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Knowledge, Attitudes, and Practices Regarding Artificial Intelligence Among Healthcare Professionals at a North Indian Tertiary Care Teaching Hospital: A Cross-Sectional Survey

Hanoakh Bhosale [1], Asmi Gamaliel [1], Girish Joseph [2], Neena Bhatti [2], Dinesh K. Badyal [2]

1. Pharmacology, Christian Medical College & Hospital, Ludhiana, IND 2. Pharmacology and Therapeutics, Christian Medical College & Hospital, Ludhiana, IND

Corresponding author: Girish Joseph, girishjoseph7@gmail.com

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Abstract

Background: Artificial intelligence (AI) is increasingly being incorporated into clinical care, medical research, and health professions education. Acceptance by practicing clinicians and trainees is a prerequisite for its safe and effective adoption, yet data from Indian teaching hospitals remain limited. This study described the knowledge, attitudes, and practices (KAP) related to AI among healthcare professionals, including perceived facilitators and barriers, and explored factors associated with clinical AI use.

Methods: A cross-sectional, questionnaire-based study was conducted by the Department of Pharmacology at Christian Medical College & Hospital, Ludhiana, among postgraduate trainees, senior residents, faculty, and consultants. All 380 eligible professionals were invited; incomplete questionnaires were excluded, and those analyzed formed a non-probability convenience sample. The author-developed, self-administered instrument underwent review by four experts and pilot testing with five faculty members (excluded from the final sample); no item changes were made, and formal psychometric validation was not undertaken, although post hoc internal consistency was good (Cronbach's α of 0.81 for benefit items and 0.82 for concern items). The questionnaire assessed AI awareness, perceived benefits and concerns, adoption intention, and self-reported practices. Proportions were reported with 95% confidence intervals (CIs), and exploratory associations were assessed using exact tests and a multivariable modified Poisson regression model.

Results: Of 380 invited professionals, 201 (52.9%) provided questionnaires usable for analysis (mean age = 31.4 ± 7.0 years; 114 women, 56.7%). Awareness of AI was high but uneven: 152 respondents (75.6%) were aware of AI tools used in clinical diagnosis or treatment planning and 161 (80.1%) were aware of AI use in medical research, whereas only 63 (31.3%) had read primary research on AI in clinical practice. Overall, 169 respondents (84.1%) had used AI for at least one professional purpose, most commonly teaching (n = 123, 61.2%) and conferencing (n = 93, 46.3%), while clinical AI use (any self-reported use of AI in clinical decision-making) was reported by 81 (40.3%; 95% CI: 33.8-47.2). The most strongly endorsed statements were that AI should support rather than replace physicians, that AI improves hospital and patient data management, and that AI enhances medical imaging and analysis (each agreed by 181 respondents, 90.0%). Data privacy and security were the most prevalent concerns (n = 144, 71.6%). Clinical AI use differed by specialty (Fisher-Freeman-Halton exact test, p = 0.034) and was associated with awareness of how AI applies to one's own specialty (69/138, 50.0% versus 12/63, 19.0%; prevalence ratio: 2.62, 95% CI: 1.54-4.49; Fisher exact test, p < 0.001); the association persisted after multivariable adjustment (adjusted prevalence ratio: 2.62, 95% CI: 1.52-4.51).

Conclusions: In this exploratory single-center survey, healthcare professionals showed high conceptual awareness of and largely favorable attitudes toward AI, with the strongest endorsement for AI as a supervised tool that supports rather than replaces clinicians. Fewer than half reported clinical AI use, which was independently associated with awareness of how AI applies to one's own specialty. Specialty-tailored education is a possible strategy that warrants implementation and evaluation in future studies.

Categories: Medical Education, Healthcare Technology
Keywords: artificial intelligence, clinical decision-making, healthcare professionals, machine learning, medical education, technology acceptance

Introduction

Artificial intelligence (AI) refers to computational systems capable of performing tasks traditionally associated with human intelligence, including learning, reasoning, problem-solving, perception, and decision-making. The term was introduced by John McCarthy in the 1955 proposal for the Dartmouth Summer Research Project. Initially confined largely to academic research, AI has progressively expanded into various sectors, including business, finance, education, and healthcare [1,2]. Advances in computational technologies have enabled its application beyond administrative and analytical functions to

clinical diagnosis, treatment planning, and patient management [3].

In healthcare, AI is increasingly being explored as a supportive tool to improve clinical decision-making rather than replace physician judgment [3,4]. Its applications include AI-assisted medical imaging, analysis of clinical data, and wearable technologies that support patient monitoring [1]. Generative AI tools such as ChatGPT have also attracted considerable attention in medical education, research, and clinical practice [5]. Alongside these developments, simulation-based medical education has provided opportunities for experiential learning and clinical decision-making through realistic training environments [6]. Despite these potential benefits, concerns regarding data privacy, clinical validation, algorithmic bias, accountability, and legal liability continue to influence the acceptance and implementation of AI in healthcare [2,3].

Previous studies have examined healthcare professionals' knowledge, attitudes, and perceptions of AI across different countries and participant groups, including physicians and medical students [7-9]. Patterns of digital-resource utilization among medical trainees in India have also been reported [10]. However, evidence addressing AI awareness, perceptions, and clinical use across multiple specialties and professional categories within Indian tertiary care teaching hospitals remains limited. Physicians' perspectives may also be influenced by country-specific factors, including healthcare infrastructure, access to AI-enabled technologies, regulatory requirements, institutional policies, and opportunities for structured training. An international survey involving 300 dermatologists from 13 countries reported descriptive variations in AI adoption and identified regulatory and ethical concerns as important considerations, although the overall association between country and AI use was not statistically significant [11]. Furthermore, the applications of AI differ across medical specialties according to clinical workflows, diagnostic requirements, and the availability of relevant technologies [12]. These differences highlight the importance of examining AI-related perceptions and practices within specific healthcare settings rather than assuming that findings from one country or specialty are directly generalizable to another.

Understanding healthcare professionals' perceptions is important for the responsible integration of AI into clinical practice. Awareness of AI applications does not necessarily translate into clinical use, while favorable attitudes may coexist with concerns regarding patient safety, professional responsibility, and institutional preparedness. Identifying these patterns may help inform specialty-specific training, institutional governance, and the development of appropriate safeguards. In the present study, AI acceptability was explored indirectly through five domains: awareness of AI applications, perceived benefits (facilitators), concerns (barriers), intention to adopt AI, and self-reported use. These domains were examined descriptively and were not combined into a validated overall acceptability measure.

