ORIGINAL ARTICLE / ÖZGÜN ARAŞTIRMA

DOI: 10.4274/tjcamh.galenos.2026.95530

Turk J Child Adolesc Ment Health

Self-Reported Medical Artificial Intelligence Readiness in Residents: Attitudes, Anxiety, and Interprofessional Identity

Uzmanlık Öğrencilerinde Öz Bildirime Dayalı Tıbbi Yapay Zeka Hazırbulunuşluğu: Tutum, Kaygı ve Meslekler Arası Kimlik

Yasemin İmrek, Mesut Sarı

Bolu Abant İzzet Baysal University Faculty of Medicine, Department of Child and Adolescent Psychiatry, Bolu, Türkiye

ABSTRACT

Objectives: Resident physicians increasingly encounter artificial intelligence (AI), but perceived readiness may reflect attitudes and other self-assessments as well as exposure to AI. This exploratory study examined self-reported medical AI readiness in relation to AI attitudes, AI anxiety, interprofessional identity, and prior AI- or health-technology-related training.

Materials and Methods: In this single-center cross-sectional online survey, all 136 residents in psychiatry, child and adolescent psychiatry, pediatrics, and family medicine at a university-affiliated training hospital in Türkiye were invited; 84 participated (61.8%). Associations among scale totals were examined using Spearman correlations with bootstrapped 95% confidence intervals (CIs) and Benjamini-Hochberg correction. A theory-informed post-hoc regression model and sensitivity analyses were used to examine independent associations with readiness.

Results: Mean scores were 64.77 [standard deviation (SD) 16.40] for medical AI readiness, 112.74 (SD 17.67) for AI attitudes, 45.90 (SD 8.71) for interprofessional identity, and 70.43 (SD 27.63) for AI anxiety. AI attitudes correlated with readiness (ρ=0.32, 95% CI 0.11-0.50, q=0.018), interprofessional identity (ρ=0.26, q=0.038), and AI anxiety (ρ=-0.29, q=0.020). In the regression model, more positive attitudes were associated with higher readiness (b=0.33, standardized β=0.36, 95% CI 0.11-0.55, p=0.004); estimates for anxiety, interprofessional identity, and prior training were imprecise. The attitude coefficient remained positive in sensitivity analyses examining influential observations, robust standard errors, and adjustment for demographic characteristics and specialty.

Conclusion: More positive AI attitudes were associated with higher self-reported medical AI readiness in this single-center sample. Partial construct overlap and common-method variance may contribute to this association. The findings do not establish objective competence or causality; prospective studies using observed performance should evaluate clinically grounded AI education.

Keywords: Artificial intelligence, specialty training, medical education, attitudes of healthcare personnel, anxiety, interprofessional relationships

ÖZ

Amaç: Uzmanlık öğrencileri giderek daha sık yapay zeka (YZ) uygulamalarıyla karşılaşmaktadır; ancak algılanan hazırbulunuşluk, YZ'ye maruz kalmanın yanı sıra tutumları ve diğer öz değerlendirmeleri de yansıtabilir. Bu keşfedici çalışmada, öz bildirime dayalı tıbbi YZ hazırbulunuşluğunun YZ'ye yönelik tutum, YZ kaygısı, meslekler arası kimlik ve daha önce alınmış YZ/sağlık teknolojileri eğitimiyle ilişkisi incelenmiştir.

Gereç ve Yöntem: Tek merkezli, kesitsel bu çevrimiçi anket çalışmasına, Türkiye'deki üniversiteye bağlı bir eğitim ve araştırma hastanesinin psikiyatri, çocuk ve ergen psikiyatrisi, çocuk sağlığı ve hastalıkları ile aile hekimliği uzmanlık programlarındaki 136 uzmanlık öğrencisinin tamamı davet edilmiş; bunların 84'ü katılmıştır (%61,8). Ölçek toplam puanları arasındaki ilişkiler Spearman korelasyon analizi, bootstrap yöntemiyle hesaplanan %95 güven aralıkları (GA) ve Benjamini-Hochberg düzeltmesi ile değerlendirilmiştir. Hazırbulunuşlukla bağımsız ilişkiler, kuram temelli post-hoc regresyon modeli ve duyarlılık analizleriyle incelenmiştir.

Bulgular: Ortalama puanlar; tıbbi YZ hazırbulunuşluğu için 64,77 [standart sapma (SS) 16,40], YZ tutumu için 112,74 (SS 17,67), meslekler arası kimlik için 45,90 (SS 8,71) ve YZ kaygısı için 70,43 (SS 27,63) olarak bulunmuştur. YZ tutumu; hazırbulunuşluk (ρ=0,32, %95 GA 0,11-0,50, q=0,018), meslekler arası kimlik (ρ=0,26, q=0,038) ve YZ kaygısı (ρ=-0,29, q=0,020) ile ilişkili bulunmuştur. Regresyon modelinde daha olumlu tutum, daha yüksek hazırbulunuşlukla ilişkili bulunmuştur (b=0,33, standardize β=0,36, %95 GA 0,11-0,55, p=0,004); kaygı, meslekler

Address for Correspondence/Yazışma Adresi: Asst. Prof. Dr. Yasemin İmrek, Bolu Abant İzzet Baysal University Faculty of Medicine, Department of Child and Adolescent Psychiatry, Bolu, Türkiye

E-mail: dr.yaseminimrek@gmail.com **ORCID:** orcid.org/0000-0002-7925-6783

Received/Geliş Tarihi: 05.10.2026 **Accepted/Kabul Tarihi:** 14.10.2026 **Epub:** 05.11.2026

Cite this article as/Atıf: İmrek Y, Sarı M. Self-reported medical artificial intelligence readiness in residents: attitudes, anxiety, and interprofessional identity. Turk J Child Adolesc Ment Health. [Epub Ahead of Print]

Copyright © 2026 by the Author(s). Published by Galenos Publishing House on behalf of the Turkish Association of Child and Adolescent Psychiatry.
This is an open access article licensed under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0) License.

