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Research Article

Artificial Intelligence Anxiety and Perceived Future Employability Among Aviation Students

Havacılık Öğrencilerinin Yapay Zekâ Kaygıları ve Gelecekteki İstihdam Edilebilirlik Algıları

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ABSTRACT

The aim of the study was to examine the effect of artificial intelligence anxiety and its sub-dimensions on perceived future employability among aviation students. Data were collected through an online survey with 909 participants. The artificial intelligence anxiety scale and the perceived future employability scale were employed as data collection instruments. The multiple linear regression analysis revealed the limited explanatory power of the artificial intelligence anxiety sub-dimensions on perceived future employability (R^2 = .024, adj. R^2 = .020). Among the sub-dimensions, artificial intelligence socio-technical blindness positively influenced PFE (β = .130, p = .009), while artificial intelligence learning had a negative impact (β = -.142, p = .001). No significant effects were found for artificial intelligence job replacement and artificial intelligence configuration. Difference tests showed significant variances among the demographic groups. The results demonstrated that the impact of artificial intelligence anxiety on perceived future employability is typically insufficient to be considered significant, reflecting the technical and human-focused structure of the aviation sector.

MAKALE BİLGİSİ

Anahtar Kelimeler:
Havacılık, İstihdam, Havacılık Eğitimi, Yapay Zekâ, Yapay Zekâ Kaygısı.

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ÖZ

Bu çalışmanın amacı havacılık ile ilgili bölümlerde öğrenim gören üniversite öğrencilerinde yapay zekâya ilişkin kaygı ve alt boyutlarının, algılanan gelecekteki istihdam edilebilirlik üzerindeki etkisini incelemektir. Araştırma verileri çevrimiçi anket aracılığıyla 909 katılımcıdan toplanmıştır. Veri toplama aracı olarak yapay zekâ kaygı ölçeği ve algılanan gelecekteki istihdam edilebilirlik ölçeği kullanılmıştır. Çoklu doğrusal regresyon analizi yapay zekâ kaygısı alt boyutlarının algılanan gelecekteki istihdam edilebilirlik üzerindeki açıklayıcı gücünün sınırlı olduğunu göstermiştir (R^2 = .024, adj. R^2 = .020). Yapay zekâ sosyoteknik körlük boyutu algılanan gelecekteki istihdam edilebilirlik üzerinde pozitif (β = .130, p = .009), öğrenme kaygısı ise negatif (β = -.142, p = .001) etkiler göstermiştir. Yapay zekâ iş değiştirme ve yapılandırma boyutlarının etkisi anlamlı bulunmamıştır. Demografik değişkenlere dayalı testler bazı gruplar arasında anlamlı farklılıklar ortaya koymuştur. Bulgular yapay zekâ kaygısının algılanan gelecekteki istihdam edilebilirlik üzerindeki etkisinin anlamlı olmadığı, havacılık sektörünün teknik ve insan odaklı yapısıyla ilişkili olduğu sonucunu desteklemiştir.

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1. INTRODUCTION

Technological advancements, particularly in the fields of artificial intelligence (AI) and machine learning, are profoundly impacting labour markets. This transformation process has given rise to significant debates concerning perceptions of job security and employability (Dwivedi et al., 2021). The findings of studies examining the effects of automation on the workforce demonstrate considerable variation. The findings of studies examining the effects of automation on the workforce demonstrate considerable variation. For instance, Frey and Osborne (2017) reported that 47% of jobs in the United States are at risk of automation, whereas Arntz, Terry, and Zieyahn (2016) estimated this figure to be only 9%. Similarly, research analyzing employment and wage dynamics shows divergent outcomes: Georgieff and Milanez (2021) observed that jobs highly exposed to automation tend to exhibit lower growth rates without producing net job losses, while Webb (2019) identified declines in both employment and wages for occupations with high automation exposure. These mixed findings highlight the complexity and context-specific nature of automation's impact on labour markets, indicating that sectoral characteristics, occupational structures, and methodological choices may shape the results. These transformations are particularly notable in highly technical and specialized fields, such as the aviation sector (Abubakar, EriOluwa, Teyei & Al-Turjman, 2022; Bendík & Novák, 2022; Kumar, Hussain, Reddy & Deep, 2022; Zou & Sun, 2021). The growing prevalence of sophisticated automation technologies has precipitated a significant transformation in the labour dynamics of the aviation industry. In this context, it is of paramount importance to gain insight into the impact of AI on perceptions of job security and future employability.

Several studies have suggested that AI could eventually replace certain human roles, potentially leading to higher unemployment (Liu & Jew, 2023; Zhang, 2023). The term "AI" refers to computer systems' ability to process complex data, learn from it, and exhibit human-like decision-making (Tecuci, 2012). Although AI and machine learning are transforming society and industry, they also raise substantial concerns regarding work and employment (Badhurunnisa & Dass, 2023). AI-related anxiety, therefore, encompasses concerns about adapting to new technologies, addressing knowledge gaps, and the risk of job displacement. Additional apprehensions concern socio-technical implications, algorithmic bias, and transparency deficits in automated decision-making, as well as ethical issues, data privacy, and broader societal impacts (Wang & Wang, 2019).

Anxiety related to AI is inextricably linked to the level of trust placed in these technologies and the perceptions held about them. Empirical evidence substantiates this link, demonstrating that varying levels of trust and risk perception are significant contributors to public anxiety. For instance, Neudert, Knuutila, and Howard (2020) found that the perceived risks associated with the use of AI directly contribute to feelings of anxiety, a conclusion based on data from 154,195 participants across 142 countries. Similarly, the survey results reflect this trust-anxiety dynamic in public attitudes: as reported by Zhang and Dafoe (2019), 41% of 2,000 American adults expressed support for AI, while 22% indicated opposition to its development. Although a European study comprising 27,901 participants demonstrated predominantly favorable attitudes towards AI and robots (European Commission & Directorate-General for Communications Networks, Content & Technology, 2017), this does not negate the underlying role of trust. In fact, Gillespie, Lockey, and Curtis (2021) specifically observed a notable lack of trust in AI in their study of 6,054 participants from diverse countries, which significantly influenced its acceptance. The relationship is further complicated by contextual factors. Park and Woo (2022) highlighted that the adoption of AI is contingent upon a multitude of factors, including personality, user experience, cost, optimism toward technology, and personal values. This complex interplay is particularly critical in safety-sensitive fields like aviation. The aviation sector, which is distinguished by its dependence on technical expertise, incorporates AI into a multitude of applications, with highly trained professionals at its core (Wickens & Dehais, 2020).

The rapid spread of AI is bringing swift and significant changes across industries. In this changing context, businesses must adapt to technological developments to remain competitive (Duran, Boz, Behdioğlu & Kutlu, 2019). In aviation, AI is increasingly used to improve efficiency, support decision making, raise safety standards, and streamline operations in areas such as air traffic management, flight operations, and maintenance (European Union Aviation Safety Agency [EASA], 2023). However, these advances may alter employment structures in the sector, and the rapid adoption of AI could heighten students' concerns about their future job prospects in aviation-related programs.