The primary objective of this study was to assess the knowledge, attitudes, and practices (KAP) regarding AI among postgraduate trainees, senior residents, faculty, and consultants at a North Indian tertiary care teaching hospital. Specifically, the study aimed to describe awareness of AI applications in clinical practice, research, and teaching; perceived benefits and concerns regarding AI; self-reported professional and clinical AI use; and intention to incorporate AI into daily practice. The secondary objective was to explore associations between clinical AI use and participant characteristics, including gender, designation, age, years of experience, medical specialty, and awareness of AI applications within one's own specialty.

Materials And Methods

Study design and setting

This was a cross-sectional, questionnaire-based observational study conducted by the Department of Pharmacology at Christian Medical College & Hospital, Ludhiana, a tertiary care teaching hospital in North India, to describe AI awareness, attitudes, perceived concerns, and self-reported practices among postgraduate students, senior residents, teaching faculty, and consultants. The study was conducted from September 2025 to March 2026. AI acceptability was not operationalized as a single validated construct. Instead, domains relevant to acceptability were explored descriptively: participants' awareness of AI applications, perceived benefits and concerns, willingness to adopt AI, and self-reported use of AI in professional and clinical practice. No overall acceptability score was derived.

Study population and sampling

The study population comprised postgraduate medical students, senior residents, teaching faculty, and consultants at the institution. The required sample size was calculated using the single-proportion formula, $n = Z^2 p(1-p)/d^2$, where Z is the standard normal deviate for a 95% confidence level (1.96), p is the expected proportion (0.5), and d is the absolute precision (0.07) [13]. This yielded a minimum sample size of 196 participants, which was rounded to 200. The use of a 50% expected proportion provides a conservative sample-size estimate when a reliable prior estimate is unavailable. The calculation was designed to estimate a single proportion with the specified precision; it was not intended to provide adequate statistical power for subgroup comparisons, which should therefore be regarded as exploratory.

A non-probability convenience sampling approach was used. All 380 eligible healthcare professionals across the institution's departments and professional categories (postgraduate trainees, senior residents, teaching

faculty, and consultants) were invited to participate; no department or professional category was deliberately excluded. None formally declined participation. However, 179 questionnaires were returned incomplete and were excluded in their entirety, whereas 201 were complete and were analyzed, yielding a usable-questionnaire response rate of 52.9% (201/380); 47.1% (179/380) were incomplete. A questionnaire was classified as incomplete when one or more of the 35 core items were unanswered. All 201 analyzed questionnaires contained a response to every one of the 35 core items. Item-level missing data were confined to designation (not specified, n = 1) and years of experience (not reported, n = 3); these respondents were excluded only from analyses involving those variables, and no imputation was performed. Because data from incomplete questionnaires were not available for analysis, the characteristics of non-completers could not be compared with those of included respondents. Recruitment aimed to obtain responses from at least 50% of the faculty members in each department, with particular efforts to engage senior faculty. Departmental faculty numbers and participation differed, and some senior faculty did not provide completed questionnaires. Consequently, achieving proportionate departmental or senior-faculty representation could not be assured.

Data collection instrument

A structured, self-administered questionnaire was developed by the authors on the basis of the study objectives. Four experts, i.e., two members of the institutional Medical Education Unit (MEU) and two faculty members from outside the MEU, reviewed the draft items for relevance to the study objectives and clarity of wording (expert content and face review). The questionnaire was then pilot-tested among five faculty members to assess clarity and comprehensibility. No changes were made following either expert review or pilot testing, and these five pilot participants were excluded from the final analytic sample. Formal psychometric validation was not undertaken before data collection: content validity was not quantified (for example, with a content validity index), the pilot sample was small and included faculty members only, and construct validity and test-retest reliability were not assessed. Internal consistency was examined post hoc in the study sample: Cronbach's α was 0.81 (95% CI: 0.75-0.85) for the 15 perceived-benefit items and 0.82 (95% CI: 0.77-0.86) for the eight concern items. These values indicate internal coherence of the two item groups in this sample but do not establish the validity of the instrument. Accordingly, the questionnaire was used for exploratory description of individual domains rather than measurement of a validated composite construct.

The final questionnaire, reproduced in full in the Appendices, comprised a demographic section (age, gender, designation, specialty, and years of experience); a multiple-response item on the purposes for which AI had been used (diagnosis, investigation, teaching, conferencing, or "not used AI yet"); and 35 items arranged in three sections covering AI in clinical practice (21 items), AI in medical research (nine items), and AI in medical teaching and training (five items). Nine of the 35 items were dichotomous (Yes/No) questions on awareness and practice, and 26 were statements rated on a five-point Likert scale ranging from strongly disagree to strongly agree, covering perceived benefits (15 items), concerns (eight items), and practice and adoption intention (three items). Perceived facilitators (benefits) and barriers (concerns) were thus assessed using dedicated Likert-scale statements.

Clinical AI use, the principal practice outcome, was operationally defined as any prior self-reported use of an AI tool to assist clinical decision-making, based on an affirmative response to the questionnaire item, "Have you ever used AI in clinical decision-making (diagnosis, treatment planning, etc.)?" This definition encompassed respondents' own interpretations of AI-assisted clinical activities. The questionnaire did not distinguish between generative AI, AI-enabled diagnostic tools, and dedicated clinical decision-support systems, or assess the frequency of use or impact on patient-management decisions. This item was analyzed separately from the multiple-response item on professional purposes of AI use.

Questionnaire administration

The questionnaire was self-administered and was administered online using Google Forms (Google, Mountain View, CA). Participants were approached through departmental meetings after the investigators had met the head of the respective department. No time limit was set for completing the questionnaire, and three reminders were sent to participants. Responses were collected through the online form, and the completed responses were exported into a Microsoft Excel spreadsheet (Microsoft Corporation, Redmond, WA) for analysis. Participation was voluntary, responses were anonymous, and no personal identifiers were collected.