ÖZ

arası kimlik ve önceki eğitime ilişkin kestirimlerin kesinliği düşüktü. Tutum katsayısı; etkili gözlemlerin incelendiği, dirençli (robust) standart hataların kullanıldığı ve demografik özellikler ile uzmanlık alanına göre düzeltme yapılan duyarlılık analizlerinde pozitif kalmıştır.

Sonuç: Bu tek merkezli örneklemde daha olumlu YZ tutumu, öz bildirime dayalı tıbbi YZ hazırbulunuşluğunun daha yüksek olmasıyla ilişkiliydi. Yapılar arasındaki kısmi kavramsal örtüşme ve ortak yöntem varyansı bu ilişkiye katkıda bulunmuş olabilir. Bulgular, nesnel yeterliliği veya nedensel bir ilişkiyi göstermemektedir; klinik temelli YZ eğitimi, gözlemlenen performansı ölçen ileriye dönük çalışmalarla değerlendirilmelidir.

Anahtar Kelimeler: Yapay zeka, uzmanlık eğitimi, tıp eğitimi, sağlık personelinin tutumu, kaygı, meslekler arası ilişkiler

Introduction

Artificial intelligence (AI) is increasingly used in healthcare for diagnostic classification, risk prediction, monitoring, clinical decision support, and education. In psychiatry and mental healthcare, AI-supported approaches have been investigated across diagnosis, monitoring, and intervention, while questions remain about clinical utility, patient safety, governance, and ethical implementation.[1,2] Medical education faces a parallel challenge: clinicians must understand not only how AI systems may support practice, but also their limitations, data requirements, potential biases, and appropriate role in human decision-making.[3,4]

Preparedness for medical AI is broader than frequency of technology use. The Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS) conceptualizes perceived readiness across cognition, ability, vision, and ethics.[5] Validation studies in several languages have supported this multidimensional structure,[6,7] while surveys of medical and health-professions students commonly report substantial interest alongside limited formal instruction and varying levels of perceived preparedness.[8,9] Studies of postgraduate trainees similarly report educational gaps and concerns about responsible clinical integration.[10-12]

In the conceptual model guiding this exploratory study, AI attitudes, AI anxiety, interprofessional identity, and previous training were treated as distinct candidate correlates of perceived readiness. Favorable attitudes may reflect willingness to learn, perceived usefulness, and confidence; anxiety may reflect learning demands, job displacement, sociotechnical risks, and human-like AI configurations.[13-16] Previous training may provide exposure to relevant concepts, although heterogeneous training cannot be assumed to represent a standardized curriculum. The present study tested only direct associations. It was not designed or powered to evaluate mediation, moderation, or indirect pathways.

Interprofessional identity was included because clinical AI is implemented within team-based care rather than by isolated users. Extended professional identity theory describes belonging, commitment, and beliefs concerning collaborative practice.[17-20] AI-supported decisions may redistribute information, roles, accountability, and communication across clinical teams. Interprofessional identity could therefore relate to openness toward new team-mediated technologies, although it is not itself a measure of technological competence. This rationale remains tentative in a sample consisting exclusively of physicians, and direct evidence remains limited. Consistent with this, an international study of mental health practitioners emphasized psychological, ethical, and professional factors in intentions to adopt AI-enabled technologies.[21]

The four departments were selected a priori because they had established clinical and educational collaboration at the study center and collectively represented mental healthcare, child-focused care, and longitudinal generalist care. These contexts rely heavily on communication, shared decision-making, and coordination across professional boundaries, while emerging postgraduate literature highlights AI-related educational needs in pediatrics and across resident groups.[12,22] The selection was not intended to represent all residency programs or technology-intensive specialties.

The primary objective was to examine whether AI attitudes, AI anxiety, interprofessional identity, and broadly defined prior AI- or health-technology-related training were independently associated with self-reported medical AI readiness. Secondary objectives were to describe self-reported AI exposure and training, examine pairwise relationships among the four constructs, and evaluate consistency between MAIRS-MS and a single global self-rating of clinical AI preparedness. Because the study had no preregistered hypotheses or confirmatory analysis plan, all inferential analyses are described as exploratory.

Materials and Methods

Design and Setting

This single-center cross-sectional online survey was conducted from April 1 to May 1, 2026, at Bolu Abant İzzet Baysal University-affiliated training and research hospital in Türkiye. The survey constituted the quantitative component of the project. An optional qualitative follow-up had been considered when the original survey form was developed, but it was not undertaken; no qualitative data were collected or analyzed.

