

ORIGINAL RESEARCH ARTICLE

Perceived barriers to artificial intelligence integration among Moroccan public health care professionals: A cross-sectional study

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Abstract

Artificial intelligence (AI) is increasingly promoted as a tool for improving health care delivery, yet successful implementation depends on workforce and organizational readiness. This cross-sectional analytical study assessed perceived barriers to AI integration and associated factors among 480 health care professionals working in public facilities in the Marrakech-Safi region of Morocco. Participants were recruited through professional and institutional networks and completed an anonymous electronic questionnaire. The final 11-item instrument measured technological, organizational, ethical and personal, and interdisciplinary collaboration barriers on a five-point scale, with higher scores indicating greater barriers. Organizational barriers had the highest mean score (3.36 ± 0.84), followed by ethical and personal barriers (2.69 ± 0.99), technological barriers (2.61 ± 0.76), and interdisciplinary collaboration barriers (2.25 ± 0.90). The overall score was 2.76 ± 0.64 , and 80.2% of participants reported no prior formal AI training. In multivariable general linear models, prior formal AI training was the only factor significantly associated with all four dimensions and the overall score, with the largest effect sizes for organizational barriers ($\eta_p^2 = 0.326$) and overall barriers ($\eta_p^2 = 0.148$); these two estimates were attenuated ($\eta_p^2 = 0.088$ and 0.078) in a sensitivity analysis excluding one scale item that overlapped conceptually with the training variable. Because of the cross-sectional, self-reported design, this association cannot be interpreted causally. Age, professional category, educational qualification, and department showed dimension-specific associations, whereas gender and professional experience were not independently associated after adjustment. These findings indicate that AI integration in Moroccan public health care is constrained primarily by organizational preparedness and limited training. Role-specific education, clear institutional policies, supportive leadership, and adequate digital infrastructure are therefore needed. Given the cross-sectional design and convenience sampling, causal inference and broad generalization should be approached with caution.

Keywords: Artificial intelligence; Health care professionals; Implementation barriers; Organizational readiness; AI training; Digital health

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1. Introduction

Artificial intelligence (AI) is increasingly shaping modern health care systems and is considered a major driver of health care transformation. Its applications span clinical and non-clinical domains such as disease diagnosis, clinical decision support, predictive analytics, resource allocation, administrative workflow optimization, and patient monitoring, and it has the potential to improve the quality, efficiency, and accessibility of health care.¹⁻⁴ With increasing challenges faced by health care systems around the globe due to demographic transitions, increasing disease burdens, workforce shortages, and increasing health care costs, AI has emerged as a promising tool to support more efficient and sustainable health service delivery.^{5,6} Recent international policy work nevertheless emphasizes that the benefits of AI depend not only on technological performance but also on the capacity of health systems to deploy these technologies responsibly, equitably, and at scale.^{7,8}

Despite these expected advantages, the adoption of AI in routine health care practice remains uneven and lags behind the pace of technological development. The successful use of AI requires not only the availability of technological solutions, but also the readiness of health care systems and professionals to adopt and use them effectively. Existing evidence suggests that barriers to AI integration are multifactorial, including technological, organizational, ethical, professional, and regulatory aspects.⁹⁻¹³

Technology barriers are still among the most frequently cited challenges. Implementation remains hindered by inadequate digital infrastructure, poor interoperability, limited access to digital tools, and varying levels of digital literacy among health care professionals⁹. In addition to these technical limitations, adoption behaviors are largely affected by the perceptions of health care professionals regarding usability, usefulness, professional autonomy, and trust in AI systems.^{10,14}

Another critical determinant of AI implementation is organizational readiness. Limited institutional support and investment in workforce training, absent governance structures, heavy workloads, and insufficient time for professional development may reduce professionals' capacity and willingness to engage with AI-based technologies.^{9,11} Moreover, the absence of strong legal, regulatory, and ethical frameworks creates uncertainty about accountability, safety, and professional responsibilities related to AI-assisted decision-making, thereby limiting adoption in health care organizations.^{12,15}

Ethical and professional concerns add further

complexity. Health care professionals and policymakers have raised valid concerns about data privacy, cybersecurity, algorithmic bias, transparency, explainability, and accountability.¹⁶⁻¹⁸ These concerns are often combined with concerns about the potential impact of AI on professional roles, clinical judgment, and the human dimension of health care, which is fundamental to patient-centered care.^{19,20} Additionally, successful AI integration depends on robust interdisciplinary cooperation and communication between health care professionals, managers, information technology specialists, and policymakers. However, these collaborative processes are often undermined by fragmentation within organizations, limited interprofessional communication, and a lack of coordinated implementation strategies.²¹

The international literature on the adoption of AI in health care has grown substantially. However, empirical evidence from low- and middle-income countries is limited, especially in North African health care systems.²²⁻²⁴ In Morocco, the current reforms of the health care system and the recent digitalization efforts have established a favorable environment for the introduction of innovative technologies in the health care services.²⁵ The accelerated implementation of digital health solutions during the COVID-19 pandemic demonstrated that the health system can deploy technological innovations at a national level.^{26,27} However, the incorporation of AI into routine health care is still at an early stage and hampered by ongoing structural and organizational problems such as the heterogeneity of digital infrastructure, unequal access to training, workforce shortages, and the underdevelopment of regulatory frameworks for novel digital technologies.^{25,28}

Building an understanding of these barriers is particularly relevant in the Moroccan context, where AI is increasingly viewed as a strategic component of health system modernization.²⁹ However, evidence is still limited. Previous Moroccan studies have focused mainly on nursing professionals and have been descriptive, providing only preliminary insights into the challenges of AI integration.²⁷ The views of other professional groups, such as physicians, health technicians, administrators, physiotherapists and health educators, are largely unexplored. Furthermore, the sociodemographic and professional factors related to perceived barriers to AI adoption across different health care settings are not well understood.

Closing these knowledge gaps is critical for informing evidence-based policies and implementation strategies that are responsive to the realities of the Moroccan health care system. The main objective of the present study was to evaluate the perceived barriers to AI integration among Moroccan health care professionals, including

technological, organizational, and ethical and personal barriers, as well as interdisciplinary collaboration. The study also aimed to identify the sociodemographic and professional determinants associated with these perceived barriers and to produce policy-relevant evidence that could support the development of sustainable, ethical, and professionally acceptable AI implementation strategies within the Moroccan health care sector.

2. Methods

2.1. Study design and setting

This was a cross-sectional descriptive and analytical study conducted with health care professionals at public health establishments in the Marrakech-Safi region of Morocco. This study aimed to assess perceived barriers to the integration of AI into health care practice and to investigate sociodemographic, professional, and training-related factors associated with these barriers.

