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Assessing Medical Students' Anxiety and Preparedness Regarding Artificial Intelligence

Henk van Dijk[1], Pieter de Vries[1], Jeroen Bakker[1]*

[1]Department of Medical Physics, Faculty of Medicine, University of Amsterdam, Amsterdam, Netherlands.

***E-mail** ✉ jeroen.bakker.lab@outlook.com

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ABSTRACT

This study investigates the levels of anxiety and preparedness for artificial intelligence (AI) among medical students and examines how these factors are related. Between April and June 2022, data were gathered from medical students via both in-person and online questionnaires. The instruments included a socio-demographic form, an AI anxiety scale, and a medical AI readiness scale. Data from 542 participants were analyzed using SPSS version 25, with reliability assessed through Cronbach's α. Structural equation modeling (SEM) was performed using AMOS 24, accompanied by a path diagram. Findings showed that students generally demonstrated moderate readiness for AI but experienced high anxiety, with a significant negative relationship between readiness and anxiety. These results highlight the importance of preparing medical students for AI applications and reducing associated anxieties, recommending the integration of AI into medical curricula and the creation of a standardized teaching framework.

Keywords: Readiness, Anxiety, Medical students, Artificial intelligence

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Introduction

Artificial Intelligence (AI) has emerged as one of the most prominent technological advancements in recent years. Its applications are expanding rapidly, increasingly influencing both everyday life and professional domains. Healthcare is a sector particularly affected by technological innovations, and interest in AI within this field has grown significantly in recent years [1, 2].

The origins of AI are often traced back to Aristotle, while the question "Can machines think?" posed by Alan Turing sparked extensive discussions in the field. The term "artificial intelligence" was first formally introduced by John McCarthy at a conference, who defined it as "the science and engineering of making intelligent machines, especially intelligent computer programs." AI began to be explored in healthcare-related studies in the 1970s [3]. Currently, AI is applied throughout the healthcare process, from diagnosis to treatment. Its applications span numerous areas, including respiratory and digestive diseases, cancer, cardiovascular conditions, ophthalmology, medical decision-making, imaging, electronic medical records, drug development, and more. AI technologies in healthcare aim to reduce unnecessary interventions, enable early disease detection, facilitate faster and more accurate analysis of medical images, and support physicians in making informed decisions for patient care [3–9]. In the future, AI is expected to positively impact many healthcare processes, and its adoption by healthcare professionals is anticipated to increase [1, 2, 8].

Although AI is unlikely to replace physicians or nurses, it is widely regarded as a reliable tool for clinical decision-making [6]. Medical students, as future healthcare providers, will inevitably encounter and use AI in their professional practice. Therefore, adapting to AI-related changes is essential [9]. Identifying potential challenges in AI applications is also crucial for ensuring their effective use [10]. Assessing medical students' readiness for

AI technologies and their levels of anxiety is important in this context. This study aims to evaluate the anxiety and preparedness of medical students regarding AI and to examine the relationship between these factors.

Materials and Methods

This study was designed as a relational screening model, targeting medical students in Türkiye. Data collection was conducted both in person and online via Google Forms between April and June 2022. Students were recruited by sharing the survey link through social media groups administered by student representatives. To ensure data integrity, each participant could submit the survey only once, with responses monitored using IP addresses and cookies.

Socio-demographic Information Form: Developed by the researchers, this form collected data on participants' gender, family structure, income level, parental education, frequency of computer use, and prior knowledge of AI.

Artificial Intelligence Anxiety Scale: Originally developed by Wang and validated for Turkish populations by Terzi, this 21-item, 7-point Likert scale measures AI-related anxiety across four dimensions: learning anxiety, job displacement concerns, sociotechnical unfamiliarity, and AI configuration apprehension. Scores range from 21 to 147, with higher scores indicating greater anxiety [11].

Medical Artificial Intelligence Readiness Scale: Created by Karaca *et al*., this 22-item, 5-point Likert scale assesses medical students' readiness for AI. It consists of five sub-dimensions: cognitive, skill, anticipation, ethical, and overall medical AI readiness, with higher scores reflecting greater preparedness [1].