Participants, Sampling, and Survey Administration

Eligibility required active residency in psychiatry, child and adolescent psychiatry, pediatrics, or family medicine at the study institution and voluntary electronic informed consent. No additional inclusion or exclusion criteria were applied. Other residency programs existed at the center but were outside the a priori sampling frame. The four included departments were selected because of established clinical and educational collaboration and their shared involvement in mental health, child-focused, and longitudinal generalist care. All 136 eligible residents in the selected departments were invited: 18 in

child and adolescent psychiatry, 27 in pediatrics, 73 in family medicine, and 18 in psychiatry.

Each eligible resident received an individually generated Google Forms survey link, distributed once by the research team. Google account-based "limit to 1 response" functionality was enabled. Google account identifiers and IP addresses were not collected, stored, or visible in the research dataset. Electronic informed consent was mandatory before the form could advance. All 84 respondents provided electronic informed consent and complete scale data and were included in the analysis. No respondent was excluded because of incomplete responses or for any other reason; no imputation was required. The overall response rate was 61.8%: child and adolescent psychiatry, 18/18 (100%); pediatrics, 17/27 (63.0%); family medicine, 36/73 (49.3%); and psychiatry, 13/18 (72.2%).

A yes/no item asked about willingness to participate in a possible qualitative follow-up. Contact information, when volunteered, was collected through a separate form and was not linked to the survey dataset. The qualitative follow-up was not conducted and the item was not analyzed.

Sociodemographic and AI-Exposure Form

The form recorded age, self-reported sex, marital status, childhood residential setting, medical school, graduation year, residency start year, department, residency year, daily professional digital-device use, the frequency and purposes of using tools that participants perceived as AI-based, prior AI- or health-technology-related training, and a single global preparedness item. Professional device use was recorded in five categories (<1, 1-2, 3-4, 5-6, or ≥7 hours/day). AI-use frequency ranged from never to almost daily. Participants could select more than one purpose of use: medical information/clinical queries, academic writing/literature searching, patient-education materials, clinical decision support, and personal/everyday use.

The questionnaire provided examples of general-purpose tools (ChatGPT, Gemini, and Copilot) but did not record application names or define "clinical decision support." Consequently, all exposure findings represent participant-interpreted purposes rather than verified use of regulated clinical systems or use during patient care. The training item asked whether participants had received "AI/health-technology" education in medical school, residency, both, or through an independent online course. No definition was provided for qualifying training; no participant selected the independent-course option. The global item asked, "How ready do you generally feel to use AI in clinical practice?" with responses ranging from 1 (not at all ready) to 5 (fully ready).

Measures

Medical Artificial Intelligence Readiness Scale for Medical Students (MAIRS-MS)

The 22-item MAIRS-MS assesses perceived readiness across cognition (items 1-8), ability (items 9-16), vision (items 17-19), and ethics (items 20-22), using a 5-point response format. Total scores range from 22 to 110, with higher scores indicating greater perceived readiness.[5] The validated Turkish wording was administered without modification. Although developed for medical students, it was selected as a structured multidimensional self-report measure; its psychometric properties in residents remain to be established.

Artificial Intelligence Attitude Scale

This 29-item Turkish instrument assesses interest in learning about AI, reluctance to adopt AI, belief in AI capabilities, and resistance to AI.[23] Items are rated from 1 to 5. Items 10-16 and 24-29 are reverse-scored so that higher total scores indicate more positive attitudes. Possible total scores range from 29 to 145. Several items concern interest, confidence, or favorable self-appraisal; these domains are conceptually distinct from medical AI readiness but may partially overlap with MAIRS-MS self-perceptions.

Extended Professional Identity Scale-Turkish (EPIS-TR)

The 12-item EPIS-TR assesses interprofessional belonging, commitment, and beliefs using a 5-point response format. No items are reverse-scored; total scores range from 12 to 60, with higher scores indicating stronger interprofessional identity.[18,19] It was validated in multidisciplinary health-professions samples rather than an exclusively physician resident sample.

Artificial Intelligence Anxiety Scale

The Turkish 21-item scale uses a 7-point response format and assesses learning anxiety (items 1-8), job-replacement anxiety (items 9-14), sociotechnical-blindness anxiety (items 15-18), and AI-configuration anxiety (items 19-21). Total scores range from 21 to 147, with higher scores indicating greater anxiety.[13,24]

Statistical Analysis

Scale scores were calculated according to published instructions. Internal consistency was assessed using Cronbach's α and McDonald's ω total for the full scales and subscales after reverse scoring. These coefficients were treated as reliability estimates, not evidence of construct validity. Continuous variables are summarized as means [standard deviations (SDs)] and medians (interquartile ranges), and categorical variables with counts and percentages.

Pairwise associations among the four scale totals were evaluated using Spearman correlations. Bootstrap 95% confidence intervals (CIs) were estimated using 5,000 resamples. Benjamini-Hochberg false discovery rate (FDR) correction was applied across the six pairwise correlations.[25] The global preparedness item was analyzed separately because of semantic overlap with MAIRS-MS. Exploratory correlations between four AI-attitude and four MAIRS-MS subscales formed a separate 16-test family with Benjamini-Hochberg correction.

