Does Artificial Intelligence Anxiety Affect Concern about Technological Unemployment?

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Abstract

Artificial intelligence (AI) applications raise many concerns alongside the convenience and benefits they offer. These concerns, referred to as AI anxiety, have brought technological unemployment concerns onto the agenda with the rapid development of AI and the rise of automation in business. In this context, the study aims to investigate the role of AI anxiety in technological unemployment concerns.

The data, conducted using a quantitative research model and correlational research design, were collected from 416 people working in different Group A travel agencies in Turkey by convenience sampling. These data were analyzed using SPSS 25 and AMOS 25 statistical programs. The analysis revealed positive and significant correlations between all the dimensions of AI anxiety and technological unemployment concerns. Additionally, the analysis revealed a positive and significant impact of the learning, job replacement, and socio-technical blindness dimensions of AI anxiety on all aspects of technology-related unemployment concerns. In contrast, the AI configuration dimension negatively and significantly impacted all these dimensions. It is anticipated that the findings will make a significant contribution to the developing literature. This contribution not only increases the body of knowledge in the relevant field but also has the potential to guide future studies by raising new questions and discussion points.

Keywords: AI anxiety, technological unemployment concern, travel agencies

Introduction

Artificial intelligence (AI) continues a long automation process, which began in the late 19th and early 20th centuries with mechanization and information technology. However, these advancements left large work areas that humans could only perform until AI was invented (Korinek & Stiglitz, 2018: 349). As AI technology evolves, it increasingly takes on tasks once thought to require human intuition and creativity (Federspiel et al., 2023: 2). This shift raises essential questions about the future of work and humans' roles in an increasingly automated World (Wang et al., 2024: 5754). AI's potential to transform economies and societies is a topic of ongoing debate, with concerns about its impact on jobs, employment, and labor markets (Mutascu, 2021: 654). People began to view AI as a potential threat to human employment. Once thought to be immune to automation, cognitive tasks now face serious challenges (Virgilio et al., 2024: 1683). As AI systems continue to evolve, many employees need to adapt to new roles emphasizing skills that machines cannot easily replicate, such as creativity and emotional intelligence (George, 2024: 19). This shift may lead to a redefined workforce where collaboration between humans and AI becomes essential for maximizing productivity and innovation (Wang et al., 2020: 2).

The tourism sector increasingly utilizes large volumes of data, including multimodal sets, for information extraction (Doborjeh et al., 2022: 1155). AI technologies have several benefits for tourism enterprises, such as enhanced production, efficiency, and profitability, as well as for tourists, offering easy and customized experiences (Samara et al., 2020: 345). The tourism industry uses AI technologies for forecasting (Essien & Chukwukelu, 2022; Kumar et al., 2022; Wu et al., 2024), improving operational efficiency (Jabeen et al., 2022; Alyasiri et al., 2024), enhancing customer experiences (Giotis & Papadionysiou, 2022; Ghesh et al., 2024), and supporting sustainability (Tong et al., 2022; Arora & Chandel; 2024; Khan et al., 2024).

This study explores how learning, job replacement, sociotechnical blindness, and AI configuration influence three pivotal outcomes of technological change: lack of technical skill, incremental technological improvements, and technological disruption. By examining these relationships, the study aims to provide insights into the challenges and opportunities posed by technological progress, particularly in addressing skill deficits and balancing incremental and disruptive innovations. The study's findings contribute to the growing literature on technological change's human and sociotechnical dimensions. They also offer practical implications for policymakers, educators, and organizations seeking to mitigate skill gaps, harness technological potential, and manage workforce transitions effectively.

Literature Review

Artificial Intelligence Anxiety

AI algorithms and the intelligent machines they support have significantly transformed the business world, mainly replacing the responsibilities of labor-intensive work. While this situation makes AI an indispensable part of business life, it also causes AI anxiety in employees, leading to various problems (Etiner & Etinkaya, 2024: 160). In addition, public figures such as Bill Gates, Elon Musk, and Stephen Hawking have expressed their concerns about the future development of AI by stating that it can get out of control and affect people and society in disastrous ways (Johnson & Verdicchio, 2017: 2267). In this context, while AI is a current field of study in the literature, one critical discussion topic in contemporary popular science is the concerns arising from potential threats associated with AI, also known as artificial intelligence anxiety (Kaya et al., 2024: 555).