Sample Size: Determined via power analysis using G*Power 3.1, the minimum sample size required was 476 participants, assuming an effect size of 0.15, a margin of error of 0.05, and a confidence level of 95%, ensuring representativeness of the population at 95% [12]. According to Cohen (1988), power values between 0.90 and 0.99 are recommended for sufficient sample sizes [13].

Ethical considerations

The study received approval from the Non-Interventional Ethics Committee of Malatya Turgut Özal University (Approval No: 2022/34). Permissions were obtained from the owners of the scales used, and all participants provided informed consent. Students were briefed on the purpose of the research, with assurances that their responses would be used solely for the study's objectives.

Research limitations

The study was limited by the online data collection method and the inability to reach all medical students.

Statistical analysis

Collected data were analyzed using SPSS version 25. Reliability was assessed with Cronbach's α. Structural equation modeling (SEM) was performed using AMOS 24, and a path diagram was created to visualize relationships. To control for multivariate normality, 26 of 568 questionnaires were excluded based on Mahalanobis Distance [14]. The skewness value for multivariate normality was 6.558, below the threshold of 8, confirming normal distribution [15].

Unlike classical regression, SEM allows simultaneous testing of multiple relationships and the examination of interactions between observed and latent variables. It incorporates measurement errors and their covariances into the model, enabling analysis of both direct and indirect relationships and providing a graphical representation for researchers [16, 17].

Results and Discussion

A total of 542 students participated, of whom 63.7% (n = 345) were female and 36.3% (n = 197) were male, with a mean age of 20.62 ± 2.04 years. Distribution by academic year was as follows: 46.1% first-year, 13.3% second-year, 17% third-year, 11.4% fourth-year, 3.7% fifth-year, and 8.5% sixth-year students. Most participants (90.8%) reported a nuclear family structure, and 86.3% indicated a moderate family income. Regarding parental education, 36.2% of mothers were secondary school graduates, while 43.4% of fathers held a bachelor's degree. Computer knowledge was reported as average by 68.8% of students, with 53.7% using computers infrequently. Although

97.8% had previously heard of artificial intelligence, only 9.4% considered their AI knowledge to be sufficient **(Table 1).**

Table 1. Demographic Characteristics of Participants

Variable	Category	Frequency (n)	Percentage (%)
Gender	Female	345	63.7
	Male	197	36.3
Family Type	Nuclear	492	90.8
	Extended	38	7.0
	Separated	12	2.2
Income Level	Low	34	6.3
	Middle	468	86.3
	High	40	7.4
Mother's Education	Illiterate	35	6.5
	Primary	148	27.3
	Secondary	196	36.2
	Bachelor's	144	26.6
	Master's	19	3.5
Father's Education	Primary	84	15.5
	Secondary	159	29.3
	Bachelor's	235	43.4
	Master's	64	11.8
Computer Knowledge	Low	53	9.8
	Moderate	373	68.8
	High	116	21.4
Prior Exposure to AI	Yes	530	97.8
	No	12	2.2
AI Knowledge Level	Insufficient	240	44.3
	Partially Sufficient	251	46.3
	Sufficient	51	9.4
Computer Usage Frequency	Never	11	2.0
	Rarely	291	53.7
	Frequently	240	44.3
Class Year	1	250	46.1
	2	72	13.3
	3	92	17.0
	4	62	11.4
	5	20	3.7
	6	46	8.5
Total	—	542	100
Age (years)	Mean ± SD	20.62 ± 2.04	Range: 18–28

The mean score for artificial intelligence readiness among the participating students was 61 ± 15.58, while the average AI anxiety score was 74.55 ± 26.03. The mean values for the sub-dimensions of each scale are summarized in **Table 2**. Cronbach's α coefficients exceeding 0.90 indicate a high level of reliability for the scales [18].

Table 2. Descriptive statistics of scale scores.