A theory-informed post-hoc multiple linear regression used MAIRS-MS total score as the dependent variable and AI-attitude total, AI-anxiety total, EPIS-TR total, and any previous AI/health-technology training (0=no; 1=any) as predictors. The global preparedness item was excluded because of conceptual

overlap. The intercept, unstandardized and standardized coefficients, 95% CIs, and model-fit statistics are reported. Coefficient-level q-values were calculated with Benjamini-Hochberg correction across the four focal predictors.

Diagnostic assessments included residual and quantile-quantile (Q-Q) plots, the Shapiro-Wilk test, the Breusch-Pagan test, variance inflation factors (VIFs), standardized residuals, leverage, Cook's distance, and exploratory quadratic terms for continuous predictors. Sensitivity analyses used type 3 heteroscedasticity-consistent (HC3) robust standard errors, removed the observation with the largest Cook distance, adjusted for age, sex, and residency year, and added specialty as a categorical fixed covariate (with child and adolescent psychiatry as the reference category). Specialty and subscale analyses were exploratory and not used to generate confirmatory claims.

All eligible residents in the selected departments were invited; recruitment was not based on an a priori power calculation. A sensitivity calculation for the achieved N=84 indicated 80% power at two-sided $\alpha=0.05$ to detect approximately $|\rho|=0.30$ and, for a four-predictor regression, Cohen $f^2=0.15$. Smaller associations and subgroup effects could therefore remain undetected. Retrospective observed power was not calculated. Analyses were conducted in IBM SPSS Statistics 26.0 (IBM Corp., Armonk, NY, USA). The bootstrap seed was 20260805. Reporting followed STROBE and CHERRIES guidance.[26,27]

Ethics

The Bolu Abant İzzet Baysal University Non-Interventional Clinical Research Ethics Committee approved the study (approval no: 2026/120; date: March 24, 2026). The study followed the Declaration of Helsinki. Electronic informed consent was obtained before survey access. Google account identifiers, IP addresses, and direct identifiers were not retained in the analytic dataset.

Results

Participant Characteristics, Response, and AI Exposure

Of 136 invited residents, 84 participated (61.8%). Response rates varied by department: 100% in child and adolescent psychiatry, 72.2% in psychiatry, 63.0% in pediatrics, and 49.3% in family medicine. Mean age was 28.30 years (SD 2.42; range 25-37); 52 participants (61.9%) were female. Family medicine accounted for 42.9% of respondents, followed by child and adolescent psychiatry (21.4%), pediatrics (20.2%), and psychiatry (15.5%).

One participant (1.2%) reported never using tools perceived as AI-based, 7 (8.3%) use a few times per month, 31 (36.9%) use several times per week, and 45 (53.6%) almost-daily use. The most frequent self-reported purposes were personal/everyday tasks (91.7%), medical information/clinical queries (85.7%), and academic writing/literature searching (64.3%). Sixty-nine participants (82.1%) reported no prior training; 2 reported training in medical school, 11 during residency, and 2 in both settings. These categories do not indicate training content or effectiveness (Table 1).

Reliability, Correlations, and Global Preparedness

Mean total scores were 64.77 (SD 16.40) for MAIRS-MS, 112.74 (SD 17.67) for AI attitudes, 45.90 (SD 8.71) for EPIS-TR, and 70.43 (SD 27.63) for AI anxiety. The α/ω coefficients for total scores were 0.957/0.957, 0.932/0.932, 0.930/0.929, and

Table 1. Sociodemographic and self-reported AI-exposure characteristics (N=84)

Variable	n (%) or mean ± SD (range)
Age, years	28.30±2.42 (25-37)
Self-reported sex	
Female	52 (61.9)
Male	32 (38.1)
Marital status	
Married	45 (53.6)
Single	38 (45.2)
Divorced/separated	1 (1.2)
Specialty	
Family medicine	36 (42.9)
Child and adolescent psychiatry	18 (21.4)
Pediatrics	17 (20.2)
Psychiatry	13 (15.5)
Residency year	
First	39 (46.4)
Second	20 (23.8)
Third	12 (14.3)
Fourth	10 (11.9)
Fifth or higher	3 (3.6)
Self-reported AI-tool use frequency	
Never	1 (1.2)
Rarely (a few times per month)	7 (8.3)
Several times per week	31 (36.9)
Almost daily	45 (53.6)
Prior AI/health-technology training	
None	69 (82.1)
Medical school	2 (2.4)
Residency	11 (13.1)
Both medical school and residency	2 (2.4)
AI-use purposes (multiple selections)	
Personal/everyday use	77 (91.7)
Medical information/clinical queries	72 (85.7)
Academic writing/literature searching	54 (64.3)
Clinical decision support	39 (46.4)
Patient-education materials	24 (28.6)

Percentages for AI-use purposes were calculated using the full sample (N=84). Participants could select multiple responses, so these percentages may sum to more than 100%. "Clinical decision support" was not defined; reported purposes reflect participants' interpretations and do not verify application type or use in patient care

AI: Artificial intelligence, SD: Standard deviation, n: Number of participants, N: Total sample size

0.958/0.959, respectively. Coefficients above 0.95 for MAIRS-MS and AI anxiety may reflect high consistency but also possible item redundancy. Subscale reliability estimates are provided in Supplementary Table S1 (Table 2).