AI anxiety can be defined as excessive fear arising from the changes and problems caused by AI technologies in personal or social life (Akçakanat, 2024: 55). Johnson and Verdicchio (2017) defined AI anxiety as "the fear of losing control over AI" (Johnson & Verdicchio, 2017: 2268). When something new enters people's lives, their first reaction is 'ignorance,' followed by 'reaction/denial,' then 'panic,' and finally 'anxiety' (Banerjee & Banerjee, 2023: 37). When this process is taken into account, it is possible to consider human anxiety about AI as a normal situation.

Wang and Wang (2022) categorized AI anxiety under the dimensions of “AI learning,” which refers to anxiety regarding learning AI technologies; “job replacement anxiety,” which refers to the fear of the adverse effects of AI on business life; “sociotechnical blindness,” which refers to the anxiety arising from a lack of complete understanding of the dependence of AI on humans; and “AI configuration,” which expresses fear regarding humanoid AI.

Among the causes of artificial intelligence anxiety is general anxiety arising from the unknowns about artificial intelligence. This anxiety refers to the uncertainties about the transformations that artificial intelligence systems can create as they become intelligent and the fears that these uncertainties create (Schmelzer, 2019). Another important cause of AI anxiety is the firm belief that AI will take away people's jobs in the future (Granulo et al., 2019; Ochmann et al., 2020). Indeed, a survey of more than 1,200 respondents found that 69% of university graduates believe that AI could take away their jobs or make them irrelevant in a few years (Rajnerowicz, 2024). Factors such as data privacy violations (Binns, 2018), discriminatory algorithmic biases (Circiumaru, 2022), and racism arising from AI-supported decision systems (Eubanks, 2018) also cause AI anxiety.

Technological Unemployment Concern

There is no doubt that the phenomenon of unemployment is a complex one (Walkowski 2019: 9). As Ricardo Campa points out, economists distinguish between frictional unemployment, which involves the individual mobility of workers between jobs, and structural unemployment, which results from the decline of particular sectors or occupations, and cyclical unemployment, which results from general but temporary fluctuations in economic activity. Furthermore, "technological unemployment" can be added to this list (Campa, 2017: 1).

Technological unemployment occurs when the number of employees required to perform the current job decreases due to new technologies increasing the productivity of some jobs or completely changing the way of doing business (Pehlivanoğlu, 2023: 343). The term was first proposed by economist John Maynard Keynes (1930). It refers to the idea that new technologies can put people out of work (Jung et al.,2024: 543). Technological unemployment anxiety concerns the possible effects of technological developments and automation on the labor force. Since the Industrial Revolution, the potential of technology to partially or wholly replace human labor in the workplace has caused social and individual anxiety (Frey & Osborne, 2017). This concern has become more pronounced in recent years with the rapid proliferation of AI, robotics, machine learning, and other advanced technologies (Campa, 2017; 11-12; Acemoğlu & Restrepo, 2018).

Technological unemployment anxiety causes increased stress levels in individuals, lowers self-motivation, decreases work engagement and job performance, and leads to less employee involvement in decision-making processes. Therefore, managing technological unemployment anxiety and employees' declining performance, engagement, and motivation are significant challenges for today's and tomorrow's managers while achieving organizational goals (Civelek & Pehlivanoğlu, 2020).

Methodology

Participants and Procedures

The research population consists of the tourism sector in Turkey. The participant sample of this study consisted of a group of travel agency employees who work in the Istanbul province in

Turkey. The reason for choosing the tourism sector in the research is that this sector has the largest share in closing Turkey's foreign trade deficit for the last 20 years (TURSAB; TÜİK, 2024; Birgücü, 2024). Travel agencies are the businesses that make the most intensive use of technology in the tourism sector. The tourism sector's advancements in information technologies have led to a decrease in travel agencies in other countries, replacing traditional agencies with online ones. In contrast, the number of agencies increases by an average of 500 annually in Turkey (turizmgazetesi.com). For these reasons, the research scope included travel agency employees in the tourism sector.

The Aydin Adnan Menderes University Social and Humanities Research Ethics Committee granted ethical approval for the study at its inception (February 9, 2024, 31906847). The study employed the convenience sampling method, a nonrandom sampling technique. In this context, a questionnaire form was sent electronically to (via Google Forms) the employees who volunteered to participate in the research between July and August 2024. Four hundred sixteen employees from 39 travel agencies responded to our research and agreed to participate in this survey.