The perceived future employability (PFE) of students represents a subjective evaluation of how individuals view their potential positions in the labour market. It is shaped by an individual's skill set, knowledge levels, and experiences, as well as external factors such as labour market conditions and economic indicators (Gunawan, Creed & Glendon, 2019). It serves as a crucial motivator for goal setting, planning, and striving toward these goals, thereby shaping individuals' future professional identities (Creed & Klisch, 2005). Individuals with high levels of perceived employability are more likely to invest greater effort in career planning, goal management, and professional endeavors. This can lead to a reduction in career-related stress and an enhancement of occupational success (Creed, Sawitri, Hood & Hu, 2021). Conversely, low perceptions may result in a lack of confidence in adapting to the labour market, an increased risk of unemployment, and a lack of strategic clarity (Yizhong et al., 2017). In this context, PFE serves as an internal benchmark, enabling students to compare their current status with their future aspirations (Lord, Diefendorff, Schmidt & Hall, 2010). It is of critical importance to support these perceptions for national development, as high unemployment rates not only negatively impact individuals but also hinder economic growth (Guilbert, Bernaud, Gouvernet & Rossier, 2016).

The advent of new technologies, including AI and automation, is prompting students to re-examine their career expectations. Empirical studies provide concrete evidence of adverse labour-market impacts: Jung and Lim (2020) show that the widespread use of industrial robots suppresses employment growth and affects low-skilled workers most severely, and Acemoglu and Restrepo (2017) estimate that one additional robot per 1,000 workers reduces the employment-to-population ratio by about 0.2 percentage points and lowers wages by roughly 0.42%. Furthermore, the potential for these effects to intensify is heightened in the absence of effective policy responses (Aghion, Antonin & Bunel, 2019). Similarly, while the use of AI in job search processes offers advantages such as reducing biases and accelerating procedures, it is also noted that it may narrow employment opportunities (Lapidus, 2023). Research has further indicated that the impacts of AI and robotics on unemployment vary based on education levels and age groups, with particularly pronounced negative effects observed among individuals with intermediate education levels (Bordot, 2022).

The impact of AI on employment in the aviation sector represents a crucial area of investigation. This highly sophisticated and rapidly evolving industry depends on technological innovation and data-driven decision-making. AI is becoming an indispensable component of aviation, enhancing autopilot systems, flight simulations, maintenance, and air traffic management. As the technological landscape continues to evolve, the skills and roles of aviation professionals may require redefinition. Addressing these changes is vital for developing workforce policies and maintaining the sector's competitiveness and sustainability.

Within the context of the literature background of the study, it is important to address the issues of AI anxiety and employability in more depth with existing theories. In this context, using frameworks such as the Technology Acceptance Model (TAM) and Expectancy-Value Theory will contribute to a more comprehensive interpretation of the research outputs. The TAM, developed by Davis (1989), aims to explain the processes of individuals accepting and using new technologies. The model suggests that two main factors, perceived usefulness and perceived ease of use, play a critical role in adopting technology. Perceived usefulness refers to the individual's belief that using technology will increase work performance, while perceived ease of use indicates the individual's perception of how much effort technology requires. These two factors shape individuals' attitudes toward technology and their intentions to use it. In the context of AI anxiety, how individuals perceive AI technologies and the effects of these perceptions on their employability can be examined within the framework of TAM. For example, it can be thought that individuals who believe that AI technologies will facilitate business processes may have reduced anxiety about these technologies and their perceptions of employability may be positively affected. The expectancy-Value Theory, put forward by Vroom (1964), argues that individuals' motivations to exhibit a certain behavior are determined by their expectations about the outcome of that behavior and their perceptions of the value of this outcome. According to this theory, individuals evaluate their likelihood of performing a behavior based on the probability that the behavior will achieve the desired outcome (expectancy) and how personally valuable the outcome is (value). In the context of AI anxiety and employability, individuals' expectations about the impact of AI technologies on their careers and their perceptions of the value of this impact can shape their anxiety levels and perceptions of employability. For example, it can be predicted that individuals who believe that AI technologies will devalue their professional skills may have increased anxiety about these technologies and their perceptions of employability may be negatively affected.

Building on these theoretical frameworks, self-efficacy theory and career adaptability theory offer additional perspectives for understanding the relationship between AI anxiety and employability. Self-efficacy theory refers to an individual's belief in their ability to successfully perform a specific task or activity (Bandura, 1977). This belief directly influences career development and the perception of success in the labour market (Betz, 2000). Self-efficacy therefore shapes how individuals interpret new work demands and new technologies. Individuals with high self-efficacy tend to view change as manageable and are more likely to pursue reskilling and upskilling. By contrast, low self-efficacy can increase worry and doubt about one's capacity to meet evolving job requirements. Career adaptability theory complements this view by identifying psychological resources such as concern, control, curiosity, and confidence that help people cope with career change. These adaptability resources interact with self-efficacy to determine whether a person treats AI as an opportunity for growth or as a threat to their role. In this context, AI anxiety and the fear that professional skills may become obsolete increase feelings of uncertainty about future careers (Mcclure, 2018). Career adaptability theory emphasizes an individual's capacity to cope with uncertainties and changes in career development (Savickas, 2013). Career adaptability, which consists of four main dimensions -concern, control, curiosity, and confidence- helps individuals develop proactive behaviors to maintain their employability despite technological changes (Hirschi, Herrmann & Keller, 2015). In particular, developing career adaptability in individuals with high AI anxiety increases psychological resilience against career uncertainties and strengthens perceptions of employability (Kong et al., 2024). Self-efficacy and career adaptability play a crucial role in managing AI-related anxiety and maintaining employability. A strong sense of self-efficacy allows individuals to remain flexible in the face of occupational changes, while career adaptability supports future planning and strategic adjustment to uncertainties. Therefore, enhancing self-efficacy and career adaptability is essential for reducing the effects of AI anxiety and sustaining employability.

The aim of the study is to provide a comprehensive examination of AI anxiety and perceptions of future employability among students engaged in aviation-related education, with a focus on understanding their concerns regarding AI and its potential impact on the industry. It seeks to contribute to the existing literature on this topic and identify potential implications for future workforce policies in the aviation sector. The findings will provide insights into how technological advancements influence human resource management and workforce planning, serving as a valuable reference for aviation professionals, researchers, and industry authorities.

2. METHOD

The study employed a quantitative research design based on a survey model. The research utilizes descriptive statistics to systematically describe the characteristics and current state of the study population, aligning with the fundamental aim of descriptive research (Karasar, 2016). Furthermore, inferential statistical methods are applied to analyze the relationships and differences between the variables. Therefore, the study is positioned as quantitative research with both descriptive and explanatory aims.

2.1. Research Question

The study examines the phenomenon of AI anxiety and its impact on perceptions of future employability among students pursuing aviation-related studies. It explores the ways in which AI affects the dynamics of the workforce, influences the perspectives of students, and contributes to the development of academic literature and practical insights. The research question is: "To what extent do aviation students' anxieties about AI and their perceptions of future employability manifest, and what is the relationship between these variables?".

2.2. Measures

2.2.1. Demographic information form

In the study, participants were requested to provide detailed demographic information. This included data regarding the participants' characteristics, such as gender, field of study, current academic level, and their level of knowledge about AI.