Scale Scores	Mean ± sd	(Min - Max)	Cronbach alfa
Cognitive	18.56 ± 5.31	8–33	0.933
Skill	23.8 ± 7.67	8–38	
Anticipation	8,58 ± 2,94	3–15	
Ethic	10,05 ± 2.9	3–15	
Artificial Intelligence Readiness	61 ± 15.58	22–96	
Learning	21.27 ± 9.42	8–54	0.943

Job Change	24.72 ± 11.05	6–42
Sociotechnical Blindness	17,82 ± 6.71	4–28
AI Configuration	10.75 ± 5.89	3–21
AI Anxiety	74.55 ± 26.03	21–145

sd; standard deviation.

Modeling the relationship between scales using SEM

Structural equation modeling (SEM) was employed to explore how medical students' readiness for artificial intelligence relates to their AI-related anxiety. A path diagram was constructed for this purpose, treating "Medical Artificial Intelligence Readiness" as the predictor variable and "Artificial Intelligence Anxiety" as the outcome variable. The resulting diagram is shown in **Figure 1.**

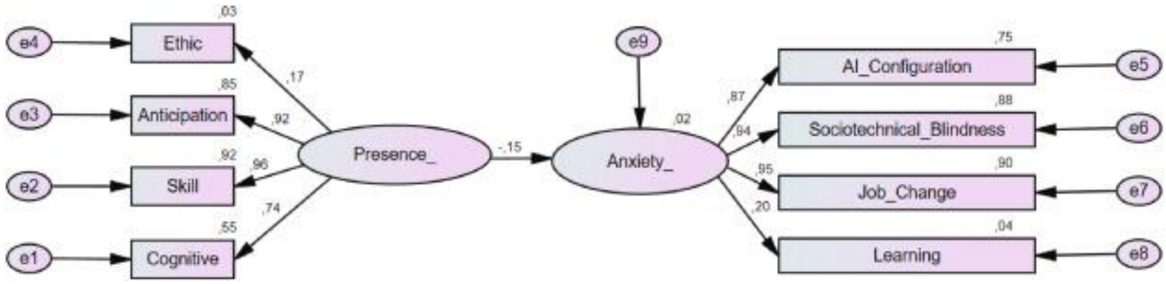

Figure 1. SEM Diagram Depicting the Link between "Medical AI Readiness" and "Artificial Intelligence Anxiety" Scales

To interpret the connections between the two scales, the significance of the regression coefficients along each path was evaluated. **Table 3** summarizes the regression coefficients and their corresponding significance values within the model.

Table 3. Regression coefficients and significance values obtained by SEM.

Independent Variables	Dependent Variables	β_1	β_2	p
Presence	**Anxiety**	−0.146	−0.189	0.001*
Cognitive	**Presence**	0.743	1	0.001*
Skill		0.961	1.868	0.001*
Anticipation		0.92	0.685	0.001*
Ethic		0.167	0.123	0.001*
AI_Configuration	**Anxiety**	0.868	1	0.001*
Sociotechnical_Blindness		0.939	1.232	0.001*
Job_Change		0.95	2.053	0.001*
Learning		0.198	0.365	0.001*

β1: Standardized regression coefficients; β2: unstandardized regression coefficients; *$p < 0.05$ indicates the significance of the regression coefficients based on the t-test.

The model's fit indices were $\chi^2 = 118.252$, df = 19, $\chi^2/df = 6.224$, CFI = 0.966, GFI = 0.949, NFI = 0.959, IFI = 0.966, and RMSEA = 0.098 **(Table 3)**. As the initial goodness-of-fit values were acceptable, adjustments were made using modification indices. Specifically, error covariances were added between residual terms e1 and e4, resulting in the updated path diagram shown in **Figure 2**. The regression coefficients and their significance levels for the revised model are presented in **Table 4.**

