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Research Article

Psychometric validation of the artificial intelligence anxiety scale: A confirmatory factor analysis for academic research

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ABSTRACT

This study introduces and validates the artificial intelligence anxiety scale (AIAS), a novel instrument designed to measure researchers' anxieties when employing artificial intelligence (AI) tools in academic writing. As AI technologies rapidly infiltrate scholarly work, however, the primary concern grows about their ethical implications, impact on traditional research skills, and the lack of institutional readiness issues that remain underexplored in existing literature. Addressing this critical gap, the AIAS offers a novel framework grounded in real-world academic concerns. Using an inductive approach, data were collected from 219 faculty members and graduate students at Taif University, Saudi Arabia, revealing four core dimensions of AI-related anxiety: (1) concerns about the accuracy of AI outputs, (2) fear of committing plagiarism, (3) lack of institutional guidelines, and (4) fear of losing research skills. Exploratory and confirmatory factor analyses confirmed the existence of these factors, and reliability testing indicated robust internal consistency. By offering the first validated tool specifically tailored to measure AI-related anxiety in academic contexts, this study provides a significant resource for researchers and institutions. Its application can guide universities in devising training and support initiatives to ensure the ethical and practical integration of AI, thereby sustaining the integrity of traditional research competencies and enhancing the overall quality and credibility of academic endeavors.

Keywords: AI anxiety, confirmatory factor analysis, academic research, psychological assessment

INTRODUCTION

Artificial intelligence (AI) is significantly transforming the landscape of academic research across various disciplines by enhancing efficiency, accuracy, and the scope of research activities. In higher education, AI tools are being integrated into research processes to streamline data analysis, literature reviews, and even the drafting of scientific texts, thereby saving researchers considerable time and effort. AI's ability to process vast amounts of data rapidly enables more efficient literature reviews, facilitating the identification of relevant studies and highlighting new research directions or gaps in the existing literature. Moreover, AI technologies such as natural language processing (NLP) and large language models are revolutionizing text generation, enabling the production of high-quality scientific texts that can assist researchers in overcoming writer's block and ensuring the accuracy of scientific publications, particularly in fields like pharmacy and medicine where precision is crucial.

Within contemporary academic settings, the use of AI-based tools has expanded significantly, offering the potential to enhance research efficiency, data processing, and complex analytics. However, concerns persist regarding research integrity, authorship, and evolving scholarly practices. AI involves replicating human cognitive processes, such as reasoning, learning, problem-solving, and language comprehension, in machines (Liu & Jagadish, 2024; Russell & Norvig, 2020). These systems can autonomously analyze large datasets, detect patterns, and make decisions with limited human oversight (AlFarsi et al., 2021; Goodfellow et al., 2016).

AI is typically classified into three categories: narrow AI, designed for specialized tasks such as recommendation algorithms (Russell & Norvig, 2020); general AI, which is theoretically capable of performing any intellectual task that a human can; and super AI, which is hypothesized to exceed human intelligence (Nilsson, 2010). Key AI domains include machine learning, which enables iterative improvements (Goodfellow et al., 2016); NLP, which recognizes and generates human language; and computer vision, which interprets visual data (Lecun et al., 2015). Robotics merges AI into physical systems, while expert systems replicate specialized decision-making (Russell & Norvig, 2020).

Still, AI has been extensively integrated into different sectors, especially in education, healthcare, and industry. The AI-driven tools can improve the creativity and efficiency of individuals who are anxious about using technology. Some of these concerns include job displacement, solving complex systems, and applying ethical implications. The essential step for academic research is to understand AI-related anxiety, particularly in education, where students are increasingly engaging with these tools and technologies that utilize AI.

Artificial intelligence anxiety scale (AIAS) has been developed to evaluate the psychological responses of individuals and ensure they do not conflict with AI technologies. However, the psychometric evaluation needs reliability and validity to ensure its effectiveness in educational and academic research. Confirmatory factor analysis (CFA) is a robust statistical method used to validate the structural integrity of psychometric instruments, providing empirical support for their application across diverse populations. This study aims to conduct a CFA of the AIAS to evaluate its validity and reliability within an academic research context. By examining the factor structure, internal consistency, and model fit indices, the study seeks to establish a scientifically sound instrument for measuring anxiety related to AI. The findings will contribute to the refinement of assessment tools in psychological and educational research, enhancing our understanding of how AI influences emotional and cognitive responses in academic settings.

Despite the widespread integration of AI tools in academic settings, particularly for tasks such as writing assistance, content generation, and literature review, no validated instrument currently exists to measure the specific anxieties researchers experience about these technologies. Existing studies have focused mainly on general attitudes toward AI, ethical concerns, or its impact on productivity. Still, they have overlooked the emotional and psychological responses that may influence the responsible use of AI in scholarly work. This gap is particularly critical as anxiety can hinder adoption, ethical decision-making, and research quality. Therefore, this study aims to fill that void by developing and validating the AIAS, providing the first psychometric tool specifically designed to assess researchers' anxieties related to AI in academic contexts.

This study is divided into several sections. First, a literature review is conducted to highlight existing studies and the impact of using AI tools on the anxiety associated with AI-driven systems. The second section presents the method and conceptual model, along with the hypotheses related to the study's topic. The third section produces the exploratory factor analysis (EFA), providing a detailed description of each factor along with relevant references in this context. The fourth section explains the findings from the tested model and checks the reliability and validity of all hypotheses. The fifth section is concerned with a discussion of the hypothesis's impact and the results compared to those of other studies. Finally, a conclusion section for the entire study.