Marrakech-Safi is a region located in the center of Morocco, composed of both urban and rural areas. It consists of one prefecture and seven provinces. The regional public health system includes the following components: primary health care facilities, hospitals, emergency departments, intensive care units, medical and technical services, maternal and child health services, rehabilitation units, administrative structures, and clinical training settings. This territorial and organizational diversity provided a relevant context for analyzing barriers to AI integration in different health care professions and work environments.

2.2 Study population and sampling

The study population comprised health care workers at public health institutions in the Marrakech-Safi region. Eligible participants included medical doctors, nursing professionals, health technicians, administrative staff, health educators and trainers, and other professionals involved in health care delivery, education, or health service organizations. Data were collected from April to June 2026.

A non-probability convenience sampling strategy was used because a complete sampling frame was unavailable for probability-based selection. To enhance sample diversity, participants were recruited through professional networks and institutional contacts across different public health care facilities, professional categories, and health care settings.

Participation was voluntary, and health care professionals who met the inclusion criteria and consented to participate were invited to complete the questionnaire.

The final analysis was based on a total of 480 completed questionnaires.

Participants were eligible if they were health care professionals working in a public health care facility and provided informed consent. Incomplete questionnaires or those without sufficient information to calculate the main study scores were excluded.

2.3. Study instrument

Data were collected using a structured questionnaire selected after reviewing the relevant literature on barriers to AI integration in health care practice. The instrument was adapted from a previously published study in Morocco on the barriers to the use of AI among nursing professionals.²⁷ The questionnaire was modified to better align with different professional roles and health care settings, given that the current study involved a broader range of health care professions.

The questionnaire was reviewed in a single round by eight experts in clinical practice, nursing science, health technology, and health services research, selected purposively for their experience with the Moroccan public health system. They assessed item clarity, relevance, and contextual appropriateness, and minor linguistic changes were made. Content validation was qualitative and consensus-based, without a quantitative content-validity index. The questionnaire was developed and administered exclusively in French, the working language of Moroccan public health care facilities; the questionnaire required no translation and was pretested on 30 professionals outside the final sample.

2.4. Questionnaire structure

The questionnaire consisted of two parts. The first section collected sociodemographic and professional data, including age group, gender, years of professional experience, professional category, department or unit, and highest educational qualification.

The second section originally included 14 items measuring perceived barriers to AI integration. Items were rated on a 5-point Likert scale. The initial item pool had four dimensions: technological barriers, organizational barriers, ethical and personal barriers, and barriers to interdisciplinary collaboration.

After the item analysis, three items were dropped due to poor psychometric properties or because they did not conceptually fit the dimensions they were designed to measure. The final instrument consisted of 11 items, including 4 technological barrier items, 3 organizational barrier items, 2 ethical and personal barrier items, and 2 interdisciplinary collaboration barrier items.

2.5. Scoring procedure

All retained items were originally worded in a facilitating direction and were reverse-scored using the transformation $6-x$, where x denotes the original response on the 1–5 scale. Thus, higher scores consistently indicated greater perceived barriers to AI integration.

Dimension scores were computed as mean item scores to allow comparisons between dimensions with different numbers of items. The technological barriers score was computed as the mean of four items, the organizational barriers score as the mean of three items, the ethical and personal barriers score as the mean of two items, and the interdisciplinary collaboration barriers score as the mean of two items. The total score for perceived barriers was calculated as the mean of all 11 retained items. All dimension scores and the overall score ranged from 1 to 5, with higher scores representing greater perceived barriers.

2.6. Psychometric assessment

Corrected item–total correlations were calculated within each dimension to evaluate item performance. Cronbach's alpha was used to evaluate the internal consistency of the technological, organizational, and overall instrument. The ethical and personal barriers dimension and the interdisciplinary collaboration barriers dimension each comprised two items; therefore, their reliability was evaluated using the Spearman–Brown coefficient and inter-item correlations.

Sampling adequacy and factorability were assessed using the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity, respectively. The four dimensions were defined a priori rather than empirically. An exploratory factor analysis (principal axis factoring, Promax rotation) was performed post hoc on the 11 retained items; as all steps used the same sample, the structure is preliminary and requires independent confirmation.

2.7. Data collection procedure

Data were collected using an anonymous self-administered questionnaire developed in Google Forms and distributed electronically via professional and institutional networks. Prior to accessing the questionnaire, participants were informed of the study aims, the voluntary nature of participation, confidentiality, and their right to withdraw at any time without consequences.

Informed consent was obtained from the participants prior to administration of the questionnaire. No personally identifiable information was collected. Response completeness was checked, and 480 complete questionnaires were included in the final analyses.

2.8. Statistical analysis

Data were analyzed using IBM SPSS Statistics version 26 (IBM Corp., United States of America). Frequencies and percentages were used to summarize categorical variables. Barrier dimension scores and the overall score were described using means and standard deviations, medians and interquartile ranges, and minimum–maximum values. The normality of each score distribution was tested using the Shapiro–Wilk test, which indicated significant departure from normality for all barrier scores.

Bivariate analyses were conducted using non-parametric tests: Mann–Whitney U test for two-group comparisons and Kruskal–Wallis H tests for comparisons involving more than two groups, followed by Dunn's post hoc test with Bonferroni adjustment, where appropriate. We investigated the correlations between total score and the four barrier dimensions using Spearman's rank correlation coefficient. Five separate multivariable general linear models were fitted with each dimension score and the overall perceived barriers score as dependent variables, adjusting for gender, age group, years of professional experience, professional category, highest educational qualification, department or unit, and prior formal training in AI. Although barrier scores were non-normal, general linear models were retained because normality concerns residuals. Assumptions were checked using residual diagnostics, Breusch–Pagan tests, Cook's distance, leverage values, and adjusted generalized variance inflation factors (GVIFs); because heteroscedasticity was present, HC3 heteroscedasticity-consistent standard errors were applied, and the training association was confirmed by 1,000 bootstrap resamples. Sensitivity analyses pooled sparse categories and removed the training-related item from organizational and overall scores. Full estimates, reference categories, diagnostics, and sensitivity results are reported in Tables S2–S4.

2.9. Ethical considerations

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. The Regional Directorate of Health and Social Protection of Marrakech-Safi and the competent health authorities granted prior administrative authorization (Authorization No. 1943/26).

Participation was voluntary. Electronic informed consent was obtained from all participants by requiring them to tick a consent box in the online questionnaire (Google Forms) before accessing the questionnaire items, regardless of whether they completed the questionnaire remotely or in person. Responses were anonymous, confidential, and used solely for research purposes.

3. Results

3.1. Sociodemographic, professional, and artificial intelligence training characteristics of participants

The study included a total of 480 health care professionals. The majority of participants were in the 21–34-year age group (64.4%), followed by the 35–44-year age group (22.3%), and only 4.0% were 55 years or older. The sample comprised 67.9% females and 32.1% males. In terms of professional experience, the largest group had 1–5 years (35.2%), followed by 11–20 years (20.0%) and less than 1 year (19.6%).

