. For instance, the United States allocated $28.5 billion to AI-focused enterprises in 2019, while the European Commission committed €20 billion annually to AI initiatives starting in 2020 (Wirtz et al., 2019). The capacity of AI to analyze vast datasets and derive actionable insights has led to its application in fields such as healthcare, where it has been instrumental in improving diagnostic accuracy. Similarly, in industrial operations, AI has been employed to optimize resource allocation and cost efficiency (Zhang & Chu, 2020). In recent years, AI technologies have profoundly transformed various industries, driving substantial innovations. AI is widely employed across various sectors, including business, healthcare, education, transportation, and aviation (Abubakar et al., 2022).

The transformative potential of AI is not limited to the private sector; it is also having a considerable impact on public administration. The application of AI results in enhanced performance at both the organizational and process levels. This is achieved by optimizing existing processes and by augmenting the effects of automation, information, and transformation (Enholm et al., 2021; Wamba-Taguimdje et al., 2020). Governments around the globe are employing AI to improve the quality of service delivery by automating routine processes and providing support for strategic decision-making. This transition is consistent with the customer-centric tenets of contemporary public administration, which prioritize citizen satisfaction and operational efficiency (Suebvises, 2018). By enabling more expeditious and precise decision-making, AI enables public employees to prioritize strategic objectives, thereby enhancing the quality and accessibility of services (Yalçın, 2024). Furthermore, the potential for AI to drive economic growth is evident in forecasts that estimate the technology's contribution to a $13 trillion global economic expansion by 2030 (Bughin et al., 2018). As nations and corporations continue to prioritize AI development, this technology is expected to remain a cornerstone of innovation, enabling societal advancements across numerous domains. However, despite these promising advancements, the accelerated expansion of AI also gives rise to anxieties about its ethical implications, potential job replacement, and the necessity for appropriate regulation to ensure fair and responsible implementation.

AI anxiety refers to the anxieties and fears individuals have toward AI technologies. This anxiety typically relates to AI's role in workplace tasks (Moore, 2019; Tang et al., 2023), job security (Huang & Rust, 2018; McClure, 2018; Rhee & Jin, 2021), privacy (Elliott & Soifer, 2022; Kronemann et al., 2023; Majeed & Hwang, 2023), and ethical issues (Boddington et al., 2017; Khan et al., 2021; Siau & Wang, 2020). AI anxiety is influenced by real and popular representations of AI's potential negative consequences, and addressing technology readiness is unlikely to mitigate its effects (Lemay et al., 2020). AI anxiety is a crucial research topic because it can affect employees' job performance, motivation, and overall psychological well-being. High anxiety traits, which contribute to individual differences in stress vulnerability, lead to behavioral, cognitive, and physiological alterations in highly anxious individuals (Weger & Sandi, 2018).

AI anxiety, a multifaceted phenomenon, has been observed since the early days of robotics, often referred to as robot-anxiety (Nomura et al., 2006). This anxiety is primarily rooted in misunderstandings and confusion about AI's capabilities and autonomy, compounded by an inaccurate conception of technological development (Dignam, 2020; Johnson & Verdicchio, 2017). Public anxieties about AI extend to ethical and legal issues, emphasizing the need to embed principles in AI algorithms to ensure social benefit (Ntoutsi et al., 2020).

Moreover, AI anxiety is exacerbated by anxieties about job replacement and the necessity for ongoing skill development in an AI-dominated job market (Huang & Rust, 2018; Manyika et al., 2017; Wang & Siau, 2019; Wang & Wang, 2019). The complexity, autonomy, and potential for AI to exploit human users further exacerbate these anxieties (Cheruvu, 2022). Additionally, anxieties were expressed regarding the functionality, transparency, potential for misuse, bias, unemployment, socio-economic inequality, moral issues, robot consciousness, dependency, and psychological and spiritual effects of AI (Green, 2018).

Specific anxieties in the medical field include data sharing and privacy, transparency of algorithms, data standardization, interoperability across platforms, and patient safety (He et al., 2019). The limitations of AI, such as its dependency on big data and lack of self-awareness, add to the anxiety (Lu et al., 2017). Overall, AI anxiety reflects broader societal anxiety about the disruptive effects of AI and its implications for future work and human well-being (Johnson & Verdicchio, 2017; Wang & Wang, 2019).

The components of AI anxiety include the learning process, job replacement, sociotechnical blindness, and AI configuration. AI has become a crucial part of modern life, impacting various aspects of both personal and professional domains, and necessitating that individuals learn new skills to adapt to these changes (Manyika et al., 2017; Wang & Siau, 2019). In the technological era, learning about AI technologies is essential for career sustainability, often requiring continuous skill updates from employees (Terzi, 2020). Motivated learning behavior refers to the effort and perseverance individuals exhibit to acquire new professional skills (Wang & Wang, 2019). With the advancement of technology, some jobs may be fully automated, reducing or eliminating the need for human workers, while the nature of other jobs may change, necessitating adaptation and job transitions, which can heighten anxiety related to AI (Manyika et al., 2017; Wang & Siau, 2019). Furthermore, the widespread adoption of AI might force individuals to change jobs, contributing to anxiety (Wang & Wang, 2019). The concept of sociotechnical blindness describes the heightened anxiety levels in individuals unaware that AI systems always operate in conjunction with human and social institutions (Johnson & Verdicchio, 2017). Anxieties about the uncontrollability of AI, its potential misuse, or the problems it might cause further exacerbate this anxiety, reflecting fears of AI operating without human intervention (Johnson & Verdicchio, 2017; Wang & Wang, 2019). Lastly, AI configuration anxiety, similar to robot-anxiety, refers to the fear and intimidation some individuals feel towards human-like AI techniques and products (Wang & Wang, 2019).