LITERATURE REVIEW

In this context, academic researchers are increasingly expressing concern about the implications of AI in their work. The development of an assessment tool, such as the AIAS, is therefore critical for accurately measuring these concerns and guiding future research. Such innovations permeate diverse sectors, including healthcare (diagnostics and personalized treatment), finance (fraud detection and algorithmic trading), and education (personalized learning and virtual assistants) (Russell & Norvig, 2020). Despite these benefits, the rapid adoption of AI has sparked concerns about the potential for societal inequalities to escalate, including economic disparities and unequal access to education (Russell & Norvig, 2020). The increasing reliance on AI in shaping social structures and learning environments amplifies these anxieties (Acemoğlu & Restrepo, 2018; Alqahtani et al., 2022).

Within the current research, AI has revolutionized traditional workflows by streamlining data analysis, literature reviews, and even early manuscript drafts to enhance efficiency (Goodfellow et al., 2016). However, this productivity also raises questions about diminished critical thinking, originality, and the overall authenticity of academic contributions (Nilsson, 2010). In education, AI-powered applications, including personalized learning platforms, hold promise for revolutionizing teaching and learning (Lecun et al., 2015). However, potential inequities in technology access, the evolving role of educators, and an over-reliance on AI at the expense of fostering creativity and independent thought have sparked concern (Chan, 2023).

Policymakers, educators, developers, and other stakeholders thus face the challenge of ensuring ethical standards, protecting privacy, and delivering equitable AI resources (Perkins et al., 2023). Although AI can advance research, education, and societal welfare, it may also exacerbate anxieties related to job security, data integrity, and professional recognition (Acemoğlu & Restrepo, 2018; Chan, 2023; Hafsa et al., 2021; Jain & Jain, 2023; Perkins et al., 2023). Against this backdrop, academic researchers often express unease about the role of AI in transforming scholarly work. Developing an AIAS is crucial for accurately gauging these concerns that safeguard both academic rigor and innovation.

When examining scales related to AI anxiety, it is apparent that this field remains in its early stages (Tatnall, 2019; Wen et al., 2024). AI anxiety is rooted in “computer anxiety,” a psychological phenomenon marked by fear or unease tied to computer use or anticipated interaction (Chua et al., 1999; Rosen & Weil, 1995). Both personal and professional domains may be affected by such apprehension. Computer anxiety and AI anxiety fall under the broader category of technophobia, where apprehension toward one technology often generalizes to others. In both cases, fear stems from a perceived lack of control, technical knowledge, or confidence (Chua et al., 1999). However, AI anxiety also encompasses specific concerns, such as ethical dilemmas, job displacement, and loss of autonomy (Tawafak et al., 2025; Zhou et al., 2023). As AI systems become more autonomous, they extend the challenges once associated with basic computer use (Rosen & Weil, 1995; Yusuf et al., 2024).

These forms of anxiety negatively affect technology adoption: higher computer anxiety correlates with lower technology usage (Chua et al., 1999), and AI anxiety may likewise hinder acceptance of AI tools (Zhou et al., 2023). Given AI’s extending role across various sectors, researchers are increasingly studying its psychological impacts. Indeed, Wang and Wang (2019) conceptualize AI anxiety as “an overall affective response of anxiety or fear that inhibits an individual from interacting with AI” (p. 621), distinguishing multiple dimensions, including AI learning anxiety, job replacement anxiety, sociotechnical blindness anxiety, and AI configuration anxiety. Others identify factors including privacy violation, bias, existential risk, ethical lapses, artificial consciousness concerns, and lack of transparency (Alqahtani et al., 2022; Li et al., 2020).

Developing an AIAS that captures these sections is crucial for understanding how scholars respond to rapid technological shifts and for guiding interventions that promote both responsible AI integration and psychological well-being. This scale is significant for several reasons. First, it identifies psychological barriers related to AI-specific concerns, such as over-reliance, ethical risks, and the potential erosion of core research competencies, factors that remain largely unquantified by existing instruments (Cheng, 2022; Evelyn, 2021). Second, insights from the scale can guide universities and institutions in designing training and support programs, thereby promoting the ethical and practical integration of AI (Zhou et al., 2023). Third, validating the scale in educational research enriches both educational technology and psychometrics by providing a tool for assessing the emotional aspects of AI adoption (Evelyn, 2021).

METHODS

An amenity sampling technique was used to select participants, given the exploration nature of the study and the limited accessibility to a comprehensive list of people. The survey link is already distributed via

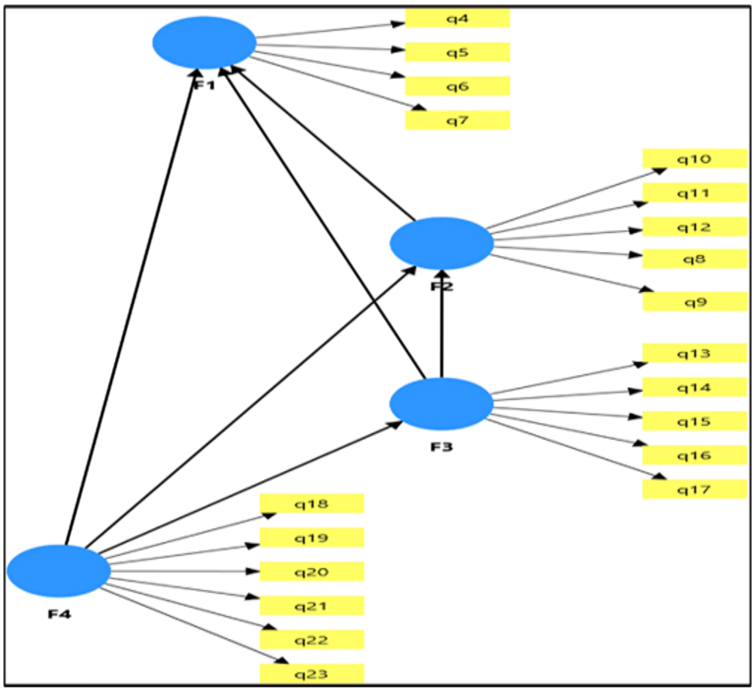

Figure 1. Conceptual research model (Source: Authors)

university mailing lists, social media platforms, and academic forums to reach faculty members and graduate students.