After FDR correction, MAIRS-MS was associated with AI attitudes (ρ=0.32, 95% CI 0.11-0.50, q=0.018). AI attitudes were associated with EPIS-TR (ρ=0.26, 95% CI 0.02-0.47, q=0.038) and inversely with AI anxiety (ρ=-0.29, 95% CI -0.48 to -0.09, q=0.020). The CIs for the remaining correlations included zero. In the exploratory subscale analysis, three of 16 associations remained statistically significant after FDR correction: interest with MAIRS-MS cognition and ability, and belief in AI capabilities with MAIRS-MS ethics (Supplementary Material). This pattern indicates that the total-score association is not uniform across domains and may partly reflect overlapping favorable self-appraisals (Table 3).

Responses to the global preparedness item were: 1, n=5; 2, n=16; 3, n=35; 4, n=23; and 5, n=5. The item was associated with MAIRS-MS (ρ=0.38, 95% CI 0.16-0.57, p<0.001). Because both are self-ratings with similar wording, this finding indicates consistency between two self-reported indicators rather than independent validation or objective preparedness.

Exploratory Multivariable Associations and Diagnostics

The four-predictor model was statistically significant, $F(4,79)=3.77$, $p=0.007$, $R^2=0.160$, adjusted $R^2=0.118$. More positive AI attitudes were associated with higher MAIRS-MS scores (b=0.330, standardized β=0.356, 95% CI 0.112-0.548, p=0.004, q=0.014). Estimates for AI anxiety, EPIS-TR, and broadly defined previous training were imprecise and included zero; they should not be interpreted as evidence of no association (Table 4).

Diagnostic results were as follows: VIF 1.04-1.31; Shapiro-Wilk p=0.648; Breusch-Pagan p=0.109; maximum leverage=0.163; maximum absolute standardized residual=2.78; and maximum Cook's distance=0.220. Six observations exceeded 4/N for

Table 2. Descriptive statistics and internal consistency of scale total scores

Scale	Possible range	Mean (SD)	Median (IQR)	Observed range	Cronbach α	McDonald ω
MAIRS-MS total	22-110	64.77 (16.40)	66.00 (22.25)	22-100	0.957	0.957
AI attitude total	29-145	112.74 (17.67)	114.50 (22.00)	60-145	0.932	0.932
EPIS-TR total	12-60	45.90 (8.71)	46.00 (12.00)	21-60	0.930	0.929
AI anxiety total	21-147	70.43 (27.63)	66.50 (42.50)	21-147	0.958	0.959

Reliability coefficients describe score consistency in this sample and do not establish construct validity in residents
AI: Artificial intelligence, MAIRS-MS: Medical Artificial Intelligence Readiness Scale for medical students, EPIS-TR: Extended Professional Identity Scale-Turkish, SD: Standard deviation, IQR: Interquartile range, α: Cronbach's alpha, ω: McDonald's omega total

Table 3. Spearman correlations among scale total scores with bootstrap 95% CIs

Pair	ρ	95% CI	p	FDR q
MAIRS-MS-AI attitudes	0.32	0.11 to 0.50	0.003	0.018
MAIRS-MS-EPIS-TR	0.11	-0.13 to 0.32	0.340	0.510
MAIRS-MS-AI anxiety	-0.07	-0.31 to 0.16	0.504	0.605
AI attitudes-EPIS-TR	0.26	0.02 to 0.47	0.019	0.038
AI attitudes-AI anxiety	-0.29	-0.48 to -0.09	0.007	0.020
EPIS-TR-AI anxiety	0.01	-0.21 to 0.23	0.959	0.959

CIs were estimated using 5,000 bootstrap resamples. The Benjamini-Hochberg procedure was applied across the six correlations
AI: Artificial intelligence, MAIRS-MS: Medical Artificial Intelligence Readiness Scale for medical students, EPIS-TR: Extended Professional Identity Scale-Turkish, CI: Confidence interval, FDR: False discovery rate, ρ: Spearman's rank correlation coefficient, p: Unadjusted p-value; q: FDR-adjusted p-value

Table 4. Theory-informed post-hoc regression of MAIRS-MS total score (N=84)

Predictor	b	SE	β	95% CI	p	FDR q
Intercept	20.196	14.755	—	-9.172 to 49.565	0.175	—
AI attitude total	0.330	0.110	0.356	0.112 to 0.548	0.004	0.014
AI anxiety total	-0.011	0.066	-0.019	-0.143 to 0.120	0.865	0.865
EPIS-TR total	0.169	0.211	0.090	-0.252 to 0.590	0.427	0.796
Any prior training	2.378	4.478	0.056	-6.536 to 11.291	0.597	0.796

b and β represent unstandardized and standardized regression coefficients, respectively. SEs and 95% CIs refer to b. p denotes the unadjusted p-value, and q denotes the FDR-adjusted p-value. The Benjamini-Hochberg procedure was applied across the four focal predictors. Prior AI/health-technology training was coded as 0=none and 1=any. The intercept is reported; dashes indicate values that are not applicable
AI: Artificial intelligence, MAIRS-MS: Medical Artificial Intelligence Readiness Scale for medical students, EPIS-TR: Extended Professional Identity Scale-Turkish, CI: Confidence interval, FDR: False discovery rate, SE: Standard error, N: Total sample size