2.2.2. Perceived future employability scale (PFES)

The PFES, developed by Gunawan, Creed, and Glendon (2019), is a 24-item self-report measurement tool designed to assess the perceptions of young adults regarding their employability when entering the workforce after completing their education. The scale comprises several sub-dimensions, including networks, experiences, personal characteristics, institutional reputation, market knowledge, and skills. Higher scores on the scale are indicative of a positive outlook on career planning and prospects, as well as a sense of preparedness for the job market. The scale uses a 6-point Likert scale ranging from

"Strongly Disagree (1)" to "Strongly Agree (6)". Alkın, Korkmaz, and Çelik (2020) adapted the original scale into Turkish while maintaining its structural integrity, with a Cronbach's alpha internal consistency coefficient of .95 during the adaptation process.

2.2.3. Artificial intelligency anxiety scale (AIAS)

The AIAS, developed by Wang and Wang (2019), is a 16-item measurement tool designed to assess individuals' concerns about AI, which has been increasing in recent years. The scale is comprised of four sub-dimensions: learning, job replacement, socio-technical blindness, and AI configuration. The scale uses a 5-point Likert-type scale ranging from "Strongly Disagree (1)" to "Strongly Agree (5)". Akkaya, Özkan, and Özkan (2021) adapted this scale into Turkish, and during the adaptation process, Cronbach's alpha internal consistency coefficient was found to be .94.

2.3. Sample

The study population comprises university students enrolled in aviation programs at higher education institutions in Türkiye. Convenience sampling was used in the study. The sample was accessed through students reached via faculty members working in aviation departments. During the data collection process, conducted online from October 1, 2024, to November 13, 2024, a total of 909 students, representing the future workforce of the aviation industry, were reached.

2.4. Data Analysis

The data obtained in the study were analyzed using the statistical software package SPSS, version 29.0. In addition to the descriptive statistical analyses, the difference tests, correlation, and regression analyses were conducted. The prerequisites for conducting a regression analysis were adhered to, in accordance with the principles established by George and Mallery (2010).

The study was approved for ethical suitability by the Ethics Committee of the International Science and Technology University with decision number: E-4651465861-204.01.07-250 and date 30 JUL 2024 (Revision: E-4651465861-204.01.07-474/ 01 NOV 2024).

3. RESULTS

The participants in the study were aviation students (n = 909) who were grouped according to their demographic characteristics. In terms of gender, the participants were reported as 58.1% female (n = 528) and 41.9% male (n = 381). When evaluated on a departmental basis, it was observed that the majority of participants were in the departments of Aviation Management (35.4%, n = 322), Civil Air Transportation Operations (21.7%, n = 197), and Civil Aviation Cabin Services (20.6%, n = 187). Other departments included Aircraft Maintenance and Repair (7.8%, n = 71), Aviation Electrics and Electronics (4.0%, n = 36), and Air Traffic Control (3.0%, n = 27). Smaller numbers of participants were represented in other departments. The distribution of participants by educational level showed that 51.7% (n = 470) were pursuing an undergraduate program, and 48.3% (n = 439) were pursuing an associate degree program in the field of aviation. Furthermore, 57.6% of the participants (n = 524) indicated that they utilize AI technologies, whereas 42.4% (n = 385) stated that they do not employ these technologies.

The factor analysis performed on the AIAS and the PFES indicated that both scales were statistically sufficient and reliable. The KMO (Kaiser-Meyer-Olkin) value for the AIAS was found to be 0.917 and the Cronbach's Alpha value was found to be 0.914, indicating that the sample size was quite suitable for factor analysis and that the scale had a high internal consistency. Similarly, the KMO value for the PFES was found to be 0.959 and the Cronbach's Alpha value was 0.942, indicating that the reliability of the scale was quite high and that it had a suitable data structure for factor analysis. Based on the acceptance criteria proposed by George and Mallery (2010) and Hair Jr, LDS Gabriel, Silva, and Braga (2019), these results prove that both scales are valid and reliable measurement tools. These findings, together with the consistency of the factor loading values, support a scale structure that is appropriate for the sample and context of the study.

When looking at the descriptive statistics of the total scale scores of the main variables, as shown in Table 1, the average total score for the AIAS was calculated as 48.25 (Sd. = 11.31) and it was observed that the scores varied between 16 and 80. The mean total score for the PFES was found to be 123.26 (Sd. = 12.98) and it was found that the scores varied between 73 and 144. The data for both scales were fully analyzed (n = 909) and it was found that the scales showed a great deal of variation.

Table 1: Descriptive Statistics of the Total Scale Scores

Scale	n	Minimum	Maximum	Mean	Sd.
AIAS	909	16	80	48.25	11.31
PFES	909	73	144	123.26	12.98

The relationships between AIAS, PFES, and their sub-dimensions were assessed using Pearson correlation analysis, as shown in Table 2. No significant relationship was found between AIAS and PFES ($r = .008$, $p > .05$). However, strong positive correlations were observed between the sub-dimensions of AIAS; for example, a significant relationship was found between socio-technical blindness and job replacement ($r = .732$, $p < .001$) and between learning and job replacement ($r = .378$, $p < .001$). Strong positive correlations were also found between the sub-dimensions of PFES, with the highest correlation found between market knowledge and skills ($r = .846$, $p < .001$). In addition, the networks dimension of PFES showed a strong positive relationship with total PFES ($r = .765$, $p < .001$). However, low-level negative correlations were also found between the sub-dimensions of AIAS and PFES; for example, the learning sub-dimension of AIAS was found to have a weak negative relationship with the experiences sub-dimension of PFES ($r = -.110$, $p < .001$). These findings suggest that the relationships between AI anxiety and PFE should be further explored at the sub-dimension level.

Although the correlation analysis did not reveal a statistically significant relationship between the two variables, a regression analysis was conducted to examine the direction and magnitude of AIA's potential influence on PFE. This approach allows for a more detailed assessment of the predictive capacity of AIA, independent of the correlation coefficient, and provides insight into whether AIA contributes to variations in PFE when considered as a predictor variable. Simple linear regression analysis was used to assess the relationship between AIA and PFE, as shown in Table 3. The results of the analysis show that AIA has no significant effect on PFE ($\beta = 0.009$, $p = .810$). The regression model could not explain the variance of the dependent variable ($R^2 = .000$, adjusted $R^2 = -.001$) and the overall significance of the model was not found to be significant ($F = .058$, $p > .05$). These results indicate that AIA levels do not directly influence participants' PFE. The R^2 value of the model is close to zero, suggesting that AIA has a negligible effect on PFE and that other variables may better explain this relationship.