Participants and Procedures

Out of approximately 400 individuals invited, 219 completed answers were submitted, yielding a response rate of 54.8%. The sample included participants from a range of academic disciplines. Descriptive demographic data was collected to explore potential subgroup differences. Future studies are encouraged to perform multi-group CFA to test for measurement invariance across these variables.

Participants included 219 faculty members and graduate students at Taif University in Saudi Arabia. Graduate students (n = 186, 84.9%) comprised the majority of the sample, with faculty members representing 15.1% (n = 33). Academic disciplines were divided among humanities (73.1%), scientific fields (21.9%), and medical studies (5.0%). This cross-section reflects the typical distribution of academic roles and offers perspectives from multiple domains. Informed consent was obtained from participants, and the study received approval from the institution's Scientific Research Ethics Committee. Data were collected through an online survey administered via Google Forms and distributed across social media platforms during the 2024 academic year.

Inclusion criteria required participants to be either faculty members or postgraduate students currently engaged in academic research. Participants with no experience using AI tools for educational purposes were excluded. Incomplete responses were excluded from the analysis. The final dataset included only participants who completed all scale items required for EFA and CFA.

Model Concept

This section explains the conceptual research model, as shown in **Figure 1**. In the proposed model, four factors are interconnected to assessing the study's aim as system usage is considered. The model uses four hypotheses, and the results are described in the next section and tables.

H1: Factor 1 was labelled concern about the accuracy of AI tools.

H2: Factor 2 was labelled fear of committing plagiarism and comprised four items.

H3: Factor 3 was labelled lack of institutional guidelines on the use of AI.

H4: Factor 4 was labelled fear of losing research skills due to frequent use of AI tools.

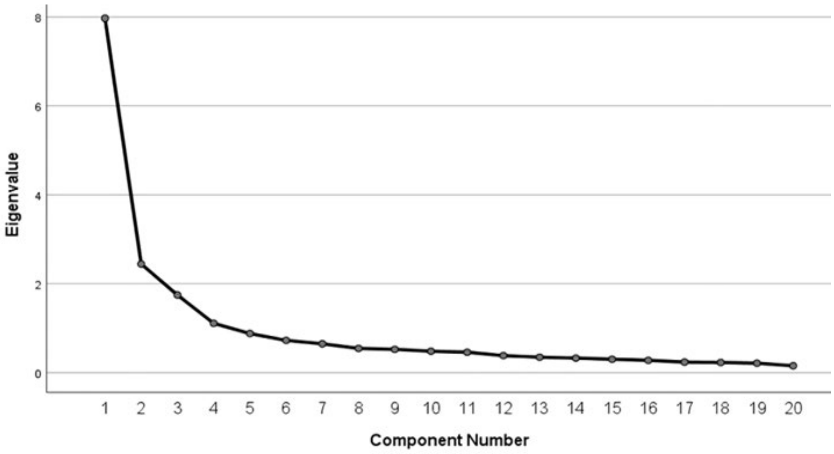

Figure 2. Scree plot of the EFA (Source: Authors)

Measure of Study

The scale was developed after reviewing previous studies that addressed the use of AI tools in academic research. Given that there is no theory behind this new concept and no prior study has explored it, the inductive method was employed (DeVellis, 2016; Hinkin, 1995). A question was posed to researchers, who are both faculty members and graduate students (the same group that would be selected to apply the scale), regarding their concerns about using AI tools in writing research papers (Boateng et al., 2018; Eldow et al., 2006). Their responses were collected, and scale items were generated based on these responses. Initially, 23 items were developed. These items were then presented to 10 expert reviewers specializing in evaluating content validity. Items with an agreement rate of 80% or higher were retained, resulting in the deletion of 3 items. Thus, the final scale consisted of 20 items. To ensure the comprehensibility of the scale, the initial version was administered to 15 participants outside the main sample to confirm that the responses yielded valid measurements. Participants were allowed to express any difficulties they encountered while providing their responses.

Statistical Analysis

Exploratory factor analysis

Skewness and kurtosis indices were estimated for the scale items, with skewness values ranging from 0.42 to 1.2 and kurtosis values ranging from 0.02 to 3.6. Therefore, the skewness and kurtosis values did not exceed 3.0 or 7.0, respectively, so normality was achieved (Kline, 2011). Following this, an EFA was conducted using SPSS. Twenty questions related to anxiety about using AI in academic research were factors analyzed using principal component analysis with Promax (oblique) rotation. The KMO was 0.90, and Bartlett's test was significant ($p < 0.01$), indicating that the set of variables is suitable for factor analysis. The analysis yielded four factors, explaining a total of 66.35% of the entire dataset.

Factor 1 was labelled concern about the accuracy of AI tools. It comprised four items reported on a 5-point Likert scale that explained 39.85% of the variance with factors loading from 0.44 to 0.92. Factor 2 was labelled fear of committing plagiarism. It comprised four items reported on a 5-point Likert scale that explained 12.21% of the variance with factors loading from 0.36 to 0.88. Factor 3 labelled 'lack of institutional guidelines on the use of artificial intelligence tools in scientific research,' comprised four items reported on a 5-point Likert scale, explaining 8.72% of the variance with factor loadings ranging from 0.40 to 0.90. Factor 4 was labelled 'Fear of losing research skills due to frequent use of AI tools' and comprised 4 items reported on a 5-point Likert scale that explained 5.54% of the variance with factor loading from 0.56 to 0.96.