Nursing professionals accounted for the largest share of the sample (71.0%), followed by medical doctors (12.7%), health technicians (7.7%), educators and trainers (5.4%), administrative staff (2.7%), and other professionals (0.4%). Participants were spread across several health care settings, with the largest proportions working in other departments or services (30.0%) and primary health care facilities (28.1%). Among the named hospital departments, emergency departments represented the largest group (11.5%), followed by mother and child health departments (11.2%) and medical-surgical departments (10.0%).

Regarding educational level, most participants had a bachelor's degree in nursing (64.8%), followed by a master's degree in health sciences (15.4%) and a medical doctorate (12.1%). Only 4.4% had a PhD in health sciences. Most participants (80.2%) reported no previous formal training in AI, and only 19.8% had occasional or regular AI-related training. This finding underscores a substantial gap in formal AI preparedness among health care professionals in the study setting (Table 1).

Table 1. Sociodemographic, professional, and AI training characteristics of participants (N = 480)

Characteristic	n	%
Age group		
21–34 years	309	64.4
35–44 years	107	22.3
45–54 years	45	9.4
≥55 years	19	4.0
Gender		
Male	154	32.1
Female	326	67.9
Years of professional experience		
<1 year	94	19.6
1–5 years	169	35.2

(Cont'd...)

Table 1. (Continued)

Characteristic	n	%
6–10 years	68	14.2
11–20 years	96	20.0
>20 years	53	11.0
Professional category		
Medical corps	61	12.7
Nursing staff	341	71.0
Health technicians	37	7.7
Administrative staff	13	2.7
Educators and trainers	26	5.4
Other	2	0.4
Department/unit		
Medical-surgical department	48	10.0
Intensive care unit	16	3.3
Emergency department	55	11.5
Mother and child health department	54	11.2
Medical technology department	21	4.4
Rehabilitation department	7	1.5
Primary health care facility (ESSP)	135	28.1
Other	144	30.0
Highest educational qualification		
Bachelor's degree in nursing	311	64.8
Master's degree in health sciences	74	15.4
PhD in health sciences	21	4.4
Medical doctorate	58	12.1
Other	16	3.3
Prior formal training in AI		
No formal training	385	80.2
Occasional or regular training	95	19.8

Note: Percentages are calculated on the total sample (N = 480) and may not sum to 100.0 owing to rounding. Abbreviations: AI: Artificial intelligence; ESSP: Établissement de Soins de Santé Primaires (primary health care facility).

3.2. Item composition, scoring, and internal consistency of the perceived artificial intelligence barriers instrument

The final perceived AI barriers instrument comprised 11 items across 4 dimensions: technological barriers, organizational barriers, ethical and personal barriers, and interdisciplinary collaboration barriers. All retained items were reverse-coded so that higher values indicated higher perceived barriers to AI integration. Item means ranged from 2.05 ± 1.04 (ineffective interdisciplinary collaboration in AI integration) to 3.55 ± 0.94 (lack of formal training

in AI technologies). Corrected item–total correlations ranged from 0.289 to 0.533. Most retained items met or approached the commonly accepted threshold of 0.30.

The whole instrument demonstrated a satisfactory internal consistency (Cronbach's $\alpha = 0.786$). Reliability estimates at the dimension level were more modest, with Cronbach's α values of 0.542 for technological barriers and 0.644 for organizational barriers. For the two-item dimensions, Spearman–Brown coefficients were 0.648 for ethical and personal barriers and 0.613 for interdisciplinary collaboration barriers, with corresponding inter-item correlations of $r = 0.480$ and $r = 0.442$, respectively. These findings support the use of the total score but caution against interpreting the results of individual dimensions.

After item analysis, three items were dropped from the original 14-item pool because of weak psychometric performance or conceptual redundancy. The removal of these items increased the reliability of the organizational, ethical and personal dimensions and of the overall instrument. For the final 11-item set, sampling adequacy was good (Kaiser–Meyer–Olkin measure = 0.790) and Bartlett's test of sphericity was significant ($\chi^2(55) = 1,339.9$, $p < 0.001$); the corresponding values for the initial 14-item pool were KMO = 0.780 and $\chi^2(91) = 1,647.2$. Exploratory factor analysis did not clearly reproduce the four a priori dimensions: three eigenvalues exceeded unity while parallel analysis supported two factors, and the four-factor

Promax solution explained 48.4% of the variance with a weak fourth factor. The four dimensions are therefore treated as conceptual rather than empirical groupings and as preliminary pending independent validation, and the overall 11-item score ($\alpha = 0.786$) is used as the primary outcome. Item composition, scoring, and internal consistency estimates are presented in Table 2, and the full loadings are provided in Table S5.

3.3. Descriptive statistics and intercorrelations among perceived artificial intelligence barrier dimensions

Organizational barriers scored the highest mean (3.36 ± 0.84), followed by ethical and personal barriers (2.69 ± 0.99) and technological barriers (2.61 ± 0.76). The mean score of barriers to interdisciplinary collaboration was the lowest (2.25 ± 0.90). The organizational barriers dimension was the only dimension with a mean above the midpoint of the five-point response scale. This implies that participants rated organizational barriers highest. The overall perceived barriers score was 2.76 ± 0.64 , with a median of 2.73 (interquartile range, 2.36–3.09), indicating a score below the scale midpoint of 3. The Shapiro–Wilk test indicated that all dimension scores and the total score significantly differed from normality (all $p < 0.001$), supporting the use of non-parametric procedures for bivariate analyses.

Spearman's correlation analysis revealed that all barrier

Table 2. Item composition, scoring, and internal consistency of the perceived AI barriers instrument (N = 480).

Dimension/item	Rev.	Mean $\pm$ standard deviation	CITC	Reliability
Technological barriers				$\alpha = 0.542$
Lack of familiarity with the concept of AI in health care	Yes	2.53 ± 1.04	0.289	
Limited ease of use of digital technologies in daily practice	Yes	2.30 ± 1.03	0.425	
Insufficient access to the digital tools required at the workplace	Yes	2.63 ± 1.31	0.308	
Current infrastructure does not support AI integration	Yes	2.97 ± 1.27	0.312	
Organizational barriers				$\alpha = 0.644$
Lack of managerial support for adopting new technologies	Yes	3.14 ± 1.22	0.490	
No formal training received on AI technologies	Yes	3.55 ± 0.94	0.356	
Lack of clarity of institutional policies and procedures on AI	Yes	3.39 ± 1.11	0.533	
Ethical and personal barriers				0.648 ^a
Discomfort with AI taking over certain aspects of care	Yes	2.45 ± 1.18	0.480	
Lack of confidence in AI for making clinical decisions	Yes	2.94 ± 1.13	0.480	
Interdisciplinary collaboration barriers				0.613 ^a
Ineffective interdisciplinary collaboration during AI integration	Yes	2.05 ± 1.04	0.442	
Insufficient interprofessional communication for AI implementation	Yes	2.46 ± 1.07	0.442	
Overall instrument (11 items)				$\alpha = 0.786$