Cook distance, six exceeded 2p/N for leverage, and two had |standardized residual|>2. Quadratic terms did not reach statistical significance at the 0.05 level (p=0.165 for attitudes, 0.062 for anxiety, and 0.054 for EPIS-TR), although the latter values warrant caution and do not establish strict linearity. The attitude estimate remained positive when the most influential observation was removed (b=0.417, 95% CI 0.199-0.634, p<0.001), with HC3 standard errors (b=0.330, 95% CI 0.064-0.596, p=0.016), after demographic adjustment (b=0.311, 95% CI 0.092-0.531, p=0.006), and after specialty adjustment (b=0.304, 95% CI 0.091-0.518, p=0.006). Full results of the sensitivity analyses are presented in Supplementary Material.

Discussion

In this exploratory single-center sample of residents from four specialties, AI attitudes were associated with self-reported medical AI readiness. The association was modest and remained positive across several sensitivity analyses. Anxiety, interprofessional identity, and broadly measured previous training had estimates that were too imprecise to establish either meaningful associations or their absence. The achieved sample had limited sensitivity to effects smaller than approximately |ρ|=0.30 and to heterogeneous subgroup differences.

The principal finding requires careful consideration of the constructs being measured. MAIRS-MS asks respondents to appraise their knowledge, ability, vision, and ethical preparedness, whereas the attitude scale includes willingness to learn, confidence in AI capabilities, and resistance. These constructs are not identical, but both can contain favorable self-appraisal, interest, and generalized positive responding. The subscale analysis suggested domain-specific rather than uniform overlap. Nevertheless, measurement from a common source, simultaneous administration, similar response formats, social desirability, acquiescence, and generalized positive-response tendencies may inflate associations among self-reported constructs.[28] The coefficient therefore does not show that changing attitudes will cause readiness to improve.

AI anxiety was inversely associated with attitudes but not independently with readiness. This is compatible with, but does not test, an indirect pathway through attitudes or acceptance.[15,16] Mediation and moderation were not examined because they were not prespecified and N=84 would yield unstable estimates. Similarly, EPIS-TR was related to attitudes but not independently to readiness. Interprofessional identity concerns collaborative belonging, commitment, and beliefs rather than technological competence; its role may be more relevant when AI changes shared workflows or accountability. Its interpretation is restricted because all participants were physicians and EPIS-TR was validated in multidisciplinary samples.

The training result is inconclusive. Only 15 participants reported any training, the item combined AI with health technology, no definition of qualifying training was provided, and content, duration, recency, depth, and assessment were not recorded. It therefore cannot evaluate curriculum effectiveness. Contemporary competency frameworks emphasize AI foundations, patient-centered use, ethics, privacy, security, bias, health equity, data science, application skills, and observable performance rather than exposure alone.[29,30] These domains should be evaluated in prospective curricula using knowledge tests, structured clinical tasks, critical-appraisal exercises, and behavioral outcomes.

Participants frequently reported using tools they perceived as AI-based, but the survey named general-purpose tools and did not identify applications or define "clinical decision support." Information retrieval, drafting assistance, diagnostic recommendations, risk prediction, and regulated clinical decision-support software differ in validation, oversight, and risk. The present data therefore describe participants' interpretations of their purposes of use; they do not establish clinical AI adoption, patient-care use, or safe performance.

The association between MAIRS-MS and the global preparedness item represents consistency between semantically related self-ratings, not validation against an external criterion. Physician self-assessment can diverge from observed competence.[31] High perceived readiness could coexist with miscalibration, unrecognized knowledge gaps, automation bias, or unsafe use. Educational evaluation should therefore examine whether training improves knowledge, calibration, critical appraisal, ethical reasoning, and supervised performance, not merely whether self-reported readiness increases.

The four specialties were selected because of established local collaboration and shared involvement in mental health, child-focused, and longitudinal generalist care. This sampling frame enabled all eligible residents to be invited but limits transferability. Pediatrics has an emerging postgraduate AI education literature,[12] and residents across specialties identify humanistic, ethical, and responsibility-related concerns.[22] However, the present sample did not include surgery, radiology, emergency medicine, laboratory specialties, or other technology-intensive fields. Differences in response rates, particularly the lower response rate in family medicine, could bias estimates if respondents differed in AI exposure or educational culture. Specialty adjustment did not materially alter the attitude coefficient, but specialty estimates were exploratory and imprecise.

Practical and Research Implications

The study did not test an educational intervention. The implications therefore concern priorities for curriculum development rather than demonstrated educational effects. Future programs should address core AI concepts and performance metrics; data quality and dataset shift; bias and health inequities; privacy and cybersecurity; hallucinations and automation bias; explainability and uncertainty; human oversight and accountability; distinctions between generative tools and regulated clinical systems; documentation of AI-assisted work; and patient communication. Competency frameworks should be translated into objective, observed assessments and longitudinal outcomes.[29,30]

Study Limitations

This study has several limitations. It was conducted at one center in four purposively selected specialties, with varying departmental response rates and no individual-level information about non-respondents. The cross-sectional, non-preregistered design precludes temporal or causal inference. All focal constructs were measured in the same online survey, creating common-method, social-desirability, acquiescence, and self-assessment biases. No knowledge test, observed clinical task, behavioral indicator, or social-desirability scale was used. The readiness and attitude measures were developed in educational populations, and EPIS-TR in multidisciplinary samples; high reliability does not establish construct validity in residents, and α/ω values above 0.95 may reflect redundancy. Training exposure was broad, heterogeneous, and defined by participants. AI-use purposes were not application-specific, "clinical decision support" was undefined, and patient-care use was not verified. The modest sample limited precision for small effects, specialty comparisons, and complex pathways; CIs that include zero should not be interpreted as proof of no relationship.

