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Assessing Physicians' Readiness for Medical Artificial Intelligence

Hekimlerde Tıbbi Yapay Zeka Hazırbulunuşluğunun Değerlendirilmesi

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Abstract

Objective: This study aims to assess the level of readiness among physicians at University of Health Sciences Türkiye, İzmir City Hospital for the adoption of medical artificial intelligence (AI) technologies.

Methods: Participants' readiness levels were assessed with the medical artificial-intelligence readiness scale devised by Karaca et al. University of Health Sciences Türkiye, İzmir City Hospital employs 1.867 physicians. Using Baş's (2006) sample-size formula with a ±0.05 margin of error and a 95% confidence level, the minimum required sample was calculated as 319, and 320 physicians ultimately completed the questionnaire. The 22-item scale was subjected to exploratory and confirmatory factor analysis (EFA). The initial solution explained 85.432% of the total variance, with excellent sampling adequacy (Kaiser-Meyer-Olkin=0.964) and a highly significant Bartlett's test of sphericity (χ^2=9.376.445, p<0.001). Inspection of the pattern matrix revealed substantial cross-loadings on three items; these items were removed, and the EFA was rerun on the refined item set.

Results: Statistical analyses showed no significant variation in physicians' medical-AI readiness (MAIR) across age, sex, or marital status, either for the composite score or for any of the sub-dimensions (p>0.05). Years in practice influenced only the third factor, Foresight, with a significant difference emerging there (p<0.05) but not on the remaining dimensions. Departmental affiliation, by contrast, proved important: except for the ethics sub-scale, all dimensions -and the overall MAIR score- differed significantly among departments (p<0.05). The grand-mean MAIR score was 3.11 on a five-point scale. Thus, physicians' readiness levels lie slightly above the midpoint, reflecting a generally positive yet essentially ambivalent attitude toward medical AI. The same "marginally above neutral" pattern applies to each individual sub-dimension.

Conclusion: The analysis reveals that physicians adopt a moderately positive stance toward AI, yet they exhibit a pronounced shortfall in the technical knowledge and practical competence required for its effective implementation.

Keywords: Artificial intelligence, readiness, management, health technologies

Öz

Amaç: Bu çalışmanın amacı, Sağlık Bilimleri Üniversitesi, İzmir Şehir Hastanesi'nde çalışan hekimlerin tıbbi yapay zeka (YZ) teknolojilerine yönelik hazırbulunuşluk düzeylerini değerlendirmektir.

Yöntem: Katılımcıların hazırbulunuşluk düzeylerini değerlendirmek amacıyla, Karaca ve ark. tarafından geliştirilen "tıbbi yapay zeka hazırbulunuşluk ölçeği" kullanılmıştır. Sağlık Bilimleri Üniversitesi, İzmir Şehir Hastanesi'nde toplam 1,867 hekim görev yapmaktadır. Örneklem yeter sayısını belirlemek için Baş'ın (2006) belirttiği formül kullanılarak örneklem sayısı ±0,05 hata toleransı ve %95 güven aralığında 319 hesaplanmış 320 kişiye ulaşılmıştır. Yirmi iki ifadeden oluşan ölçeğe açıklayıcı faktör analizi (AFA)-doğrulayıcı faktör analizi uygulanmış ve toplam açıklanan varyans=85,432, Kaiser-Meyer-Olkin=0.964, Bartlett'ın küresellik testi (χ^2=9,376.445, p<0,001) olarak bulunmuştur. Ancak yapılan incelemede ölçekte yer alan üç ifadede binişiklik olduğu saptanarak bu üç ifade analizden çıkarılarak tekrar AFA yapılmıştır.

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Öz

Bulgular: Analizlerde yaşa, cinsiyete ve medeni duruma göre hekimlerin tıbbi YZ hazırbulunuşluk (TYZH) durumunun tüm alt boyutlar da dahil olmak üzere istatistiksel olarak anlamlı biçimde farklılaşmadığı (p>0,05) saptanmıştır. Meslekteki çalışma süresine göre hekimlerin üçüncü faktörde farklılaştığı (p<0,05) ancak diğer boyutlarda bir farklılık olmadığı saptanmıştır. Bölümlere göre etik faktör dışında tüm faktörler ve ölçek genelinde farklılaştığı (p<0,05) saptanmıştır. Ölçeğin tamamının ortalaması 3,11'dir. Genel olarak katılımcıların TYZH düzeyleri, ortalamanın biraz üzerinde olmakla birlikte durumları kararsız olarak değerlendirilmektedir. Aynı durum tüm alt boyutlar için de geçerlidir.