Notes: All items were reverse-scored using , with higher scores indicating greater perceived barriers. Cronbach's α was used for dimensions with ≥ 3 items and the Spearman–Brown coefficient for two-item dimensions. ^aFor the two-item dimensions, the inter-item correlations were $r = 0.480$ for ethical and personal barriers and $r = 0.442$ for interdisciplinary collaboration barriers. Three items were excluded following item analysis. Abbreviations: AI: Artificial intelligence; CITC: Corrected item–total correlation; Rev.: Reverse-scored.

dimensions were positively and statistically significantly associated (all $p < 0.001$). The highest interdimensional association was found between ethical and personal barriers and interdisciplinary collaboration barriers ($\rho = 0.480$), followed by the association between technological and organizational barriers ($\rho = 0.478$). The other correlations ranged from $\rho = 0.181$ to $\rho = 0.389$, indicating that the dimensions were related but measured different aspects of perceived barriers to AI integration.

The total score of perceived barriers was positively associated with all four dimensions. The strongest association was with technological barriers ($\rho = 0.800$) followed by organizational barriers ($\rho = 0.741$), ethical and personal barriers ($\rho = 0.701$), and interdisciplinary collaboration barriers ($\rho = 0.530$) (all $p < 0.001$). These correlations should be interpreted as part-whole relationships, as the total score was calculated from the items that comprise the four dimensions (Table 3; Figure 1).

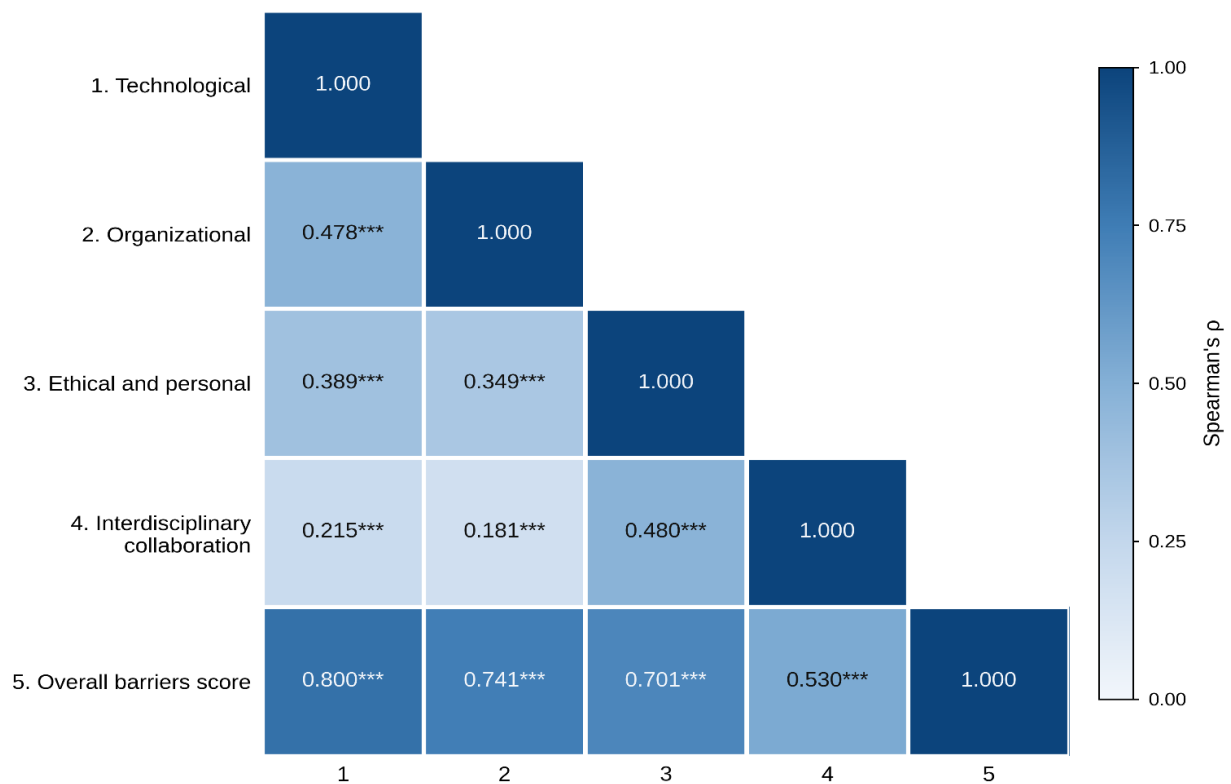


Figure 1. Correlations among perceived artificial intelligence barrier dimensions ($N = 480$).
Note: *** $p < 0.001$.

Table 3. Descriptive statistics for perceived artificial intelligence-integration barriers ($N = 480$)

Dimension	k	Mean $\pm$ standard deviation	Median (interquartile range)	Minimum–maximum
1. Technological barriers	4	2.61 $\pm$ 0.76	2.50 (2.00–3.00)	1.00–5.00
2. Organizational barriers	3	3.36 $\pm$ 0.84	3.33 (2.67–4.00)	1.00–5.00
3. Ethical and personal barriers	2	2.69 $\pm$ 0.99	2.50 (2.00–3.00)	1.00–5.00
4. Interdisciplinary collaboration barriers	2	2.25 $\pm$ 0.90	2.00 (1.50–2.62)	1.00–5.00
5. Overall perceived barriers score	11	2.76 $\pm$ 0.64	2.73 (2.36–3.09)	1.00–4.91

Notes: k = number of items. Scores range from 1 to 5, with higher values indicating greater perceived barriers.

3.4. Bivariate analysis of perceived artificial intelligence barriers according to participant characteristics

Bivariate analyses identified significant differences in perceived AI barriers according to several sociodemographic and professional characteristics. Barrier scores differed by gender only for interdisciplinary collaboration barriers, with males reporting higher scores than females (2.38 ± 0.91 vs. 2.19 ± 0.88 ; $U = 27,913$, $p = 0.044$). No significant gender differences were observed in technological, organizational, ethical and personal, or overall barrier scores.

Age group was significantly associated with all four barrier dimensions and with the overall barrier score. The differences were observed for technological barriers ($H = 27.37$, $p < 0.001$), organizational barriers ($H = 8.99$, $p = 0.029$), ethical and personal barriers ($H = 21.66$, $p < 0.001$), interdisciplinary collaboration barriers ($H = 8.41$, $p = 0.038$), and the overall score ($H = 24.54$, $p < 0.001$). Bonferroni-adjusted post hoc comparisons showed that participants aged 55 years or older reported higher technological barrier scores than those aged 21–34 years and 35–44 years. Participants aged 45–54 years and those aged 55 years or older also reported higher ethical and personal and overall barrier scores than the youngest age group. No individual pairwise comparisons remained significant for organizational or interdisciplinary collaboration barriers after adjustment. Detailed Bonferroni-adjusted pairwise comparisons are provided in **Table S1**.

