DOI: 10.4274/anatoljmed.2025.08370
Anatol J Gen Med Res

CLINICAL RESEARCH / KLİNİK ARAŞTIRMA

ANATOLIAN JOURNAL of GENERAL MEDICAL RESEARCH

The Association Between Family Physicians' Artificial Intelligence Anxiety Levels and Medical Artificial Intelligence Readiness

Aile Hekimlerinin Yapay Zeka Kaygı Düzeyinin Tıbbi Yapay Zeka Hazırbulunuşluk ile İlişkisi

Nazmiye Kaçmaz Ersü[1], Abdurrahman Ersü[1], Yeliz Mercan[2]

[1]Aydın Efeler Family Health Center No. 5, Aydın, Türkiye
[2]Kırklareli University Faculty of Health Sciences, Department of Health Management, Kırklareli, Türkiye

Cite as: Kaçmaz Ersü N, Ersü A, Mercan Y. The association between family physicians' artificial intelligence anxiety levels and medical artificial intelligence readiness. Anatol J Gen Med Res. [Epub Ahead of Print]

Abstract

Objective: This study aimed to investigate the association between family physicians' artificial intelligence (AI) anxiety levels and their readiness for medical AI.

Methods: This descriptive and cross-sectional study included 199 family physicians working in primary healthcare. The AI anxiety scale (AIAS) and medical AI readiness scale were used as data collection tools.

Results: Significant gender differences were observed in AI anxiety levels. Female physicians demonstrated significantly higher AI anxiety scores compared to male physicians across all dimensions of the AIAS ($p<0.001$ for the total score, $p<0.001$ for learning, $p=0.001$ for job replacement, $p=0.024$ for socio-technical blindness, and $p=0.004$ for AI configuration). Physicians with an educational background in information and communication technology (ICT) showed significantly lower AI anxiety levels (57.84±27.11 vs. 74.17±28.20, $p=0.007$) and higher medical AI readiness scores (76.04±18.19 vs. 64.50±16.27, $p=0.001$) compared to those without such background. Similarly, physicians with higher interest levels in ICT and AI demonstrated progressively lower anxiety levels and higher readiness scores ($p<0.05$ for all comparisons).

Conclusion: Family physicians with lower learning and AI configuration anxiety showed greater readiness for medical AI. Female physicians experienced higher anxiety levels across all areas, while those with technology backgrounds were more prepared for AI integration. These findings suggest that targeted education programs and gender-sensitive training approaches are essential for successful AI adoption in primary care.

Keywords: Artificial intelligence anxiety, medical artificial intelligence readiness, family physician

Address for Correspondence/Yazışma Adresi: Nazmiye Kaçmaz Ersü, MD, Aydın Efeler Family Health Center No. 5, Aydın, Türkiye
E-mail: nazmiye_kacmaz@hotmail.com
ORCID ID: orcid.org/0000-0002-3319-2884

Received/Geliş tarihi: 29.04.2025
Accepted/Kabul tarihi: 06.08.2025
Epub: 18.09.2025

Öz

Amaç: Bu çalışmada aile hekimlerinin yapay zeka (YZ) kaygı düzeyleri ile tıbbi YZ'ye hazırbulunuşluk düzeyleri arasındaki ilişkinin araştırılması amaçlanmıştır.

Yöntem: Tanımlayıcı ve kesitsel tipteki bu çalışmaya birinci basamak sağlık hizmetlerinde çalışan 199 aile hekimi dahil edildi. Veri toplama aracı olarak YZ kaygı ölçeği (YZKÖ) ve tıbbi YZ hazırbulunuşluk ölçeği kullanılmıştır.

Bulgular: YZ kaygı düzeylerinde anlamlı cinsiyet farklılıkları gözlenmiştir. Kadın hekimler, YZKÖ'nün tüm boyutlarında erkek hekimlere kıyasla anlamlı derecede yüksek YZ kaygı puanları göstermiştir (toplam puan için p<0,001, öğrenme için p<0,001, iş yerini alma için p=0,001, sosyo-teknik körlük için p=0,024 ve YZ yapılandırması için p=0,004). Bilgi ve iletişim teknolojileri (BİT) alanında eğitim geçmişi olan hekimler, böyle bir geçmişi olmayanlara kıyasla anlamlı derecede düşük YZ kaygı düzeyleri (57,84±27,11'e karşı 74,17±28,20, p=0,007) ve daha yüksek tıbbi YZ hazırbulunuşluk puanları (76,04±18,19'a karşı 64,50±16,27, p=0,001) göstermiştir. Benzer şekilde, BİT ve YZ alanlarında daha yüksek ilgi düzeyine sahip hekimler, aşamalı olarak daha düşük kaygı düzeyleri ve daha yüksek hazırbulunuşluk puanları sergilemiştir (tüm karşılaştırmalar için p<0,05).