Sonuç: Analiz sonucunda elde edilen bulgular, hekimlerin yapay zekaya kısmen olumlu bir tutum sergilediğini ancak teknik bilgi açısından ve uygulama yeterliliği konusunda belirgin bir eksiklik yaşadığını ortaya koymuştur.

Anahtar Kelimeler: Yapay zeka, hazırbulunuşluk, yönetim, sağlık teknolojileri

Introduction

In recent years, health-care systems have been among the domains most profoundly affected by technological integration. Rapid population growth, the escalating prevalence of chronic diseases, shortages of health professionals, and persistent concerns over patient safety now necessitate the delivery of care that is more effective, efficient, and universally accessible. One of the principal drivers of this ongoing transformation is, unquestionably, artificial intelligence (AI) technology[1].

AI applications are currently spearheading an extensive process of change and transformation within health and medical domains[2]. This technological evolution promises numerous benefits-chief among them greater sector-wide efficiency, improved patient-care services, and a reduction in clinicians' workload[2,3]. Far from simply easing that workload, AI systems actively support professional judgment across a broad spectrum of functions, ranging from clinical decision support systems and patient-monitoring tools to image-processing technologies and digital triage platforms[4]. Yet the ultimate success of these innovations hinges on whether the health-care personnel who will use them are cognitively, affectively, and ethically prepared for such sweeping change.

Because physicians occupy a central position in the provision of health care services, it is crucial that they interact directly with emerging technologies and be fully prepared to employ them in their decision-making processes[5]. Accordingly, the present study has been undertaken to evaluate physicians' readiness for AI. Its specific objective is to measure the level of readiness among hospital-based physicians with respect to the adoption of AI technologies in clinical practice.

AI: Conceptual and Clinical Perspectives

AI is a set of cognitive algorithms that enables machines to develop human-like capacities for thinking, learning, decision-making, and problem-solving[6]. Broadly speaking, AI is defined as the technologies that allow computers to emulate human intelligence. In other words, it describes the reasoning and learning processes of information-technology systems that behave as if endowed with human intellect[7]. Yet another formulation defines AI as a system's ability to interpret data accurately, draw inferences from those data, and-through flexible adaptation-use those inferences to achieve specified goals and execute designated tasks[8]. Recent definitions go further, positing the complete transfer of the knowledge stored in the human brain to machines. It is now claimed that a machine can perform cognitive functions traditionally associated with the human mind-perception, inference, learning, environmental interaction, problem-solving, and decision-making-and can even display creativity beyond these capabilities[9].

In the health sector, AI-most notably through machine learning, deep learning, and radiological image-analysis techniques-helps orchestrate the entire treatment pathway by supporting tasks such as disease diagnosis, radiography, pathology, electronic record keeping, risk prediction, patient monitoring, and personalised therapy[6,10]. Beyond these capabilities, AI technologies confer additional advantages, including higher diagnostic accuracy, more practical and effective treatment planning, and easier patient access to care. By harnessing information on patients' medical histories and drug reactions, AI algorithms allow physicians to design treatment plans more efficiently and to deliver the required interventions in a timely manner[11].

The coronavirus disease-2019 pandemic has made the role of AI in health-care systems even more conspicuous, particularly through its capacity to lighten patient loads, generate data-driven predictions, and supply robust decision-support tools[12]. At the same time, the expanding use of AI in the health sector has prompted fresh debates over system explainability, legal liability, ethical limits, and the distribution of professional responsibilities[13,14].

Today, significant strides are being made toward the integration of routine medical practice with AI technologies[15]. Physicians are expected to become adept users who can employ these tools on a broad scale, critically analyse their outputs, and develop a deeper grasp of the underlying algorithms[1]. By devising solutions to a wide range of clinical problems and simplifying workflows, medical AI applications hold revolutionary potential in health care-potential that will likely accelerate their incorporation into everyday clinical practice.

