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Artificial Intelligence in Clinical Practice and Its Impact on the Quality of Care Among Healthcare Professionals in Saudi Arabia: A Cross-Sectional Study

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ABSTRACT:

Background: Generative artificial intelligence (AI) is entering clinical practice rapidly, yet the extent to which healthcare professionals rely on it, and the implications for quality of care, remain poorly defined in Saudi Arabia. This study determined the extent of reliance on AI and its determinants and perceived impact.

Methods: In a national cross-sectional study, 502 healthcare professionals across diverse settings completed a validated electronic questionnaire assessing trust, attitudes, reliance, and perceived impact on 5-point Likert domains. High reliance was defined a priori as a mean reliance score of 3.5 or higher, and its independent predictors were identified by multivariable logistic regression.

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Results: Of the 502 participants, 74.7% used AI-based tools and 43.6% did so at least weekly; generative LLMs predominated (65.1%). Attitudes were the most favorable domain (mean, 3.41 [SD, 0.65]), whereas trust (2.95 [0.72]) and reliance (3.07 [0.74]) were moderate, and perceived impact was the lowest (2.80 [0.57]), with strong concern about deskilling. High reliance was identified in 150 participants (29.9%) and was independently associated with younger age, fewer years of experience, prior AI training, and higher self-rated AI knowledge (all $P < .05$) but not with gender, nationality, profession, workplace, or qualification. All domains showed good internal consistency (Cronbach α, 0.81-0.89).

Conclusions: Reliance on AI was moderate but concentrated among younger, less experienced professionals and those with prior AI training and higher self-rated AI knowledge, and favorable attitudes coexisted with substantial deskilling and patient-safety concerns. These findings support AI-literacy training, explicit verification safeguards, and governance that preserve independent clinical judgment.

INTRODUCTION

During the past two decades, the global health care sector has undergone a profound information and digital transformation, driven by the widespread adoption of electronic health records, mobile health applications, and data-driven clinical systems. Saudi Arabia has been at the forefront of this transformation in the region: under Vision 2030 and the National Strategy for Data and Artificial Intelligence, the Kingdom has invested substantially in digital-health infrastructure to improve the accessibility, efficiency, and quality of care (1,2). The COVID-19 pandemic acted as a powerful catalyst that accelerated this digital shift. Restrictions on physical contact necessitated a rapid expansion of telemedicine and remote care, and national platforms such as the Ministry of Health applications enabled millions of virtual consultations across the Kingdom, normalizing the use of digital tools among health care professionals and patients alike (3).

Building on this momentum, artificial intelligence (AI) has emerged as the next major development in health technology. Machine-learning algorithms, natural-language processing, computer-vision systems, and, most recently, generative large language models (LLMs) such as ChatGPT, Gemini, Copilot, and Claude are increasingly used to retrieve medical information, generate differential diagnoses, interpret investigations, and support documentation. Guidance from the World Health Organization has recognized both the benefits and the risks of these tools in health (4), and surveys of health care professionals across several countries report rapid and widespread adoption in clinical, educational, and research activities (5,6). Within Saudi Arabia and internationally, a growing body of research has assessed professionals' awareness, attitudes, and concerns regarding AI, documenting generally favorable perceptions alongside persistent worries about accuracy, privacy, and accountability (7), and studies of health-information seeking show that professionals and the public increasingly consult LLM-based tools as a first source of medical information (8).

However, most of this literature has focused on attitudes and intention to adopt AI rather than on actual reliance—the degree to which professionals depend on AI outputs when seeking information and making clinical decisions. Reliance is conceptually distinct from a favorable attitude, as a professional may hold reservations about AI yet still depend on it heavily under time pressure. Reliance carries both benefits and risks. A randomized study reported that access to an LLM could improve aspects of physicians' diagnostic reasoning (9). Conversely, the human-factors literature has long described automation bias—the tendency to excessively trust automated recommendations and to discount contradictory evidence—as a recognized source of clinical error (10,11), and sustained excessive reliance may contribute to deskilling, the gradual erosion of independent clinical reasoning and professional confidence.

Beyond individual decisions, reliance on AI has direct implications for the quality of care and for the clinician–patient relationship. Person-centered care depends on empathy, communication, trust, and shared decision-making; the introduction of AI into the consultation may either support these values, by freeing clinician time, or undermine them, by displacing human judgment and interaction (12). To measure these constructs robustly, the present study drew on established, validated instruments: general attitudes were assessed with items adapted from the General Attitudes Towards Artificial Intelligence Scale (GAAIS) (13,14), and trust and reliance behaviors with items adapted from the foundational scale of trust in automated systems (15). Despite the rapid integration of AI into Saudi health care, local evidence on measured reliance and its consequences for

quality of care remains limited. This study therefore aimed to determine the extent of reliance on AI for health information and clinical decision-making among healthcare professionals in Saudi Arabia and to evaluate its perceived impact on professional practice, quality of care, and patient safety.