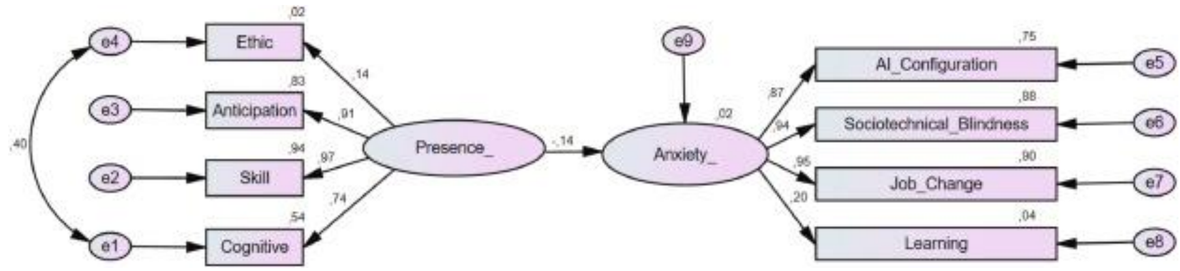

Figure 2. Modified SEM Model Illustrating the Relationship between "Medical AI Readiness" and "Artificial Intelligence Anxiety" Scales

Table 4. Regression coefficients and significance values obtained with modified SEM.

Independent Variables	Dependent Variables	β1	β2	p	R²
Presence	**Anxiety**	−0.141	−0.184	0.002*	0,020
Cognitive	**Presence**	0.737	1	0.001*	
Skill		0.97	1.9	0.001*	
Anticipation		0.912	0.685	0.001*	
Ethic		0.14	0.104	0.001*	
AI Configuration	**Anxiety**	0.868	1	0.001*	
Sociotechnical Blindness		0.939	1.232	0.001*	
Job Exchange		0.95	2.053	0.001*	
Learning		0.198	0.365	0.001*	

β1: Standardized regression coefficients; β2: unstandardized regression coefficients; *p < 0.05 indicates significance based on the t-test; R^2: coefficient of determination.

The "Medical Artificial Intelligence Readiness" score accounts for 2% of the variance in the "Artificial Intelligence Anxiety" score ($R^2 = 0.020$). A significant negative relationship was observed between the two scales, indicating that higher readiness is associated with lower anxiety. Specifically, a one-point increase in the Medical AI Readiness score corresponds to a 0.184-point decrease in the AI Anxiety score ($\beta2 = -0.184$; $p = 0.002 < 0.05$). The model's fit indices are detailed in **Table 5.**

Table 5. SEM Goodness-of-Fit Index Values

Fit Index	Initial Model	Modified Model	Acceptable Fit	Ideal Fit
CMIN	118.252	30.091	Lower values indicate better fit	—
χ²/df	6.224[a]	1.672	3–5	≤3
IFI	0.966	0.996	0.90–0.95	≥0.95
NFI	0.959	0.990	0.90–0.95	≥0.95
CFI	0.966	0.996	0.90–0.95	≥0.95
GFI	0.949	0.986	0.90–0.95	≥0.95
RMSEA	0.098[a]	0.035	0.05–0.08	≤0.05

In the modified model, the fit indices were calculated as $\chi^2 = 30.091$, df = 18, and $\chi^2/df = 1.672$. The substantial decrease in χ^2 and a χ^2/df ratio below 3 indicate an excellent model fit. The RMSEA value of 0.035, which assesses sample adequacy, further confirms that the sample size is highly suitable for the model. Other fit indices were also very strong, with GFI = 0.986, CFI = 0.996, IFI = 0.996, and NFI = 0.990, indicating a very good correspondence between the model and the data for the "Artificial Intelligence Anxiety" and "Medical Artificial Intelligence Readiness" scales [19].

[a]Values in the initial model were insufficient for an acceptable fit. χ^2: Chi-Square Goodness of Fit; NFI: Normed Fit Index; IFI: Incremental Fit Index; CFI: Comparative Fit Index; RMSEA: Root Mean Square Error of Approximation; GFI: Goodness of Fit Index.