Readiness: Conceptual Framework

The concept of readiness refers to the extent to which individuals are mentally, cognitively, emotionally, and socially equipped before undertaking a task. It has also been framed as "the cognitive-emotional disposition to consciously accept, embrace, or reject a specific plan intended to alter the status quo"[16]. Although the term has long been used in educational research, it is now widely examined in the contexts of digital transformation and organisational alignment. For health-care professionals, readiness involves far more than possessing relevant knowledge; it also includes an openness to change, the ability to operate new systems, and the capacity to evaluate those systems within ethical and legal frameworks[17].

Successful adoption and implementation of any technology demand a high degree of user acceptance that is calibrated to the specific needs of those who will operate the system[18]. In the context of technologies such as AI, readiness should be construed not merely as cognitive awareness but equally as professional competence and digital literacy. The requisite level of technological readiness in an individual provides the essential foundation for learning about-and meaningfully engaging with-the technology[19].

Materials and Methods

Aim and Significance

Given physicians' pivotal role in health-care delivery, it is essential that they engage directly with emerging technologies and be adequately prepared to employ them in their decision-making processes[5]. The present research, entitled "assessment of physicians' readiness for AI," seeks to determine whether hospital-based physicians possess a sufficient level of readiness for AI technologies in clinical care. Beyond this overarching aim, the study also examines whether AI readiness varies according to physicians' age, gender, marital status, department, and years of professional experience.

A review of the domestic literature shows that prior investigations have focused on emergency medical personnel as well as medical-school and nursing students. Notable examples include Boillat et al.'s[20] survey study, "Readiness to Adopt AI among Medical Doctors and Students", and AlZaabi et al.'s[21] work, "Are Physicians and Medical Students Ready for AI Applications in Health Care?", both of which compared doctors with students. By contrast, the present study is the first to concentrate exclusively on physicians' medical-AI readiness.

Research Hypotheses

Drawing on the findings reported in the literature, the study tests the following main and subsidiary hypotheses:

H_1 Physicians' total medical AI-readiness (MAIR) differs significantly by age.

- **H_{1a}** The cognitive factor differs by age.
- **H_{1b}** The skill factor differs by age.
- **H_{1c}** The foresight factor differs by age.
- **H_{1d}** The ethics factor differs by age.

H_2 Physicians' total AI-readiness differs significantly by sex.

- **H_{2a}** The cognitive factor differs by sex.
- **H_{2b}** The skill factor differs by sex.
- **H_{2c}** The foresight factor differs by sex.
- **H_{2d}** The ethics factor differs by sex.

H_3 Physicians' total AI-readiness differs significantly by marital status.

- **H_{3a}** The cognitive factor differs by marital status.
- **H_{3b}** The skill factor differs by marital status.
- **H_{3c}** The foresight factor differs by marital status.
- **H_{3d}** The ethics factor differs by marital status.

H_4 Physicians' total AI-readiness differs significantly by years of professional experience.

- **H_{4a}** The cognitive factor differs by years of experience.
- **H_{4b}** The skill factor differs by years of experience.

- **H_{4c}** The foresight factor differs by years of experience.
- **H_{4d}** The ethics factor differs by years of experience.

H_5 Physicians' total AI-readiness differs significantly by department.

- **H_{5a}** The cognitive factor differs by department.
- **H_{5b}** The skill factor differs by department.
- **H_{5c}** The foresight factor differs by department.
- **H_{5d}** The ethics factor differs by department.

Population and Sample

The study was deliberately situated within the health sector-an arena of paramount importance to human well-being-and focused on physicians, whose contributions are pivotal to disease diagnosis and treatment. The target population therefore consisted of all physicians employed at University of Health Sciences Türkiye, İzmir City Hospital, where 1.867 doctors are currently on staff. Applying Baş's[22] formula, the minimum required sample size was calculated as 319, assuming a ±0.05 margin of error and a 95% confidence level. During the online data-collection phase, 320 physicians completed the survey, thereby surpassing the threshold for adequacy.

Ethical Approval

Ethical approval for the study was granted by the University of Health Sciences Türkiye, İzmir City Hospital Social Research Ethics Committee (decision no: 2025/193, dated: 18 April 2025), and data collection commenced only after this clearance had been obtained.