Measures

Artificial Intelligence Anxiety

Wang and Wang (2022) developed the Artificial Intelligence Anxiety Scale (AIAS), which Akkaya et al. (2021) first adapted into Turkish. The scale has 16 items in 4 dimensions (learning, job replacement, sociotechnical blindness, and AI configuration). The scale rates items from 1 (strongly disagree) to 5 (strongly agree). The AIAS, which does not have reverse-coded items, includes statements such as “Learning to use AI techniques/products makes me anxious,” “I am afraid that an AI technique/product may replace humans,” and “I am afraid that an AI technique/product may be misused.” Cronbach’s α coefficient was .94.

Technological Unemployment Concern

Civelek and Pehlivanolu (2020) developed the Technological Unemployment Concern Scale (TUCS). The TUCS has no reverse-coded items and consists of 12 items in three dimensions (lack of technical skill, incremental technological improvements, and technological disruption). The scale rates items from one (strongly disagree) to five (strongly agree). The scale asks respondents to rate statements such as “I think I will lag in terms of performance as technology advances,” “I think that the change in the business processes due to the technological advancements will make me unhappy in the future,” and “I think that technological advances may cause the organization I am working for to close down in the future.” Cronbach’s α coefficient was .83.

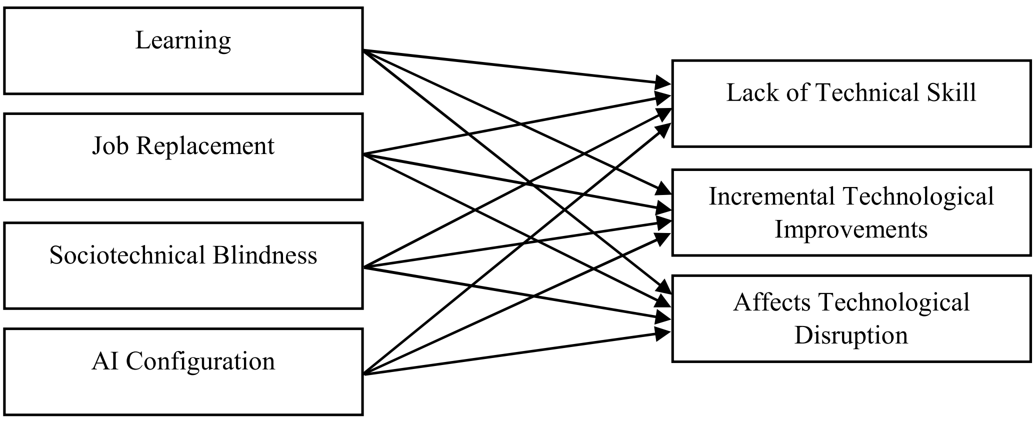
Data Analysis

The study used IBM SPSS Statistics 25 and AMOS 25 for data analysis. The research first conducted a confirmatory factor analysis (CFA) to test the structural validity of the scales used, followed by a reliability analysis to determine internal consistency. Secondly, we conducted a descriptive statistical analysis of the research variables, followed by a correlation analysis to ascertain their relationship. The final part of the analysis phase involved the construction of a structural equation model (SEM) to test the hypotheses and the performance of latent variable structural model analysis.

The Research Model

The study employed a scanning model. Within the scope of the developed hypotheses, the dependent variables of the research are lack of technical skill, incremental technological improvements, and technological disruption. Figure 1 displays the conceptual model, which includes the independent variables of learning, job replacement, sociotechnical blindness, and AI configuration.

Figure-1 A Conceptual Model of this Research



The hypotheses of the research;

H_1: Learning, positively affects lack of technical skill.

H_2: Learning, positively affects incremental technological improvements.

H_3: Learning, positively affects technological disruption.

H_4: Job replacement, positively affects lack of technical skill.

H_5: Job replacement, positively affects incremental technological improvements.

H_6: Job replacement, positively affects technological disruption.

H_7: Sociotechnical blindness, positively affects lack of technical skill.

H_8: Sociotechnical blindness, positively affects incremental technological improvements.

H_9: Sociotechnical blindness, positively affects technological disruption.

H_{10}: AI configuration, positively affects lack of technical skill.

H_{11}: AI configuration, positively affects incremental technological improvements.

H_{12}: AI configuration, positively affects technological disruption.

Results

Table 1 shows the descriptive statistics of the employees who participated in this study. According to this table, 50.5% of the sample was male and 49.5% of female employees. The majority of them, 74.3%, are single. Participants from Generation Z make up 51.9% of the sample, and the highest level of education is a bachelor's degree at 53.8%. The table reveals that 42.3% of the sample possesses sufficient AI knowledge.