Statistical analysis

Responses were compiled in a spreadsheet and analyzed using descriptive and inferential statistics. Categorical data were summarized as frequencies and percentages, and continuous data as mean ± standard deviation (SD). For descriptive purposes, Likert responses were also summarized as mean scores after coding from 1 (strongly disagree) to 5 (strongly agree). Proportions are reported with 95% CIs calculated using the Wilson score method. Because several subgroups contained small numbers, associations between participant characteristics and clinical AI use were examined using exact tests: the Fisher exact test for two-by-two comparisons and the Fisher-Freeman-Halton exact test for variables with more than two categories. For the Fisher-Freeman-Halton test, exact p-values were obtained by complete enumeration for designation, age

group, and experience group; for specialty group, for which complete enumeration was computationally impractical, the p-value was estimated by Monte Carlo simulation with 1,000,000 permutations. For the association between awareness of AI in one's own specialty and clinical AI use, the prevalence ratio (PR) and its 95% CI (log method) were calculated. A p-value of less than 0.05 was considered statistically significant. No adjustment was made for multiple comparisons; for context, the Bonferroni-adjusted threshold for the six participant characteristics tested ($p < 0.0083$) is also reported. To examine whether the association between awareness of AI in one's own specialty and clinical AI use was independent of other participant characteristics, a multivariable modified Poisson regression model (log link with robust standard errors) was fitted to estimate adjusted prevalence ratios (aPRs) with 95% CIs. The model included awareness of AI in one's own specialty, specialty group (with surgical specialties, the largest group, as the reference), designation (postgraduate trainees, senior residents, and faculty, with assistant professors, associate professors, and professors combined), and gender. Age group and years of experience were not entered in the main model because both were closely related to designation; in sensitivity analyses, age group (≤29, 30-39, and ≥40 years) was entered in place of, and in addition to, designation. The overall contribution of specialty group was assessed with a joint Wald test. Because the model estimated 12 parameters from 80 outcome events, it was regarded as exploratory. Internal consistency of the perceived-benefit and concern item groups was assessed post hoc using Cronbach's α, with 95% CIs from 5,000 bootstrap resamples. All analyses were performed using Python version 3.13 (Python Software Foundation, Wilmington, DE) with the SciPy (version 1.18), NumPy (version 2.5), and statsmodels (version 0.15) libraries. No single composite acceptability score was calculated; acceptability was evaluated descriptively across these domains.

Ethical considerations

The study received approval from the Institutional Ethics Committee (Biomedical & Health Research), Christian Medical College & Hospital, Ludhiana, Punjab, India (Approval Reference No. IECBMHR/202508-408/Apprvl-Student-Proj/CMC &H), at the expedited review meeting held on July 2, 2025; the formal approval letter was issued on August 18, 2025. Informed consent was obtained from all participating respondents before questionnaire completion. Participation was voluntary, responses were anonymous, and no personal identifiers were collected.

Results

Participant characteristics

Of the 380 eligible professionals invited, 201 (52.9%) submitted questionnaires usable for analysis; 179 (47.1%) questionnaires were incomplete and excluded, and none formally declined participation. The mean age of the respondents was 31.4 ± 7.0 years (median = 29; range = 23-60), and the mean clinical experience was 5.2 ± 6.3 years. Women constituted 114 respondents (56.7%) and men 87 (43.3%). Postgraduate trainees formed the largest group (n = 125, 62.2%), followed by faculty (n = 50, 24.9%) and senior residents (n = 25, 12.4%). Respondents were drawn from a broad range of clinical and diagnostic specialties, summarized in Table *1*.

Characteristic	Category	n (%) or mean ± SD
Age (years)	Mean ± SD (n = 201)	31.4 ± 7.0
	≤29	111 (55.2)
	30–39	67 (33.3)
	40–49	14 (7.0)
	≥50	9 (4.5)
Gender	Female	114 (56.7)
	Male	87 (43.3)
Designation	Postgraduate	125 (62.2)
	Assistant professor	29 (14.4)
	Senior resident	25 (12.4)
	Professor	17 (8.5)
	Associate professor	4 (2.0)
	Not specified	1 (0.5)
Experience (years)	Mean ± SD (n = 198)	5.2 ± 6.3
Specialty group	Surgical specialties	51 (25.4)
	Medicine and allied	33 (16.4)
	Diagnostic (pathology/microbiology/biochemistry)	32 (15.9)
	Radiology and radiation	22 (10.9)
	Pediatrics	18 (9.0)
	Obstetrics and gynecology	14 (7.0)
	Preclinical/community	13 (6.5)
	Other/not specified	13 (6.5)
	Anesthesia/critical care/emergency	5 (2.5)

TABLE 1: Demographic and professional characteristics of the respondents (N = 201).

Percentages are calculated with N = 201 as the denominator. Years of experience were not reported by three respondents; the mean was therefore calculated for 198 respondents.

SD: standard deviation.

Knowledge and awareness of AI

Awareness of AI applications was generally high but uneven across domains (Table *2*). Three-quarters of respondents were aware of AI tools used in clinical diagnosis or treatment planning (n = 152, 75.6%; 95% CI: 69.2-81.0), and 161 (80.1%; 95% CI: 74.0-85.0) were aware of AI use in medical research. Awareness of how AI applies to one's own specialty was lower (n = 138, 68.7%). Practical, hands-on familiarity lagged behind general awareness: only 63 respondents (31.3%; 95% CI: 25.3-38.1) had read a research publication involving AI in clinical practice, and fewer than half (n = 97, 48.3%) had seen or used simulation-based AI tools in education.

Awareness item	Yes, n (%)	No, n (%)
Aware of AI tools in clinical diagnosis/treatment planning	152 (75.6)	49 (24.4)
Aware of how AI applies to own specialty	138 (68.7)	63 (31.3)
Aware of AI use in medical research	161 (80.1)	40 (19.9)
Read research publications involving AI in clinical practice	63 (31.3)	138 (68.7)
Know AI tools for literature review/data mining	113 (56.2)	88 (43.8)
Aware of AI applications in medical teaching/training	143 (71.1)	58 (28.9)
Seen/used simulation-based AI tools in education	97 (48.3)	104 (51.7)

TABLE 2: Knowledge and awareness of AI applications (N = 201).

Awareness of selected applications of artificial intelligence among respondents (N = 201). Bars represent the percentage of respondents who answered "Yes" to each awareness item across clinical, research, and educational domains.

Self-reported use of AI

Overall, 169 respondents (84.1%; 95% CI: 78.4-88.5) reported having used AI for at least one professional purpose, whereas 32 (15.9%) had never used AI. The most common uses were teaching (n = 123, 61.2%) and conferencing (n = 93, 46.3%), followed by investigation (n = 80, 39.8%) and diagnosis (n = 78, 38.8%). Clinical AI use was more limited: 81 respondents (40.3%; 95% CI: 33.8-47.2) reported having used AI in clinical decision-making, and only 28 (13.9%; 95% CI: 9.8-19.4) had advised patients to use AI health applications. Adoption intention was moderate: 91 respondents (45.3%; 95% CI: 38.5-52.2) indicated that they were likely to incorporate AI into daily practice (Table *3* and Figure *1*).