The four factors concern accuracy, fear of plagiarism, lack of institutional guidelines, and fear of losing research skills collectively explain a substantial portion of the variance (66.35%) and exhibit acceptable loadings and normality indices. These findings determine the scale and its potential as a valuable tool for investigating researchers' apprehensions regarding AI integration in scholarly work, as shown in **Figure 2**.

Table 1 shows the EFA results.

Table 1. The EFA results

Items	Component				Communality
	Factor 1	Factor 2	Factor 3	Factor 4	
1. I am concerned about the accuracy of the results generated by AI tools in the research.				.684	0.59
2. I find it difficult to interpret the results generated by AI tools in the research.				.977	0.72
3. The results obtained from AI tools may not align with the standards of scientific research.				.589	0.65
4. I feel uneasy using AI tools because I am unsure how to assess their accuracy.				.565	0.69
5. Using AI tools might lead to plagiarism in the research.		.790			0.66
6. I feel anxious when using plagiarism detection tools with content generated by AI.		.824			0.67
7. I fear that AI tools might create content that violates academic integrity and research ethics.		.889			0.73
8. I am afraid that AI tools might unintentionally produce work that is not original.		.812			0.68
9. I am concerned about the impact of AI on the future of academic research.	.440	.369			0.52
10. There is no clear guidance from universities on how to use AI tools in scientific research.			.906		0.70
11. I worry about the lack of standardized policies from publishers regarding the Use of AI in academic writing.			.742		0.65
12. I feel concerned about using AI tools due to the absence of a clear framework for their application in academic research.			.642		0.67
13. I feel concerned about using AI tools due to the absence of a clear framework for their application in academic research.			.405		0.39
14. There is a lack of official guidelines regarding the use of AI tools in scientific research.			.788		0.60
15. Reliance on AI tools will weaken traditional research skills.	.756				0.58
16. I fear that using AI tools will reduce the ability to develop research skills through practice.	.801				0.71
17. The reliance on AI tools will render researchers less capable of critical thinking.	.915				0.79
18. I am concerned that AI tools might hinder my growth as an independent researcher.	.896				0.75
19. I fear that researchers will lose essential research skills due to increased reliance on AI tools.	.879				0.78
20. The use of AI tools in scientific research may reduce the demand for researchers.	.812				0.65
Eigenvalue	7.97	2.44	1.74	1.11	
Percentage of the total variance	39.85	12.21	8.72	5.54	
Total variance	66.35				

Notes: Extraction method: Principal component analysis; Rotation method: Promax with Kaiser normalization.

Confirmatory factor analysis

CFA was performed to rigorously assess the construct validity of the newly developed scale, building upon the four factors identified through the EFA. These four latent constructs capture distinct dimensions of anxiety concerning the use of AI tools in academic research. In conducting the CFA, each item was treated as ordinal and weighed at least squares estimation with a mean- and variance-adjusted Chi-square (WLSMV) was employed (Lei & Shiverdecker, 2020). A polychoric covariance matrix with probit factor loadings was utilized to account for the ordinal nature of the responses (Chubb et al., 2021).

The overall model fit proved to be satisfactory. Specifically, the WLSMV χ^2 statistic was 2.621 (34, N = 219, $p < .001$), while the comparative fit index (CFI) and Tucker-Lewis's index (TLI) were both 0.96, surpassing the more stringent threshold of 0.95 recommended by Hu and Bentler (1999). Additionally, the root mean square error of approximation (RMSEA) was 0.08 (90% confidence interval [CI]: 0.08–0.11), which meets the more relaxed cutoff of 0.10 (Kline, 2011), indicating marginal fit. The weighted root mean square residual was 1.074, which aligns with guidelines suggesting that values around 1.00 are acceptable (DiStefano et al., 2018).

Table 2. Reliability using SPSS

Factor	Coefficient omega	Coefficient alpha
Factor 1	0.922	0.918
Factor 2	0.859	0.857
Factor 3	0.804	0.802
Factor 4	0.789	0.798
Total	0.947	0.909

Table 3. Path coefficients

Factors	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1				
Factor 2	0.572			
Factor 3	0.111	0.440		
Factor 4	0.060	0.354	0.510	

Collectively, these fit indices reinforce the validity of the four-factor model initially derived from the EFA. Crucially, no post-hoc modifications were necessary, indicating that the specified model aligns well with the observed data. The standardized factor loadings ranged from 0.56 to 0.93, comfortably meeting the recommended range of 0.50–0.95 (Brown, 2015). Standardized covariance estimates revealed correlations among the latent factors, ranging from 0.49 to 0.79 ($p < .001$), indicating moderate to strong interrelationships without undermining the distinctiveness of each factor.

Regarding error variances, standardized values ranged from 0.16 to 0.68, indicating the proportion of variance not accounted for by the latent factors. While most residuals were low, one item showed a relatively higher error variance of 0.68, suggesting a need for a more careful interpretation of that particular indicator. Nevertheless, these results, as a whole, offer robust evidence supporting the appropriateness of the four-factor solution and highlight the model's capacity to accurately capture the multifaceted anxiety researchers experience when integrating AI tools into their academic work.

Table 2 shows the reliability of using SPSS.

FINDINGS USING PLS-SEM

All tables describe the results and their positive impact on the proposed model. Once the alpha Cronbach value is calculated, which is only accepted if it is greater than 0.7, CR also checks if it is greater than 0.7 to be accepted. The AVE value must be greater than or equal to 0.5 to be accepted (Dahri et al., 2023; Tawafak et al., 2019).