Table 2: Means, Standard Deviations and Bi-Variate Correlation Among the Research Variables

Variables	M	Sd.	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	48.24	11.30	.008	.666**	.859**	.828**	.808**	-.008	.016	.014	-.010	.031	.008
(2)	123.25	12.98	-	-.101**	.031	.077*	.022	.765**	.823**	.827**	.689**	.870**	.839**
(3)	10.84	3.61		-	.378**	.331**	.387**	-.088**	-.110**	-.130**	.032	-.123**	-.154**
(4)	13.88	3.76			-	.732**	.594**	.019	.049	.059	-.060	.082*	.069*
(5)	14.25	3.36				-	.574**	.038	.106**	.098**	-.020	.106**	.104**
(6)	9.25	3.55					-	.009	.009	.020	.019	.037	.012
(7)	20.30	2.46						-	.641**	.581**	.363**	.633**	.587**
(8)	20.95	2.51							-	.742**	.353**	.696**	.693**
(9)	21.33	2.35								-	.365**	.731**	.740**
(10)	18.15	4.42									-	.432**	.364**
(11)	21.09	2.37										-	.846**
(12)	21.41	2.33											-

* $p < .05$; ** $p < .01$

(1)= AIAS; (2)= PFES; (3)= AIAS- learning; (4)= AIAS job replacement; (5)= AIAS sociotechnical blindness; (6)= AIAS AI configuration; (7)= PFES networks; (8)= PFES experience; (9)= PFES personal characteristics; (10)= PFES institution reputation; (11)= PFES market knowledge; (12)= PFES skills

Table 3: Result of Simple Linear Regression

Variable	*β*	*F*	*R²*	*Adjust R²*	*p*
Artificial Intelligence Anxiety	0.009	.058	.000	-.001	.810
Dependent Variable: Perceived Future Employability					

Multiple linear regression analysis was used to assess the effects of the AIAS sub-dimensions on PFES, as shown in Table 4.

The other sub-dimensions, job replacement (β = -.019, p = .707) and AI configuration (β = .014, p = .740) of AIA, did not have a significant effect on the dependent variable.

Table 4: Results of Multiple Linear Regression

Variables	*β*	*t*	*p*
AIA- Learning	-.142	-3.916	.001*
AIA- Job Replacement	-.019	-.376	.707
AIA- Sociotechnical Blindness	.130	2.610	.009*
AIA- AI Configuration	.014	.332	.740
R^2	.024		
Adjust R^2	.020		
Dependent Variable: Perceived Future Employability			

* p < .05

The model was only able to explain 2.4% of the variance in the dependent variable (R^2 = .024, adjusted R^2 = .020), suggesting that other factors may be effective in explaining the dependent variable. When examined at the sub-dimension level, the socio-technical blindness sub-dimension of AIA was found to have a positive and significant effect on PFE (β = .130, p = .009). This suggests that increasing socio-technical blindness may increase participants' confidence in the labour market and their perception of employability. On the other hand, the learning sub-dimension of AIA had a negative and significant effect on the PPI (β = -.142, p = .001), indicating that individuals' perceptions of employability decreased as their learning anxiety increased.

According to the independent samples t-test, it was found that there were significant differences in the perceptions of the first- and second-year associate degree program students on various variables, as shown in Table 5. With regard to the PFE variable, it was found that the scores of first year students were significantly higher than those of second year students (p = .020). Similarly, it was observed that the scores of the first-year students were significantly higher than those of the second-year students for the variable PFE Experience (p = .039). In addition, a significant difference was found in the PFE Market Knowledge variable and it was found that first year students had higher scores for this variable (p = .004). In the PFE Skills variable, it was observed that the average scores of the first-year students were significantly higher than those of the second-year students (p = .007).

Table 5: Differences in PFES and Sub-dimensions Based on Associate Degree Students' Class Levels

Variables	**Groups**	**n**	**Mean**	**Sd.**	**t**	**df**	**p**	**Mean Difference**	**Std. Error Difference**
PFES	1st year	294	123.07	12.42	2.327	438	.020*	3.016	1.296
	2nd year	146	120.06	13.52					
PFES Experience	1st year	294	20.96	2.41	2.070	438	.039*	0.513	0.870
	2nd year	146	20.45	2.52					
PFES Market Knowledge	1st year	294	21.13	2.17	2.857	438	.004*	0.673	0.235
	2nd year	146	20.46	2.60					
PFES Skills	1st year	294	21.39	2.25	2.711	438	.007*	0.641	0.236
	2nd year	146	20.75	2.49					

*p < .05

These results show that there are significant differences in the elements such as employability, experience, market knowledge and skills perceived by the students depending on their year. This situation shows that first year students have higher perceptions of these issues.

According to the results of the independent samples t-test, no statistically significant difference was found in the scale scores in terms of gender, use of AI (yes vs. no) and education level (associate degree program vs. undergraduate program). This result shows that these variables do not have a significant effect on the participants' perceptions of future employability.

In addition, in the "Skills" sub-dimension, the scores of the first-year students are significantly higher (F = 4.985, p = .002) compared to the third-year (difference: 0.98452, p <.05) and fourth-year students (difference: 0.91859, p <.05). These findings indicate that the first-year students' perceptions of future employability and their positive evaluations in the relevant sub-dimensions decreased in the later years of their education. This could be explained by the academic and professional challenges that students face in later grades, increased job market uncertainty, or changes in their perceptions of knowledge-based self-efficacy.

Table 6: Differences in PFES and Sub-dimensions Based on Undergraduate Students' Class Levels

Variables	Groups	n	Mean	Sd.	F	p	Difference
PFES	1st year	200	125.16	12.05	5.029	.002*	"1st year" > "3rd year"; "1st year" > "4th year"
	2nd year	107	122.26	13.09			
	3rd year	84	119.91	13.52			
	4th year	78	119.85	14.07			
PFES Experience	1st year	200	21.33	2.19	4.968	.002*	"1st year" > "3rd year"
	2nd year	107	20.77	2.64			
	3rd year	84	20.22	2.46			
	4th year	78	20.52	2.66			
PFES Personal Characteristics	1st year	200	21.59	2.08	3.356	.019*	"1st year" > "3rd year"
	2nd year	107	21.32	2.38			
	3rd year	84	20.69	2.30			
	4th year	78	21.10	2.40			
PFES Networks	1st year	200	21.52	2.04	6.599	.001*	"1st year" > "3rd year"; "1st year" > "4th year"
	2nd year	107	20.97	2.33			
	3rd year	84	20.48	2.54			
	4th year	78	20.37	2.70			
PFES Skills	1st year	200	21.67	2.12	4.985	.002*	"1st year" > "3rd year"; "1st year" > "4th year"
	2nd year	107	21.32	2.40			
	3rd year	84	20.69	2.45			
	4th year	78	20.75	2.62			

*p < .05

The ANOVA analysis revealed that there were significant differences in PFE and its sub-dimensions according to undergraduate program's level, as shown in Table 6. First-year undergraduate program students scored significantly higher than both third-year (difference: 5.24833, p < .05) and fourth-year students (difference: 5.30603, p < .05) in the total score of PFES (F = 5.029, p = .002). Similarly, first-year students had higher scores than third-year students in the "Experience" sub-dimension (difference: 1.10881, p < .05) (F = 4.968, p = .002). In the "Networks" sub-dimension, the scores of the first-year students were significantly higher than both the third-year (difference: 1.03190, p <.05) and fourth-year students (difference: 1.14821, p <.05) (F = 6.599, p < .001).