Practice/behavior	n (%)	95% CI
Any prior use of AI (any purpose)	169 (84.1)	78.4–88.5
Used AI for teaching	123 (61.2)	54.3–67.7
Used AI for conferencing	93 (46.3)	39.5–53.2
Used AI for investigation	80 (39.8)	33.3–46.7
Used AI for diagnosis	78 (38.8)	32.3–45.7
Not used AI yet	32 (15.9)	11.5–21.6
Clinical AI use (used AI in clinical decision-making)	81 (40.3)	33.8–47.2
Advised patients to use AI health applications	28 (13.9)	9.8–19.4
Uses AI literature-summarization tools (agree)	127 (63.2)	56.3–69.5
Likely to incorporate AI in daily practice (agree)	91 (45.3)	38.5–52.2
In favor of AI for patient monitoring (agree)	93 (46.3)	39.5–53.2

TABLE 3: Practices and adoption intention regarding AI (N = 201).

Purpose categories (diagnosis, investigation, teaching, conferencing) were presented as self-explanatory checkbox options, and respondents could select all that applied. Clinical AI use was assessed with a separate Yes/No item. "Agree" combines agree and strongly agree responses.

AI: artificial intelligence; CI: confidence interval (Wilson score method).

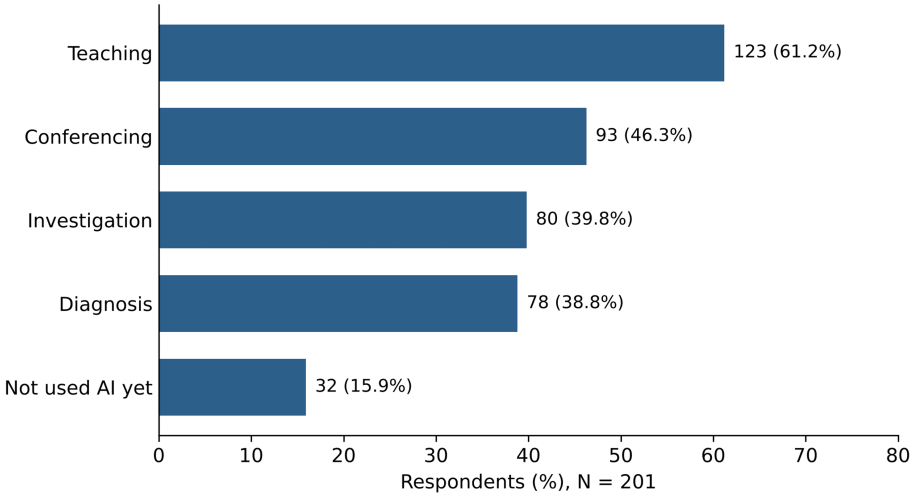


FIGURE 1: Purposes for which artificial intelligence has been used by respondents (N = 201).

Bars show the percentage of respondents selecting each purpose; data labels show the number (%) of respondents. Multiple responses were permitted; therefore, percentages do not sum to 100%.

AI: artificial intelligence.

Perceived benefits and facilitators

Attitudes toward the potential benefits of AI were strongly positive and represented important perceived facilitators of adoption (Table 4). The most strongly endorsed statements were that AI should support rather than replace physician decision-making, that AI improves hospital and patient data management, and that AI enhances medical imaging and analysis (each agreed by 181 respondents, 90.0%; 95% CI: 85.1-93.5). Large majorities also agreed that AI can advance medical research (n = 171, 85.1%), that AI tools should be supervised and regulated (n = 172, 85.6%), and that AI can accelerate drug discovery (n = 161, 80.1%) and improve diagnostic accuracy (n = 161, 80.1%). Endorsement was more modest for AI providing round-the-clock virtual assistance (n = 123, 61.2%) and for including AI topics in the curriculum (n = 116, 57.7%), indicating that enthusiasm was tempered where AI approached direct, autonomous patient contact.

Statement	Strongly disagree, n (%)	Disagree, n (%)	Neutral, n (%)	Agree, n (%)	Strongly agree, n (%)	Agree or strongly agree, n (%)	95% CI	Mean score ± SD
AI should support, not replace, physicians	3 (1.5)	3 (1.5)	14 (7.0)	98 (48.8)	83 (41.3)	181 (90.0)	85.1–93.5	4.27 ± 0.78
Improves hospital/patient data management	0 (0.0)	2 (1.0)	18 (9.0)	136 (67.7)	45 (22.4)	181 (90.0)	85.1–93.5	4.11 ± 0.58
Enhances medical imaging and analysis	0 (0.0)	2 (1.0)	18 (9.0)	141 (70.1)	40 (19.9)	181 (90.0)	85.1–93.5	4.09 ± 0.57
AI tools should be supervised and regulated	1 (0.5)	2 (1.0)	26 (12.9)	125 (62.2)	47 (23.4)	172 (85.6)	80.0–89.8	4.07 ± 0.67
Can significantly advance medical research	2 (1.0)	1 (0.5)	27 (13.4)	151 (75.1)	20 (10.0)	171 (85.1)	79.5–89.3	3.93 ± 0.58
Improves the accuracy of disease diagnosis	1 (0.5)	7 (3.5)	32 (15.9)	135 (67.2)	26 (12.9)	161 (80.1)	74.0–85.0	3.89 ± 0.68
Accelerates drug discovery and development	0 (0.0)	7 (3.5)	33 (16.4)	138 (68.7)	23 (11.4)	161 (80.1)	74.0–85.0	3.88 ± 0.64
Improves accuracy and efficiency of diagnosis	2 (1.0)	3 (1.5)	37 (18.4)	141 (70.1)	18 (9.0)	159 (79.1)	73.0–84.2	3.85 ± 0.63
Can help reduce medical errors	0 (0.0)	7 (3.5)	35 (17.4)	147 (73.1)	12 (6.0)	159 (79.1)	73.0–84.2	3.82 ± 0.58
Supports personalized treatment plans	0 (0.0)	16 (8.0)	42 (20.9)	135 (67.2)	8 (4.0)	143 (71.1)	64.5–77.0	3.67 ± 0.68
Supports care in remote/rural areas	1 (0.5)	25 (12.4)	45 (22.4)	111 (55.2)	19 (9.5)	130 (64.7)	57.9–71.0	3.61 ± 0.84
AI simulation improves learning/retention	1 (0.5)	16 (8.0)	54 (26.9)	107 (53.2)	23 (11.4)	130 (64.7)	57.9–71.0	3.67 ± 0.80
Would recommend AI for teaching	2 (1.0)	5 (2.5)	65 (32.3)	103 (51.2)	26 (12.9)	129 (64.2)	57.3–70.5	3.73 ± 0.75
Provides effective 24/7 virtual assistance	1 (0.5)	17 (8.5)	60 (29.9)	108 (53.7)	15 (7.5)	123 (61.2)	54.3–67.7	3.59 ± 0.77
AI topics should be in the curriculum	0 (0.0)	16 (8.0)	69 (34.3)	92 (45.8)	24 (11.9)	116 (57.7)	50.8–64.3	3.62 ± 0.80