The aviation industry is a technology-focused sector that drives global advancements (Otuokwu & Chikwanda, 2022), and must master a wide range of technologies while collaborating to integrate them (Arnolda Valdes et al., 2019). Additionally, unmanned aerial vehicle (UAV) technology has played a pivotal role in the advancement of the aviation industry (Torija & Clark, 2021). It is therefore important to consider the impact of AI on employees in the aviation sector. The increasing use of AI technologies is altering the job descriptions and responsibilities in the aviation industry. AI's impact on service-related tasks involves automating routine functions, which enhances efficiency and reduces human error (Huang & Rust, 2018). In the field of engineering, AI is being applied to aircraft design and manufacturing to not only improve aircraft performance but also to meet future mission requirements, thereby driving innovation and operational excellence (Zou & Sun, 2021). AI techniques in air traffic management are particularly noteworthy, with advancements such as machine learning-configured cognitive human-machine interfaces, which contribute significantly to optimizing air traffic control operations and reducing workload for controllers (Kistan et al., 2018). Furthermore, in pilot operations, AI, particularly cognitive computing, is utilized to enhance human decision-making and facilitate interaction through technologies like augmented reality, proving to be pivotal in the development of single-pilot operations (Liu et al., 2016; Minaskan et al., 2021; Piera et al., 2022). AI also significantly boosts customer service by providing personalized experiences (Daqar & Smoudy, 2019). Cybersecurity and safety risk management are bolstered through AI's threat detection and risk assessment capabilities (European Union Aviation Safety Agency [EASA], 2023). This shift may lead to uncertainty and insecurity among some traditional jobs. Although the potential of AI to reduce human errors and enhance performance and efficiency in the aviation industry is viewed favorably, anxieties about job loss and changes in professional roles that may cause anxiety should not be overlooked.

The impact of demographic and occupational variables, including gender, education, age, experience, and sub-sector, on AI anxiety is considerable. Each of these variables has the potential to influence individuals' attitudes and anxieties regarding AI. For instance, younger employees may demonstrate greater capacity for adaptation to novel technologies, whereas older employees may tend to exhibit greater resistance to change (Meyer, 2007). Similarly, gender (Çetiner & Çetinkaya, 2023) and educational level (Çobanoğlu & Oğuzhan, 2023) were found to be significant factors influencing variations in AI anxiety levels. Additionally, in a study determining the level of anxiety toward computer technology, it was found that males have less computer anxiety than females (Broos, 2005). Moreover, a higher level of education has demonstrated a protective effect against anxiety (Bjelland et al., 2008), indicating that individuals with more education may feel more confident in their ability to understand and utilize AI technologies. It was also demonstrated that work experience is a significant factor influencing anxiety levels (Sharma & Devi, 2011). This indicates that individuals with greater experience may either feel more secure in their roles or, conversely, more threatened by new technologies that could disrupt established practices. Additionally, the applications of AI in different sub-sectors of aviation may result in varying levels of anxiety. It is therefore essential to gain a detailed understanding of these nuances in order to develop effective strategies to mitigate AI anxiety in diverse employee populations.

Although the number of studies on AI anxiety is increasing, research specific to the aviation sector is limited. Existing studies generally address the overall effects of AI but do not adequately explore sector-specific anxieties and their relationships with demographic and occupational factors. The study aims to fill these gaps in the literature by providing new insights into how AI anxiety varies across different contexts and demographics.

The aim of the study is to investigate the level of AI anxiety in the aviation sector and to examine whether this level varies based on factors such as gender, education, age, experience, and sub-sector. The research question is: "To what extent does AI anxiety occur in the aviation sector, and does this level vary among groups based on gender, education, age, experience, and sub-sector, considering learning, job replacement, sociotechnical blindness, and AI configuration?".

This research is important both theoretically and practically. Theoretically, understanding sub-dimensions of AI anxiety and their relationships with demographic and occupational variables will contribute significantly to the AI anxiety literature. The findings of the study will inform the practices of aviation sector managers and policymakers with regard to the effective management of AI applications and the development of strategies designed to mitigate employee anxiety and enhance human-technology interaction.

METHODOLOGY

The accelerated integration of AI technologies into the aviation sector has brought both opportunities and challenges, with a growing anxiety among professionals about AI anxiety. This anxiety reflects apprehensions about AI's potential impact on learning processes, job replacement, and sociotechnical systems. The study aims to investigate the level of AI anxiety among aviation professionals and examine whether it varies based on factors such as gender, education, age, experience, and sub-sector. By addressing these factors, the research is expected to provide insights into how different groups perceive and adapt to AI advancements, contributing to the broader understanding of this critical issue. To achieve this aim, the study employs a survey model, a descriptive research method frequently applied in social sciences and aviation-related studies. The survey model is designed to identify interrelationships between variables and test the validity of specific hypotheses (Goodman, 1972). The online questionnaire was selected as the data collection instrument due to its efficiency in reaching a large and diverse sample, its ability to collect data within a short timeframe, and its ease of administration and analysis. Additionally, considering the irregular working hours and shift-based system prevalent in the aviation sector, this method was considered the most suitable for ensuring accessibility and flexibility for participants, allowing them to complete the questionnaire at their convenience without disrupting their professional responsibilities.

Convenience sampling was implemented to address the practical constraints of the aviation sector, particularly the increased workload during the summer period when aviation operations experience heightened activity. This method was selected due to its accessibility, efficiency, and cost-effectiveness in data collection (Etikan et al., 2016), and it is frequently applied in similar studies (Haşıloğlu et al., 2015). To mitigate potential biases associated with convenience sampling, several measures were taken to enhance the sample's representativeness. These efforts included targeting employees from diverse professional groups and sub-sectors within the aviation industry. The survey was disseminated via multiple channels, including social media platforms, organizational mailing lists, and industry-specific communities, to ensure broad accessibility and participation from different demographic groups. Furthermore, the demographic characteristics of the sample were continuously monitored and compared to national data reported by the Directorate General of Civil Aviation. This comparison enabled the identification and inclusion of diverse groups, thereby enhancing the sample's diversity. Despite the unavoidable limitations of convenience sampling with regard to randomness, these measures were implemented to ensure a more comprehensive cross-section of the population, thereby enhancing the credibility and generalizability of the findings.

Survey Instrument

Information form: A form was used to collect demographic information from participants, including gender, age, education level, work experience, and sub-sectors. Additionally, the form included questions about the use of AI applications, the specific AI applications currently in use at participants' companies or organizations, and the processes in which participants expect AI to be involved within the aviation sector. It also assessed participants' attitudes toward AI.

Artificial intelligence anxiety (AIA) scale: The AIA scale, developed by Wang and Wang (2019) to measure the increasing AI anxiety among individuals in recent years and adapted to Turkish by Akkaya et al. (2021), was used. The scale was used with permission. The adapted scale consists of 16 items with four sub-dimensions. The learning dimension of the scale includes items 1 to 5, the job replacement dimension includes items 6 to 9, the sociotechnical/blindness dimension covers items 10 to 13, and the AI configuration dimension consists of items 14 to 16. It employs a 5-point Likert scale ranging from "(1) Strongly Disagree" to "(5) Strongly Agree".