The measurement model for the AIAS was assessed using multiple reliability and validity criteria. Cronbach's alpha output results for the four constructs ranged from 0.818 to 0.929, exceeding the recommended threshold of 0.70 (Nunnally, 1978), indicating strong internal consistency. Composite reliability (CR) also confirmed reliability, with all constructs scoring above 0.79, further supporting the consistency of the scale items (Hair et al., 2019). Convergent validity was identified by average variance extracted (AVE) values ranging from 0.580 to 0.741, all above the acceptable cutoff of 0.50 (Fornell & Larcker, 1981), confirming that the items adequately represent their underlying constructs.

Discriminant validity was confirmed through multiple criteria. The Fornell-Larcker criterion revealed that the AVE for each construct was greater than its correlations with other constructs, indicating distinctiveness among the factors. Additionally, the heterotrait-monotrait ratio (HTMT) values were below the conservative threshold of 0.85, providing further evidence of discriminant validity. Discriminant validity was evaluated using the Fornell-Larcker criterion and the HTMT. The square root of AVE for each construct was greater than its correlations with other constructs, satisfying the Fornell-Larcker criterion. Moreover, HTMT values were all below 0.85, further confirming that each construct is empirically distinct.

The path coefficients (**Table 3**) indicate significant positive relationships among constructs. For example, the path from F1 to F2 has a standardized coefficient of 0.572, indicating a moderate positive effect, whereby increases in F1 are associated with increases in F2. Similarly, F2 has a positive influence on F3 ($\beta = 0.440$), and F4 affects F3 ($\beta = 0.510$), indicating interconnected dynamics among the anxiety dimensions.

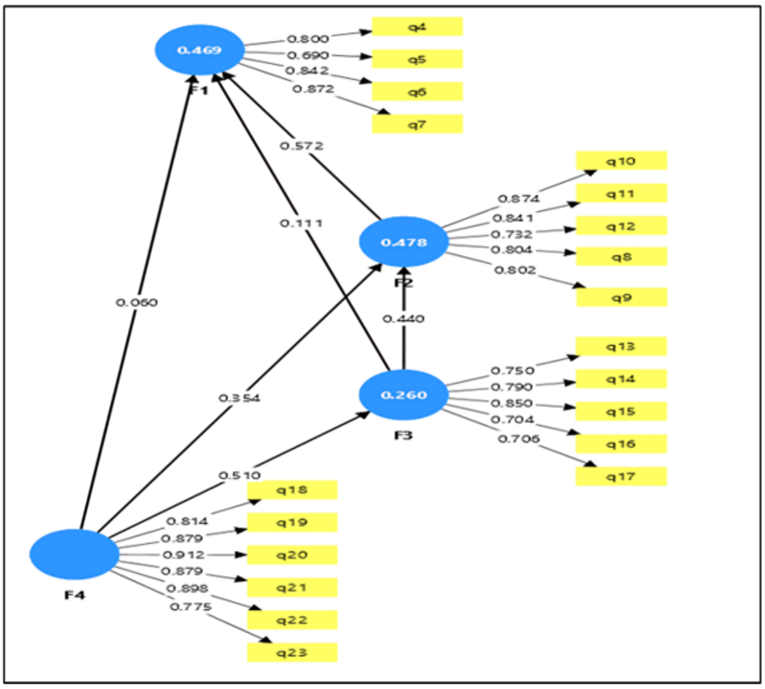

Figure 3. Model results (Source: Authors)

The CR estimates for the four measured constructs, feelings of acceptance, role clarity, task mastery, and one additional factor, were 0.922, 0.859, 0.804, and 0.789, respectively. Each of these values exceeded the widely accepted threshold of 0.70 (Hair et al., 2019; Nunnally, 1978), thereby indicating robust internal consistency for all four constructs. High CR estimates suggest that the individual items within each factor measure the underlying construct consistently and with minimal measurement error (Fornell & Larcker, 1981; Mohammadkarimi, 2023).

Overall, the four-factor measurement model demonstrated marginal fit to the data, as indicated by the relevant fit indices (e.g., CFI, TLI, and RMSEA). Nevertheless, the acceptable CR estimates, in conjunction with this marginal fit, collectively provide support for the reliability and validity of the constructions under investigation. **Figure 3** presents the path diagram for the four-factor model of AI anxiety in writing academic research scales (Ullah et al., 2020).

To further assess the validity of the AIAS, a cross-loading analysis was conducted (**Table 4**). Cross-loadings compare each indicator's loading on its assigned construct against its loadings on other constructs. For valid constructs, each item should load highest on its intended factor compared to other factors. In this study, all items demonstrated more substantial loadings on their respective constructs than on any other factor, supporting convergent validity and confirming that each item uniquely represents its intended dimension.

Table 5 shows the validity of the discriminant. Evaluating discriminant validity ensures that a construct is truly distinct from other constructs in the model.

Fornell-Larcker criterion: This strategy compares the square root of the AVE for each build with the relationships between that develop and others that have developed. Discriminant validity is set up in case the square root of the AVE of each expansion is more prominent than the relationships with other developments.

Reliability could be a prerequisite for validity: An instrument must be dependable (reliable) to be substantial (exact). In any case, a dependable instrument is not fundamentally substantial, as shown in **Table 5**. For the occasion, a scale that reliably mismeasures weight is solid but not substantial. Reliability and validity are principal concepts in investigating and estimating hypotheses, fundamental for ensuring that robust estimates deliver accurate and consistent results. Reliability refers to the consistency or hardness of an estimation instrument. A solid instrument yields the same results under reliable conditions. Measures the consistency of results that come about overtime in a test.