The results of the ANOVA analysis conducted on the level of knowledge about AI showed that there were statistically significant differences between the knowledge level groups, as shown in Table 7. In terms of total scores on the AIAS, it was determined that the averages of individuals with advanced knowledge were significantly lower than those with no knowledge (F = 8.940, p <.001). In particular, individuals with advanced knowledge had lower anxiety scores than those with no knowledge (difference: 8.07731, p < .05), those with low knowledge (difference: 7.10594, p <.05), and those with moderate knowledge (difference: 4.72053, p <.05). When examined at the level of sub-dimensions, it was found that individuals with advanced knowledge had lower AI anxiety levels compared to those with no knowledge (difference: 2.67395, p <.05) and those with little knowledge (difference: 1.84566, p < .05) in the "AIA

Learning" sub-dimension (F = 8.782, p<.001). Similarly, individuals with advanced knowledge had significantly lower anxiety scores compared to other groups in the "AIA AI Configuration" sub-dimension (F = 12.032, p < .001). In addition, it was observed that individuals with advanced knowledge had higher averages in terms of "PFE Networks" and "PFE Personal Characteristics" from the PFE dimensions. In the "PFE Networks" sub-dimension, individuals with advanced knowledge were found to have significantly higher scores than those with no knowledge (difference: 1.38319, p <.05) and those with little knowledge (difference: 1.34292, p < .05) (F = 6.811, p < .001). Similarly, in the "PFE Personal Characteristics" sub-dimension, individuals with advanced knowledge were found to have higher averages than other groups (F = 5.151, p = .002). Finally, in the "PFE Skills" dimension, individuals with advanced knowledge were found to have significantly higher scores than those with no knowledge (difference: 1.09277, p <.05) (F = 3.393, p = .018).

The results of the analysis indicated that there is no statistically significant difference between the departments in which the students are engaged in their studies. This finding suggests that the perceptions of employability among students pursuing their studies in different departments are, in general, at comparable levels.

4. DISCUSSION AND CONCLUSION

The analysis evaluating the effect of AI anxiety on PFE indicated that general AI anxiety levels do not significantly influence PFE. A weak negative relationship observed in some analyses can be attributed to sectoral differences in the impact of AI on labour (Zhou, Chu, Li & Meng, 2019). While AI may reduce workforce demand in certain areas, it significantly increases demand in technology-driven sectors, thereby creating new expertise areas (Sheıkhı, 2022; Xie et al., 2021). The aviation sector, which requires a high-quality technical workforce and values the human factor, aligns with this trend (Gorbachev, Shestakov & Stefański, 2019). According to TURKSTAT (Turkish Statistical Institute), indicators such as higher education employment rate, time to first employment, and average monthly earnings were subjected to maximum normalization across 216 bachelor's degree programs. As a result, aviation electrical and electronics (3), aviation and space engineering (4), pilot training (5), aeronautical engineering (8), and aircraft maintenance and repair (9) ranked among the top 10 due to their short employment time and high earnings (Kılanç, 2024). This finding emphasizes the importance of the employment dimension in aviation.

Table 7: Differences in AIAS and Sub-dimensions Based on Students' Knowledge of Artificial Intelligence

Variables	Groups	n	Mean	Sd.	F	p	Difference
AIAS	(1)	119	50.27	11.50	8.940	.001*	(1)> (4); (2)> (4); (1)> (3); (3)> (4); (2)> (3)
	(2)	438	49.30	10.63			
	(3)	302	46.92	11.64			
	(4)	50	42.20	11.88			
AIAS Learning	(1)	119	11.87	3.91	8.782	.001*	(1)> (4); (2)> (4); (1)> (3)
	(2)	438	11.04	3.45			
	(3)	302	10.41	3.52			
	(4)	50	9.20	3.92			
AIAS AI Configuration	(1)	119	9.78	3.34	12.032	.001*	(1)> (4); (2)> (4); (3)> (4); (2)> (3)
	(2)	438	9.67	3.48			
	(3)	302	8.83	3.59			
	(4)	50	6.90	3.32			
PFES Networks	(1)	119	20.01	2.80	6.811	.001*	(4)> (1); (4)> (2); (3)> (2)
	(2)	438	20.05	2.37			
	(3)	302	20.59	2.38			
	(4)	50	21.40	2.46			
PFES Personal Characteristics	(1)	119	20.82	2.76	5.151	.002*	(4)> (1); (3)> (1); (3)> (2)
	(2)	438	21.18	2.26			
	(3)	302	21.65	2.21			
	(4)	50	21.84	2.69			
PFES Skills	(1)	119	21.06	2.50	3.393	.018*	(4)> (1)
	(2)	438	21.31	2.27			
	(3)	302	21.58	2.29			
	(4)	50	22.16	2.55			

*p < .05; (1)= No knowledge; (2)=Little knowledge; (3)= Moderate knowledge; (4)= Advanced knowledge

In regression analyses, the sociotechnical blindness variable emerged as a positive predictor of PFE. This finding suggests that individuals with limited awareness of the sociotechnical dimensions of AI may have more confidence in the labour market and perceive their employability to be higher. Considering that sociotechnical blindness is associated with individuals' limited acceptance of the integration of AI into human-centered systems, it can be argued that this situation may increase the individual's self-confidence in their indispensability in the workforce (Schepman & Rodway, 2020). This result is consistent with Acemoglu and Restrepo's (2018) findings that human skills (such as complex reasoning, empathy, and communication) have sustainable value in the face of automation. However, this situation should be evaluated paradoxically; because individuals who do not sufficiently understand the impact of AI technologies on labour dynamics may underestimate the possibility of losing their jobs and see themselves as more secure in the labour market. In this context, the finding should be related to the broader discussions on trust in AI and the indispensability of human workers. How trust in AI systems shapes individuals' integration processes with technology and its impact on their PFE should be addressed more comprehensively in future research. On the other hand, the learning anxiety sub-dimension was found to have a negative effect on PFE. This suggests that individuals' concerns about adapting to new skills or work conditions may negatively affect their perception of employability. However, no statistically significant effect was found on PFE for other sub-dimensions such as AI configuration.

The negative impact of learning anxiety on PFE can be attributed to individuals' anxieties regarding their inability to adapt to the evolving demands of the job. Such anxiety can evoke fears of obsolescence, even though it does not necessarily lead to unemployment (Belchik, 2022; Lukyanenko, Maass & Storey, 2022). The extent to which employees perceive technology as usable significantly influences their engagement with learning processes. For effective adaptation, re-skilling initiatives are essential, enabling workers to acquire the knowledge and skills required for evolving roles (Morandini et al., 2023).

First-year students exhibit higher optimism about PFE compared to upper-year students. This trend is also supported by existing literature (Jackson & Wilton, 2016; Tymon, 2013). As students progress through their academic careers, they become more aware of the competitive nature of the labour market, which may lead to a decrease in their confidence in their employability. Qenani, MacDougall, and Sexton (2014) reported that students experience a decrease in their perception of employability as the time spent at university increases, and this can be explained by the relationship between academic progress and increased awareness of the labour market. As students progress through their academic careers, their initial high motivation and optimism may diminish as they more closely observe the dynamics and potential challenges of the labour market. The academic and professional uncertainties encountered during this process may cause students' perceptions of employability to become more cautious over time. In this context, educational programs need to be structured to ensure that students maintain their perceptions of employability throughout their academic journey. For students to maintain their high perception of employability, internship programs that provide early contact with the business world, sector-related projects, and career development-focused education policies are important. These findings can be supported by qualitative data from student experiences. In particular, in-depth interviews or focus groups aimed at understanding how students at different academic levels shape their PFE can help explain changes in their perceptions over time. Such an approach can provide a more nuanced understanding of the impact of student's individual academic and professional experiences on their employability perceptions and provide important clues on how to design more effective educational interventions.