TABLE 4: Perceived benefits of AI and related attitudes (five-point Likert scale; N = 201).

Agreement combines agree and strongly agree responses. Mean scores were calculated by coding responses from 1 (strongly disagree) to 5 (strongly agree).

AI: artificial intelligence; CI: confidence interval (Wilson score method); SD: standard deviation.

Concerns and perceived barriers

Alongside this optimism, respondents expressed consistent concerns that constituted the main perceived barriers to AI adoption (Table *5*). The most prevalent concern was data privacy and security (n = 144, 71.6% agreement; 95% CI: 65.1-77.4), followed by a perceived lack of clinical validation of AI tools (n = 137, 68.2%), reduced use of clinical judgment (n = 132, 65.7%), and a lack of regulation surrounding AI in medicine (n = 132, 65.7%). Concerns about transparency and accountability (n = 130, 64.7%), loss of the human touch in patient care (n = 127, 63.2%), and algorithmic bias (n = 123, 61.2%) were also widely shared. Anticipated patient distrust of AI was the least endorsed concern, though it was still held by a majority (n = 112, 55.7%). Notably, mean scores for every concern item fell between 3.57 and 3.85 on the five-point scale, indicating that these reservations were held with moderate but broad consensus rather than by a small, vocal minority.

Concern item	SD	D	N	A	SA	Agree % (95% CI)	Mean ± SD
Data privacy and security issues	0	4	53	113	31	71.6 (65.1–77.4)	3.85 ± 0.69
Lack of clinical validation of AI tools	0	6	58	114	23	68.2 (61.4–74.2)	3.77 ± 0.69
Lack of regulation in medicine	0	5	64	109	23	65.7 (58.9–71.9)	3.75 ± 0.69
Reduced use of clinical judgment	0	17	52	98	34	65.7 (58.9–71.9)	3.74 ± 0.84
Lack of transparency and accountability	0	7	64	107	23	64.7 (57.9–71.0)	3.73 ± 0.71
Loss of human touch in patient care	1	15	58	93	34	63.2 (56.3–69.5)	3.72 ± 0.85
AI may introduce/perpetuate bias	1	11	66	104	19	61.2 (54.3–67.7)	3.64 ± 0.75
Patients may not trust AI tools	2	9	78	96	16	55.7 (48.8–62.4)	3.57 ± 0.75

TABLE 5: Concerns regarding AI in medicine (five-point Likert scale; N = 201).

Cell values are counts unless otherwise indicated. “Agree %” combines agree and strongly agree responses.

SD: strongly disagree; D: disagree; N: neutral; A: agree; SA: strongly agree; CI: confidence interval (Wilson score method).

Factors associated with clinical AI use

Clinical AI use varied significantly by specialty (Fisher-Freeman-Halton exact test, $p = 0.034$), being highest among radiology and radiation specialties (14/22, 63.6%) and lowest among diagnostic laboratory specialties (7/32, 21.9%) and pediatrics (4/18, 22.2%). Awareness of how AI applies to one’s own specialty was significantly associated with clinical AI use: 69 of 138 respondents (50.0%; 95% CI: 41.8-58.2) who were aware reported clinical AI use, versus 12 of 63 (19.0%; 95% CI: 11.2-30.4) who were not (PR: 2.62, 95% CI: 1.54-4.49; Fisher exact test, $p < 0.001$). Gender, designation, age group, and years of experience were not significantly associated with clinical AI use (all $p > 0.05$), although no respondent aged 50 years or older (0/9) reported clinical AI use (Table *6* and Figure *2*).

Variable	Category	Clinical AI use, n/N (%)	p value
Gender	Female	48/114 (42.1)	0.565
	Male	33/87 (37.9)	
Designation	Assistant professor	16/29 (55.2)	0.224
	Associate professor	1/4 (25.0)	
	Postgraduate	51/125 (40.8)	
	Professor	4/17 (23.5)	
	Senior resident	8/25 (32.0)	
Age group (years)	≤29	46/111 (41.4)	0.056
	30–39	30/67 (44.8)	
	40–49	5/14 (35.7)	
	≥50	0/9 (0.0)	
Experience (years)	≤2	38/88 (43.2)	0.683
	3–5	22/55 (40.0)	
	6–10	12/31 (38.7)	
	>10	7/24 (29.2)	
Specialty group	Anesthesia/critical care/emergency	2/5 (40.0)	0.034
	Diagnostic (pathology/microbiology/biochemistry)	7/32 (21.9)	
	Medicine and allied	16/33 (48.5)	
	Obstetrics and gynecology	4/14 (28.6)	
	Other/not specified	8/13 (61.5)	
	Pediatrics	4/18 (22.2)	
	Preclinical/community	6/13 (46.2)	
	Radiology and radiation	14/22 (63.6)	
	Surgical specialties	20/51 (39.2)	
Aware of how AI applies to own specialty	Yes	69/138 (50.0)	<0.001
	No	12/63 (19.0)	

TABLE 6: Factors associated with the use of AI in clinical decision-making.

Clinical AI use was defined as a “Yes” response to “Have you ever used AI in clinical decision-making (diagnosis, treatment planning, etc.)?”

P-values are from the Fisher exact test (two-category variables) or the Fisher–Freeman–Halton exact test (variables with more than two categories; complete enumeration, except Monte Carlo estimation with 1,000,000 permutations for specialty group).

The “not specified” designation (n = 1) and respondents with missing years of experience (n = 3) were excluded from the respective analyses.