Table 4. Outer loadings

	Factor 1	Factor 2	Factor 3	Factor 4
q4	0.800			
q5	0.690			
q6	0.842			
q7	0.872			
q8		0.804		
q9		0.802		
q10		0.874		
q11		0.841		
q12		0.732		
q13			0.750	
q14			0.790	
q15			0.850	
q16			0.704	
q17			0.706	
q18				0.814
q19				0.879
q20				0.912
q21				0.879
q22				0.898
q23				0.775

Table 5. Construct reliability and validity

	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE	R^2	Key paths (β)
Factor 1 (accuracy)	0.818	0.852	0.879	0.646	0.469	F1 → F2: 0.572
Factor 2 (plagiarism)	0.870	0.873	0.906	0.660	0.478	F2 → F3: 0.440
Factor 3 (guidelines)	0.821	0.841	0.873	0.580	0.260	F4 → F3: 0.510
Factor 4 (skills loss)	0.929	0.934	0.945	0.741	-	

Table 6. HTMT–matrix

Factors	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1				
Factor 2	0.773			
Factor 3	0.556	0.713		
Factor 4	0.502	0.645	0.556	

The internal consistency of the AIAS constructs was assessed using Cronbach's alpha and CR. As shown in **Table 5**, Cronbach's alpha values ranged from 0.818 to 0.929, exceeding the commonly accepted threshold of 0.70 (Nunnally, 1978), indicating strong reliability. Correspondingly, CR values were robust across all constructs, ranging between 0.852 and 0.945, confirming consistent measurement across items within each factor (Hair et al., 2019). Convergent validity was supported by AVE values from 0.580 to 0.741, all above the 0.50 criterion (Fornell & Larcker, 1981), confirming that the scale items explain a substantial portion of the variance in their respective constructs.

Discriminant validity is evaluated by analyzing whether the pointer loads higher on its particular build than on other constructs. Check cross-loadings: Guarantee that each pointer loads more emphatically on its related build than on any other development. HTMT: The HTMT could be a more rigid basis that equates the proportion of between-trait relationships to the within-trait relationships. Values underneath 0.90 (or 0.85 for stricter criteria) demonstrate discriminant validity.

In addition to cross-loadings, the study evaluated discriminant validity through the HTMT and the Fornell-Larcker criterion. The HTMT matrix (**Table 6**) showed values below 0.85, indicating that the constructions are distinct and do not overly correlate with one another, which reduces the risk of multicollinearity. Similarly, the Fornell-Larcker criterion (**Table 7**) confirmed that the AVE for each construct exceeded the correlations between constructs, providing further evidence of discriminant validity.

Table 8 shows that the R-squared (R^2) results show high tolerance for some factors but low tolerance for others. R^2 is a statistical measure that characterizes the proportion of variance in a dependent variable explained by one or more independent variables in a regression model (Jang & Byon, 2020; Tawafak et al.,

Table 7. Fornell-Larcker criterion

Factors	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	0.804			
Factor 2	0.676	0.812		
Factor 3	0.497	0.621	0.762	
Factor 4	0.448	0.579	0.510	0.861

Table 8. R^2

Factor	R^2	R^2 adjusted
Factor 1	0.469	0.461
Factor 2	0.478	0.473
Factor 3	0.260	0.257

Table 9. (A) Collinearity statistics (VIF), (B) Inner model, & (C) Model fit

(A) Outer model		(B) Inner model		(C) Model fit		
	VIF		VIF		Saturated model	Estimated model
q10	2.726	F2 → F1	1.916	SRMR	0.076	0.076
q11	2.195	F3 → F1	1.723	d_ULS	1.200	1.200
q12	1.656	F3 → F2	1.352	d_G	0.400	0.400
q13	1.837	F4 → F1	1.592	Chi-square	499.286	499.286
q14	1.873	F4 → F2	1.352	NFI	0.827	0.827
q15	2.018	F4 → F3	1.000			
q16	1.427					
q17	1.639					
q18	2.362					
q19	3.277					
q20	4.488					
q21	3.542					
q22	3.617					
q23	2.019					
q4	1.760					
q5	1.517					
q6	1.949					
q7	2.066					
q8	1.903					
q9	2.025					

2020). In other words, it tells us how well independent variables explain the variability of the dependent variable. $R^2 = 0$: The free factors do not clarify any of the changeability of the subordinate variable. $R^2 = 1$: The autonomous factors clarify all the inconstancy of the subordinate variable. $< R^2 < 1$: Indicates the extent of the fluctuation within the subordinate variable that's predictable from the free factors. For this case, an R^2 of 0.70 implies that the autonomous factors explain 70% of the change within the subordinate variable.

R^2 values (**Table 8**) ranged from 0.260 to 0.478, indicating that the independent constructs explain between 26% and 48% of the variance in the dependent variables, which is acceptable in social science research contexts. Variance inflation factor (VIF) statistics were examined to identify potential issues of multicollinearity among the indicators and latent variables. VIF values ranged from 1.427 to 4.488, all of which were below the critical value of 5, suggesting no serious collinearity problems that could bias the results (**Table 9**). Multicollinearity was assessed using the VIF, with all values below 5 demonstrating no critical issues of collinearity among indicators and constructs (**Table 9**). Model fit indices demonstrated an overall acceptable fit for the measurement model (**Table 9**). The standardized root mean square residual was 0.076, which is below the recommended threshold of 0.08, indicating a good fit between the model and the observed data (Hu & Bentler, 1999). The normed fit index of 0.827 further supports model adequacy. Chi-square and related indices were reported for completeness but should be interpreted cautiously, given their sensitivity to sample size.