Sonuç: Düşük öğrenme ve YZ yapılandırma kaygısına sahip aile hekimleri, tıbbi YZ için daha fazla hazırbulunuşluk göstermiştir. Kadın hekimler tüm alanlarda daha yüksek kaygı düzeyleri yaşarken, teknoloji geçmişi olanlar YZ entegrasyonu için daha hazırlıklı bulunmuştur. Bu bulgular, birinci basamakta başarılı YZ adaptasyonu için hedeflenmiş eğitim programları ve cinsiyete duyarlı eğitim yaklaşımlarının gerekli olduğunu göstermektedir.

Anahtar Kelimeler: Yapay zeka kaygısı, tıbbi yapay zeka hazırbulunuşluluk, aile hekimi

Introduction

Artificial intelligence (AI) refers to computer systems capable of mimicking certain aspects of human intelligence, including learning, reasoning, and problem-solving[1]. AI has emerged as one of the most rapidly evolving domains in contemporary science and technology, with goals encompassing simulating human intelligence, solving complex problems, data analytics, making predictions, and decision-making[2,3].

The healthcare sector is a significant AI application domain. This technology promises an array of advantages, including enhanced diagnostic accuracy, optimization of treatment plans, and early disease detection[4,5]. AI-driven systems are adept at processing large volumes of healthcare data, offering clinicians an opportunity for more accurate diagnoses, developing effective treatment modalities, and ultimately improving patients' quality of life. Furthermore, AI plays a critical role in medical imaging, aiding early diagnosis and treatment in fields such as radiology, pathology, and neurology by analyzing images to identify abnormal structures[6,7].

The application of AI in healthcare has brought about a transformative wave, with an extensive range of tools designed to assist diagnostics, treatment planning, and patient management[8-11]. However, seamless and effective integration of these AI applications into clinical settings requires a comprehensive readiness strategy for healthcare providers. The concept of "readiness in medical AI" goes beyond simply installing software or deploying algorithms; it encompasses the clinical, educational, and ethical readiness to utilize these new tools effectively[12]. Healthcare providers, especially primary care physicians, must critically evaluate the reliability and clinical relevance of AI-based tools. Although many of these algorithms may be validated through rigorous trials or studies, physicians should understand the specific conditions under which the AI models are trained and tested[13-15].

It is crucial for clinicians to understand the fundamental principles of AI technologies. Medical schools and continuing education programs should offer courses and training sessions that delve into the basics of machine learning, data analysis, and types of algorithms most commonly used in healthcare applications. In practice, these foundational technologies support informed decisions. The landscape of medical AI is continuously changing with advancements in machine-learning models and algorithms. To keep healthcare providers up to date, ongoing professional development initiatives should offer workshops, webinars, and updated training modules that focus on the latest innovations.

Although existing studies have largely focused on secondary and tertiary healthcare settings, limited research has addressed physicians' concerns and readiness for AI in primary care. Notably, the scarcity of studies on the relationship between AI anxiety levels and medical AI readiness in family physicians attracts attention. Given these gaps, this study aimed to investigate the relationship between anxiety levels and readiness for medical AI among family physicians.

Materials and Methods

Study Design

This descriptive and cross-sectional study was conducted between April and July 2022 in Türkiye, using social media platforms such as WhatsApp and Telegram. The study population consisted of general practitioners and family medicine specialists working in public and private primary healthcare services in Türkiye (n=24.082). The required minimum sample size was calculated as 191, based on a 0.20 effect size for correlation analysis in the G*Power 3.1.9.7 program, with an alpha level of 0.05 and 80% power[16]. A total of 199 volunteers were recruited from the target population.

Data Collection

Data were collected by a self-administered method with the help of a survey form. In the study conducted as an e-survey, a Google form was created and social media tools such as WhatsApp and Telegram were used. Participants were reached through simple random sampling. The first question sought informed consent from participants to ensure voluntary participation. When they agreed to participate in the study, they were asked to answer the e-survey. The e-survey included a personal information form, an AI anxiety scale (AIAS), and a medical AI readiness scale for medical students (MAIRS-MS).

AIAS

AIAS was developed by Wang and Wang[17]. Terzi[18] conducted the Turkish validity and reliability study with teachers in 2020. The scale consists of 21 items and four sub-dimensions: learning, job replacement, socio-technical blindness, and AI configuration. Scoring ranges from 21 to 147, with higher scores indicating increased levels of anxiety towards AI. Terzi[18] found, Cronbach's alpha reliability coefficient of the scale to be 0.96 for the total score, and reported Cronbach's alpha reliability coefficients of the learning, job replacement, socio-technical blindness, and AI configuration subscales as 0.89, 0.95, 0.89, and 0.95, respectively. The scale was applied to family physicians and family medicine specialists by Kolcu et al.[19]. and the validity and reliability of the scale was re-evaluated Cronbach's alpha reliability coefficient for the total score of the scale was found to be 0.95.

MAIRS-MS

MAIRS-MS developed by Karaca et al.[20]. The scale consists of 22 items and four sub-dimensions: cognition, ability, vision, and ethics. Scoring ranges from 22 to 110, with higher scores indicating higher levels of readiness. Karaca et al. [20] found Cronbach's alpha reliability coefficient of the scale 0.87 for the total score, and reported Cronbach's alpha reliability coefficients of the cognition, ability, vision, and ethics subscales as 0.83, 0.77, 0.72, and 0.63, respectively.