Statistical Analysis

The survey instrument comprised two sections. The first contained seven items eliciting participants' demographic characteristics. The second employed the medical AI readiness scale developed by Karaca et al.[1] which consists of 22 items grouped into four sub-dimensions-cognitive, skills, foresight, and ethical factors. Data were therefore gathered with a 22-item questionnaire formatted on a five-point Likert scale.

The questionnaire was created online (see link) and circulated to all potential respondents via WhatsApp messaging groups. Alongside demographic information, participants rated every statement on a scale from 1 ("strongly disagree") to 5 ("strongly agree") and submitted their responses electronically. Because the entire physician workforce at University of Health Sciences Türkiye, İzmir City Hospital was targeted and the population size was substantial, web-based data collection was deemed most practical.

All data were analysed with appropriate statistical software. Demographic variables were summarised by frequency and cross-tabulation analyses, and overall reliability was assessed by Cronbach's (1951) alpha. Construct validity and dimensionality were investigated through principal-components analysis with Varimax rotation-initially via exploratory factor analysis (EFA) and subsequently via confirmatory factor analysis (CFA). Hypotheses involving two groups were tested with independent-samples t-tests, whereas comparisons across more than two groups were conducted using One-Way Analysis of Variance (ANOVA). When ANOVA indicated a statistically significant difference, post-hoc multiple comparisons were performed with Tukey's test to pinpoint specific group differences.

Statistical Thresholds and Study Design

All analyses were performed at the 95% confidence level, and results were deemed statistically significant when $p<0.05$. The five-point Likert means were interpreted as follows:

Mean range	Interpretation
1.00-1.79	Strongly disagree
1.80-2.59	Disagree
2.60-3.39	Undecided
3.40-4.19	Agree
4.20-5.00	Strongly agree

This cross-sectional, descriptive field study was conducted online between May and June 2025 and reached 320 physicians.

Results

Demographic Characteristics

A summary of participants' descriptive statistics is presented in Table 1.

Of the physicians surveyed, 39.7% (n=127) were aged 20-30 years, 22.2% (n=71) were 31-40 years, 23.8% (n=76) were 41-50 years, 10.3% (n=33) were 51-60 years and 4.1% (n=13) were over 61 years. Women accounted for 51.9% (n=166) of respondents, men for 48.1% (n=154). With respect to marital status, 54.1% (n=173) of participants were married, while 45.9% (n=147) were single. In terms of academic rank, 49.4% (n=158) were resident physicians, 34.1% (n=109) were specialists, and 16.6% (n=53) held associate- or full-professor titles. Departmental distribution showed that 57.5% (n=184) worked in internal-medicine disciplines, 38.4% (n=123) in surgical disciplines, 2.5% (n=8) in basic medical sciences and 1.6% (n=5) in health-sciences units. Regarding professional seniority, 53.8% (n=172) had 1-10 years of service, 19.7% (n=63) had 11-20 years and 26.6% (n=85) had 21 years or more. Finally, 90.6% (n=290) reported having at least one social-media account, whereas 9.4% (n=30) did not.

Findings from the Factor-structure and Reliability Analyses

Scale reliability was assessed with Cronbach's (1951) alpha, while the factor structure and construct validity were evaluated first by EFA and subsequently by CFA. Physicians' overall MAIR scores were then calculated via descriptive (mean) statistics.

An initial EFA on the 22-item instrument yielded excellent sampling adequacy (KMO=0.964) and a highly significant Bartlett's test of sphericity (χ^2=9.376.445, sig.=0.000). Close inspection revealed cross-loadings on three items; after removing those items, the EFA was repeated. The consolidated outcomes of the final EFA, the CFA fit indices, the sub-scale means and the reliability coefficients are summarised in Table 2.

As Table 2 shows, the scale and all four sub-dimensions display very high internal consistency EFA revealed a four-factor solution, and the subsequent CFA demonstrated that this structure provides the best overall fit: every fit index lies within acceptable limits[19,23-28], and the CFA factor loadings are uniformly strong. Hence, all further analyses were conducted on the basis of these four factors: Cognitive-6 items, Skill-5 items, Foresight-6 items, Ethics-2 items. The grand-mean score for the scale was 3.11, indicating that, on average, physicians were undecided about their readiness for medical AI-a pattern that held across each sub-dimension as well.