Standard deviation (SD) could be a degree of the sum of variety or scattering in a set of values. In bootstrapping, the SD of the bootstrapped path coefficients provides an assessment of the standard error of the path coefficient (Habes et al., 2023; Hamari et al., 2014). **Table 10** shows MV descriptive.

Table 10. MV descriptive

	Mean	Observed minimum	Observed maximum	SD	Excess kurtosis	Skewness
q10	3.986	1.000	5.000	1.036	0.102	–0.916
q11	3.904	1.000	5.000	1.045	–0.347	–0.726
q12	3.721	1.000	5.000	1.159	–0.860	–0.486
q13	4.242	1.000	5.000	0.855	0.764	–1.061
q14	4.027	1.000	5.000	0.854	0.782	–0.849
q15	4.037	1.000	5.000	0.885	0.785	–0.946
q16	3.895	1.000	5.000	1.061	–0.471	–0.689
q17	4.242	2.000	5.000	0.765	0.527	–0.874
q18	3.849	1.000	5.000	1.115	–0.495	–0.655
q19	3.767	1.000	5.000	1.117	–0.694	–0.559
q20	3.703	1.000	5.000	1.162	–0.801	–0.510
q21	3.539	1.000	5.000	1.213	–1.178	–0.261
q22	3.740	1.000	5.000	1.151	–0.465	–0.689
q23	3.516	1.000	5.000	1.298	–1.113	–0.383
q4	3.735	1.000	5.000	1.078	–0.364	–0.578
q5	3.283	1.000	5.000	1.008	–0.561	–0.080
q6	3.840	1.000	5.000	1.019	0.275	–0.874
q7	3.621	1.000	5.000	1.114	–0.658	–0.527
q8	3.982	1.000	5.000	1.051	–0.157	–0.866
q9	3.858	1.000	5.000	1.070	–0.540	–0.661

DISCUSSION

While the use of artificial tools in academic research holds substantial promise, it is vital for the scholarly community to adopt a reflective and proactive stance in mitigating any potential risks (Teng, 2023; Yusuf et al., 2024). Indeed, integrating cutting-edge technologies into the research process can foster innovation and expedite discovery by streamlining data collection, analysis, and dissemination (Clustering, 2019). At the same time, the ethical implications of employing these tools cannot be overlooked, particularly in maintaining the integrity and trustworthiness of academic endeavors. Scholars have repeatedly emphasized the importance of clear guidelines, rigorous oversight, and ongoing professional development aimed at equipping researchers with the technical and ethical competencies necessary to manage these emerging methodologies responsibly (Fornell & Larcker, 1981; Hair et al., 2019).

The statistical findings of this study reveal a significant correlation between F2 and F1 (plagiarism and accuracy) *and recommend* that their trust significantly influence unethical use of content in AI-generated outputs. This relationship highlights a form of technostress wherein the pressure to use AI tools effectively is compounded by anxiety over potential academic or professional misconduct. According to the cognitive appraisal theory, individuals evaluate AI tools not only based on their usefulness but also on the potential risks they pose to personal or institutional integrity. Therefore, interested educators must focus on enhancing transparency in AI outputs and embedding features that promote citation or accountability to reduce fear and increase trust.

The relatively lower AVE values in some constructs suggest that while the items used in measurement have acceptable reliability, they may not fully capture the conceptual richness or distinctiveness of the latent variables. It could indicate overlapping constructs or the need for further refinement of items. From a measurement theory perspective, this points to a potential threat to discriminant validity. Practically, it calls for caution in interpreting the constructs as fully independent without acknowledging conceptual overlap, for instance, between AI anxiety and technostress.

Similarly, lower R^2 values (e.g., below 0.5 for specific dependent constructs) indicate that, while the model provides the variance of the factors, a substantial part of the behavioral outcome may still be influenced by external factors not included in the model. It aligns with the TAM and UTAUT frameworks, which acknowledge that perceived ease of use and usefulness are not sole predictors; social influence, facilitating conditions, or individual innovativeness might also play a role. To elevate the discussion beyond description, we interpret these findings to suggest a growing cognitive burden among users–driven by conflicting feelings of opportunity (efficiency and creativity through AI) and threat (ethical, academic, or credibility risks). It supports the need for a more holistic approach in future models that blend technology appraisal, trust theory, and cognitive load to fully understand users' behavioral intentions in adopting AI technologies.

Moreover, the application of generative AI tools to produce or co-author academic manuscripts intensifies concerns surrounding algorithmic bias, transparency, and accountability (Jain & Jain, 2023; Perkins & Roe, 2024). Inconsistencies introduced by automated analyses, combined with the potential for AI-driven authorship disputes, may undermine the reliability of scholarship and reputable publication practices. As such, vigilance verifying the outcomes generated by AI mechanisms is warranted to ensure methodological rigor and to protect against misinterpretations of data (Hu & Bentler, 1999; Kline, 2011). Training researchers in both technical acumen and ethical discernment will therefore be essential in upholding academic standards and reassuring stakeholders of the validity and replicability of findings, even as new technologies continue to reshape the academic landscape (Brown, 2015; DiStefano et al., 2018). By striking a balance between capitalizing on the benefits afforded by AI tools and safeguarding the core tenets of scholarship, the research community can leverage technological advances to drive responsible innovation and sustained knowledge creation that continues to command trust and credibility.

The findings of this study offer timely and significant contributions to academic research, as well as institutional policy, concerning the integration of AI tools in scholarly environments. The validation of the AIAS fills a notable gap in the literature by providing a standardized, empirically supported measure to assess emotional and psychological responses to AI adoption in academic writing.