Individuals' levels of knowledge about AI significantly influence their anxiety and perceptions of employability. Those with advanced AI knowledge report lower anxiety and higher employability perceptions, a finding that corroborates those of Li and Huang (2020) and Sanusi, Olaleye, Oyelere, and Dixon (2022). These studies highlight the importance of AI awareness programs in alleviating anxiety and enhancing technology adoption.

Among students studying aviation, levels of anxiety regarding AI are moderate. The highest level of anxiety is associated with socio-technical blindness, followed by concerns about AI job replacement and configuration. Learning-related anxiety is the lowest-ranking factor, indicating a relatively positive attitude toward acquiring AI-related skills (Takıl, Erden & Sarı, 2022). The uniformity in students' perceptions of employability reflects confidence in their future career prospects, despite potential gaps in understanding AI's broader labour market implications. These findings emphasize the importance of comprehensive research on AI's

effects, utilizing diverse methodologies and larger samples.

The lack of significant relationships between specific AI anxiety sub-dimensions and perceived future employability necessitates examining the effects of possible mediating or moderating variables such as academic preparation level and sector-specific technological familiarity. Students' academic achievements and educational processes may have a significant impact on AI anxiety and PFE. In a study conducted by Özbek (2024), it was found that accounting professionals' AI anxiety had a significant impact on their PFE. This finding suggests that academic preparation level may play a mediating or moderating role in the relationship between AI anxiety and PFE In addition, individuals' familiarity with technological developments in the sectors in which they work or receive education may have an impact on AI anxiety and PFE. Yılmaz and Yılmaz (2024), in their study examining the AI anxiety levels of potential employees of the digital age, stated that individuals' levels of experience with technology shape their attitudes and anxiety levels towards AI. This finding suggests that industry-specific technological familiarity may serve as a moderator variable in the relationship between AI anxiety sub-dimensions and PFE. In this context, it is recommended that future research examine the effects of variables such as academic preparation level and industry-specific technological familiarity on AI anxiety and PFE in more detail. Such studies may provide important information on how educational programs and professional development processes should be structured to help individuals adapt to AI technologies and strengthen their PFE.

The findings of the study align with global trends examining the impacts of AI technologies on labour markets. In particular, the potential of AI to reshape labour markets has been widely discussed in existing literature. For example, the 2025 Global Labour Resilience Index (GLRI) report prepared by Whiteshield notes that countries such as the United States and Singapore demonstrate resilience in their labour markets due to their strong entrepreneurial ecosystems, flexible labour markets, and leadership in AI innovation. These countries are strengthening their labour markets with AI investments and personalized data-driven strategies (GLRI, 2025). However, the integration of AI into labour markets creates opportunities and challenges across countries and sectors. For example, while some occupations are being transformed by AI and automation, jobs that require human contact, such as caregiving and hairdressing, are less affected (Abay, 2024). Evaluating the findings of the study in different cultural and economic contexts allows us to understand the impact of AI on employability perceptions more comprehensively. Cross-cultural studies allow us to compare the effects of factors such as AI adoption rates, education systems, and labour market dynamics in different countries on individuals' attitudes toward AI and their employability perceptions. For example, McKinsey & Company's Türkiye report contributes to the comparison of transformation processes in different countries by examining the potential impacts of automation and digitalization on the labour market in Türkiye (McKinsey & Company, 2020).

4.1. Theoretical Implications

This study examined the effect of AI anxiety on PFE among aviation students. Although no significant linear relationship was found between AI anxiety and PFE, the findings provide valuable theoretical insights. They suggest that students' concerns about AI may not directly affect employment expectations but could be influenced by other psychological or contextual factors. This points to the importance of considering mediating and moderating variables in future research. Integrating AI anxiety into broader frameworks, such as Social Cognitive Theory and Career Adaptability Theory, can enhance our understanding of how emerging technologies indirectly shape students' career perceptions. By highlighting multidimensional pathways rather than simple direct effects, the study extends theoretical discussions on AI's impact on employability.

4.2. Practical Implications

The findings also offer practical guidance for AI-related training and strategies. First, trust in automated systems can be systematically developed through targeted training, as demonstrated in research with student air traffic controllers (Miramontes et al., 2015). Increasing perceived safety and reducing AI-related anxiety can further enhance trust and system usability (Gillath et al., 2021). Second, according to the Technology-Mediated Learning Theory, learners benefit from access to diverse resources and tools that support knowledge acquisition and skill development (Bower, 2019). Virtual simulations and online tutorials, frequently used in aviation psychology training, allow trainees to interact with advanced AI systems in a controlled environment and prepare for complex tasks. Finally, organizations aiming to integrate AI effectively should prioritize reskilling initiatives. Providing training in data analytics, machine learning, and programming equips employees with the competencies needed to work efficiently alongside AI technologies (Makarius, Mukherjee, Fox, & Fox, 2020).

4.3. Limitations

The study, while providing valuable insights into the relationship between AI anxiety and PFE among aviation students, is subject to several limitations. First, the study relied on self-report scales (AI Anxiety Scale and PFE Scale), which may be subject to social desirability bias, common method variance, and participants' subjective interpretations of the items. The incorporation of objective performance indicators or mixed-method approaches would facilitate a more comprehensive understanding. Secondly, the explained variance of the regression models between AI anxiety sub-dimensions and PFE was relatively low (adjusted R^2 = .020). While these findings suggest a potential association between AI anxiety sub-dimensions and PFE, they also indicate that other individual or educational factors may play a more decisive role in shaping employability perceptions. Future research should integrate additional predictors, such as technological readiness, career adaptability, or organizational support, to capture a fuller picture. The study was conducted within a specific cultural and sectoral context. Given that perceptions of AI and employability are influenced by technological infrastructure, labour market dynamics, and cultural attitudes toward technology, replication of the study across different countries and sectors would enhance the external validity of the findings. Notwithstanding these limitations, the study offers an inaugural investigation into the intricate relationship between AI anxiety and PFE in aviation education, providing significant directions for future research.

ETHICS DECLARATIONS

Support Information: This study has not received support from any organization such as government, commercial or non-profit organizations.

Conflict of Interest: The corresponding author declares no conflict of interest.

Author Contribution Declaration: 1st author's contribution rate is 50%, 2nd author's contribution rate is 50%.

Ethical Approval: All procedures performed in studies involving human participants conform to the ethical standards of the institutional and/or national research committee and the 1964 Helsinki declaration and its subsequent amendments or comparable ethical standards.

The study was approved for ethical suitability by the Ethics Committee of the International Science and Technology University with decision number: E-4651465861-204.01.07-250 and date 30 JUL 2024 (Revision: E-4651465861-204.01.07-474/ 01 NOV 2024). Informed Consent Form: Informed consent form was obtained from all individual participants who participated in the study.