Study Population & Data Collection

The study sample comprised employees in the aviation sector, working across various companies and organizations in both the public and private sectors in Türkiye. According to the 2023 annual report of the Directorate General of Civil Aviation (n.d.), there are 262,925 employees in the aviation sector in Türkiye. A power analysis was conducted using G*Power 3.1.9.7 (Faul et al., 2007) to determine the sample size required for the study. Using a medium effect size (f=0.25), an alpha level of 0.05, and a power level of 0.80, the analysis indicated that a minimum of

200 participants were required to detect significant differences across demographic groups (e.g., experience levels, sub-sectors, gender). Furthermore, a sample size of 300 is considered sufficient and appropriate for ensuring reliable and valid results in factor analysis for the most common purposes (Comrey & Lee, 1992; Field, 2013). In addition, the study accounted for the requirement that each comparison group consist of at least 30 participants (n > 30) (Orhunbilge, 2000). Ultimately, 345 participants were included in the study, exceeding both the minimum recommended sample size for power analysis and the threshold for factor analysis. This larger sample size not only strengthens the validity and generalizability of the findings but also ensures adequate representation of all demographic subgroups.

Data for the study were collected between June 29 and July 20, 2024. Ethical approval for the study was obtained from the International Science and Technology University Ethics Committee, as documented in the report dated June 28, 2024 (Report No: 202406-02).

Research Question and Hypotheses

The study examines the prevalence of AIA in the aviation sector and whether this prevalence varies among groups based on gender, education, age, experience, and sub-sectors. It considers sub-dimensions of the AIA scale, including learning, job replacement, sociotechnical/blindness, and AI configuration. In this context, the research question is determined as "To what extent does AI anxiety occur in the aviation sector, and does its level vary among groups based on gender, education, age, experience, and service sector, when considering the sub-dimensions of learning, job replacement, sociotechnical/blindness, and AI configuration?". The research hypotheses are shown in Table 1.

Table 1: Research Hypotheses

H1a: There is a statistically significant difference in AIA levels in aviation based on gender.
H1b: There is a statistically significant difference in AIA-L levels in aviation based on gender.
H1c: There is a statistically significant difference in AIA-JR levels in aviation based on gender.
H1d: There is a statistically significant difference in AIA-SB levels in aviation based on gender.
H1e: There is a statistically significant difference in AIA-C levels in aviation based on gender.
H2a: There is a statistically significant difference in AIA levels in aviation based on education.
H2b: There is a statistically significant difference in AIA-L levels in aviation based on education.
H2c: There is a statistically significant difference in AIA-JR levels in aviation based on education.
H2d: There is a statistically significant difference in AIA-SB levels in aviation based on education.
H2e: There is a statistically significant difference in AIA-C levels in aviation based on education.
H3a: There is a statistically significant difference in AIA levels in aviation based on age.
H3b: There is a statistically significant difference in AIA-L levels in aviation based on age.
H3c: There is a statistically significant difference in AIA-JR levels in aviation based on age.
H3d: There is a statistically significant difference in AIA-SB levels in aviation based on age.
H3e: There is a statistically significant difference in AIA-C levels in aviation based on age.
H4a: There is a statistically significant difference in AIA levels in aviation based on experience.
H4b: There is a statistically significant difference in AIA-L levels in aviation based on experience.
H4c: There is a statistically significant difference in AIA-JR levels in aviation based on experience.
H4d: There is a statistically significant difference in AIA-SB levels in aviation based on experience.
H4e: There is a statistically significant difference in AIA-C levels in aviation based on experience.
H5a: There is a statistically significant difference in AIA levels in aviation based on sub-sector.
H5b: There is a statistically significant difference in AIA-L levels in aviation based on sub-sector.

H5c: There is a statistically significant difference in AIA-JR levels in aviation based on sub-sector.
H5d: There is a statistically significant difference in AIA-SB levels in aviation based on sub-sector.
H5e: There is a statistically significant difference in AIA-C levels in aviation based on sub-sector.

AIA= AI anxiety; AIA-L= AI learning anxiety; AIA-JR=AI job replacement anxiety; AIA-SB=AI sociotechnical/blindness anxiety; AIA-C= AI configuration anxiety

Statistical Analysis

The initial stage of the analysis involved the use of descriptive statistics, including the calculation of frequency (n), percentage (%), mean, and standard deviation values. Factor analysis was conducted to assess the survey's validity, and Cronbach's Alpha was calculated to measure its reliability. Once the normality assumption (Tabachnick & Fidell, 2019) was confirmed, an independent samples t-test and one-way ANOVA were performed for group comparisons. These statistical analyses were conducted using IBM SPSS (Statistical Package for the Social Sciences) V27.

FINDINGS

Findings on Demographic Variables

The sample comprised 345 participants as shown in Table 2, with a near-equivalent distribution of males and females, with 50.1% of the sample being female and 49.9% male. The balanced representation permitted a comprehensive analysis of AI anxiety across genders within the aviation industry. The majority of participants were in the 26-35 age group (34.8%) and the 36-45 age group (33.9%). The remaining participants were distributed among the 18-25 age group (12.2%) and the 46-year-olds and older (19.1%). The diversity in age afforded a comprehensive perspective on AI anxiety from both younger and older professionals in the field of aviation. In terms of educational background, 64.3% of participants had obtained an undergraduate degree, while 35.7% held a graduate degree. This high level of educational attainment indicated that the participants were suitably qualified to provide insights into the implications of AI in their field. The participants' professional experience was found to vary considerably. A total of 27.2% of the participants had less than 2 years of experience, while 30.4% had more than 15 years. Other groups included those with 3-5 years (11.9%), 6-10 years (16.5%), and 11-15 years (13.9%) of experience. This range of experience levels proved invaluable in understanding how AI anxiety might affect both novice and seasoned professionals in different ways. The participants were divided into various sub-sectors within the field of aviation. The distribution included airline transportation (25.5%), airport management (11.0%), air navigation services (26.4%), and training (9.0%). A notable proportion (28.1%) was classified as "Other", encompassing sectors such as regulatory/supervisory activities (n=14), ground services (n=19), and aircraft manufacturing, maintenance, and repair (n=11). These groups were aggregated due to their smaller sample sizes (n<30) to ensure the reliability of the statistical analysis. A significant majority of participants (68.1%) had used AI applications. Conversely, 31.9% had not used AI, highlighting a divide in AI adoption. Upon inquiry regarding the presence of AI applications within their organizations, 35.7% confirmed their use, while 38.3% (n=132) reported no such applications. Additionally, 26.1% were unsure, suggesting varying levels of awareness or implementation of AI across organizations. Participants expected AI to be involved in various processes. The distribution included automated/repetitive core processes (43.5%), support tools and analytical processes (39.7%), and full automation (16.8%). These expectations reflected a general anticipation of AI's growing role in enhancing efficiency and decision-making within the aviation sector.