For awareness of how AI applies to one’s own specialty, the prevalence ratio (yes versus no) was 2.62 (95% CI 1.54–4.49).

n/N: respondents reporting clinical AI use/respondents in the category; AI: artificial intelligence; CI: confidence interval.

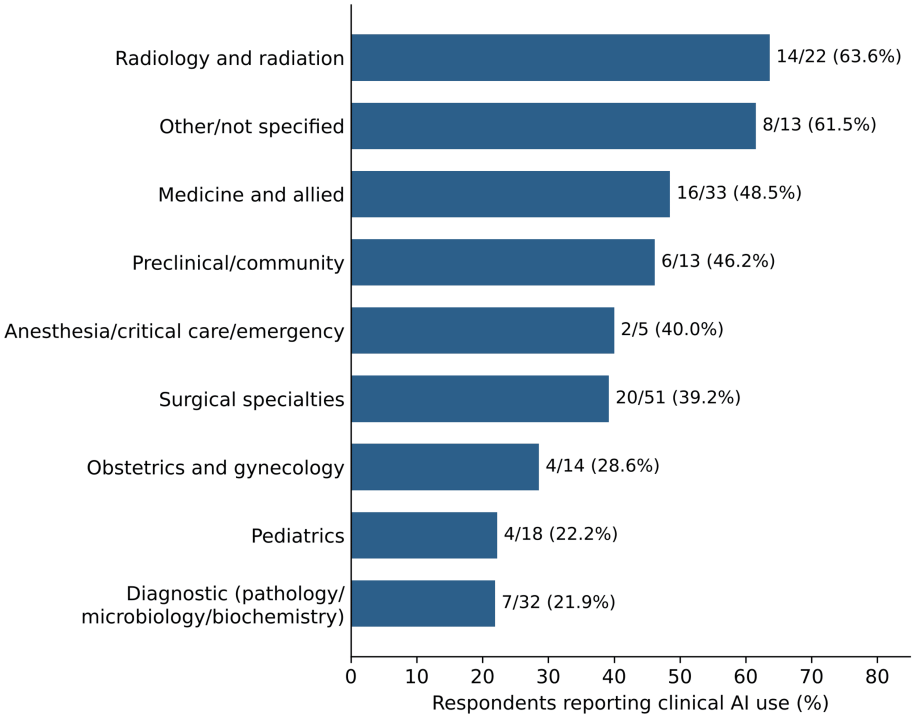


FIGURE 2: Use of artificial intelligence in clinical decision-making according to professional specialty.

Bars show the percentage of respondents in each specialty group reporting clinical AI use; data labels show n/N (%), where N is the number of respondents in each specialty group (total N = 201). The overall between-group difference was statistically significant (Fisher–Freeman–Halton exact test, p = 0.034); however, some specialty groups were small, and the descriptive proportions should be interpreted with caution.

AI: artificial intelligence.

Multivariable analysis

In the multivariable model (n = 200; 80 respondents reporting clinical AI use), awareness of how AI applies to one's own specialty remained independently associated with clinical AI use (aPR: 2.62, 95% CI: 1.52-4.51; p = 0.001), with an estimate almost identical to the unadjusted prevalence ratio (Table 7). After adjustment, no individual specialty group differed significantly from surgical specialties, and the overall contribution of specialty group was not statistically significant (joint Wald test, p = 0.069). Designation and gender were not associated with clinical AI use. The association with awareness was similar when age group was entered in place of designation (aPR: 2.65, 95% CI: 1.54-4.56) and when both were included (aPR: 2.58, 95% CI: 1.49-4.49).

Variable	Category	Clinical AI use, n/N (%)	aPR (95% CI)	p-value
Aware of how AI applies to own specialty	Yes	68/137 (49.6)	2.62 (1.52–4.51)	0.001
	No	12/63 (19.0)	1 (reference)	Reference
Gender	Female	48/114 (42.1)	1.22 (0.85–1.74)	0.286
	Male	32/86 (37.2)	1 (reference)	Reference
Designation	Postgraduate	51/125 (40.8)	1 (reference)	Reference
	Senior resident	8/25 (32.0)	0.77 (0.44–1.36)	0.371
	Faculty	21/50 (42.0)	0.93 (0.61–1.42)	0.728
Specialty group (overall p = 0.069)	Surgical specialties	20/51 (39.2)	1 (reference)	Reference
	Radiology and radiation	14/22 (63.6)	1.38 (0.83–2.29)	0.218
	Medicine and allied	16/33 (48.5)	1.21 (0.71–2.06)	0.492
	Preclinical/community	5/12 (41.7)	1.15 (0.53–2.52)	0.727
	Anesthesia/critical care/emergency	2/5 (40.0)	1.17 (0.53–2.59)	0.703
	Obstetrics and gynecology	4/14 (28.6)	0.71 (0.29–1.71)	0.439
	Pediatrics	4/18 (22.2)	0.73 (0.31–1.75)	0.486
	Diagnostic (pathology, microbiology, biochemistry)	7/32 (21.9)	0.51 (0.24–1.12)	0.095
	Other/not specified	8/13 (61.5)	1.78 (1.00–3.19)	0.051

TABLE 7: Multivariable analysis of factors associated with clinical AI use (n = 200).

Modified Poisson regression (log link, robust standard errors) including all variables shown. One respondent whose designation was not specified was excluded (n = 200). “1 (reference)” and “Reference” denote the reference category, for which no ratio or p-value is estimated. Faculty combines assistant professors, associate professors, and professors. The overall p-value for the specialty group is from a joint Wald test.

aPR: adjusted prevalence ratio; AI: artificial intelligence; CI: confidence interval; n/N: respondents reporting clinical AI use/respondents in the category.

Discussion

This cross-sectional survey of 201 healthcare professionals at a tertiary care North Indian teaching hospital shows a pattern consistent with that described in the AI-adoption literature: good conceptual awareness and largely favorable attitudes, coupled with caution and uneven translation into clinical practice [2,7,14]. A general consensus was evident, with approximately three-quarters of respondents aware of the use of AI in diagnosis (n = 152, 75.6%) and research (n = 161, 80.1%). However, only about one-third (n = 63, 31.3%) had engaged with the primary literature on AI in clinical practice, and fewer than half (n = 97, 48.3%) had encountered simulation-based AI tools in their own training. This gap between awareness and exposure may indicate that general awareness has not necessarily been accompanied by direct, hands-on, structured engagement. This finding is consistent with earlier observations that institutional and curricular exposure to AI in Indian medical education remains limited relative to the pace of technological change [2,6,8,9].