Conclusion

More positive AI attitudes were associated with higher self-reported medical AI readiness among residents from four specialties at one center. Partial construct overlap and common-method variance may contribute to this association. Associations with anxiety, interprofessional identity, and heterogeneous previous training were estimated imprecisely. Multicenter longitudinal and educational-intervention studies should distinguish AI categories and use objective performance measures to determine whether structured education improves safe, calibrated, and responsible AI practice.

Ethics

Ethics Committee Approval: The Bolu Abant İzzet Baysal University Non-Interventional Clinical Research Ethics Committee approved the study (approval no: 2026/120; date: March 24, 2026).

Informed Consent: Electronic informed consent was obtained before survey access.

Footnotes

Authorship Contributions

Concept: Y.İ., Design: Y.İ., M.S., Data Collection or Processing: Y.İ., M.S., Analysis or Interpretation: Y.İ., M.S., Literature Search: Y.İ., Writing: Y.İ., M.S.

Conflict of Interest: The authors declared no conflicts of interest.

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

Supplementary Tables S1-S7 and Appendices S1-S2 Link: https://d2v96fxpocvxx.cloudfront.net/beb8919b-f013-4ea1-b1c8-40332e840fe1/content-images/fd274c82-5a34-4ac4-a0df-39fd50ee1bc9.pdf

References

1. Cruz-Gonzalez P, He AW, Lam EP, Ng IMC, Li MW, Hou R, Chan JN, Sahni Y, Vinas Guasch N, Miller T, Lau BW, Sánchez Vidaña DI. Artificial intelligence in mental health care: a systematic review of diagnosis, monitoring, and intervention applications. Psychol Med. 2025;55:e18.
2. Lee EE, Torous J, De Choudhury M, Depp CA, Graham SA, Kim HC, Paulus MP, Krystal JH, Jeste DV. Artificial intelligence for mental health care: clinical applications, barriers, facilitators, and artificial wisdom. Biol Psychiatry Cogn Neurosci Neuroimaging. 2021;6:856-864.
3. Gordon M, Daniel M, Ajiboye A, Uraiby H, Xu NY, Bartlett R, Hanson J, Haas M, Spadafore M, Grafton-Clarke C, Gasiea RY, Michie C, Corral J, Kwan B, Dolmans D, Thammasitboon S. A scoping review of artificial intelligence in medical education: BEME Guide No. 84. Med Teach. 2024;46:446-470.
4. Grunhut J, Wyatt AT, Marques O. Educating future physicians in artificial intelligence (AI): an integrative review and proposed changes. J Med Educ Curric Dev. 2021;8:23821205211036836.
5. 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.
6. Moodi Ghalibaf A, Moghadasin M, Emadzadeh A, Mastour H. Psychometric properties of the persian version of the medical artificial intelligence readiness scale for medical students (MAIRS-MS). BMC Med Educ. 2023;23:577.
7. Chen X, Chen Y, Xie Y, Cheng L. Translation and ps ychometric validation of the medical artificial intelligence readiness scale (MAIRS-MS) for Chinese medical students. BMC Nurs. 2025;24:1210.
8. Al Shahrani A, Alhumaidan N, AlHindawi Z, Althobaiti A, Aloufi K, Almughamisi R, Aldalbahi A. Readiness to embrace artificial intelligence among medical students in Saudi Arabia: a national survey. Healthcare (Basel). 2024;12:2504.
9. Almalki M, Alkhamis MA, Khairallah FM, Choukou MA. Perceived artificial intelligence readiness in medical and health sciences education: a survey study of students in Saudi Arabia. BMC Med Educ. 2025;25:439.
10. Al Kindi R, Al Salmani A, Hadhrami RA, Shaqsi JA, Hadhrami AA, Hatmi SA, Maashani MA. Knowledge, attitude, and perception of artificial intelligence among medical residents in Oman: readiness for clinical practice. BMC Med Educ. 2026;26:939.
11. Syeda AF, Alriyami F, Alshebli A, Alketbi M, Rahma A, Al-Houqani M. Preparing tomorrow's physicians for AI-driven healthcare: insights from a study on medical students', interns', and residents' knowledge, attitudes, and educational needs. Front Med (Lausanne). 2026;13:1799061.
12. Nadarajah A, Malekzadeh G, Ratnapalan S. The use of artificial intelligence in paediatric postgraduate medical education: a scoping review. Paediatr Child Health. 2025;30:694-704.
13. Wang YY, Wang YS. Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. Interactive Learning Environments. 2022;30:619-634.
14. El Arab RA, Alshakihs AH, Alabdulwahab SH, Almubarak YS, Alkhalifah SS, Abdrbo A, Hassanein S, Sagbakken M. Artificial intelligence in nursing: a systematic review of attitudes, literacy, readiness, and adoption intentions among nursing students and practicing nurses. Front Digit Health. 2025;7:1666005.