Years of professional experience was significantly associated with technological barriers ($H = 20.84$, $p < 0.001$), ethical and personal barriers ($H = 15.00$, $p = 0.005$), and the overall barriers score ($H = 18.61$, $p < 0.001$), but not with organizational barriers ($H = 8.89$, $p = 0.064$) or interdisciplinary collaboration barriers ($H = 6.55$, $p = 0.161$). Participants with more than 20 years of experience reported higher technological barrier scores than those with < 1 year, 1–5 years, and 6–10 years of experience. They also reported higher ethical and personal barriers than participants with 1–5 years of experience and higher overall barriers than those with < 1 year or 1–5 years of experience.

Professional category was significantly associated with all barrier dimensions and the overall barriers score. Medical professionals generally reported higher perceived barriers than nursing professionals and health technicians. Post hoc analyses showed that medical professionals had higher technological barrier scores than nursing professionals and health technicians. They also reported higher organizational barriers than health technicians and administrative staff, higher ethical and personal barriers

than health technicians and educators/trainers, and higher overall barriers than nursing professionals, health technicians, and educators/trainers. Nursing professionals also reported higher organizational and overall barrier scores than health technicians. Although the global test for interdisciplinary collaboration was significant ($H = 13.16$, $p = 0.022$), no adjusted pairwise comparison remained statistically significant.

Highest educational qualification was significantly associated with all barrier dimensions and the overall score. Participants holding a medical doctorate reported higher technological barrier scores than those with a bachelor's degree in nursing, a master's degree, a PhD in health sciences, or another qualification. They also reported higher organizational barriers than participants with a bachelor's degree or another qualification, and higher ethical and personal barriers than those with a master's degree. Medical doctorate holders reported higher overall barrier scores than all other educational groups. A significant difference in the barriers to interdisciplinary collaboration was observed only between participants with a master's degree and those with other qualifications.

Department or unit was associated with organizational barriers ($H = 30.34$, $p < 0.001$), ethical and personal barriers ($H = 28.28$, $p < 0.001$), and the overall barriers score ($H = 16.90$, $p = 0.018$), but not with technological or interdisciplinary collaboration barriers. Organizational barrier scores were higher in medical-surgical departments and primary health care facilities than in departments classified as other. Participants working in primary health care facilities also reported higher ethical and personal barriers than those working in emergency departments or other services, and higher overall barriers than those in other services.

Prior formal training in AI was significantly associated with all barrier dimensions and with the overall score. Participants with no formal AI training reported higher technological ($U = 23,502$, $p < 0.001$), organizational ($U = 32,618$, $p < 0.001$), ethical and personal ($U = 22,465$, $p < 0.001$), interdisciplinary collaboration ($U = 22,152$, $p = 0.001$), and overall barrier scores ($U = 28,773$, $p < 0.001$) than participants who had received occasional or regular training. This consistent pattern indicates that formal AI training is an important characteristic associated with lower perceived barriers across all dimensions. The corresponding bivariate analyses are presented in **Table 4**.

3.5. Multivariable analysis of factors associated with perceived artificial intelligence barriers

For each barrier dimension and the overall perceived barriers score, separate multivariable general linear models

Table 4. Bivariate analysis of perceived AI barrier scores according to participant characteristics (N = 480)

Characteristic	n	Technological	Organizational	Ethical & personal	Interdisciplinary collaboration	Overall barriers
Gender						
Male	154	2.64 ± 0.83	3.30 ± 0.88	2.77 ± 1.16	2.38 ± 0.91	2.80 ± 0.73
Female	326	2.59 ± 0.73	3.39 ± 0.82	2.66 ± 0.90	2.19 ± 0.88	2.75 ± 0.58
Test statistic		U = 26,044; p = 0.505	U = 23,566; p = 0.276	U = 25,672; p = 0.684	U = 27,913; p = 0.044*	U = 25,648; p = 0.700
Age group						
21–34 years	309	2.50 ± 0.68	3.30 ± 0.80	2.54 ± 0.88	2.19 ± 0.85	2.67 ± 0.55
35–44 years	107	2.70 ± 0.83	3.37 ± 0.91	2.85 ± 1.14	2.38 ± 0.96	2.85 ± 0.74
45–54 years	45	2.78 ± 0.78	3.60 ± 0.80	3.03 ± 0.98	2.19 ± 0.92	2.94 ± 0.64
≥ 55 years	19	3.50 ± 0.92	3.68 ± 0.97	3.50 ± 1.24	2.74 ± 1.08	3.41 ± 0.85
Test statistic		H = 27.37; p < 0.001*	H = 8.99; p = 0.029*	H = 21.66; p < 0.001*	H = 8.41; p = 0.038*	H = 24.54; p < 0.001*
Years of professional experience						
< 1 year	94	2.59 ± 0.62	3.26 ± 0.86	2.64 ± 0.88	2.26 ± 0.85	2.72 ± 0.55
1–5 years	169	2.47 ± 0.78	3.31 ± 0.83	2.49 ± 0.85	2.14 ± 0.89	2.64 ± 0.60
6–10 years	68	2.56 ± 0.53	3.38 ± 0.67	2.82 ± 1.12	2.36 ± 0.87	2.79 ± 0.54
11–20 years	96	2.66 ± 0.82	3.36 ± 0.89	2.80 ± 1.09	2.31 ± 0.92	2.81 ± 0.71
> 20 years	53	3.03 ± 0.90	3.65 ± 0.89	3.09 ± 1.11	2.39 ± 0.95	3.09 ± 0.75
Test statistic		H = 20.84; p < 0.001*	H = 8.89; p = 0.064	H = 15.00; p = 0.005*	H = 6.55; p = 0.161	H = 18.61; p < 0.001*
Professional category						
Medical staff	61	3.05 ± 0.86	3.68 ± 0.71	3.16 ± 1.18	2.55 ± 1.04	3.15 ± 0.73
Nursing staff	341	2.58 ± 0.72	3.37 ± 0.85	2.69 ± 0.93	2.24 ± 0.86	2.75 ± 0.60
Health technicians	37	2.30 ± 0.68	3.00 ± 0.73	2.32 ± 1.04	2.03 ± 0.87	2.44 ± 0.58
Administrative staff	13	2.40 ± 0.58	2.97 ± 0.54	2.92 ± 0.91	2.69 ± 1.09	2.71 ± 0.47
Educators and trainers	26	2.48 ± 0.90	3.15 ± 1.01	2.19 ± 0.92	1.92 ± 0.67	2.51 ± 0.65
Other	2	2.75 ± 0.00	4.00 ± 0.00	2.00 ± 0.00	2.00 ± 0.00	2.82 ± 0.00
Test statistic		H = 22.80; p < 0.001*	H = 23.86; p < 0.001*	H = 27.42; p < 0.001*	H = 13.16; p = 0.022*	H = 32.47; p < 0.001*
Highest educational qualification						
Bachelor's degree in nursing	311	2.54 ± 0.72	3.35 ± 0.82	2.72 ± 0.93	2.22 ± 0.89	2.73 ± 0.60
Master's degree in health sciences	74	2.62 ± 0.78	3.31 ± 0.93	2.36 ± 1.00	2.05 ± 0.80	2.66 ± 0.60
PhD in health sciences	21	2.35 ± 0.78	3.02 ± 1.01	2.48 ± 0.60	2.26 ± 0.44	2.54 ± 0.57
Medical doctorate	58	3.11 ± 0.83	3.71 ± 0.70	3.16 ± 1.20	2.55 ± 1.06	3.18 ± 0.73
Other	16	2.38 ± 0.42	3.00 ± 0.71	2.41 ± 1.17	2.84 ± 0.89	2.64 ± 0.63
Test statistic		H = 25.13; p < 0.001*	H = 15.89; p = 0.003*	H = 20.48; p < 0.001*	H = 14.68; p = 0.005*	H = 22.66; p < 0.001*
Department/unit						
Medical-surgical	48	2.44 ± 0.65	3.62 ± 0.70	2.62 ± 0.93	2.21 ± 0.85	2.75 ± 0.55
Intensive care unit	16	2.72 ± 0.66	3.67 ± 0.49	2.28 ± 0.95	1.84 ± 0.75	2.74 ± 0.42