Ethics Approval

The study was approved by the Kırklareli University Local Ethics Committee (approval no: E-35523585-302.99-45759, date: 11.04.2022) and was conducted in accordance with the Declaration of Helsinki. Informed consent was obtained from the volunteers. Permission to use these scales was obtained from the authors.

Statistical Analysis

Descriptive statistics, including frequency (n), percentage (%), mean, and standard deviation, were used for data analysis. Reliability analysis was conducted for the AIAS and MAIRS, and the results were evaluated with Cronbach's alpha coefficient. The normality of distribution was tested with the Shapiro-Wilk test. Differences between two independent groups in parametrically distributed AIAS and MAIRS total scores were analyzed using the independent t-test, and differences between three or more independent groups were examined with one-way analysis of variance. The difference between two independent groups in the non-parametric distributed AIAS and MAIRS subscale scores was examined with the Mann-Whitney U test, and the difference between three or more independent groups was examined with the Kruskal-Wallis H test. The relationship between two numeric variables was examined with Pearson correlation analysis in parametric distributions and with Spearman's correlation analysis in non-parametric distributions. Both unadjusted and adjusted multivariate linear regression analyses were performed to identify predictors associated with AIAS and MAIRS. Models were adjusted for age and sex. Since the sub-dimensions of AIAS and MAIRS were not distributed normally, Z transformation was performed before they were included in the model. The change in variance in the created models was explained by adjusted R-square. Data were analyzed using the Statistical Package for the Social Sciences version 26.0 (SPSS 26.0, SPSS, Inc., Chicago, IL, USA); $p<0.05$ was considered statistically significant.

Results

The mean age of the participants is 45.93±9.19 years (min: 27, max: 63), and their average professional experience is

20.88±9.55 years (min: 2, max: 39). Among the participants, 63.8% were male, and of all participants, 44.2% worked in provincial centers. In the research group, 19.1% had specialized training in family medicine and 12.6% had received education in information technology or computer science. Of the family physicians, 30.2% are interested in information technology or computer science, while 21.1% are interested in the field of AI. Table 1 presents the distribution of participants' descriptive characteristics.

Table 1. Distribution of descriptive characteristics of the participants

Variables	n	%
Sex		
Female	72	36.2
Male	127	63.8
Age		
<45	71	35.7
45-49	40	20.1
>49	88	44.2
≥50	88	44.2
Professional seniority		
<20	72	36.2
20-29	87	43.7
≥30	40	20.1
Place of work		
City center	88	44.2
Subway	78	39.2
Town/village	33	16.6
Family medicine specialty training		
Yes	38	19.1
No	161	80.9
Education in the field of ICT		
Yes	25	12.6
No	174	87.4
Level of interest in the field of ICT		
Irrelevant	29	14.6
Middle	110	55.3
Interested	60	30.2
Level of interest in the field of AI		
Irrelevant	92	46.2
Middle	65	32.7
Interested	42	21.1

ICT: Information and communication technology, AI: Artificial intelligence

Reliability analysis confirmed the internal consistency of both scales in this study population. For the AIAS, Cronbach's alpha coefficients were 0.96 for the total scale, and 0.94, 0.94, 0.93 and 0.98 for the learning, job replacement, socio-technical blindness, and AI configuration subscales, respectively. For the MAIRS, Cronbach's alpha coefficients were 0.96 for the total scale, and 0.94, 0.91, and 0.83 for the cognition, ability, vision, and ethics subscales, respectively (with 0.94 for both cognition and ability).

This study investigated the distribution of total and sub-dimension scores on the AIAS and MAIRS based on participants' descriptive characteristics (Table 2 and Table 3).

Table 4 presents the correlation analysis between AI anxiety and medical AI readiness. Significant negative correlations were found between overall medical AI readiness and most anxiety dimensions, with the strongest relationships observed for learning anxiety ($r=-0.311$, $p<0.001$) and AI configuration anxiety ($r=-0.256$, $p<0.001$). Learning anxiety showed consistent negative correlations with all readiness dimensions, particularly ability ($r=-0.337$, $p<0.001$) and vision ($r=-0.286$, $p<0.001$). Job replacement anxiety demonstrated weaker associations, while socio-technical blindness showed minimal correlation with most readiness dimensions except vision, ($r=-0.145$, $p=0.041$).

Table 5 presents a multivariate linear regression analysis of predictors associated with AIAS and MAIRS. Learning anxiety and AI configuration anxiety were significant negative predictors of overall AI readiness, while socio-technical blindness showed a positive association (Table 5).