The attitudinal findings are notable for their internal consistency. The three most strongly endorsed

statements (each agreed by 181 respondents, 90.0%) were that AI should support rather than replace a physician's judgment, that AI improves hospital and patient data management, and that AI enhances medical imaging and analysis, all relatively low-risk, augmentative applications. Enthusiasm was visibly lower for applications approaching autonomous patient contact, such as round-the-clock virtual assistance (n = 123, 61.2%), which may reflect the ethical and liability concerns raised in the background literature [3]. Read together with the concerns data, this pattern suggests that respondents were not opposed to AI in principle but favored its use as a supervised, augmentative tool rather than an independent decision-maker. Because these were agreement ratings on individual statements, this interpretation should be confirmed using validated acceptability measures. This distinction may have implications for how AI tools for clinical decision support should be designed, labeled, and regulated as aids to clinicians [3,15,16].

The concerns expressed by respondents centered primarily on data privacy and security, with 144 respondents (71.6%) agreeing that this was a major issue, alongside limited clinical validation, an absence of regulatory frameworks, and threats to clinical judgment arising from over-reliance on AI-concerns that map closely onto the ethical and legal challenges to AI adoption in healthcare described elsewhere [3,14]. These concerns should also be interpreted within the context of the Indian healthcare setting. The availability of AI-enabled technologies, regulatory requirements governing their clinical use, institutional approval processes, healthcare infrastructure, and access to formal training may influence physicians' willingness and ability to adopt AI. International research has similarly identified regulatory and ethical concerns as important considerations in AI implementation [11]. However, the present study did not assess the availability or approval status of individual AI tools, institutional implementation policies, or access to specialty-specific technologies. Consequently, these factors represent possible influences on the observed perceptions and practices rather than explanations established by the present findings.

Notably, every concern item was endorsed by more than half of respondents, suggesting that these reservations were widely shared in this sample. Such concerns may limit the uptake of AI tools that are promoted solely on the basis of their benefits, and visibly addressing privacy safeguards, validation evidence, and lines of accountability may be important for meaningful changes in practice; this possibility was not tested in the present study.

Despite concerns about a lack of regulation, accountability, and validation, a large majority of respondents (n = 169, 84.1%) had used AI for some professional purpose, most often for teaching, conferencing, and literature-related tasks, reflecting the growing popularity of AI tools such as ChatGPT, Google Gemini, and Claude among trainees and faculty alike [4,5,9]. Although the use of AI for non-clinical purposes has grown substantially since its introduction, clinical AI use was reported by fewer than half of respondents (n = 81, 40.3%), suggesting that, in this sample, familiarity with general-purpose AI tools had not yet translated into clinical AI use. Only a small minority (n = 28, 13.9%) had gone as far as recommending AI health applications to patients, which may indicate that respondents were more comfortable using AI to support their own work than to extend it directly into the patient-facing relationship [17].

Two exploratory findings are relevant to this gap. First, clinical AI use differed significantly by specialty, with radiology and radiation specialties reporting the highest use (14/22, 63.6%), consistent with the established application of AI tools for image interpretation in these fields. Previous literature has described differences in the applications of AI across medical specialties, particularly in fields where imaging, pattern recognition, and structured diagnostic information are prominent [12]. Such differences may contribute to variation in physicians' exposure to and use of AI. However, the unadjusted specialty association observed in this study did not remain statistically significant after correction for multiple comparisons, and the overall specialty effect was not significant in the multivariable analysis. Therefore, the observed differences should be considered exploratory rather than evidence that medical specialty independently predicts clinical AI use. Second, awareness of how AI applies to one's own specialty was associated with clinical AI use in these unadjusted analyses: clinical AI use was approximately 2.6-fold higher among respondents who were aware of how AI applied to their own specialty than among those who were not (69/138, 50.0% versus 12/63, 19.0%; PR: 2.62, 95% CI: 1.54-4.49). Because the outcome was any self-reported use at any time, this association indicates exposure rather than routine or sustained use. Only the awareness association remained significant after Bonferroni adjustment, and in the multivariable model it persisted after adjustment for specialty, designation, and gender (aPR: 2.62, 95% CI: 1.52-4.51), whereas the overall difference by specialty was no longer statistically significant. The specialty difference should therefore be regarded as hypothesis-generating, and may partly reflect differences in specialty-relevant awareness. Demographic factors more traditionally associated with technology adoption (age, gender, designation, and years of experience) showed no significant association, although the complete absence of clinical AI use among respondents aged 50 years or older (0/9) is a pattern worth monitoring in larger samples. Because the analyses were cross-sectional, it cannot be determined whether specialty-relevant awareness leads to clinical use, results from it, or reflects other factors such as the availability of AI tools within a specialty. Specialty-specific education is therefore proposed only as a possible strategy, whose effect on appropriate clinical AI use would need to be evaluated in future implementation studies, a direction consistent with recommendations from prior KAP studies among healthcare professionals [2,14]. More broadly, the consistency with which privacy, validation, and accountability concerns were expressed suggests that education alone may be insufficient; institutional clinical-governance and data-protection frameworks, transparent validation of tools before deployment, and clearly defined lines of accountability may also be

needed to convert cautious optimism into safe, sustained clinical AI use. In this way, the present findings may help inform curriculum design, institutional clinical governance, and the responsible, supervised implementation of AI at comparable teaching hospitals.

Limitations

This study has several limitations. It was conducted at a single tertiary care teaching hospital using non-probability convenience sampling. Although all eligible professionals were invited, only 201 of 380 (52.9%) contributed questionnaires usable for analysis, while 179 (47.1%) questionnaires were incomplete. This raises concerns about nonresponse and selection bias. Exclusion of a substantial proportion of incomplete questionnaires may have introduced additional selection bias, particularly if respondents who completed the survey differed systematically in their familiarity with or attitudes toward AI from those who did not; because data from non-completers were unavailable, this could not be examined. The potential effect is substantial: if none of the 179 non-completers had used AI clinically, clinical AI use among all 380 invited professionals would be 21.3% (81/380), and if all had, it would be 68.4% (260/380), compared with 40.3% (81/201) among respondents. The number of faculty members differed between departments, and the recruitment aim of reaching at least 50% of each department's faculty was not assured; some senior faculty did not return completed questionnaires, resulting in possible underrepresentation of senior staff and certain departments. Postgraduate trainees comprised nearly two-thirds (n = 125, 62.2%) of included respondents, so the overall estimates mainly reflect trainee perspectives and may not generalize to other professional mixes or institutions.