Hypothesis Tests

Age

An ANOVA was performed to determine whether physicians' total MAIR differs significantly across age groups. The results are summarised in Table 3.

Gender

A series of independent-samples t-tests compared female and male respondents on each readiness dimension and on the overall MAIR score. Descriptive statistics and test results are presented in Table 4.

Independent-samples t-tests showed no statistically significant differences between female and male physicians on the total MAIR score or on any of the four sub-dimensions ($p>0.05$ for every comparison). Consequently, H_2 was rejected.

Table 1. Descriptive profile of the physician sample (n=320)

		n	%			n	%
Age (years)	20-30	127	39.7	**Gender**	Female	166	51.9
	31-40	71	22.2		Male	154	48.1
	41-50	76	23.8	**Marital status**	Married	173	54.1
	51-60	33	10.3		Single	147	45.9
	61+	13	4.1	**Academic rank**	Assistant	158	49.4
Department	Internal medical sciences	184	57.5		Specialist	109	34.1
	Surgical medical sciences	123	38.4		Associate Professor-Professor	53	16.6
	Basic medical sciences	8	2.5	**Social-media account**	Yes	290	90.6
	Health	5	1.6		No	30	9.4
Years in practice	1-10	172	53.8				
	11-20	63	19.7				
	21+	85	26.6				

Table 2. Summary of the EFA and CFA, scale means and internal-consistency coefficients					
ITEM	Exploratory-factor loadings				CFA factor loading
	Cognitive factor	Skill factor	Foresight factor	Ethics factor	
A12	**0.773**	0.268	0.350	0.267	0.886
A10	**0.753**	0.411	0.357	0.162	0.937
A11	**0.750**	0.406	0.373	0.163	0.943
A9	**0.735**	0.413	0.386	0.190	0.943
A14	**0.721**	0.118	0.430	0.317	0.806
A13	**0.627**	0.511	0.431	0.140	0.909
A4	0.229	**0.830**	0.254	0.240	0.834
A3	0.156	**0.825**	0.238	0.259	0.775
A6	0.408	**0.723**	0.280	0.238	0.917
A5	0.447	**0.692**	0.311	0.244	0.927
A7	0.503	**0.671**	0.299	0.177	0.900
A22	0.240	0.217	**0.801**	0.276	0.801
A21	0.484	0.210	**0.734**	0.236	0.864
A19	0.388	0.413	**0.730**	0.158	0.939
A20	0.429	0.241	**0.728**	0.307	0.866
A18	0.400	0.459	**0.681**	0.113	0.922
A17	0.390	0.454	**0.659**	0.126	0.900
A2	0.297	0.325	0.287	**0.770**	0.846
A1	0.237	0.474	0.285	**0.713**	0.908
	KMO=0.958 Bartlett's test of sph.=7894.421 Sig.=0.000 Total variance explained=85.432				
	α=0.977				
	x̄=3.11				
	α=0.965	α=0.946	α=0.958	α=0.868	
	x̄=3.32	x̄=2.78	x̄=3.18	x̄=3.10	
	χ^2= 551.580; DF=143; p=0.000; χ^2/DF=3.857				
	RMR=0.056; GFI=0.841; AGFI=0.788; PGFI=0.633; NFI=0.932; CFI=0.948; RFI=0.918; IFI=0.948; TLI=0.938; PNFI=0.779; RMSEA=0.095				

EFA: Exploratory factor analysis, CFA: Confirmatory factor analyses, SD: Standard deviation, KMO: Kaiser-Meyer-Olkin, DF: Degrees of freedom, RMR: Root mean square residual, TLI: Tucker–lewis index, AGFI: Adjusted goodness-of-fit index, NFI: Normed fit index, IFI: Incremental fit index, PGFI: Parsimonious goodness-of-fit index, RMSEA: Root mean square error of approximation, PNFI: Parsimonious normed fit index

Table 3. MAIR by age group (n=320)