Table 2: Demographic Information

		n	%
Gender	Female	173	50.1
	Male	172	49.9
Age	18-25	42	12.2
	26-35	120	34.8
	36-45	117	33.9
	46-year-old and older	66	19.1
Education	Undergraduate	222	64.3
	Graduate	123	35.7
Experience	< 2 years	94	27.2
	3-5 years	41	11.9
	6-10 years	57	16.5
	11-15 years	48	13.9
	> 15 years	105	30.4
Sub-sectors	Airline Transportation	88	25.5
	Airport Management	38	11.0
	Air Navigation Services	91	26.4
	Training	31	9.0
	Other	97	28.1
Have you ever used any AI applications?	Yes	235	68.1
	No	110	31.9
Are there any AI applications currently in use at your company/organization?	Yes	123	35.7
	No	132	38.3
	I don’t know	90	26.1
In which processes do you expect AI to be involved if it is used in the aviation sector?	Automated/repetitive core processes	150	43.5
	Support tools and analytical processes	137	39.7
	Full automation	58	16,8
Total		**345**	**100.0**

The level of support for the utilization of AI in the aviation sector was measured on a 5-point Likert scale. As shown in Table 3, the mean score was 3.97 with a standard deviation of 0.935, indicating a generally positive attitude towards AI integration in aviation among the participants.

Table 3: AI Support in Aviation

	Mean	Std. Deviation
Do you support the use of AI in the aviation sector? (Y/N)	3.97	.935

As shown in Table 4, participants identified several positive factors associated with AI. A total of 27.78% of participants expressed the view that AI has the potential to enhance the convenience and quality of people's lives by offering new opportunities. Another area of positive perception was workforce productivity, as indicated by 23.87% of the participants. 20.05% of participants acknowledged the potential role of AI in the field of education. A further 16.75% of participants identified the environmental and sustainability contributions of AI. Additionally, 11.55% of participants indicated that AI could potentially offer new job and career opportunities.

Table 4: AI Positive Factors

	%
AI can make people's lives easier with the opportunities it provides.	27.78%
AI can increase workforce productivity.	23.87%
AI can play an important role in the field of education.	20.05%
AI can contribute to environmental and sustainability areas.	16.75%
AI can offer people new job and career opportunities.	11.55%

Despite the positive aspects, several negative factors associated with AI were identified, as shown in Table 5. The primary concern was data privacy violations and security risks, as indicated by 36.88% of the participants. The potential for AI technologies to displace human workers was a concern for 29.69% of the participants. Ethical issues in areas such as discrimination and justice were noted by 19.22% of the participants. Finally, 14.22% expressed concerns about AI increasing social inequalities.

Table 5: AI Negative Factors

	%
AI can cause data privacy violations and security risks.	36.88%
AI technologies can take jobs away from people.	29.69%
AI can lead to ethical issues in areas such as discrimination and justice.	19.22%
AI can increase social inequalities.	14.22%

Findings Related to the AIA Scale

Factor analysis of the AIA scale revealed a KMO (Kaiser–Meyer–Olkin) of 0.919, Bartlett's sphericity test with a p-value of 0.000 ($\chi 2$= 4576.594; df:120; $p<0.001$). The factor loadings were between 0.501 and 0.915, and the Cronbach's alpha value was 0.930, all of which are considered acceptable levels (George & Mallery, 2003; Tabachnick & Fidell, 2019). According to the explanatory factor analysis, the distribution of items across the factors showed similarity to the original scale. The distribution of items across the factors is shown in Table 6.

Table 6: Factor Loads of AIA Scale

	1	**2**	**3**	**4**
Item 3. Learning to use specific functions of an AI technique/product makes me anxious.	.915			

Item 4. Learning how an AI technique/product works makes me anxious.	.882			
Item 2. Learning to use AI techniques/products makes me anxious.	.866			
Item 5. Learning to interact with an AI technique/product makes me anxious.	.800			
Item 1.Learning to understand all of the special functions associated with an AI technique/product makes me anxious.	.751			
Item 7. I am afraid that widespread use of humanoid robots will take jobs away from people.		.822		
Item 6. I am afraid that an AI technique/product may replace humans.		.815		
Item 9. I am afraid that AI techniques/products will replace someone's job.		.806		
Item 8. I am afraid that if I begin to use AI techniques/products I will become dependent upon them and lose some of my reasoning skills.		.517		
Item 10. I am afraid that an AI technique/product may be misused.			.813	
Item 11. I am afraid of various problems potentially associated with an AI technique/ product.			.771	
Item 12. I am afraid that an AI technique/product may get out of control and malfunction.			.755	
Item 13. I am afraid that an AI technique/product may lead to robot autonomy.			.501	
Item 14. I find humanoid AI techniques/products (e.g. humanoid robots) scary.				.887
Item 15. I find humanoid AI techniques/products (e.g. humanoid robots) intimidating.				.886
Item 16. I don't know why, but humanoid AI techniques/products (e.g. Humanoid robots) scare me.				.837
Eigenvalues (Cumulative %) = 77.908 Extraction Method: Principal Component Analysis. Rotation Method: Varimax				

1=AI Learning; 2=AI Job Replacement; 3=AI Sociotechnical/ Blindness; 4=AI Configuration

The results for each sub-dimension of the AIA scale are shown in Table 7. The mean score for the AIA Scale was found to be 2.8047 on a 5-point Likert scale, indicating that participants demonstrated a moderate level of anxiety regarding AI. The standard deviation was 0.74164, indicating a certain degree of variability in anxiety levels among participants. For the first sub-dimension of AI learning, the mean score was found to be 2.1055 on a 5-point Likert scale. This indicates that the participants generally exhibited minimal anxiety with regard to acquiring knowledge about AI. The standard deviation of 0.77565 indicates a moderate level of variability in the responses provided. The mean score for the AI job replacement was 3.1123 on a 5-point Likert scale. This score indicates a heightened level of anxiety regarding the potential replacement of jobs by AI. The standard deviation was 0.97938, indicating a notable degree of variability in anxiety levels among participants. For the sub-dimension of AI sociotechnical/blindness, the mean score was 3.3775 on a 5-point Likert scale. This mean score indicates a notable degree of anxiety regarding the sociotechnical implications and potential blindness to issues caused by AI. The standard deviation was 0.88329, indicating a moderate level of variability in responses. Finally, the mean score for the AI configuration was 2.7961 on a 5-point Likert scale. This indicates a moderate level of anxiety related to the setup and configuration of AI systems. The standard deviation was 1.12895, reflecting a significant variability in the participants' responses.