Furthermore, country-specific and institutional factors, including access to AI-enabled technologies, regulatory approval requirements, institutional policies, healthcare infrastructure, and availability of AI-related training, were not systematically evaluated. These unmeasured factors may influence physicians' perspectives and clinical use of AI and limit comparisons with findings from other healthcare systems. Differences in access to specialty-specific AI applications may also have contributed to the observed variation across medical specialties, although this could not be established from the available data. The cross-sectional design cannot establish causal or temporal relationships, and self-report introduces recall and social-desirability bias. Although four experts reviewed the questionnaire and five faculty members pilot-tested it without subsequent changes, formal psychometric validation was not undertaken; the pilot sample was small and did not include trainees, and the post hoc internal consistency estimates do not establish validity. AI acceptability itself was not measured directly, and the findings are therefore exploratory and do not represent a validated overall measure of AI acceptability. Clinical AI use was determined by a single broadly worded question about any prior use and did not distinguish AI tool categories or assess the frequency, effectiveness, or influence of AI use on patient-management decisions. The sample size was calculated to estimate a single proportion, not to ensure adequate power for subgroup comparisons; several subgroup counts were small, and findings should be interpreted cautiously despite the use of exact tests. No correction was applied for multiple comparisons, and the difference by specialty did not remain significant after Bonferroni adjustment. Finally, the multivariable model was exploratory: it estimated 12 parameters from 80 outcome events; several specialty groups were small; age and experience could not be modeled together with designation because of their close relationship; and residual confounding by unmeasured factors, such as the availability of AI tools within a specialty, cannot be excluded.

Conclusions

In this exploratory survey, healthcare professionals at a North Indian tertiary care teaching hospital reported high conceptual awareness of and predominantly favorable attitudes toward AI, with the strongest endorsement for AI as a supervised tool that supports, rather than replaces, clinical judgment. General-purpose use of AI for teaching, conferencing, and literature-related tasks was common, whereas clinical AI use was reported by fewer than half of respondents. Concerns about data privacy, clinical validation, regulation, and the erosion of clinical judgment were widely shared. Awareness of how AI applies to one's own specialty was associated with clinical AI use, and this association persisted after adjustment for specialty, designation, and gender. Specialty-tailored education, accompanied by clear regulatory frameworks, validation evidence, and defined lines of accountability, is a possible strategy to support the safe adoption of AI; its effect should be evaluated in future studies, preferably multicenter studies using validated instruments.

Appendices

Questionnaire

Section A: Demographic Information

1. Age

2. Gender

3. Designation

a. Postgraduate

b. Senior resident

c. Assistant professor

d. Associate professor

e. Professor

4. Specialty

5. Years of experience

6. Have you ever used AI for any of the following purposes? (Select all that apply)

a. Diagnosis

b. Investigations

c. Teaching

d. Conferencing

e. Not used AI yet

Section B: Clinical Domain Knowledge

1. Are you aware of any AI tools currently used in clinical diagnosis or treatment planning?

a. Yes

b. No

2. Are you aware of how AI is applied in your clinical specialty?

a. Yes

b. No

Attitude

1. AI could be used to improve the accuracy and efficiency of medical diagnosis.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

2. AI tools should support, but not replace, physician decision-making in patient care.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

3. I am concerned about the lack of clinical validation of AI tools used in healthcare.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

4. I am concerned that AI algorithms may introduce or perpetuate bias in medical decision-making.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

5. I am concerned that the use of AI could lead to a loss of human touch in patient care.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

6. I am concerned that reliance on AI may reduce the use of clinical judgment by healthcare professionals.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

7. I am concerned about the lack of regulation surrounding the use of AI in medicine.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

8. I am concerned about the lack of transparency and accountability in AI decision-making processes.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

9. I am concerned that patients may not trust AI-based medical tools or recommendations.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

10. AI can improve the accuracy of disease diagnosis.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

11. AI can help reduce medical errors.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

12. AI can support the development of personalized treatment plans.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

13. AI enhances medical imaging and analysis.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

14. AI can provide 24/7 virtual health assistance effectively?

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

15. AI can support healthcare delivery in remote and rural areas?

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

Practice

1. Have you ever used AI in clinical decision-making (diagnosis, treatment planning, etc.)?

a. Yes

b. No

2. Have you referred patients using AI-powered health apps (e.g., wearable ECG, symptom checkers)?

a. Yes

b. No

3. How likely are you to incorporate AI tools in your daily medical practice?

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

4. I am in favor of recommending AI tools for patient monitoring or follow-up.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

Section C: Research Domain Knowledge

1. Are you aware of the use of AI in medical research for data analysis?

a. Yes

b. No

2. Have you read any research publications involving AI in clinical practice?

a. Yes

b. No

3. Do you know about any AI tools used for literature review, data mining, or systematic reviews?

a. Yes

b. No

Attitude

1. AI has the potential to significantly advance medical research.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

2. AI-driven healthcare tools be subjected for supervision and regulation in medical research.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

3. I am concerned about data privacy and security issues related to AI in medicine.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

4. AI can accelerate drug discovery and development.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

5. AI can improve the efficiency of hospital and patient data management.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

Practice

1. I use AI-based literature summarization tools (e.g., ChatGPT, Scite, Semantic Scholar) in my medical research.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

Section D: Education Domain Knowledge

1. Are you aware of the use of AI applications in strengthening medical teaching and training?

a. Yes

b. No

2. Have you seen or used simulation-based AI tools in medical education?

a. Yes

b. No

Attitude

1. Should medical colleges include AI-related topics in their curriculum?

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

2. Simulation-based training in medicine using AI provides a more realistic learning experience and improves knowledge retention compared to traditional methods.

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

Practice

1. I would recommend the use of AI for teaching purposes (e.g., interactive modules, chabots).

a. Strongly Disagree

b. Disagree

c. Neutral

d. Agree

e. Strongly Agree

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Girish Joseph, Hanoakh Bhosale

Acquisition, analysis, or interpretation of data: Girish Joseph, Neena Bhatti, Dinesh K. Badyal, Hanoakh Bhosale, Asmi Gamaliel

Drafting of the manuscript: Girish Joseph, Neena Bhatti, Dinesh K. Badyal, Hanoakh Bhosale, Asmi Gamaliel

Supervision: Girish Joseph, Neena Bhatti, Dinesh K. Badyal

Critical review of the manuscript for important intellectual content: Hanoakh Bhosale, Asmi Gamaliel

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