Dimension	Age group (years)	n	x̄	SD	F	p
Cognitive factor	20-30	127	3.4016	1.15572	0.592	0.669
	31-40	71	3.3380	1.24944		
	41-50	76	3.2193	1.14219		
	51-60	33	3.3636	1.27778		
	61 and over	13	2.9615	1.31964		
Skill factor	20-30	127	2.8882	1.09360	1.394	0.236
	31-40	71	2.7634	0.98811		
	41-50	76	2.6816	0.97334		
	51-60	33	2.8485	1.20523		
	61 and over	13	2.2462	0.82119		
Forsight factor	20-30	127	3.2874	1.12681	0.746	0.561
	31-40	71	3.0775	1.16252		
	41-50	76	3.1075	1.09535		
	51-60	33	3.2424	1.20768		
	61 and over	13	2.8846	1.20451		
Ethics factor	20-30	127	3.0866	1.14970	1.202	0.310
	31-40	71	3.0563	1.11339		
	41-50	76	3.1250	1.14346		
	51-60	33	3.3788	1.15265		
	61 and over	13	2.5769	1.30458		
Total scale	20-30	127	3.2874	1.03264	0.881	0.475
	31-40	71	3.0749	1.07288		
	41-50	76	3.0325	1.00334		
	51-60	33	3.1914	1.09050		
	61 and over	13	2.7085	1.04969		

MAIR: Medical-AI readiness, SD: Standard deviation

Table 4. MAIR by gender

Dimension	Gender	n	x̄	SD	t	DF	p
Cognitive factor	Female	166	3.3665	1.15590	0.687	318	0.493
	Male	154	3.2749	1.22823			
Skill factor	Female	166	2.7783	1.00569	-0.052	318	0.959
	Male	154	2.7844	1.09629			
Forsight factor	Female	166	3.2048	1.12391	0.452	318	0.651
	Male	154	3.1472	1.15422			
Ethics factor	Female	166	3.1175	1.13073	0.307	318	0.759
	Male	154	3.0779	1.17034			
Total scale	Female	166	3.1344	1.00494	0.426	318	0.670
	Male	154	3.0848	1.08074			

MAIR: Medical-AI Readiness, SD: Standard deviation, DF: Degrees of freedom

Marital Status

Whether readiness varies by marital status was examined with another independent-samples t-test. The descriptive statistics and test results are displayed in Table 5.

Physicians' overall AI-readiness does not differ by marital status in any dimension ($p>0.05$), so H_3 is rejected.

Years in Practice

A One-Way ANOVA tested whether readiness varies across three seniority bands (1-10 y, 11-20 y, ≥21 y). Descriptive statistics and results appear in Table 6.

Only the foresight dimension shows a significant tenure-related difference: physicians with 1-10 years in practice are more optimistic than those with 11-20 years ($p<0.05$). No significant contrasts appear in the cognitive, skill, ethics, or composite MAIR scores, so H_4 is supported solely for the foresight factor.

Department

Whether physicians' levels of Medical AI Readiness (MAIR) differ according to their department of employment was examined using One-Way Analysis of Variance (ANOVA), and the findings are presented in Table 7.

Table 5. MAIR by marital status (n=320)

Dimension	Marital status	n	x̄	SD	t	DF	p
Cognitive factor	Married	173	3.2832	1.20831	-0.638	318	0.524
	Single	147	3.3685	1.17110			
Skill factor	Married	173	2.7699	1.05567	-0.209	318	0.835
	Single	147	2.7946	1.04369			
Forsight factor	Married	173	3.1233	1.15842	-0.917	318	0.360
	Single	147	3.2404	1.11226			
Ethics factor	Married	173	3.1358	1.18875	0.631	318	0.528
	Single	147	3.0544	1.10126			
Total scale	Married	173	3.0821	1.06568	-0.529	318	0.597
	Single	147	3.1439	1.01326			

MAIR: Medical-AI readiness, SD: Standard deviation, DF: Degrees of freedom

Table 6. MAIR by years of professional experience (n=320)