Table 7: Mean, Std. Deviation, Skewness, Kurtosis, and Cronbach's Alpha Values of Scale

	Mean	Sd.	Cronbach's Alpha
AIA Scale	**2.8047**	**.74164**	**.930**
AI Learning	2.1055	.77565	.926
AI Job Replacement	3.1123	.97938	.868
AI Sociotechnical/ Blindness	3.3775	.88329	.845
AI Configuration	2.7961	1.12895	.957

AIA Findings Based on Gender

A gender-based analysis of AIA in the aviation sector is shown in Table 8. The mean score for females on the AIA Scale was 2.8775, with a standard deviation of 0.79787. In comparison, the mean score for males was 2.7315, with a standard deviation of 0.67484. The observed difference was not statistically significant (t = 1.836, df = 334.418, p = 0.067). For AI learning, the mean score for females was 2.1214, with a standard deviation of 0.81230, while the mean score for males was slightly lower at 2.0895, with a standard deviation of 0.73898. This difference was also not statistically significant (t = 0.381, df = 343, p = 0.704). For AI job replacement, the mean score for females was 3.1835 (Sd. = 1.02224), which was higher than the mean score for males, who had a mean score of 3.0407 (Sd. = 0.93178). The observed difference was not statistically significant (t = 1.356, df = 343, p = 0.176). For AI sociotechnical/blindness, the mean score for females was 3.4668, with a standard deviation of 0.86559, while the mean score for males was 3.2878, with a standard deviation of 0.89428. The observed difference was not statistically significant (t = 1.889, df = 343, p = 0.060). The only statistically significant difference was observed in the AI configuration anxieties, where females exhibited higher scores (mean = 2.9441, Sd. = 1.23476) compared to males (mean = 2.6473, Sd. = 0.99296), with a t-value of 2.460 and a p-value of 0.014 (df = 343).

Table 8: AIA Findings Based on Gender (t-test)

	Gender	Mean	Sd.	t	df	p
AIA Scale	Female	2.8775	.79787	1.836	334.418	.067
	Male	2.7315	.67484			
AI Learning	Female	2.1214	.81230	0.381	343	.704
	Male	2.0895	.73898			
AI Job Replacement	Female	3.1835	1.02224	1.356	343	.176
	Male	3.0407	.93178			
AI Sociotechnical / Blindness	Female	3.4668	.86559	1.889	343	.060
	Male	3.2878	.89428			
AI Configuration	Female	2.9441	1.23476	2.460	343	.014*
	Male	2.6473	.99296			

(*) $p<0.05$

The results of the hypothesis testing concerning gender differences in the AIA scale are shown in Table 9. The hypotheses H1a (AIA Scale), H1b (AI

Learning), H1c (AI Job Replacement), and H1d (AI Sociotechnical Blindness) were all rejected, indicating that no significant gender differences were observed in these areas. However, hypothesis H1e (AI Configuration) was accepted, indicating a significant gender difference in the AI Configuration.

Table 9: Test Results of Hypotheses Based on Gender

H1a: There is a statistically significant difference in AIA levels in aviation based on gender.	Rejected
H1b: There is a statistically significant difference in AIA-L levels in aviation based on gender.	Rejected
H1c: There is a statistically significant difference in AIA-JR levels in aviation based on gender.	Rejected
H1d: There is a statistically significant difference in AIA-SB levels in aviation based on gender.	Rejected
H1e: There is a statistically significant difference in AIA-C levels in aviation based on gender.	**Accepted**

AIA Findings Based on Education

The analysis of AIA based on education level in the aviation sector is presented in Table 10. The mean score for undergraduate students on the AIA Scale was 2.8806, with a standard deviation of 0.73438. In comparison, the mean score for graduates was 2.6677, with a standard deviation of 0.73792. This difference was found to be statistically significant ($t = 2.575$, $df = 343$, $p = 0.010$). For AI learning, the mean score for undergraduates was 2.1586, with a standard deviation of 0.80681, while the mean score for graduates was 2.0098, with a standard deviation of 0.70912. The observed difference was not statistically significant ($t = 1.712$, $df = 343$, $p = 0.088$). For AI job replacement, the mean score for undergraduates was 3.2455 (Sd. = 0.94473), which was higher than the mean score for graduates (2.8720; Sd. = 0.99865). This difference was found to be statistically significant ($t = 3.446$, $df = 343$, $p = 0.001$). For AI sociotechnical/blindness, the mean score for the undergraduate was 3.4189, with a standard deviation of 0.84162, while the mean score for the graduate was 3.3028, with a standard deviation of 0.95291. The observed difference was not statistically significant ($t = 1.129$, $df = 226.852$, $p = 0.260$). For AI configuration, the mean score for undergraduates was 2.8799, with a standard deviation of 1.14578, while the mean score for graduates was 2.6450, with a standard deviation of 1.08621. The observed difference was not statistically significant ($t = 1.858$, $df = 343$, $p = 0.064$).

Table 10: AIA Findings Based on Education (t-test)

	Gender	Mean	Sd.	t	df	p
AIA Scale	Undergraduate	2.8806	.73438	2.575	343	.010*
	Graduate	2.6677	.73792			
AI Learning	Undergraduate	2.1586	.80681	1.712	343	.088
	Graduate	2.0098	.70912			
AI Job Replacement	Undergraduate	3.2455	.94473	3.446	343	.001*
	Graduate	2.8720	.99865			
AI Sociotechnical / Blindness	Undergraduate	3.4189	.84162	1.129	226.852	.260
	Graduate	3.3028	.95291			
AI Configuration	Undergraduate	2.8799	1.14578	1.858	343	.064
	Graduate	2.6450	1.08621			

(*) $p<0.05$

The results of the hypothesis testing concerning education differences in the AIA scale are shown in Table 11. The hypotheses H2a (AIA Scale) and H2c (AI Job Replacement) were accepted, indicating significant differences based on education level in these areas. However, the hypotheses H2b (AI Learning), H2d (AI Sociotechnical Blindness), and H2e (AI Configuration) were all rejected, indicating no significant differences in these areas based on education level.