This study aimed to assess medical students' knowledge and readiness regarding artificial intelligence. The path analysis revealed a weak negative relationship between "Artificial Intelligence Anxiety" and "Medical Artificial Intelligence Readiness," which was supported by the model's goodness-of-fit indices. Multiple fit indices—

including χ^2/df, RMSEA, GFI, CFI, IFI, and NFI—were evaluated to determine the adequacy of the SEM model, as assessing several indices together provides a more accurate evaluation of model fit [20, 21].

Previous research indicates that multivariate analysis methods are underutilized due to difficulties in application and interpretation, with univariate approaches often preferred [22]. The American Academy of Health's Task Force on Postdoctoral Studies emphasized that quality research should present relationships between variables using multivariate analyses rather than single-variable methods [23].

In our study, multivariate analysis showed that students' anxiety toward AI was at a moderate level. Similarly, Filiz *et al*. reported moderate concern among health professionals regarding AI in healthcare [24], and *Başer et al*. found a moderate anxiety score among family physicians [25]. Other studies indicated that physicians generally experience less AI-related anxiety than other healthcare workers, likely due to greater familiarity with AI applications; AI users also show lower anxiety than non-users [24, 26, 27].

The moderate anxiety observed among students in this study may be attributed to limited knowledge and lack of hands-on experience with AI technologies. Although most students (97.8%) had heard of AI, only a small fraction (9.4%) reported having sufficient understanding. Supporting this, Santos *et al*. found that while 263 students were aware of discussions about AI in radiology, 68% were unfamiliar with the relevant technologies [28]. Civaner *et al.* reported that only 6% of students felt competent to explain AI features and risks to patients [29], and Grunhut *et al*. similarly highlighted the alarmingly low level of AI knowledge among medical students [30]. In Pakistan, Zabor *et al*. observed that although most students were positive about AI applications in medicine and interested in using them, they lacked adequate knowledge to do so effectively [31].

Research indicates that insufficient knowledge about artificial intelligence is not limited to students but also extends to active healthcare professionals. For example, studies involving radiologists and radiographers have shown a notable lack of understanding of AI [32], and research on AI applications in breast disease management revealed that most participating physicians possessed inadequate knowledge in this area [33].

Increasing knowledge, awareness, and preparedness is considered the most effective approach to reducing anxiety. In our study, students demonstrated limited knowledge of AI and only moderate readiness. Previous research suggests that individuals lacking AI knowledge tend to experience higher levels of fear and anxiety [24–26]. Öcal *et al*. reported that although 93.6% of students (n = 383) had heard of AI, 59.4% (n = 243) expressed disinterest in the subject [34]. Furthermore, a significant proportion of students who were hesitant to use AI in healthcare cited fear as a primary reason [34]. These findings underscore the necessity of enhancing students' knowledge and readiness, as our feed analysis also indicates that improved AI understanding reduces anxiety levels.

Our study highlights the importance of preparing medical students for the growing presence of AI in healthcare. As noted by Sapci and Sapci in their systematic review, integrating AI education into medical and health informatics curricula is an essential future requirement [35]. Supporting this, Bisdalari *et al*. found that 85.6% of students anticipated AI being part of their medical education, and 99% expressed willingness to incorporate AI into their future practice [36]. In a national study, 85% of medical students indicated their intention to utilize AI applications professionally [34]. Additionally, studies with nurses have shown that targeted AI training sessions significantly reduced anxiety levels [37], and Ramazan and Ahmed (2015) similarly reported that education helps alleviate anxiety [38].

Conclusion

Our findings suggest that as AI becomes increasingly integrated into medical practice, reducing anxiety among medical students through enhanced readiness is crucial. It is recommended that AI be incorporated into medical curricula, and that research be conducted to establish a competency framework to guide the development of standardized undergraduate AI education. Moreover, students should be educated on the use, development, and benefits of AI, with experts providing guidance to healthcare professionals to address concerns and reduce confusion. Larger-scale studies using more extensive samples and assessment tools are needed to validate these findings and provide a reference for future research.

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