Discussion

Our study found that female family physicians consistently felt more anxious about AI technology compared to their male colleagues, especially when it came to configuring AI systems ($p=0.004$). This pattern isn't unique to medicine, researchers have been documenting similar gender differences with technology for decades[21]. Park[22] found that women often feel less in control when using digital tools, contributing to increased anxiety. Mayall's[23] research showed that women tend to doubt their computer abilities more than men, even when their actual skills are similar. This trend has historical roots; as observed by Shashaani[24], these differences in computer attitudes were evident during the 1990s. Fetler[25] found that male students consistently scored higher on computer literacy tests. Interestingly, Kaya

Table 2. Distribution of AIAS total and subscale mean scores according to the descriptive characteristics of the participants

Variables	n	Total		Learning		Job replacement		Socio-technical blindness		AI configuration	
		Mean ± SD	p-value	Mean ± SD	p-value	Mean ± SD	p-value	Mean ± SD	p-value	Mean ± SD	p-value
Sex											
Female	72	83.22±24.95	**<0.001**[1]	30.03±12.42	**<0.001**[2]	21.88±7.53	**0.001**[2]	19.19±6.11	**0.024**[2]	12.13±5.51	**0.004**[2]
Male	127	65.83±28.59		21.40±11.38		17.86±9.02		16.74±7.21		9.83±5.95	
Age											
<45	71	71.32±29.91		24.44±12.21		18.87±9.30		17.45±6.96		10.56±6.37	
45-49	40	72.35±26.69	0.957[3]	24.78±11.57	0.928[4]	19.78±8.02	0.819[4]	16.93±7.00	0.584[4]	10.88±5.50	0.926[4]
≥50	88	72.66±28.48		24.48±13.14		19.45±8.59		18.09±6.90		10.64±5.72	
Professional seniority											
<20	72	71.50±29.89		24.38±12.26		18.82±9.37		17.61±6.98		10.69±6.44	
20-29	87	72.78±27.78	0.958[3]	24.23±13.06	0.683[4]	20.14±8.42	0.467[4]	17.78±6.88	0.898[4]	10.63±5.44	0.990[4]
≥30	40	71.80±28.29		25.43±11.67		18.40±8.14		17.33±7.07		10.65±5.94	
Place of work											
City center	88	71.19±27.95	0.684[1]	24.53±11.99	0.820[2]	19.49±8.72	0.877[2]	17.14±7.04	0.420[2]	10.03±5.47	0.246[2]
District/town/village	111	72.86±29.07		24.51±12.86		19.17±8.74		18.02±6.83		11.15±6.18	
Family medicine specialty training											
Yes	38	70.97±26.43	0.784[1]	24.76±11.13	0.627[2]	19.16±9.02	0.979[2]	17.47±6.77	0.827[2]	9.58±5.19	0.267[2]
No	161	72.39±29.06		24.47±12.77		19.35±8.66		17.66±6.97		10.91±6.03	
Education in the field of ICT											
Yes	25	57.84±27.11	**0.007**[1]	17.72±9.63	**0.001**[2]	15.96±8.43	0.050[2]	15.36±7.81	0.111[2]	8.80±6.16	0.064[2]
No	174	74.17±28.20		25.50±12.53		19.79±8.67		17.95±6.74		10.93±5.82	
Level of interest in the field of ICT											
Irrelevant	29	75.86±30.05		29.69±14.79		19.24±7.74		16.34±7.16		10.59±5.94	
Middle	110	76.48±27.65	**0.006**[3]	26.09±12.35	**<0.001**[4]	20.51±8.52	0.062[4]	18.35±6.77	0.190[4]	11.53±5.74	**0.027**[4]
Relating to	60	62.32±27.36		19.15±9.37		17.15±9.19		16.92±7.03		9.10±5.91	
Level of interest in the field of AI											
Irrelevant	92	75.20±29.18		27.02±14.26		19.80±8.33		17.25±7.11		11.12±5.83	
Middle	65	75.63±26.74	**0.007**[3]	24.97±10.33	**0.001**[4]	20.40±8.77	0.070[4]	18.77±6.60	0.239[4]	11.49±5.51	**0.006**[4]
Interested	42	59.95±27.01		18.36±8.80		16.55±9.06		16.69±6.91		8.36±6.12	

[1]: Independent samples t-test, [2]: Mann-Whitney U test, [3]: ANOVA, [4]: Kruskal-Wallis-H test, AI: Artificial intelligence, AIAS: Artificial intelligence anxiety scale, SD: Standard deviation, ICT: Information and communication technology

Table 3. Distribution of MAIRS total and subscale score averages according to the descriptive characteristics of the participants