15. Ayed A, Ejheisheh MA, Al-Amer R, Aqtam I, Ali AM, Othman EH, Farajallah M, Qaddumi J, Batran A. Insights into the relationship between anxiety and attitudes toward artificial intelligence among nursing students. BMC Nurs. 2025;24:812.
16. Dönmez E, Temiz G, Mete B, Marangoz E, Ortabağ T. Artificial intelligence: readiness, attitudes, and AI-related anxiety among oncology nurses. Healthcare (Basel). 2026;14:848.
17. Reinders JJ, Krijnen W. Interprofessional identity and motivation towards interprofessional collaboration. Med Educ. 2023;57:1068-1078.
18. Reinders JJ, Lycklama À Nijeholt M, Van Der Schans CP, Krijnen WP. The development and psychometric evaluation of an interprofessional identity measure: extended professional identity scale (EPIS). J Interprof Care. 2025;39:818-830.
19. Kolcu G, Başer Kolcu Mİ, Krijnen W, Reinders JJ. Turkish translation and validation of an interprofessional identity measure: EPIS-TR. J Interprof Care. 2024;38:1117-1126.
20. Reinders JJ. When I say … Interprofessional identity. Med Educ. 2026;60:224-226.
21. Cecil J, Kleine AK, Lermer E, Gaube S. Mental health practitioners' perceptions and adoption intentions of AI-enabled technologies: an international mixed-methods study. BMC Health Serv Res. 2025;25:556.
22. McFarlane A, Sadri S, Schwartz E, Gowda D. Resident physicians' perceptions of artificial intelligence and implications for medical education: a qualitative study. MedEdPublish (2016). 2025;15:29.
23. Alan B, Kırbağ Zengin F, Keçeci G. Yapay zekâ tutum ölçeği (YZTÖ): geçerlik ve güvenirlik çalışması. Cumhuriyet Int J Educ. 2024;13:789-800.
24. Terzi R. An adaptation of artificial intelligence anxiety scale into Turkish: reliability and validity study. Int Online J Educ Teach. 2020;7:1501-1515.
25. Benjamini Y, Hochberg Y. Controlling the false discovery rate: a practical and powerful approach to multiple testing. J R Stat Soc Series B Stat Methodol. 1995;57:289-300.
26. von Elm E, Altman DG, Egger M, Pocock SJ, Gøtzsche PC, Vandenbroucke JP; STROBE Initiative. The strengthening the reporting of observational studies in epidemiology (STROBE) statement: guidelines for reporting observational studies. Lancet. 2007;370:1453-1457.
27. Eysenbach G. Improving the quality of web surveys: the checklist for reporting results of internet e-surveys (CHERRIES). J Med Internet Res. 2004;6:e34.
28. Podsakoff PM, MacKenzie SB, Podsakoff NP. Sources of method bias in social science research and recommendations on how to control it. Annu Rev Psychol. 2012;63:539-569.
29. Car J, Ong QC, Erlikh Fox T, Leightley D, Kemp SJ, Švab I, Tsoi KKF, Sam AH, Kent FM, Hertelendy AJ, Longhurst CA, Powell J, Hamdy H, Nguyen HVQ, Aoun Bahous S, Wang M, Baumgartner M, Mahendradhata Y, Popovic N, Khong AWH, Prober CG, Atun R; Digital Health Systems Collaborative; Bekele Zerihun A, Poncette AS, Molina AJR, Ferreira AVL, Fajkic A, Kaushal A, Farmer AJ, Lane AS, Kononowicz AA, Bhongir AV, Alayande BT, Bene BA, Dameff CJ, Hallensleben C, Back DA, Hawezy DJ, Tulantched DSM, Kldiashvili E, Achampong EK, Ramachandran G, Hauser G, Grove J, Cheung JPY, Imaralu JO, Sotunsa JO, Bulnes Vides JP, Lawrence KS, Agha-Mir-Salim L, Saba L, Zhang L, Elfiky MMA, Hesseling MW, Guppy MP, Phatak MS, Al Saadoon MAA, Lai NM, Chavannes NH, Kimberger O, Povoa P, Goh PS, Grainger R, Nannan Panday RS, Forsyth R, Vento S, Lee SY, Yadav SK, Syed-Abdul S, Appenzeller S, Denaxas S, Garba SE, Flügge T, Bokun T, Dissanayake VHW, Ho V, Obadiel YA. The digital health competencies in medical education framework: an international consensus statement based on a Delphi study. JAMA Netw Open. 2025;8:e2453131.
30. Cai C, Zhu G, Zhou SM, Ng O, Duell J, Ho WK, Chen DM, Lee B, Li F, Liu S, Sudarshan V, Wang LR, Choi C, Fan X. A competency framework for medical AI education: mixed methods study. JMIR Med Educ. 2026;12:e91116.
31. Davis DA, Mazmanian PE, Fordis M, Van Harrison R, Thorpe KE, Perrier L. Accuracy of physician self-assessment compared with observed measures of competence: a systematic review. JAMA. 2006;296:1094-1102.