The four key dimensions identified–concerns about output accuracy, fear of plagiarism, lack of institutional guidance, and fear of losing research skills–underscore the multifaceted nature of anxiety experienced by academic professionals and students. These anxieties may impact individuals negatively, as well as systemic policies, such as insufficient training on AI ethics and usage. As such, the study's implications extend beyond the individual level and call for organizational and policy-level responses (Al-Obaydi et al., 2024).

The results of this study can inform university leadership, research ethics committees, and academic development centers (Jain & Jain, 2023). By understanding the psychological barriers researchers face when engaging with AI, institutions can design targeted training, support frameworks, and clear usage guidelines that handle these points. After this stage, this study will help encourage the use of AI tools in an ethical, confident, and effective manner without compromising academic integrity or the development of core research competencies (Al-Obaydi et al., 2025).

Moreover, the AIAS offers a makeup-acceptable model for future studies examining technological anxiety across various cultural, disciplinary, and educational contexts (Pikhart et al., 2024). It provides an opportunity for comparative research overseas, facilitating the development of common standards for the responsible use of AI. Importantly, this study suggests a scenario about how technological change is reshaping the identity of academic research. Ultimately, the broader implication of this study is to support a balanced, ethically grounded, and psychologically informed approach to digital transformation in higher education. By clarifying and addressing anxiety as a genuine barrier, this study promotes a more beneficial integration of AI in academic life.

CONCLUSION AND FUTURE RESEARCH

This study provides insight into how learners perceive and respond to the integration of AI in academic contexts, particularly regarding concerns such as plagiarism, trust, and ethical usage. By linking empirical findings with established theoretical frameworks such as technostress, cognitive appraisal, and the Technology Acceptance Model, our results offer more profound insight into the psychological and behavioral dimensions that shape AI adoption in education. The study reveals a pattern of cognitive tension: users are drawn to AI's efficiency and accuracy yet are also concerned about its misuse and associated ethical risks. These worries suggest that an active AI integration depends not only on improving technological functionality but also on building frameworks for ethical assurance, clear attribution, and support for user confidence.

This scale pinpoints four primary factors that contribute to this anxiety. First, concerns about the accuracy of AI tools are evident, encompassing worries about the reliability and interpretability of the results produced by AI. Researchers expressed concern about the accuracy of AI outputs and whether these outputs would align with the standards of scientific research. Second, the fear of committing plagiarism was identified, highlighting concerns that the use of AI tools could inadvertently lead to plagiarism or the creation of content that breaches academic integrity. Researchers showed anxiety about using plagiarism detection tools with AI-generated content.

The third factor is the lack of institutional guidelines, revealing apprehension due to the absence of clear guidance from universities and publishers on the appropriate use of AI in research. Researchers noted the lack of standardized policies and a clear framework for the application of AI (Iqbal Malik et al., 2021). The final factor identified is the fear of losing research skills, which includes worries that over-reliance on AI tools will diminish traditional research skills, critical thinking abilities, and the development of independent research capabilities. Researchers also expressed concerns that the increased reliance on AI could lead to a reduction in the demand for researchers.

The validity of the scale was established using both EFA and CFA. The EFA identified the four factors, collectively accounting for a substantial amount of the variance. The CFA confirmed the four-factor model, and fit indices indicated a good fit with the data. The standardized factor loadings were within the recommended ranges, demonstrating the model's robustness. A reliability analysis confirmed the scale's strong internal consistency.

The development of this scale is important because no standardized instrument previously measured the anxiety researchers experience when using AI in scientific writing. The scale can guide universities in designing training and support programs to promote the ethical and practical integration of AI. It can also contribute to the fields of educational technology and psychometrics by providing a tool to assess the emotional aspects of AI adoption. Ultimately, understanding researcher anxieties can help ensure that AI tools are used to enhance, rather than undermine, scholarly work.

While this study provides a validated tool for measuring AI-related anxiety in academic writing, some suggestions for future research remain helpful and powerful. First, include this study in diverse cultural and institutional contexts for testing and validating the results. Second, researchers with long-term work experience could examine how anxiety levels evolve as individuals gain more experience with AI tools over time or receive formal training (Al-Obaydi et al., 2025). Third, future studies could explore the relationship between AI anxiety and variables such as academic productivity, research quality, or ethical decision-making. Additionally, experimental designs could assess the impact of targeted interventions (e.g., workshops and policy changes) on reducing anxiety related to AI. Finally, expanding the scale to include other AI-related domains (e.g., teaching, peer review, data analysis) would provide a more comprehensive understanding of how AI affects academia holistically.

Building on the validated AIAS, this study provides a practical suggestion for academics and policymakers. Universities are encouraged to develop clear guidelines and ethical policies for the use of AI in research, along with comprehensive training programs to address common concerns, such as plagiarism and the loss of skills. Establishing support systems and open dialogues about AI integration can foster a positive research culture that strikes a balance between innovation and academic integrity.

Given that this study was conducted within a specific regional context (Taif University, Saudi Arabia), future research should investigate the applicability and relevance of the AIAS in diverse cultural and institutional environments. Cross-cultural validation studies are crucial for understanding how AI-related anxieties manifest globally and for adapting support mechanisms accordingly (Jang & Byon, 2020; Tawafak et al., 2020). Furthermore, this type of study could test how anxiety fluctuates over time in response to AI technologies. Extending the research method to encompass other roles and disciplines beyond faculty and graduate students would provide a more comprehensive picture of AI anxiety in higher education. Lastly, exploring the effectiveness of intervention programs designed to alleviate AI anxiety could further support the ethical and productive integration of AI tools in academia.

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Data availability: Data generated or analyzed during this study are available from the authors on request.

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