Variables	n	Total		Cognition		Ability		Vision		Ethics	
		Mean ± SD	p-value	Mean ± SD	p-value	Mean ± SD	p-value	Mean ± SD	p-value	Mean ± SD	p-value
Sex											
Female	72	65.74±15.20	0.894[1]	20.67±6.36	0.254[2]	26.54±6.33	0.547[2]	8.47±2.70	0.904[2]	10.06±2.57	0.577[2]
Male	127	66.07±17.86		21.97±7.20		25.82±6.95		8.52±2.85		9.76±2.67	
Age											
<45	71	68.17±17.29		22.37±6.88		26.89±7.10		9.01±3.06		9.90±2.71	
45-49	40	69.78±16.60	**0.028**[3]	23.75±6.93	**0.003**[4]	26.95±6.16	0.107[4]	8.83±2.44	**0.025**[4]	10.25±2.40	0.648[4]
≥50	88	62.42±16.23		19.77±6.60		25.03±6.59		7.94±2.63		9.67±2.67	
Professional seniority											
<20	72	68.28±17.25		22.50±6.85		26.88±7.08		9.01±3.05		9.89±2.72	
20-29	87	67.26±17.28	**0.011**[3]	21.85±7.33	**0.027**[4]	26.63±6.52	**0.015**[4]	8.55±2.70	**0.012**[4]	10.23±2.55	0.057[4]
≥30	40	58.90±13.67		18.93±5.53		23.45±5.98		7.48±2.22		9.05±2.51	
Place of work											
City center	88	66.85±16.97	0.504[1]	21.74±7.02	0.747[2]	26.70±6.59	0.405[2]	8.41±2.95	0.481[2]	10.00±2.70	0.754[2]
District/town/village	111	65.23±16.91		21.31±6.87		25.59±6.82		8.58±2.66		9.77±2.58	
Family medicine specialty training											
Yes	38	72.63±17.10	**0.006**[1]	24.79±6.77	**0.001**[2]	28.18±6.57	**0.021**[2]	9.42±2.78	**0.014**[2]	10.24±2.74	0.418[2]
No	161	64.37±16.53		20.72±675		25.58±6.69		8.29±2.76		9.78±2.60	
Education in the field of ICT											
Yes	25	76.04±18.19	**0.001**[1]	26.12±7.88	**0.002**[2]	29.04±6.37	**0.027**[2]	10.08±2.64	**0.004**[2]	10.80±2.43	0.086[2]
No	174	64.50±16.27		20.83±6.54		25.66±6.69		8.28±2.74		9.74±2.64	
Level of interest in the field of ICT											
Irrelevant	29	53.24±13.96		16.66±5.25		21.41±5.83		6.59±2.40		8.59±2.73	
Middle	110	63.05±13.91	**<0.001**[3]	20.19±5.51	**<0.001**[4]	25.27±6.15	**<0.001**[4]	8.10±2.48	**<0.001**[4]	9.49±2.53	**<0.001**[4]
Relating to	60	77.40±16.77		26.23±7.37		29.82±6.31		10.17±2.66		11.18±2.23	
Level of interest in the field of AI											
Irrelevant	92	57.05±14.42		18.18±5.51		22.68±6.37		7.22±2.48		8.97±2.64	
Middle	65	69.02±12.46	**<0.001**[3]	22.17±5.56	**<0.001**[4]	27.66±5.21	**<0.001**[4]	8.94±2.26	**<0.001**[4]	10.25±2.32	**<0.001**[4]
Interested	42	80.69±16.19		27.71±7.14		31.07±5.55		10.64±2.69		11.26±2.35	

[1]: Independent samples t-test, [2]: Mann-Whitney U test, [3]: ANOVA, [4]: Kruskal-Wallis-H test, AI: Artificial intelligence, MAIRS: Medical artificial intelligence readiness scale, SD: Standard deviation, ICT: Information and communication technology

Table 4. Relationship between the AIAS and MAIRS

MAIRS										
AIAS	**Total**		**Cognition**		**Ability**		**Vision**		**Ethics**	
	r	**p-value**	**r**	**p-value**	**r**	**p-value**	**r**	**p-value**	**r**	**p-value**
Total	-0,283	**<0.001**[1]	-0.235	**0.001**[2]	-0.258	**<0.001**[2]	-0.255	**<0.001**[2]	-0.142	**0.045**[2]
Learning	-0.311	**<0.001**[2]	-0.235	**0.001**[2]	-0.337	**<0.001**[2]	-0.286	**<0.001**[2]	-0.260	**<0.001**[2]
Job replacement	-0.165	**0.020**[2]	-0.179	**0.011**[2]	-0.136	0.056[2]	-0.160	**0.024**[2]	-0.033	0.644[2]
Socio-technical blindness	-0.102	0.154[2]	-0.132	0.062[2]	-0.064	0.370[2]	-0.145	**0.041**[2]	0.040	0.572[2]
AI configuration	-0.256	**<0.001**[2]	-0.221	**0.002**[2]	-0.263	**<0.001**[2]	-0.213	**0.002**[2]	-0.153	**0.031**[2]

[1]: Pearson correlation analysis, [2]: Spearman correlation analysis, AI: Artificial intelligence, AIAS: Artificial intelligence anxiety scale, MAIRS: Medical artificial intelligence readiness scale

Table 5. Multivariate linear regression analysis of predictors associated with AIAS and MAIRS