REFERENCES

Abay, E. G. (2024). *Yapay zekanın küresel ekonomi ve istihdamı kökten değiştirmesi bekleniyor*. Anadolu Ajansı. 23.01.2024. Retrieved from https://www.aa.com.tr/tr/bilim-teknoloji/yapay-zekanin-kuresel-ekonomi-ve-istihdami-kokten-degistirmesi-bekleniyor/3116087

Abubakar, M., EriOluwa, O., Teyei, M. & Al-Turjman, F. (2022). AI application in the aviation sector. In *2022 International Conference on Artificial Intelligence of Things and Crowdsensing (AIoTCs)*, 26-28 October, Nicosia.

Acemoglu, D., & Restrepo, P. (2018). *Artificial intelligence, automation, and work* (NBER Working Paper No. 24196). National Bureau of Economic Research. Retrieved from https://www.nber.org/system/files/working_papers/w24196/w24196.pdf

Acemoglu, D., & Restrepo, P. (2017). Robots and jobs: evidence from US labor markets. *Journal of Political Economy*, 128, 2188 - 2244.

Aghion, P., Antonin, C. & Bunel, S. (2019). Artificial intelligence, growth and employment: The role of policy, *Economie & Statistique, 510-511-512,* 149-164.

Akkaya, B., Özkan, A. & Özkan, H. (2021). Yapay zeka kaygı (YZK) ölçeği: Türkçeye uyarlama, geçerlik ve güvenirlik çalışması. *Alanya Akademik Bakış*, *5*(2), 1125-1146.

Alkın, S., Korkmaz, O. & Çelik, S. B. (2020). Algılanan gelecekteki istihdam edilebilirlik ölçeğinin Türkçeye uyarlanması. *İş ve İnsan Dergisi*, *7*(1), 33-47.

Arntz, M., Gregory, T., & Zierahn, U. (2016). *The risk of automation for jobs in OECD countries* (OECD Social, Employment and Migration Working Papers, No. 189). OECD Publishing. Retrieved from https://wecglobal.org/uploads/2019/07/2016_OECD_Risk-Automation-Jobs.pdf

Badhurunnisa, M. & Dass, V. (2023). Challenges and opportunities involved in implementing AI in workplace. *International Journal for Multidisciplinary Research, 5*(6), 1-7.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215.

Belchik, T.A. (2022). Artificial intelligence as a factor in labor productivity. In: Bogoviz, A.V., Suglobov, A.E., Maloletko, A.N., Kaurova, O.V. (eds) *Cooperation and Sustainable Development*. Lecture Notes in Networks and Systems, vol 245. Springer, Cham. https://doi.org/10.1007/978-3-030-77000-6_62

Bendík, D. & Novák, A. (2022). Artificial intelligence and its use in air transport. *Práce a Štúdie, 11*, 106-113. https://doi.org/10.26552/pas.z.2022.1.18

Betz, N. (2000). Self-Efficacy theory as a basis for career assessment. *Journal of Career Assessment, 8,* 205 - 222.

Bordot, F. (2022). Artificial intelligence, robots and unemployment: Evidence from OECD countries. *Journal of Innovation Economics & Management*, (1), 117-138.

Bower, M. (2019). Technology-mediated learning theory. *British Journal of Educational Technology*, *50*(3), 1035-1048.

Creed, P. A. & Klisch, J. (2005). Future outlook and financial strain. *Journal of Occupational Health Psychology, 10*, 251–260.

Creed, P. A., Sawitri, D. R., Hood, M. & Hu, S. (2021). Career goal setting and goal pursuit in young adults: The role of financial distress. *Journal of Career Development, 48*(6), 801-816.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

Duran, C., Boz, D., Behdioğlu, S. & Kutlu, S. (2019). Yetenek yönetimi uygulamaları ölçeği geçerlilik ve güvenilirlik çalışması. *Eskişehir Osmangazi Üniversitesi Sosyal Bilimler Dergisi, 20(*2), 158-189.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994.

European Commission & Directorate-General for Communications Networks, Content and Technology (2017). *Attitudes towards the impact of digitization and automation on daily life: Report. European Commission*. Retrieved from https://op.europa.eu/en/publication-detail/-/publication/ce5d5948-6778-11e7-b2f2-01aa75ed71a1/language-en

European Union Aviation Safety Agency (EASA). (2023). *Artificial intelligence roadmap- A human-centric approach to AI in aviation*. Retrieved from https://www.easa.europa.eu/en/domains/research-innovation/ai

Frey, C. B. & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerization?. *Technological Forecasting and Social Change*, *114*, 254-280.

George, D. & Mallery, M. (2010). *SPSS for Windows step by step: A simple guide and reference* (10th Ed.). Boston: Pearson.

Georgieff, A. & Milanez, A. (2021). *What happened to jobs at high risk of automation?*. (OECD Social, Employment and Migration Working Papers, No. 225). OECD Publishing. Retrieved from https://www.oecd.org/content/dam/oecd/en/publications/reports/2021/01/what-happened-to-jobs-at-high-risk-of-automation_ffdb138f/10bc97f4-en.pdf

Gillath, O., Ai, T., Branicky, M. S., Keshmiri, S., Davison, R. B. & Spaulding, R. (2021). Attachment and trust in artificial intelligence. *Computers in Human Behavior*, *115*, 106607.

Gillespie, N., Lockey, S. & Curtis, C. (2021). *Trust in artificial intelligence: A five country study*. The University of Queensland and KPMG Australia, Research Report. Retrieved from https://doi.org/10.14264/e34bfa3

Global Labour Resilience Index (GLRI). (2025, January 23). *Global Labour Resilience Index 2025: The transformative impact of AI on economies & labour markets.* Whiteshield & Google @ Davos 2025. Retrieved from https://whiteshield.ai/insights/resilience-of-jobs/whiteshield-google-davos-2025

Gorbachev, O., Shestakov, V. & Stefański, K. (2019). *Assessment of professionally important qualities aviation technical staff*. In AIP Conference Proceedings (Vol. 2077, No. 1). AIP Publishing.

Guilbert, L., Bernaud, J. L., Gouvernet, B. & Rossier, J. (2016). Employability: review and research prospects. *International Journal for Educational and Vocational Guidance, 16*, 69-89.

Gunawan, W., Creed, P. A. & Glendon, A. I. (2019). Development and initial validation of a perceived future employability scale for young adults. *Journal of Career Assessment, 27*(4), 610-627.

Hair Jr, J. F., LDS Gabriel, M., Silva, D. D. & Braga, S. (2019). Development and validation of attitudes measurement scales: fundamental and practical aspects. *RAUSP Management Journal*, *54*(4), 490-507.

Hirschi, A., Herrmann, A., & Keller, A. (2015). Career adaptivity, adaptability, and adapting: A conceptual and empirical investigation. *Journal of Vocational Behavior, 87*, 1-10.

Jackson, D. & Wilton, N. (2016). Developing career management competencies among undergraduates and the role of work-integrated learning. *Teaching in Higher Education, 21*(3), 266-286.

Jung, J., & Lim, D. (2020). Industrial robots, employment growth, and labor cost: A simultaneous equation analysis. *Technological Forecasting and Social Change*, 159, 120202. https://doi.org/10.1016/j.techfore.2020.120202.