Table 11: Test Results of Hypotheses Based on Education

H2a: There is a statistically significant difference in AIA levels in aviation based on education.	**Accepted**
H2b: There is a statistically significant difference in AIA-L levels in aviation based on education.	**Rejected**
H2c: There is a statistically significant difference in AIA-JR levels in aviation based on education.	**Accepted**
H2d: There is a statistically significant difference in AIA-SB levels in aviation based on education.	**Rejected**
H2e: There is a statistically significant difference in AIA-C levels in aviation based on education.	**Rejected**

AIA Findings Based on Age

An age-based analysis of AIA in the aviation sector is shown in Table 12. The mean scores on the AIA Scale varied across different experience groups, ranging from a minimum of 2.7521 for the 36-45 age group to a maximum of 2.8795 for the 18-25 age group. The differences among the variables were not statistically significant ($F = 0.410$, $p = 0.746$). For AI learning, the mean scores varied from a minimum of 2.0617 for the 26-35 age group to a maximum of 2.1606 for the 46-year-old and older group. The differences among the variables were not statistically significant ($F = 0.308$, $p = 0.819$). For AI job replacement, the mean scores ranged from a minimum of 2.9850 for the 36-45 age group to a maximum of 3.2798 for the 18-25 age group. The differences among the variables were not statistically significant ($F = 1.504$, $p = 0.213$). For AI sociotechnical/blindness, the mean scores varied from a minimum of 3.3333 for the 18-25 age group to a maximum of 3.4886 for the 46-year-old and older group. The differences among the variables were not statistically significant ($F = 0.442$, $p = 0.723$). For AI configuration, the mean scores ranged from a minimum of 2.6838 for the 36-45 age group to a maximum of 3.0873 for the 18-25 age group. The differences among the variables were not statistically significant ($F = 1.397$, $p = 0.243$).

Table 12: AIA Findings Based on Age (ANOVA)

		Mean	Sd.	F	p	Dif.
AIA Scale	18-25	2.8795	.95101	0.410	.746	-
	26-35	2.8063	.78387			
	36-45	2.7521	.67244			
	46-year-olds and older	2.8475	.63095			
AI Learning	18-25	2.0714	.91898	0.308	.819	-
	26-35	2.0617	.83002			
	36-45	2.1316	.69191			
	46-year-olds and older	2.1606	.72597			
	18-25	3.2798	1.19858	1.504	.213	-

AI Job Replacement	26-35	3.2063	1.01907			
	36-45	2.9850	.87117			
	46-year-olds and older	3.0606	.92097			
AI Sociotechnical/ Blindness	18-25	3.3333	1.06877	0.442	.723	-
	26-35	3.3625	.89575			
	36-45	3.3462	.85780			
	46-year-olds and older	3.4886	.78131			
AI Configuration	18-25	3.0873	1.48900	1.397	.243	-
	26-35	2.7722	1.16995			
	36-45	2.6838	1.01318			
	46-year-olds and older	2.8535	.96278			

The results of the hypothesis testing concerning age differences in the AIA scale are shown in Table 13. The hypotheses H3a (AIA Scale), H3b (AI Learning), H3c (AI Job Replacement), H3d (AI Sociotechnical/Blindness), and H3e (AI Configuration) were all rejected, indicating that no significant age differences were observed in these areas.

Table 13: Test Results of Hypotheses Based on Age

H3a: There is a statistically significant difference in AIA levels in aviation based on age.	**Rejected**
H3b: There is a statistically significant difference in AIA-L levels in aviation based on age.	**Rejected**
H3c: There is a statistically significant difference in AIA-JR levels in aviation based on age.	**Rejected**
H3d: There is a statistically significant difference in AIA-SB levels in aviation based on age.	**Rejected**
H3e: There is a statistically significant difference in AIA-C levels in aviation based on age.	**Rejected**

AIA Findings Based on Experience

An experience-based analysis of AIA in the aviation sector is shown in Table 14. The mean scores on the AIA Scale varied across different experience groups, ranging from a minimum of 2.7018 for the group with 6-10 years of experience to a maximum of 2.9368 for the group with less than 2 years of experience The differences among the variables were not statistically significant ($F = 1.198$, $p = 0.312$). For AI learning, the mean scores varied across different experience groups, ranging from a minimum of 1.9754 for the group with 6-10 years of experience to a maximum of 2.1809 for the group with less than 2 years of experience. The differences among the variables were not statistically significant ($F = 0.700$, $p = 0.592$). For AI job replacement, the mean scores varied across experience groups, ranging from a minimum of 2.9583 for the group with 11-15 years of experience to a maximum of 3.2952 for the group with less than 2 years of experience. The differences among the variables were not statistically significant (($F = 1.252$, $p = 0.289$). For AI sociotechnical/blindness, the mean scores ranged from a minimum of 3.2368 for the group with 6-10 years of experience to a maximum of 3.4792 for the group with 11-15 years of experience. The differences among the variables were not statistically significant ($F = 0.762$, $p = 0.551$). For AI configuration, the mean scores varied from a minimum of 2.6381 for the group with more than 15 years of experience to a maximum of 3.0496 for the group with less than 2 years of experience. The differences among the variables were not statistically significant (F = 1.915, p = 0.108).

Table 14: AIA Findings Based on Experience (ANOVA)

		Mean	Sd.	F	p	Dif.
AIA Scale	< 2 years	2.9368	.82857	1.198	.312	-
	3-5 years	2.7851	.81479			
	6-10 years	2.7018	.75731			
	11-15 years	2.8138	.73018			
	>15 years	2.7458	.61239			
AI Learning	< 2 years	2.1809	.89446	0.700	.592	-
	3-5 years	2.1220	.87279			
	6-10 years	1.9754	.64705			
	11-15 years	2.1542	.86466			
	> 15 years	2.0800	.63403			
AI Job Replacement	< 2 years	3.2952	1.05746	1.252	.289	-
	3-5 years	3.0488	1.03715			
	6-10 years	3.0526	1.04661			
	11-15 years	2.9583	.86192			
	> 15 years	3.0762	.88736			
AI Sociotechnical / Blindness	< 2 years	3.4388	.94662	0.762	.551	-
	3-5 years	3.4390	.81160			
	6-10 years	3.2368	.93711			
	11-15 years	3.4792	.89001			
	> 15 years	3.3286	.81991			
AI Configuration	< 2 years	3.0496	1.26619	1.915	.108	-
	3-5 years	2.6667	1.22701			
	6-10 years	2.7310	1.16401			
	11-15 years	2.8333	1.05857			
	> 15 years	2.6381	.93497			

The results of the hypothesis testing concerning experience differences in the AIA scale are shown in Table 15. The hypotheses H4a (AIA Scale), H4b (AI Learning), H4c (AI Job Replacement), H4d (AI Sociotechnical/Blindness), and H4e (AI Configuration) were all rejected, indicating that no significant experience differences were observed in these areas.