Predictors	**Unadjusted**				**Adjusted**[1]			
	B	**SE**	**β**	**p-value**	**B**	**SE**	**β**	**p-value**
Total								
Learning	-5.524	1.373	-0.327	**<0.001**	-5.948	1.407	-0.352	**<0.001**
Job replacement	0.243	1.913	0.014	0.899	0.179	1.894	0.011	0.925
Socio-technical blindness	3.900	1.992	0.231	0.052	3.901	1.970	0.231	**0.049**
AI configuration	-4.493	1.803	-0.266	**0.014**	-4.463	1.782	-0.264	**0.013**
	(Adj.R^2: 0.135, F:8.721***)					(Adj.R^2: 0.155, F:7.036***)		
Cognition								
Learning	-0.197	0.084	-0.197	**0.020**	-0.185	0.087	-0.185	**0.035**
Job replacement	-0.075	0.117	-0.075	0.525	-0.069	0.117	-0.069	0.557
Socio-technical blindness	0.148	0.122	0.148	0.228	0.144	0.122	0.144	0.239
AI configuration	-0.184	0.111	-0.184	0.097	-0.182	0.110	-0.182	0.099
	(Adj.R^2: 0.069, F:4.683**)				(Adj.R^2: 0.080, F:3852**)			
Ability								
Learning	-0.370	0.080	-0.370	**<0.001**	-0.421	0.081	-0.421	**<0.001**
Job replacement	0.062	0.111	0.062	0.577	0.051	0.109	0.051	0.639
Socio-technical blindness	0.290	0.116	0.290	**0.013**	0.293	0.113	0.293	**0.010**
AI configuration	-0.320	0.105	-0.320	**0.003**	-0.318	0.102	-0.318	**0.002**
	(Adj.R^2: 0.168, F:10.980***)				(Adj.R^2: 0.202, F:9.357***)			
Vision								
Learning	-0.271	0.083	-0.271	**0.001**	-0.289	0.085	-0.289	**0.001**
Job replacement	0.010	0.116	0.010	0.931	0.009	0.115	0.009	0.937
Socio-technical blindness	0.049	0.121	0.049	0.689	0.047	0.119	0.047	0.693
AI configuration	-0.131	0.110	-0.131	0.234	-0.129	0.108	-0.129	0.235
	(Adj.R^2: 0.085, F:5.613***)				(Adj.R^2: 0.141, F:5.261***)			
Ethics								
Learning	-0.346	0.082	-0.346	**<0.001**	-0.394	0.084	-0.394	**<0.001**
Job replacement	0.120	0.114	0.120	0.293	0.109	0.113	0.109	0.339
Socio-technical blindness	0.302	0.119	0.302	**0.012**	0.306	0.118	0.306	**0.010**
AI configuration	-0.267	0.107	-0.267	**0.014**	-0.267	0.107	-0.267	**0.013**
	(Adj.R^2: 0.121, F:7.846***)				(Adj.R^2: 0.136, F:6.181***)			

*: p<0.05, **: p<0.01, ***: p<0.001, Adj.R^2: Adjusted for age and sex, AI: Artificial intelligence, AIAS: Artificial intelligence anxiety scale, MAIRS: Medical artificial intelligence readiness scale

et al.'s[26] more recent work suggested these gender gaps might be shrinking, though our findings show they are still very much present among practicing physicians.

The higher anxiety levels we observed among female doctors likely stem from less exposure to computing during their medical training, simply working in environments where they felt less supported when learning new tech skills. What this means for hospitals and clinics is clear: the typical one-size-fits-all approach to AI training simply won't work. Medical organizations need to create learning programs that meet people where they are technologically, offering safe spaces where doctors can ask questions without feeling judged and take time to experiment with AI tools at their own pace. We also need research that follows physicians over time to see whether these anxiety differences actually affect how they use AI with patients and whether thoughtful, supportive training can help close these gaps in real-world practice.

Contrary to the initial hypotheses, having specialized training in family medicine did not result in a noteworthy decrease in AI anxiety. Conversely, a noticeable reduction in AI anxiety was discerned in participants with an educational background or vested interest in computing or IT, thus substantiating previous studies[26,27]. This revelation directs us toward a pivotal intervention point: the enhancement of technological familiarity and proficiency may play a crucial role in mitigating anxiety related to AI, irrespective of specialized medical training. Thus, the findings imply that the incorporation of specialized training and computer literacy into medical education or specialty training curricula is necessary, warranting thoughtful deliberation.

A decrease in learning and AI configuration anxiety was positively correlated with enhanced medical AI readiness. This finding emphasizes the potential efficacy of meticulous and targeted educational interventions in alleviating AI anxiety, subsequently fortifying AI readiness, and aligning with Shinners et al.[28] propositions. These findings have substantial implications for the refinement of training curricula, suggesting that the incorporation of AI-related knowledge and ability development could be crucial for cultivating competencies in prospective healthcare professionals[29,30]. While the utility of AI in medicine is largely acknowledged, most healthcare practitioners do not possess comprehensive knowledge of AI's fundamentals and express concerns about the possible repercussions of its extensive implementation in clinical settings[31]. Given these findings, it is imperative to further investigate whether there is a causal relationship between learning anxiety, AI configuration anxiety, and medical AI readiness, to delineate the underlying dynamics more precisely and develop more tailored and effective interventions.

The results of the study revealed that an increase in socio-technical blindness is linked to better readiness in abilities, a phenomenon that is unique and seemingly contradictory. This implies a complicated relationship between understanding technological repercussions, and readiness to adopt them. Such complexity prompts critical reflections on whether heightened cognizance of AI's restrictions and potential adverse impacts might obstruct the eagerness or perceived capability to apply AI applications proficiently. The potential of AI innovations to enhance care and reduce workload is compelling for organizations. However, skepticism exists among healthcare entities regarding the feasibility of integrating technologies such as AI, owing to the substantial resources needed for infrastructure, training, and policy formulation[30,32]. Socio-technical systems theory advocates balanced attention to individuals, organizations, and technology prior to introducing new technology. It is vital to delve into the perceptions of healthcare staff to ascertain the hurdles in technology integration and tailor education and training programs based on their requirements, ensuring the optimal utilization of emerging technologies[33,34].