Dimension	Time (years)	n	x̄	SD	F	p	Pairwise comparison (mean difference)*
Cognitive factor	1-10 (a)	172	3.4012	1.19327	1.133	0.323	
	11-20 (b)	63	3.1402	1.20230			
	21+(c)	85	3.2980	1.17319			
Skill factor	1-10 (a)	172	2.8453	1.07738	1.336	0.264	
	11-20 (b)	63	2.5937	0.96317			
	21+(c)	85	2.7906	1.04558			
Forsight factor	1-10 (a)	172	3.2636	1.13425	3.059	0.048	a-b (0.40113)
	11-20 (b)	63	2.8624	1.13416			
	21+(c)	85	3.2353	1.11783			
Ethics factor	1-10 (a)	172	3.0610	1.13454	0.943	0.390	
	11-20 (b)	63	3.0079	1.09799			
	21+(c)	85	3.2412	1.21158			
Total scale	1-10 (a)	172	3.1756	1.04944	1.730	0.179	
	11-20 (b)	63	2.8947	1.02349			
	21+(c)	85	3.1387	1.02662			

MAIR: Medical-AI readiness, SD: Standard deviation

To test H_5, we ran a ANOVA on total MAIR and each sub-dimension across the hospital's four departmental clusters (internal medicine, surgical sciences, basic medical sciences, health sciences).

Post-hoc Analysis (Tukey)

Homogeneous subsets are indicated by letter codes, with the mean difference between significantly different pairs shown in parentheses within the same column. The ANOVA revealed that-with the exception of the ethics factor-all sub-dimensions and the overall MAIR score varied significantly across departments ($p<0.05$). Accordingly, H_5 is partially supported. Follow-up comparisons showed that: Physicians working in basic medical sciences achieved higher scores than their colleagues in internal medicine and surgical sciences on the total scale and on both the cognitive and skill factors. They also outperformed physicians in surgical sciences on the foresight factor. No departmental differences emerged for the ethics factor.

Table 7. MAIR levels by department

Dimension	Department	N	x̄	SD	F	p	Pairwise comparison (mean difference)
Cognitive factor	Internal medical sciences (a)	184	3.4067	1.15110	3.668	0.013	c-b (1.26846) c-a (0.98913)
	Surgical medical sciences (b)	123	3.1274	1.23568			
	Basic medical sciences (c)	8	4.3958	0.73968			
	Health sciences (d)	5	3.3000	1.01653			
Skill factor	Internal medical sciences (a)	184	2.8293	1.01066	3.632	0.013	c-a (0.97065) c-b (1.13659)
	Surgical medical sciences (b)	123	2.6634	1.07347			
	Basic medical sciences (c)	8	3.8000	1.20949			
	Health sciences (d)	5	2.2800	0.57619			
Forsight factor	Internal medical sciences (a)	184	3.2183	1.07472	3.041	0.029	c-b (1.19715)
	Surgical medical sciences (b)	123	3.0528	1.22815			
	Basic medical sciences (c)	8	4.2500	0.59761			
	Health sciences (d)	5	3.0000	0.87401			
Ethics factor	Internal medical sciences (a)	184	3.1196	1.13770	1.065	0.364	
	Surgical medical sciences (b)	123	3.0325	1.15719			
	Basic medical sciences (c)	8	3.7500	1.25357			
	Health sciences (d)	5	2.9000	1.14018			
Total scale	Internal medical sciences (a)	184	3.1650	1.00120	3.588	0.014	c-a (0.95995) c-b (1.15324)
	Surgical medical sciences (b)	123	2.9718	1.08742			
	Basic medical sciences (c)	8	4.1250	0.72925			
	Health sciences (d)	5	2.8947	0.82633			

MAIR: Medical-AI readiness, SD: Standard deviation

Discussion

Identifying physicians' MAIR via a web-based survey-and examining how that readiness varies across demographic strata-helps forecast both the likely pace of technology adoption and its eventual impact on diagnostic and therapeutic workflows. Because AI systems now permeate virtually every stage of health-care delivery, such insight is indispensable. The present analyses revealed no statistically significant differences ($p>0.05$) in overall readiness or any sub-dimension with respect to age, sex or marital status. These findings echo those of Çankaya[29], who likewise observed no demographic variation in either total MAIR scores or their sub-scales among emergency-service personnel. By contrast, AlZaabi et al.[21] reported significant discrepancies when comparing physicians with medical students-suggesting that mixed or trainee-inclusive samples may yield patterns that do not apply to practising doctors alone.

Length of professional experience influenced only the foresight dimension of readiness ($p<0.05$); no differences emerged for the other sub-scales. Hence, H_4 was partially supported. Post-hoc analysis showed that physicians with 1-10 years of service were significantly more optimistic than those with 11-20 years. Çankaya's[29], study of emergency-service staff found no tenure-related differences in either the overall scale or its sub-dimensions, whereas AlZaabi et al.[21] did report significant experience effects.