(Cont'd...)

Table 4. (Continued)

Characteristic	n	Technological	Organizational	Ethical & personal	Interdisciplinary collaboration	Overall barriers
Emergency	55	2.69 ± 0.71	3.29 ± 0.67	2.55 ± 1.08	2.26 ± 0.83	2.75 ± 0.55
Mother and child health	54	2.46 ± 0.64	3.35 ± 0.86	2.75 ± 0.92	2.15 ± 1.00	2.70 ± 0.58
Medical technology	21	2.43 ± 0.75	3.33 ± 0.61	2.38 ± 0.72	1.93 ± 0.68	2.58 ± 0.50
Rehabilitation	7	2.36 ± 0.92	2.71 ± 0.91	2.36 ± 1.31	2.36 ± 0.63	2.45 ± 0.86
Primary health care facility (ESSP)	135	2.75 ± 0.84	3.53 ± 0.88	3.03 ± 1.00	2.36 ± 0.98	2.94 ± 0.71
Other	144	2.58 ± 0.76	3.14 ± 0.89	2.54 ± 0.96	2.30 ± 0.86	2.68 ± 0.64
Test statistic		$H = 11.22; p < 0.001^*$	$H = 30.34; p < 0.001^*$	$H = 28.28; p < 0.001^*$	$H = 9.31; p = 0.231$	$H = 16.90; p = 0.018^*$
Prior formal training in AI						
No formal training	385	2.69 ± 0.77	3.60 ± 0.68	2.79 ± 1.01	2.32 ± 0.92	2.89 ± 0.61
Occasional or regular training	95	2.28 ± 0.64	2.37 ± 0.69	2.33 ± 0.82	1.98 ± 0.71	2.26 ± 0.49
Test statistic		$U = 23.502; p < 0.001^*$	$U = 32.618; p < 0.001^*$	$U = 22.465; p < 0.001^*$	$U = 22.152; p = 0.001^*$	$U = 28.773; p < 0.001^*$

Notes: Data are presented as mean ± standard deviation. Mann–Whitney U tests were used for two-group comparisons, and Kruskal–Wallis H tests were used for comparisons involving more than two groups. * $p < 0.05$. Parameter estimates with 95% confidence intervals, diagnostics, and sensitivity analyses in Tables S2–S4. Abbreviations: AI: Artificial intelligence; ESSP: Établissement de Soins de Santé Primaires (primary health care facility).

were fitted. All five models were statistically significant (all $p < 0.001$). The explanatory power of each varied across the outcomes, with adjusted R^2 ranging from 0.077 for barriers to interdisciplinary collaboration to 0.382 for organizational barriers. The adjusted R^2 was 0.134 for technological barriers, 0.133 for ethical and personal barriers, and 0.240 for the overall perceived barriers score.

Prior formal training in AI was the only factor significantly associated with all five outcomes. Participants' training status was associated with technological barriers ($F = 17.38, p < 0.001, \eta_p^2 = 0.037$), organizational barriers ($F = 219.15, p < 0.001, \eta_p^2 = 0.326$), ethical and personal barriers ($F = 11.75, p < 0.001, \eta_p^2 = 0.025$), interdisciplinary collaboration barriers ($F = 15.63, p < 0.001, \eta_p^2 = 0.033$), and the overall barriers score ($F = 79.03, p < 0.001, \eta_p^2 = 0.148$). The largest effect sizes were observed for organizational barriers and the overall barriers score, indicating that prior AI training was particularly strongly associated with these outcomes.

Age group remained significantly associated only with technological barriers ($F = 2.81, p = 0.039, \eta_p^2 = 0.018$). Professional category was associated with technological barriers ($F = 2.41, p = 0.036, \eta_p^2 = 0.026$), organizational barriers ($F = 2.41, p = 0.036, \eta_p^2 = 0.026$), and interdisciplinary collaboration barriers ($F = 2.45, p = 0.033, \eta_p^2 = 0.026$), but not with ethical and personal barriers or the overall score. Educational qualification was independently associated only with barriers to interdisciplinary collaboration ($F = 3.27, p = 0.012, \eta_p^2 = 0.028$).

Department or unit was significantly associated with organizational barriers ($F = 2.13, p = 0.039, \eta_p^2 = 0.032$) and ethical and personal barriers ($F = 2.72, p = 0.009, \eta_p^2 = 0.040$). Gender and years of professional experience were not independently associated with any barrier dimension or with the overall barriers score after adjustment. Overall, the findings indicate that prior formal AI training was the most consistent factor associated with perceived barriers, although several professional and organizational characteristics retained dimension-specific associations. Each model comprised 25 and 454 degrees of freedom. Residuals were approximately normal in most models, with minor departures for the ethical and personal and collaboration models; the Breusch–Pagan test indicated heteroscedasticity in four of the five models, no observation exceeded a Cook's distance of 1, and multicollinearity was negligible (GVIF: 1.07–1.68). With HC3 robust standard errors, prior AI training remained significantly associated with all five outcomes (all $p \leq 0.001$), and bootstrap confidence intervals matched the model-based ones; pooling the sparse categories left the pattern unchanged.