The relation between reduced learning and AI configuration anxieties, and enhanced readiness for ethical challenges, especially when coupled with increased socio-technical blindness, calls for more nuanced and multifaceted approaches to AI education in healthcare. This emphasizes the necessity for robust training frameworks that go beyond technical competencies to address ethical considerations and ensure responsible and mindful incorporation of AI technologies into healthcare[27,30].

There is an urgent need to adequately equip the healthcare workforce for the integration of AI within healthcare settings. Gaining insights into workforce perceptions of AI is crucial, as it can reveal potential challenges and barriers that organizations might encounter while using this transformative technology. In this study, we examined the levels of AI anxiety and medical AI readiness among family physicians to identify and elucidate existing gaps and disparities. Similarly, amplifying such studies across the entire spectrum of healthcare providers is paramount. Identifying strategic measures to prepare healthcare professionals for the integration of emerging technologies and AI, which are poised to become integral components of their lives, is crucial. This preparation is essential for the seamless adaptation and maximization of the benefits that these innovations can bring to healthcare outcomes.

Study Limitations

A limitation of the study is that it does not represent all family physicians because the research was conducted via social media. Despite the initial studies providing noteworthy insights, follow-up studies are needed to corroborate results, considering the varied geographical, cultural, and institutional contexts. Additionally, future research should delve deeper into exploring causal relationships between learning anxiety, AI configuration anxiety, and medical AI readiness, while aiming to understand the underlying mechanisms between socio-technical blindness and ability readiness.

Conclusion

In conclusion, this study illuminates how diminishing learning and AI configuration anxieties can lead to an elevation in medical AI readiness across cognition, ability, vision, and ethics dimensions. The elucidated gender differences, the impact of computer literacy and specialized training, and novel and intricate relationships between socio-technical blindness and ability readiness are critical areas that require further exploration and validation. Above all, these insights emphasize the need for holistic approaches to AI education in healthcare, incorporating technical, ethical, and socio-technical components to ensure the responsible and proficient use of AI in family medicine, thereby bridging the existing gap in primary healthcare research on AI readiness and anxiety.

Future research could benefit from longitudinal studies that track changes in AI anxiety and readiness over time, especially as family physicians gain more exposure to AI technologies in their practice. This could help in understanding how attitudes and readiness evolve with increased familiarity and use of AI in medical contexts. Studies should be designed to assess the effectiveness of targeted educational interventions aimed at reducing AI anxiety and enhancing readiness. This could include developing specific training modules or simulation-based learning environments that address the identified cognition, ability-based, and ethical concerns. Comparing AI anxiety and readiness between family physicians and other medical specialties could provide insight into specialty-specific concerns and readiness levels. This might also reveal unique educational needs or resistance points that are specific to different areas of practice. Research should also focus on how the integration of AI into clinical practice affects patient outcomes, physician decision-making, and workflow efficiency. This could help to understand the tangible benefits and potential pitfalls of AI in healthcare. By addressing these recommendations, future research could contribute to a deeper understanding of the factors that influence the adoption of AI in healthcare and support the development of strategies to optimize its integration, benefiting healthcare providers and patients.

Ethics

Ethics Committee Approval: The study was approved by the Kırklareli University Local Ethics Committee (approval no: E-35523585-302.99-45759, date: 11.04.2022) and was conducted in accordance with the Declaration of Helsinki.

Informed Consent: Informed consent was obtained from the volunteers. Permission to use these scales was obtained from the authors.

Footnotes

Authorship Contributions

Surgical and Medical Practises: N.K.E., A.E., Y.M., Concept: N.K.E., A.E., Y.M., Design: N.K.E., A.E., Y.M., Data Collection or Processing: N.K.E., A.E., Y.M., Analysis or Interpretation: N.K.E., A.E., Y.M., Literature Search: N.K.E., A.E., Y.M., Writing: N.K.E., A.E., Y.M.

Conflict of Interest: No conflict of interest was declared by the authors.

Financial Disclosure: The authors declared that this study received no financial support.

References

1. McCarthy J, Minsky ML, Rochester N, Shannon CE. A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. AI Magazine. 2006;27:12-4.
2. Ramamoorthy CV, Shekhar S, Garg V. Software development support for AI programs. Computer. 1987;20:30-40.
3. Jiang DY, Zhang H, Kumar H, et al. Automatic control model of power information system access based on artificial intelligence technology. Mathematical Problems in Engineering. 2022;2022:1-6.
4. Gunes O, Gunes G, Celik Seyitoglu D. The use of artificial intelligence in different medical branches: an overview of the literature. Med Science. 2019;8:770-3.
5. Greaves RF, Bernardini S, Ferrari M, et al. Key questions about the future of laboratory medicine in the next decade of the 21st century: a report from the IFCC-emerging technologies division. Clin Chim Acta. 2019;495:570-89.