Table-1 Sample Characteristics

		Frequency	Percentage
Gender	Female	206	49.5
	Male	210	50.5
Marital status	Single	309	74.3
	Married	107	25.7
Generation	Y	200	48.1
	Z	216	51.9
Education status	High school	38	9.1
	Associate	111	26.7
	Bachelor	224	53.8
	Postgraduate	43	10.3
AI knowledge level	No	47	11.3
	Some	135	32.5
	Sufficient	176	42.3
	Detailed	58	13.9

This study used confirmatory factor analysis (CFA) to determine the structural validity of the scales, and Table 2 presents the fit values obtained from the factor analysis for the AIA and TUC scales. During the analysis, it was noted that the standardized regression coefficient of the statements in the scale should not be lower than 0.70, and the p-value should not be greater than 0.05 (Hair et al. 2009:679).

Table-2 Fit Values of the Scales

	CMIN/DF (0< χ2/sd ≤ 5)	IFI (≥.90)	CFI (≥.90)	RMSEA (≤.90)	SRMR (≤.10)
Artificial Intelligence Anxiety	1.99	.98	.98	.04	.02
Technological Unemployment Concern	2.81	.98	.98	.06	.03

Analysis of Table 2 reveals that the fit indices of the scales fall within the range of the reference fit index values. Following the CFA analyses, the necessary reliability analyses of the scales were carried out. Reliability analyses showed that the Cronbach alpha coefficients (the entirety of artificial intelligence anxiety scale =.97, learning =.96, job replacement =.92, sociotechnical blindness =.91, AI configuration =.91; the entirety of technological unemployment concern =.96, lack of technical skill =.91, incremental technological improvements =.92, technological disruption =.92) were higher than .70 (Hair et al., 2009).

Table 3 presents the descriptive statistics for the variables used in the study and the relationships between the variables.

Table-3 Descriptive Statistics and Relationships between Variables

Variable	1	2	3	4	5	6	7	8	9
1.Artificial Intelligence Anxiety (AIA)	-								
2.Learning (Lrng)	.960*	-							
3.Job Replacement (JR)	.956*	.889*	-						
4.Sociotechnical Blindness (SB)	.913*	.806*	.860*	-					
5.AI Configuration (AIC)	.915*	.861*	.834*	.775*	-				
6.Technological Unemployment Concern (TUC)	.905*	.858*	.847*	.846*	.846*	-			
7.Lack of Technical Skill (LTS)	.866*	.837*	.794*	.794*	.822*	.828*	-		
8.Incremental Technological Improvements (ITI)	.869*	.815*	.818*	.815*	.819*	.954*	.837*	-	
9.Technological Disruption (TD)	.841*	.789*	.798*	.801*	.768*	.953*	.837*	.880*	-
Mean	57.94	17.80	14.57	14.84	10.72	43.19	14.30	14.39	14.49
SD	16.63	6.08	4.22	4.13	3.25	11.49	4.12	4.00	3.98

Skewness	-.768	-.685	-.773	-.924	-.725	-.806	-.739	-.792	-.853
Kurtosis	-.978	-1.147	-.818	-.521	-.929	-.819	-.829	-.725	-.626
*p<.01. SD: Standard Deviation.									

Analysis of Table 3 shows that the skewness and kurtosis coefficients of the scales are within ±1,5. The fact that these coefficients are within this range of values indicates that the data are suitable for a normal distribution (Tabachnick & Fidell, 2013). When analysing the correlations between the variables, it can be seen that the relationships between all the dimensions of AI anxiety and the dimensions of technological unemployment concern are positive and significant at the .01 level.

The measurement model was tested before testing the research hypotheses through the structural model. Due to the normal distribution of the data, the covariance matrix was created using the Maximum Likelihood calculation method (Gürbüz, 2021: 109). The analysis determined that the fit index values (X2/df = 2.07; IFI =.97; CFI =.97; SRMR =.02; RMSEA =.05) were acceptable (Thakkar, 2020). This case validates the tested measurement model.

Following the validation of the measurement model, we tested the research hypotheses using the latent variable structural model, and Table 4 presents the analysis results.

Table-4 Parameter Estimation Values for SEM Analysis

H	**Parameter Estimates**	**β**	**SE**	**Hypothesis Result**
H_1	Lrng → LTS	.556*	.144	Supported
H_2	Lrng → ITI	.638**	.215	Supported
H_3	Lrng → TD	.537**	.143	Supported
H_4	JR → LTS	.666*	.211	Supported
H_5	JR → ITI	.491**	.198	Supported
H_6	JR → TD	1.123**	.664	Supported
H_7	SB → LTS	1.003*	.632	Supported
H_8	SB → ITI	.834*	.521	Supported
H_9	SB → TD	.741*	.331	Supported
H_{10}	AIC → LTS	.442	.265	Unsupported
H_{11}	AIC → ITI	.354	.313	Unsupported
H_{12}	AIC → TD	.084	.473	Unsupported
*p<.01; ** p<.05.				