Table 15:Test Results of Hypotheses Based on Experience

H4a: There is a statistically significant difference in AIA levels in aviation based on experience.	**Rejected**
H4b: There is a statistically significant difference in AIA-L levels in aviation based on experience.	**Rejected**
H4c: There is a statistically significant difference in AIA-JR levels in aviation based on experience.	**Rejected**
H4d: There is a statistically significant difference in AIA-SB levels in aviation based on experience.	**Rejected**
H4e: There is a statistically significant difference in AIA-C levels in aviation based on experience.	**Rejected**

AIA Findings Based on Sub-sectors

A sub-sector based analysis of AIA in the aviation sector is shown in Table 16. The mean scores on the AIA Scale varied across different experience groups, ranging from a minimum of 2.6382 for the airport management sub-sector to a maximum of 2.9491 for the other sub-sector. The differences among the variables were not statistically significant (F = 1.601, p = 0.174). For AI learning, mean scores ranged from a minimum of 1.9684 for the airport management sub-sector to a maximum of 2.1806 for the training sub-sector. The differences among the variables were not statistically significant (F = 0.834, p = 0.504). For AI job replacement, mean scores varied from a minimum of 2.7742 for the training sub-sector to a maximum of 3.2397 for the other sub-sector. The differences among the variables were not statistically significant (F = 2.247, p = 0.064). For AI sociotechnical/blindness, mean scores ranged from a minimum of 3.1776 for the airport management sub-sector to a maximum of 3.5515 for the other sub-sector. The differences among the variables were not statistically significant (F = 2.114, p = 0.079). For AI configuration, mean scores varied from a minimum of 2.6557 for the air navigation services sub-sector to a maximum of 3.0790 for the other sub-sector. The differences among the variables were not statistically significant (F = 2.187, p = 0.070).

Table 16: AIA Findings Based on Sub-Sectors (ANOVA)

		Mean	Sd.	F	p	Dif.
AIA Scale	Airline Transportation	2.7585	.80354	1.601	.174	-
	Airport Management	2.6382	.80265			
	Air Navigation Services	2.7940	.61509			
	Training	2.7198	.78010			
	Other	2.9491	.74577			
AI Learning	Airline Transportation	2.1636	.88593	0.834	.504	
	Airport Management	1.9684	.66662			
	Air Navigation Services	2.0264	.69552			
	Training	2.1806	.74001			
	Other	2.1567	.79227			
AI Job Replacement	Airline Transportation	3.0597	.98333	2.247	.064	-
	Airport Management	2.8947	1.05208			
	Air Navigation Services	3.2335	.86104			
	Training	2.7742	1.00282			
	Other	3.2397	1.01801			
AI Sociotechnical / Blindness	Airline Transportation	3.2301	.90276	2.114	.079	-
	Airport Management	3.1776	1.03797			
	Air Navigation Services	3.4176	.83421			
	Training	3.3790	.95715			
	Other	3.5515	.79708			
AI Configuration	Airline Transportation	2.7197	1.14010	2.187	.070	-
	Airport Management	2.6930	1.06931			
	Air Navigation Services	2.6557	.98313			
	Training	2.6667	1.11555			
	Other	3.0790	1.24049			

The results of the hypothesis testing concerning sub-sector differences in the AIA domains are shown in Table 17. The hypotheses H5a (AIA Scale), H5b (AI Learning), H5c (AI Job Replacement), H5d (AI Sociotechnical/Blindness), and H5e

(AI Configuration) were all rejected, indicating that no significant sub-sector differences were observed in these areas.

Table 17: Test Results of Hypotheses Based on Sub-Sector

H5a: There is a statistically significant difference in AIA levels in aviation based on sub-sector.	**Rejected**
H5b: There is a statistically significant difference in AIA-L levels in aviation based on sub-sector.	**Rejected**
H5c: There is a statistically significant difference in AIA-JR levels in aviation based on sub-sector.	**Rejected**
H5d: There is a statistically significant difference in AIA-SB levels in aviation based on sub-sector.	**Rejected**
H5e: There is a statistically significant difference in AIA-C levels in aviation based on sub-sector.	**Rejected**

DISCUSSION

The findings of the study highlight several critical aspects of the adoption and perception of AI within the aviation sector. It is notable that despite a significant majority of participants having experience with AI applications, there remains a considerable divide in AI adoption, with a portion of participants and organizations either not utilizing AI or being unsure of its presence. This indicates a difference in awareness and implementation of AI, suggesting that while some segments of the sector are integrating AI into their operations, others are lagging behind. The participants' expectations of AI's role in automating core processes and supporting analytical tasks reflect an anticipation of AI's potential to enhance efficiency and decision-making. Nevertheless, this optimism is constrained by anxieties pertaining to data privacy, job replacement, and ethical issues. These anxieties contribute to a moderate level of anxiety about AI, consistent with findings in other sectors such as healthcare and finance. Furthermore, while there is a generally positive attitude towards AI's potential benefits, including improved convenience, productivity, and sustainability, these are balanced by significant anxieties about privacy, job security, and social equity.

AI anxiety in the aviation sector is found to be at a moderate level among participants, aligning with broader trends observed across various industries. Similar findings were reported in the healthcare sector, where a study involving 330 health professionals identified a moderate level of AI anxiety (Filiz et al., 2022). Additionally, research conducted among 559 university students from various faculties, including Education, Arts and Sciences, Fine Arts, Law, Communication, Engineering, and Medicine, also revealed moderate AI anxiety levels (Takıl et al., 2022). Furthermore, a study of 46 participants working in the service sector found a moderate level of AI anxiety (Belber & Özmen, 2024). These findings suggest that, although specific sources of anxiety may differ across sectors, overarching concerns regarding job security, ethical considerations, and data privacy remain consistent. Cross-sectoral comparisons highlight the pervasive nature of AI-related anxieties and emphasize the importance of developing comprehensive strategies to address these anxieties, tailored to the unique contexts of each industry. This comparative perspective is crucial for understanding the broader implications of AI integration and for formulating policies that mitigate anxiety while maximizing the benefits of AI technologies.