Because the item “No formal training received on AI technologies” overlapped with the training predictor ($r = -0.90$), the organizational and overall models were refitted without it: the reduced two-item organizational and ten-item overall scores remained strongly correlated with the originals ($\rho = 0.945$ and 0.989), and prior AI training remained statistically significant but with smaller effect sizes (organizational $\eta_p^2 = 0.088$ vs. 0.326 ; overall $\eta_p^2 = 0.078$ vs. 0.148). Direction and significance were unchanged, and these reduced estimates should be regarded as more accurate. Full diagnostics, robust estimates, and sensitivity analyses are reported in **Tables S2–S4**, and the multivariable general linear model results are summarized in [Table 5](#).

4. Discussion

4.1. Principal findings

This study provides a multidimensional assessment of perceived barriers to AI integration among health care professionals working in public health care facilities in Morocco. Organizational barriers were the most prominent dimension and the only one with a mean score above the midpoint of the five-point scale. Moreover, 80.2% of participants had received no prior formal training in AI. Training status was the only factor consistently associated with all four barrier dimensions and the overall score after multivariable adjustment, with the largest effect sizes observed for organizational barriers and the overall perceived barriers score. Age, professional category, educational qualification, and department retained more specific associations, whereas gender and professional experience were no longer independently associated with the outcomes after adjustment.

These findings support a multidimensional and sociotechnical interpretation of AI implementation. Recent reviews have similarly shown that health care AI adoption depends not only on the availability or technical performance of AI tools but also on organizational leadership, workflow integration, professional engagement, trust, training, governance, and adequate infrastructure^{9,30–34}. The positive correlations observed among the four dimensions further suggest that barriers interact, while their moderate magnitude indicates that they capture partly distinct aspects of implementation readiness.

4.2. Organizational barriers and formal artificial intelligence training

Organizational barriers were rated highest. The highest-rated individual barriers were lack of formal training, unclear institutional policies, and lack of managerial support. This is consistent with recent implementation

research showing that leadership, organizational buy-in, workflow adaptation, human resources, training, legal guidance, evaluation, and maintenance are essential conditions for sustainable AI implementation.^{9,31,33} Similar results were reported in previous studies among nursing professionals in Morocco, which found inadequate training, limited managerial support, and uncertainty regarding AI implementation, indicating that these challenges are not profession-specific.²⁷

This predominance of organizational barriers may reflect the importance of institutional readiness in the Moroccan context, where AI adoption requires not only individual acceptance but also coordinated investment in training, technological infrastructure, interoperability, institutional support, and ethical guidance.²⁸

These contextual conditions may reinforce the importance of managerial support, workforce preparation, and clear institutional governance for AI adoption.

Prior formal AI training was the most consistent correlate of perceived barriers. Untrained participants had higher scores on all dimensions, and this association remained significant after adjustment for demographic, professional, and workplace characteristics. This finding is consistent with an integrative review that shows needs-based training increases health care professionals' acceptance of AI, especially when supported by the right infrastructure and early involvement of end users.³⁰ A systematic review of AI literacy also found that health care professionals and students are often insufficiently prepared and structured training is needed to support safe use.³⁵

The cross-sectional, self-reported design does not permit causal interpretation, and the association cannot be taken as evidence that training reduces barriers. Trained participants may differ systematically from others: greater interest in AI, institutional support, or digital access could raise both the likelihood of training and the tendency to report fewer barriers, and reverse pathways are equally plausible. Part of the association for organizational and overall barriers also reflected item–predictor overlap and weakened once the item was removed. Prior AI training should therefore be read as a marker of broader individual and institutional readiness rather than an isolated cause, with its long-term effects yet to be tested longitudinally.

The present analysis considered AI training as an associated factor rather than a mediator; potential indirect pathways linking age or professional category to perceived barriers through training should be examined in longitudinal studies.

Some findings may inform other resource-constrained systems, whereas others remain context-specific. The

Table 5. Multivariable general linear models of factors associated with perceived artificial intelligence (AI) barriers (N = 480)

Factor	Technological barriers	Organizational barriers	Ethical and personal barriers	Interdisciplinary collaboration barriers	Overall barriers
Gender	$F = 0.10; p = 0.749; \eta_p^2 = 0.000$	$F = 0.00; p = 0.958; \eta_p^2 = 0.000$	$F = 0.00; p = 0.963; \eta_p^2 = 0.000$	$F = 0.81; p = 0.368; \eta_p^2 = 0.002$	$F = 0.01; p = 0.913; \eta_p^2 = 0.000$
Age group	$F = 2.81; p = 0.039; \eta_p^2 = 0.018^*$	$F = 0.57; p = 0.635; \eta_p^2 = 0.004$	$F = 1.65; p = 0.176; \eta_p^2 = 0.011$	$F = 1.79; p = 0.148; \eta_p^2 = 0.012$	$F = 1.77; p = 0.153; \eta_p^2 = 0.012$
Years of professional experience	$F = 0.73; p = 0.574; \eta_p^2 = 0.006$	$F = 2.09; p = 0.082; \eta_p^2 = 0.018$	$F = 1.55; p = 0.186; \eta_p^2 = 0.013$	$F = 1.20; p = 0.311; \eta_p^2 = 0.010$	$F = 1.57; p = 0.181; \eta_p^2 = 0.014$
Professional category	$F = 2.41; p = 0.036; \eta_p^2 = 0.026^*$	$F = 2.41; p = 0.036; \eta_p^2 = 0.026^*$	$F = 1.28; p = 0.272; \eta_p^2 = 0.014$	$F = 2.45; p = 0.033; \eta_p^2 = 0.026^*$	$F = 2.18; p = 0.055; \eta_p^2 = 0.023$
Highest educational qualification	$F = 2.16; p = 0.072; \eta_p^2 = 0.019$	$F = 1.13; p = 0.339; \eta_p^2 = 0.010$	$F = 2.22; p = 0.066; \eta_p^2 = 0.019$	$F = 3.27; p = 0.012; \eta_p^2 = 0.028^*$	$F = 1.05; p = 0.382; \eta_p^2 = 0.009$
Department/unit	$F = 1.21; p = 0.298; \eta_p^2 = 0.018$	$F = 2.13; p = 0.039; \eta_p^2 = 0.032^*$	$F = 2.72; p = 0.009; \eta_p^2 = 0.040^*$	$F = 1.77; p = 0.091; \eta_p^2 = 0.027$	$F = 1.79; p = 0.087; \eta_p^2 = 0.027$
Prior formal AI training	$F = 17.38; p < 0.001; \eta_p^2 = 0.037^*$	$F = 219.15; p < 0.001; \eta_p^2 = 0.326^*$	$F = 11.75; p < 0.001; \eta_p^2 = 0.025^*$	$F = 15.63; p < 0.001; \eta_p^2 = 0.033^*$	$F = 79.03; p < 0.001; \eta_p^2 = 0.148^*$
Corrected model, F	3.96***	12.82***	3.94***	2.59***	7.04***
R^2	0.179	0.414	0.178	0.125	0.279
Adjusted R^2	0.134	0.382	0.133	0.077	0.240