When Table 4 is examined, it is determined that the learning, job replacement, and sociotechnical blindness dimensions of artificial intelligence anxiety positively and significantly affect the dimensions of technological unemployment concern. In this context, hypotheses H1, H2, H3, H4, H5, H6, H7, H8, and H9 are supported.

As seen in Table 4, since the effect of the AI Configuration dimension of AI anxiety on all dimensions of technological unemployment concern is not significant (p>.05), hypotheses H10, H11, and H12 are not supported.

Discussion and Conclusion

AI is increasingly used in various aspects of travel and tourism, including personalization, robots, conversational systems, intelligent travel agents, prediction, language translation, and natural language processing. This study examined the connections between learning, job replacement, sociotechnical blindness, AI configuration, and the consequences of technical skill deficiencies, incremental technological advancements, and technological disruption. This study underscores the multifaceted nature of technological change and its interplay with human and sociotechnical factors. The findings highlight the pivotal roles of learning, job replacement, and sociotechnical alignment in addressing skill gaps, fostering incremental improvements, and managing technological disruption. While AI configuration did not show significant direct effects, its role may emerge as AI adoption matures and organizations better integrate AI into strategic decision-making. The findings provide valuable insights into how these factors interact in the context of technological change.

All hypotheses (1, 2, and 3) about learning were accepted. Learning positively influences lack of technical skill, incremental technological improvements, and technological disruption. This indicates that acquiring knowledge and skills significantly drives gradual and disruptive technological changes while simultaneously revealing skill gaps (possibly due to outdated knowledge).

The hypotheses (4, 5, and 6) about job replacement were also accepted. Job replacement also positively affects the lack of technical skill, incremental technological improvements, and technological disruption. This suggests that the reallocation of roles or displacement caused by technological advancements highlights skill deficits and contributes to gradual and transformative changes.

The hypotheses (7, 8, and 9), which are about sociotechnical blindness, were accepted too. Sociotechnical blindness positively affects lack of technical skill, incremental technological improvements, and technological disruption. This implies that overlooking the interplay between technology and society exacerbates skill gaps and drives incremental and disruptive changes, likely due to unintended consequences or misaligned priorities.

The study rejected all hypotheses (10, 11, and 12) regarding AI configuration. The lack of support for these hypotheses suggests that AI configuration, as conceptualized in the study, does not significantly affect the lack of technical skill, incremental technological improvements, or technological disruption. The operational definition or measurement of "AI configuration" may not align well with the constructs of skill gaps, incremental improvements, or disruption. The participants in the study may not perceive AI configuration as a primary factor influencing these outcomes, possibly due to limited exposure or understanding. Other mediating factors (e.g., organizational readiness, leadership, or regulatory environments) may moderate the relationship between AI configuration and the dependent variables, diluting the direct effects.

Implications

Focusing on learning and job replacement are strong predictors of technological change and skill-related challenges. Policymakers, educators, and organizations can prioritize reskilling programs to address gaps and prepare for incremental and disruptive changes. By fostering a culture of continuous learning, they can equip the workforce with the necessary tools to adapt to evolving job demands. This proactive approach mitigates job displacement risks and enhances overall economic resilience in the face of rapid technological advancement.

The second implication is about addressing sociotechnical blindness. Recognizing and mitigating the blind spots in the technology-society interface is critical for managing skill deficits and directing innovation responsibly. Fostering a deeper understanding of how technological advancements impact various communities and ensuring the inclusion of diverse perspectives in the development process is crucial. By doing so, we can create more inclusive solutions that enhance efficiency and promote equity and social well-being.

Businesses have to reevaluate AI configuration because they should consider revising the operationalization of this variable or exploring its indirect effects through mediators such as organizational practices or workforce readiness. Additionally, businesses must engage in ongoing assessment and adaptation of their AI strategies, ensuring alignment with evolving industry standards and employee skill sets. Doing so can enhance overall productivity and foster a culture of innovation within the organization.

Limitations and future research

Future studies should explore temporal changes in these relationships and consider additional variables, such as organizational readiness and cultural factors that may moderate the observed effects. Practitioners and policymakers should focus on fostering adaptable workforces, promoting sociotechnical balance, and leveraging displacement as an opportunity for innovation.

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