6. Iqbal U, Celi LA, Li YJ. How can artificial intelligence make medicine more preemptive? J Med Internet Res. 2020;22:e17211.
7. Vikas, Parhi DR. Humanoid path planning on even and uneven terrains using an efficient memory-based gravitational search algorithm and evolutionary learning strategy. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science. 2023;238:1542-60.
8. Rotolo D, Hicks D, Martin BR. What is an emerging technology? Research Policy. 2015;44:1827-43.
9. Ganesh V, Seshia SA, Jha S. Machine learning and logic: a new frontier in artificial intelligence. Form Methods Syst Des. 2022;60:426-51.
10. Bajwa J, Munir U, Nori A, Williams B. Artificial intelligence in healthcare: transforming the practice of medicine. Future Healthc J. 2021;8:e188-94.
11. Hazarika I. Artificial intelligence: opportunities and implications for the health workforce. Int Health. 2020;12:241-5.
12. Challen R, Denny J, Pitt M, Gompels L, Edwards T, Tsaneva-Atanasova K. Artificial intelligence, bias and clinical safety. BMJ Qual Saf. 2019;28:231-7.
13. Al-Medfa MK, Al-Ansari AMS, Darwish AH, Qreeballa TA, Jahrami H. Physicians' attitudes and knowledge toward artificial intelligence in medicine: benefits and drawbacks. Heliyon. 2023;9:e14744.
14. Wehkamp K, Krawczak M, Schreiber S. The quality and utility of artificial intelligence in patient care. Dtsch Arztebl Int. 2023;120:463-9.
15. Top M, Yılmaz A. Computer anxiety in nursing: an investigation from Turkish nurses. J Med Syst. 2015;39:163.
16. Faul F, Erdfelder E, Buchner A, Lang AG. Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses. Behav Res Methods. 2009;41:1149-60.
17. Wang YY, Wang YS. Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. Interactive Learning Environments. 2019;30:619-34.
18. Terzi R. An adaptation of artificial intelligence anxiety scale into Turkish: reliability and validity study. International Online Journal of Education and Teaching (IOJET). 2020;7:1501-15.
19. Kolcu G, Özceylan G, Başer A, Baktır Altuntaş S. Evaluation of the validity and reliability of the artificial intelligence anxiety scale in family physicians. RJBB. 2021;2:20-8.
20. Karaca O, Çalışkan SA, Demir K. Medical artificial intelligence readiness scale for medical students (MAIRS-MS)-development, validity and reliability study. BMC Med Educ. 2021;21:112.
21. Pagani L, Argentin G, Gui M, Stanca L. The impact of digital skills on educational outcomes: evidence from performance tests. University of Milan Bicocca Department of Economics, Management and Statistics Working Paper No. 304. 2015;42:1-32.
22. Park YJ. Digital literacy and privacy behavior online. Communication Research. 2011;40:215-36.
23. Mayall HJ. Differences in gender based technology self-efficacy across academic levels. International Journal of Instructional Media. 2008;35:145-56.
24. Shashaani L. Gender-based differences in attitudes toward computers. Computers & Education. 1993;20:169-81.
25. Fetler M. Sex differences on the California statewide assessment of computer literacy. Sex Roles. 1985;13:181-91.
26. Kaya F, Aydin F, Schepman A, Rodway P, Yetişensoy O, Demir Kaya M. The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. International Journal of Human-Computer Interaction. 2022;40:497-514.
27. Sindermann C, Yang H, Elhai JD, et al. Acceptance and fear of artificial intelligence: associations with personality in a German and a Chinese sample. Discov Psychol. 2022;2:8.
28. Shinners L, Grace S, Smith S, Stephens A, Aggar C. Exploring healthcare professionals' perceptions of artificial intelligence: piloting the shinners artificial intelligence perception tool. Digit Health. 2022;8:20552076221078110.
29. Bohr A, Memarzadeh K. Chapter 2-the rise of artificial intelligence in healthcare applications. Artificial Intelligence in healthcare. 2020:25-60.
30. Shinners L, Aggar C, Grace S, Smith S. Exploring healthcare professionals' perceptions of artificial intelligence: validating a questionnaire using the e-Delphi method. Digital Health. 2021;7:20552076211003433.
31. Castagno S, Khalifa M. Perceptions of artificial intelligence among healthcare staff: a qualitative survey study. Front Artif Intell. 2020;3:578983.
32. Shinners L, Aggar C, Grace S, Smith S. Exploring healthcare professionals' understanding and experiences of artificial intelligence technology use in the delivery of healthcare: an integrative review. Health Informatics J. 2020;26:1225-36.
33. Stevenson JE, Nilsson GC, Petersson GI, Johansson PE. Nurses' experience of using electronic patient records in everyday practice in acute/inpatient ward settings: a literature review. Health Informatics J. 2010;16:63-72.
34. Moen A. A nursing perspective to design and implementation of electronic patient record systems. J Biomed Inform. 2003;36:375-8.