Notes: Five separate general linear models were fitted, one for each outcome. Each model was mutually adjusted for gender, age group, years of professional experience, professional category, highest educational qualification, department/unit, and prior formal AI training. Type III sums of squares were used. η_p^2 = partial eta squared; R^2 = coefficient of determination. *Statistically significant effects. *** $p < 0.001$ for the corrected model.

transferable elements are structural: the predominance of organizational over technological barriers, unmet training needs, and unclear policies.³² The training gap (80.2%) and the differences across categories reflect this single-region, nurse-predominant convenience sample and require independent confirmation.³²

4.3. Professional and contextual differences

Age was independently associated only with technological barriers, with older participants reporting greater barriers in the bivariate analyses. This may reflect differences in exposure to digital technologies or perceived ease of use, although caution is merited given the small number of participants aged 55 years or over. Professional category was independently associated with barriers to technological, organizational, and interdisciplinary collaboration, suggesting that implementation needs vary according to clinical responsibilities, professional autonomy, exposure to digital systems, and participation in decision-making.³⁶

The department or unit remained associated with organizational and ethical/personal barriers after adjustment. This suggests that the sense of readiness may depend on local management, workflow, resources, and the clinical setting. Recent evidence supports the context dependence of AI adoption drivers, which may operate differently across professional groups, primary care, hospitals, and resource settings.^{32,33} Evidence from low- and middle-income countries also points to unreliable infrastructure, insufficient equipment, limited health data literacy, uneven resource allocation, unclear policies, and cybersecurity concerns as interconnected barriers to AI deployment.³⁷

Years of professional experience demonstrated bivariate associations with technological, ethical and personal, and overall barriers, but none remained statistically significant after multivariable adjustment.

It is also informative that several bivariate associations disappear after adjustment. No independent association was found between gender and work experience and the outcomes. Educational qualification was associated only with barriers to interdisciplinary collaboration. These results indicate that the differences attributed to personal characteristics may be partly explained by professional roles, access to training, or working conditions. Hence, implementation strategies cannot be based solely on demographic profiles but should also take into account the actual competencies, responsibilities, and organizational environments of targeted users.

4.4. Implications for implementation

The findings suggest that coordinated interventions at

the workforce and organizational levels are required to improve AI readiness. Training should be continuous, practical, and role-relevant. Core content should include basic AI concepts, interpretation of AI-supported recommendations, limitations and potential errors, ethical responsibilities, data protection, and preservation of human oversight.³⁸⁻⁴⁰ Managers and educators also require training in procurement, governance, workflow redesign, and evaluation.^{9,30,31,35}

Training alone will not be enough without clear institutional policies, managerial support, adequate infrastructure, and opportunities for interdisciplinary participation. Health care facilities should assess their digital and organizational readiness before implementing AI tools, establish clear accountability and safe-use procedures, and engage professionals in decision-making. In resource-limited environments, these measures should be coupled with investment in interoperable information systems, data quality, cybersecurity and equitable access to digital resources.^{31,37,41}

4.5. Strengths and limitations

This study included a large multiprofessional sample from different public health care settings and explored technological, organizational, ethical and collaborative dimensions using bivariate, post hoc, and adjusted analyses. The inclusion of prior AI training is particularly pertinent to understanding workforce readiness.

However, convenience sampling may have introduced selection bias, as professionals who were more accessible or interested in AI may have been more likely to participate, while the inclusion of only public health care facilities limits the generalizability of the findings. Nevertheless, the inclusion of 480 participants from multiple professional categories and diverse public health care settings provides a broad view of perceived AI barriers within the regional public health system. Extrapolation to private-sector professionals and other Moroccan regions, however, should be made with caution.

The cross-sectional and self-reported nature of the study precludes causal inference and may have introduced response and social desirability biases, as well as variability in participants' understanding of AI. The sample was predominantly nurses, with smaller numbers of professional and departmental groups, which should be taken into account when interpreting comparisons between subgroups. Overall internal consistency was good, though moderate for some dimensions. Content validation was qualitative, without a quantitative content-validity index, and item reduction, reliability estimation, and factor analysis were all performed in the main

sample; the exploratory factor analysis did not clearly reproduce the four a priori dimensions, so the structure is preliminary and dimension-level results should therefore be interpreted more cautiously than the overall score. One organizational item overlapped with the training predictor, and its effect size decreased after the overlapping item was removed. Some professional, educational, and departmental groups were small, limiting the precision of their adjusted estimates. Despite these considerations, the study offers a comprehensive assessment in a large multiprofessional sample.

Future research should examine the instrument's structure in independent samples and further investigate organizational readiness, training interventions, and actual AI use using longitudinal and mixed-method designs.

5. Conclusion

The main obstacles to the integration of AI among health professionals in the Moroccan public health system were identified as organizational barriers. In particular, the main concerns identified were lack of formal training, lack of clarity in institutional policies, and poor managerial support. Prior formal AI training was the only variable consistently associated with perceived barriers across all dimensions and the overall score after adjustment; participants with previous training reported fewer barriers, although this association was attenuated after accounting for item overlap and cannot be interpreted causally. The associations of age, professional category, educational qualification, and department were more specific, highlighting the importance of tailoring implementation strategies to professional roles and clinical context.

These findings show that successful AI integration depends on more than technological availability. Successful integration requires a coordinated sociotechnical solution involving role-specific and continuous training, supportive leadership, clear governance and accountability frameworks, adequate digital infrastructure and genuine interdisciplinary involvement. Health care institutions should therefore assess workforce and organizational readiness prior to the deployment of AI-based tools and involve professionals actively in the process. The results provide useful evidence for developing context-sensitive policies and capacity-building programs. However, the cross-sectional design does not allow any causal conclusions. More longitudinal, interventional, and multicenter studies, together with independent validation of the instrument's dimensional structure, are warranted to determine whether structured training and organizational readiness can improve AI acceptance, safe use, and

sustainable integration into clinical practice.

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Conflict of interest

The authors declare that they have no competing interests.

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Ethical approval and consent to participate

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. Formal institutional approval to conduct the research was granted by the Regional Directorate of Health and Social Protection of Marrakech-Safi and the relevant regional health care authorities (Authorization No. 1943/26). Participation was entirely voluntary. Before completing the questionnaire, all participants received information regarding the study objectives, the confidentiality and anonymity of their responses, their right to decline participation, and their right to withdraw at any time without consequences. Electronic informed consent was obtained from all participants prior to data collection. No directly identifiable personal information was collected.

Consent for publication

Not applicable. The manuscript does not contain identifiable personal information, individual clinical data, images, or other materials requiring specific consent for publication.

Availability of data

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The dataset is not publicly available because its sharing is subject to applicable institutional, ethical, and participant confidentiality requirements.

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