Analyses showed that, with the sole exception of the ethics sub-scale, every readiness dimension-and the total MAIR score-varied significantly by physicians' departmental affiliation ($p<0.05$); thus, H_5 is partially supported. Post-hoc Tukey comparisons reveal that physicians based in basic medical sciences score more favourably than their internal medicine and surgical sciences colleagues on the overall scale as well as on the cognitive and skill factors. They also outperform surgical-sciences physicians on the foresight factor. No departmental differences emerged for ethics. By contrast, Çankaya's[29], study of emergency-service staff detected no department-related variation in either the composite scale or its sub-dimensions.

The overall mean score for the scale was 3.11, indicating that participants' readiness for medical AI hovers just above the midpoint and can best be characterised as ambivalent. The same ambivalence holds across all four sub-dimensions. These findings align with several international studies[6,12], which likewise report mildly positive-yet still uncertain-attitudes among physicians. Although clinicians view AI favourably, gaps in conceptual understanding and hands-on technical training appear to hinder seamless adoption. Accordingly, we recommend embedding core content on AI, machine learning and ethical data use into both undergraduate and residency curricula. In parallel, national guidance that clarifies the legal framework surrounding medical AI is essential to ensure that technological advances proceed in harmony with health-policy objectives.

Study Limitations

Several constraints should be acknowledged. First, the investigation was limited to physicians working at University of Health Sciences Türkiye, İzmir City Hospital; future studies could widen the sample to encompass all hospitals in İzmir and include other health-care professionals in addition to physicians. Second, the demographic section of the questionnaire was restricted to a narrow set of variables-sex, age, marital status, department, years in practice, academic title, and social-media use-thereby excluding potentially relevant factors. Finally, owing to the large target population and the heavy workload within the hospital, data were collected online rather than through face-to-face administration.

Conclusion

This study offered a multidimensional assessment of physicians' readiness for medical-AI technologies at University of Health Sciences Türkiye, İzmir City Hospital in Türkiye. The analyses show that clinicians hold a moderately positive attitude toward AI, yet they exhibit clear deficits in technical knowledge and hands-on competence. Although their awareness of ethical and legal issues is slightly higher than in other domains, that knowledge remains largely theoretical and has not yet translated into the practical skills needed to evaluate, select or integrate AI systems effectively. In broad terms, the present results are consistent with much of the international literature, even if a few discrepancies emerge across individual studies.

This shortfall can undermine both the effective use of management- and clinical-decision-support systems and the quality of physician–patient–technology communication. A lack of familiarity with algorithmic logic, data types, model-training workflows and system limitations may also erode clinicians' trust in AI-based tools. In this light, technological adaptation must be treated not merely as the installation of new devices but as a broader cognitive and cultural transformation. To raise physicians' AI readiness, we recommend the following:

1. Curricular integration – embed core content on algorithm design, machine learning and data ethics in undergraduate and specialty-training syllabi.

2. Continuous professional development – offer regular digital-literacy workshops that focus on hands-on use of AI platforms.

3. Specialty-specific guidance – develop branch-tailored clinical AI guidelines to help physicians select and evaluate tools relevant to their fields.

4. Legal and ethical frameworks – establish national regulations that clarify accountability, data governance and malpractice boundaries for medical AI.

5. Collaborative decision-support models – integrate AI modules into existing clinical-decision workflows so that algorithms and physicians function as partners rather than substitutes.

6. Digital health-communication training – equip clinicians with strategies for explaining AI-assisted care to patients in clear, accessible language.

Treating AI adoption as a composite of technical proficiency, ethical competence and cultural change will position health professionals-and the systems they serve-to realise the full potential of AI in clinical practice.

Ethics

Ethics Committee Approval: Ethical approval for the study was granted by the University of Health Sciences Türkiye, İzmir City Hospital Social Research Ethics Committee (decision no: 2025/193, dated: 18 April 2025), and data collection commenced only after this clearance had been obtained.

Informed Consent: Physicians who agreed to participate in the study were informed about the study and their consent was obtained.

Footnotes

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

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