Karasar, N. (2016). *Bilimsel araştırma yöntemi: bilimsel irade algı çerçevesi ile kavramlar - ilkeler – teknikler*. Ankara: Nobel Akademik Yayıncılık.

Kılanç, B. (2024). *Meslek-istihdam atlası (Lisans)- TÜİK 2024 yükseköğretim istihdam istatistikleri*. Retrieved from https://drive.google.com/file/d/1cYC6o7-lNd4TFo79US3oE_Wzc1QFmOfI/view

Kong, H., Jiang, X., Zhou, X., Baum, T., Li, J., & Yu, J. (2024). Influence of artificial intelligence (AI) perception on career resilience and informal learning. *Tourism Review, 79*(1), 219-233.

Kumar, P., Hussain, M., Reddy, K. & Deep, S. (2022). Methods of air traffic management using artificial intelligence in India. *International Journal of Scientific Research in Science and Technology*, *9*(4), 560-569. https://doi.org/10.32628/ijsrst229490

Lapidus, L. (2023). Using artificial intelligence in employment decisions. *Risk Management, 70*(2), 4-6.

Li, J. & Huang, J. S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society*, *63*, 101410.

Liu, N. & Jew, L. (2023). The impact of social capital on career adaptability in the era of artificial intelligence: The mediating role of career choice. *Journal of Logistics, Informatics and Service Science*, *10*, 166-179.

Lord, R. G., Diefendorff, J. M., Schmidt, A. M. & Hall, R. J. (2010). Self-regulation at work. *Annual Review of Psychology, 61*, 543–568.

Lukyanenko, R., Maass, W. & Storey, V. C. (2022). Trust in artificial intelligence: From a foundational trust framework to emerging research opportunities. *Electronic Markets*, *32*(4), 1993-2020.

Makarius, E. E., Mukherjee, D., Fox, J. D. & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organisation. *Journal of Business Research, 120*, 262-273.

Mcclure, P. (2018). "You're fired," says the Robot. *Social Science Computer Review*, *36*, 139 - 156. https://doi.org/10.1177/0894439317698637.

McKinsey & Company. (2020). *İşimizin geleceği: Dijital çağda Türkiye'nin yetenek dönüşümü.* Retrieved from https://www.mckinsey.com/tr/our-insights/future-of-work-turkey

Miramontes, A., Tesoro, A., Trujillo, Y., Barraza, E., Keeler, J., Boudreau, A., ... & Vu, K. P. L. (2015). Training student air traffic controllers to trust automation. *Procedia Manufacturing*, *3*, 3005-3010.

Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D. & Pietrantoni, L. (2023). The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. *Informing Science*, *26*, 39-68.

Neudert, L. M., Knuutila, A. & Howard, P. N. (2020). *Globalattitudes towards AI, machine learning & automated decision-making: Implications for involving artificial intelligence in public service and good governance.* Oxford Internet Institute. Retrieved from https://oxcaigg.oii.ox.ac.uk/wp-content/uploads/sites/11/2020/10/GlobalAttitudesTowardsAIMachineLearning2020.pdf

Özbek, A. (2024). Muhasebe meslek mensuplarının yapay zekâ kaygılarının gelecekte istihdam edilebilirlik algıları üzerine bir çalışma. *Alanya Akademik Bakış, 8*(1), 254-267.

Park, J. & Woo, S. E. (2022). Who likes artificial intelligence? Personality predictors of attitudes toward artificial intelligence. *The Journal of Psychology*, *156*(1), 68–94.

Qenani, E., MacDougall, N., & Sexton, C. (2014). An empirical study of self-perceived employability: Improving the prospects for student employment success in an uncertain environment. *Active Learning in Higher Education*, *15*(3), 199-213.

Sanusi, I. T., Olaleye, S. A., Oyelere, S. S. & Dixon, R. A. (2022). Investigating learners' competencies for artificial intelligence education in an African K-12 setting. *Computers and Education Open*, *3*, 100083.

Savickas, M. L. (2013). Career construction theory and practice. In S. D. Brown, & R. W. Lent, *Career development and counseling: putting the ory and research to work* (2nd ed., pp. 147-183). John Wiley & Sons.

Schepman, A. & Rodway, P. (2020). Initial validation of the general attitudes towards artificial intelligence scale. *Computers in Human Behavior Reports, 1*, 100014.

Sheıkhı, M. (2022). Yapay zeka kullanımının iş piyasasına etkisi. *Journal of Economics and Political Sciences*, *2*(1), 102-111.

Takıl, N., Erden, N. K. & Sarı, A. B. (2022). Farklı meslek grubu adaylarının yapay zekâ teknolojisine yönelik kaygı seviyesinin incelenmesi. *Balıkesir Üniversitesi Sosyal Bilimler Enstitüsü Dergisi, 25*(48), 343-353.

Tecuci, G. (2012). Artificial intelligence. *Wiley Interdisciplinary Reviews: Computational Statistics*, *4*(2), 168-180. https://doi.org/10.1002/wics.200

Tymon, A. (2013). The student perspective on employability. *Studies in Higher Education*, *38*(6), 841-856.

Vroom, V.H. (1964). *Work and motivation*. New York, NY: Wiley.

Wang, Y. Y. & Wang, Y. S. (2019). Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. *Interactive Learning Environments*, *30*(4), 619-634.

Webb, M. (2019). *The impact of artificial intelligence on the labor market*. Available at SSRN 3482150.

Wickens, C. D., & Dehais, F. (2020). Expertise in aviation. In P. Ward, J. M. Schraagen, J. Gore, & E. Roth (Eds.), *The Oxford handbook of expertise* (pp. 662–689). Oxford University Press.

Xie, M., Ding, L., Xia, Y., Guo, J., Pan, J. & Wang, H. (2021). Does artificial intelligence affect the pattern of skill demand? Evidence from Chinese manufacturing firms. *Economic Modelling*, *96*, 295-309.

Yılmaz, H. U., & Yımaz, A. (2024). Dijital çağın potansiyel çalışanlarının yapay zekâ kaygılarının belirlenmesi. *Business and Economics Research Journal*, *15*(2), 171-188.

Yizhong, X., Lin, Z., Baranchenko, Y., Lau, C. K., Yukhanaev, A. & Lu, H. (2017). Employability and job search behavior: A six-wave longitudinal study of Chinese university graduates. *Employee Relations, 39*, 223–239.

Zhang, B., & Dafoe, A. (2019). Artificial intelligence: American attitudes and trends. *Available at SSRN 3312874*. https://dx.doi.org/10.2139/ssrn.3312874

Zhang, X. (2023). Research on the impact of artificial intelligence on the labor market. *Advances in Economics and Management Research*, *8*(1), 252-252.

Zhou, G., Chu, G., Li, L. & Meng, L. (2019). The effect of artificial intelligence on China's labor market. *China Economic Journal*, *13*(1), 24–41.

Zou, T., & Sun, K. (2021). Application and prospect of artificial intelligence in aircraft design. In *2021 International Conference on Networking Systems of AI (INSAI)* (pp. 201-205). IEEE.