The AI sociotechnical/blindness sub-dimension shows a higher level of anxiety in comparison to the overall average, whereas the AI learning sub-dimension shows lower anxiety levels. This seems to indicate that due to the limited potential impacts of AI (Dean et al., 2021), there are broader and more complex anxieties regarding the sociotechnical impacts of AI. In contrast, anxiety related to AI learning is lower because of widespread training in the aviation sector and a general lack of anxiety about learning, which contributes to this lower level of anxiety.

The gender-based analysis of AIA in the aviation sector reveals interesting but largely non-significant differences between male and female participants. Overall, females reported slightly higher anxiety levels on the AIA Scale compared to males, yet this difference was not statistically significant. This trend was consistent across AI learning, AI job replacement, and AI sociotechnical blindness, where females consistently scored higher but without significant differences. The only exception was found in the AI configuration, where females showed significantly higher anxiety levels than males. The higher level of AI configuration anxiety in females can be attributed to a lack of self-efficacy stemming from underrepresentation in STEM (science, technology, engineering, and mathematics) and robotic studies fields (Schuster & Martiny, 2017) and societal gender norms in developing countries (Antonio & Tuffley, 2014). These findings suggest that while there are some gender-based differences in AI-related anxiety, they are generally not pronounced, except in specific areas such as AI configuration. A meta-analysis of computer technology anxiety found no significant gender-based differences, although it did reveal that males generally experience lower levels of anxiety compared to females, similar to the results of the study (Esgin et al., 2016). This aligns with existing literature, which shows that gender differences in technology-related anxieties are often nuanced and context-dependent (Whitley, 1996). Understanding these subtle differences is crucial for developing gender-sensitive approaches to AI integration in the aviation sector.

Conversely, the analysis based on education level reveals more pronounced differences. Undergraduate participants exhibited significantly higher anxiety levels on the AIA scale compared to graduates, particularly regarding anxieties about AI job replacement. This may reflect a perceived vulnerability among less experienced or less educated individuals regarding the impact of AI on job security. Notably, higher educational levels appear to have a protective effect against anxiety (Bjelland et al., 2008), suggesting that greater knowledge and understanding of AI may alleviate some anxieties. These findings are consistent with previous studies in other sectors, such as healthcare, where lower educational attainment is often associated with higher levels of AI anxiety (Çobanoğlu & Oğuzhan, 2023). The significant differences observed in the overall AIA Scale and the AI job replacement sub-dimension emphasize the importance of educational interventions to mitigate anxiety and build confidence in AI technologies among less educated populations. The findings highlight the need for targeted support and training to ensure that all employees, regardless of educational background, can effectively engage with and benefit from AI advancements.

AIA across varying levels of experience and age groups within the aviation industry, contrary to the existing literature on technology anxiety (Meyer, 2007; Sharma & Devi, 2011), shows no statistically significant differences and indicates a widespread and consistent perception of AI-related anxieties among aviation professionals. This consistency is also observed across various sub-sectors of aviation. This uniformity is likely attributable to the standardized nature of aviation training and operational protocols, which address AI technologies and ensure consistent exposure and familiarity regardless of individual experience, specific roles, or age. Furthermore, the industry-wide communication and dissemination of information about AI advancements help to mitigate differences in anxiety levels, fostering a collective understanding and shared anxiety towards AI's potential impacts. The highly regulated environment of the aviation industry ensures that all professionals, irrespective of their experience, sector, or age, are continually updated on technological changes, thereby reducing variations in AI anxiety. This convergence indicates that AI anxiety is not influenced by specific demographic factors but is instead a broader, industry-wide phenomenon shaped by overarching technological, economic, and social factors inherent to the aviation sector as a whole.

CONCLUSION

The aim of the study was to examine the phenomenon of AIA within the aviation sector. The study addresses a significant gap in the existing literature on this topic by focusing on how AIA varies across different demographic groups and sub-sectors. Despite a growing body of research on technology anxiety, there is a limited number of sector-specific studies on AI, particularly in the field of aviation.

The outcomes of the study demonstrate that AI anxiety is a significant anxiety among aviation professionals, regardless of their level of experience or age. This comprehensive anxiety, evident across numerous sub-sectors, indicates that anxieties about AI are more indicative of broader industry-wide issues than of specific demographic differences. The standardized nature of aviation training and industry protocols likely contributes to a consistent perception of AI-related anxiety.

The analysis revealed that gender-based differences were primarily evident in the AI configuration, with females showing higher levels of anxiety. However, the overall impact of gender on AI anxiety was not substantial across other sub-dimensions. The educational background showed a notable influence on AI anxiety, with undergraduates expressing higher levels of anxiety, especially about job replacement due to AI. This highlights the protective effect of higher education in mitigating AI-related anxiety, emphasizing the need for targeted educational interventions. The heightened anxiety in the AI sociotechnical/blindness sub-dimension, compared to the overall average, and the lower anxiety in AI learning indicate that broader concerns regarding AI's sociotechnical impacts outweigh specific technical apprehensions related to AI learning.

The accelerated evolution of AI technology represents a significant limitation of the study, as it may affect the long-term relevance and applicability of the findings. It would be beneficial for future research to prioritize examining the unique structures and challenges of individual sub-sectors within the field of aviation. Such sector-specific studies could facilitate a more precise understanding of AI anxiety and its implications. Furthermore, ongoing monitoring is essential to evaluate the influence of AI on a range of professional settings and to develop strategies to address specific anxieties within each sector.

The study highlights the necessity for the implementation of targeted strategies and educational initiatives to address AI anxiety in the aviation sector. To accommodate the evolving nature of AI, future research should adopt a more concentrated approach, investigating sector-specific variations and the unique requirements of each aviation sub-sector. A more profound comprehension of these complexities will empower policymakers and industry stakeholders to devise efficacious strategies to mitigate AI-related anxieties, facilitate seamless integration, and maximize the potential benefits of AI in the aviation sector. Such insights will contribute to the enhancement of human-technology interactions and the provision of support to the industry in overcoming the challenges associated with the adoption of AI.

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