METHODS

Study Design and Setting

This was a descriptive, analytical cross-sectional, questionnaire-based study conducted among healthcare professionals providing clinical care in the Kingdom of Saudi Arabia, across governmental, private, academic, and primary-care settings. Because data were collected through a secure online platform, the study was national in scope and was not restricted to a single facility or employer.

Participants

Eligible participants were healthcare professionals of all specialties (physicians, dentists, pharmacists, nurses, and allied health professionals) who were engaged in direct clinical (patient-facing) practice, regardless of place of work, and who had at least 6 months of professional experience. Professionals not involved in direct clinical care (eg, purely administrative, managerial, or research roles without patient contact) and undergraduate students or trainees who had not yet commenced supervised clinical practice were excluded. Participation required the ability to read English and the provision of informed electronic consent.

Sample Size and Sampling

The sample size was calculated on the basis of the total number of healthcare professionals in Saudi Arabia, estimated at approximately 590 000 across the physician, dental, nursing, pharmacy, and allied-health categories (17). Using the single-population-proportion (Cochran) formula with a 95% confidence level, an expected reliance proportion of 50% (the most conservative estimate), and an absolute precision of 5%, the minimum required sample was 385 (16); after a finite-population correction and inflation of approximately 20% for nonresponse and incompleteness, the target was approximately 480. A non-probability convenience sampling technique was used; the electronic questionnaire was distributed through professional networks, departmental mailing lists, and relevant professional groups, and eligible professionals who consented were enrolled until the target was exceeded. A total of 502 professionals completed the questionnaire.

Questionnaire and Measurements

Data were collected with a structured, self-administered electronic questionnaire in English comprising seven sections: (1) sociodemographic and professional characteristics; (2) patterns of AI use; (3) trust in AI; (4) general attitudes toward AI; (5) reliance on AI for decision-making, including automation-bias–prone behaviors; (6) perceived impact on professional practice and quality of care; and (7) barriers, concerns, and training needs. Attitudinal items were rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The instrument was adapted from previously validated instruments—the GAAIS (13,14) and the foundational trust-in-automation scale (15)—with permission from the original developers, and was supplemented by purpose-built reliance and perceived-impact items derived from the automation-bias and deskilling literature (10,11). Content validity was confirmed by an expert panel of 8 reviewers (item-level content validity index ≥ 0.83; scale-level content validity index [S-CVI/Ave], 0.94). Internal consistency was good (overall Cronbach $\alpha = 0.89$; trust, 0.85; attitudes, 0.88; reliance, 0.87; perceived impact, 0.81), and test–retest reliability across a 2-week interval was satisfactory (intraclass correlation coefficient, 0.86). A pilot study of 30 to 40 professionals, excluded from the main analysis, confirmed clarity, timing, and platform functionality.

Statistical Analysis

Data were analyzed with IBM SPSS Statistics version 29. Categorical variables were summarized as frequencies and percentages and continuous variables as mean (SD) or median (IQR) according to distribution (Shapiro-Wilk test). Composite and subscale scores (trust, attitudes, reliance, perceived impact) were computed as item means after recoding reverse-scored items. Associations were assessed using the χ^2 test, the independent-samples t test, or one-way analysis of variance, as appropriate, with Pearson or Spearman correlation. High reliance on AI, the primary binary outcome, was defined a priori as a mean reliance-domain score of 3.5 or higher, and its independent predictors were identified by multivariable logistic regression including all participant characteristics simultaneously, with results reported as adjusted odds ratios (ORs) and 95% CIs. A 2-sided P value less than .05 was considered statistically significant.

Ethical Considerations

The study adhered to the Declaration of Helsinki and was approved by the Institutional Review Board of the King Abdullah International Medical Research Center (KAIMRC), Ministry of National Guard Health Affairs, Saudi Arabia (protocol number NRJ26/015/8). Informed electronic consent was obtained from all participants; participation was voluntary, and responses were anonymous, stored securely, and handled in accordance with the Saudi Personal Data Protection Law.

RESULTS

Characteristics of the study participants

Of the 502 healthcare professionals who completed the questionnaire, the largest proportion were 30 to 39 years of age (40.6%), and all principal clinical disciplines were represented, with nurses (36.5%) and physicians (26.5%) forming the two largest groups. More than half of the participants (54.5%) rated their knowledge of AI as good or excellent, whereas only 26.3% had received prior formal training in AI or health informatics. The complete demographic and professional profile of the sample is presented in **Table 1**.

Patterns of AI use

As illustrated in **Figure 1**, approximately three-quarters of participants (74.7%) reported using AI-based tools in their professional practice, and 43.6% did so at least weekly. Generative large language models were the predominant tools employed (65.1%), while the most common purposes were seeking health or medical information (64.3%) and academic writing (48.6%). Among AI users, most addressed only a limited share of their weekly information needs with these tools, whereas 20.3% relied on AI for more than half of their needs.

Trust, attitudes, reliance, and perceived impact

General attitudes toward AI were the most favorable domain (mean, 3.41 [SD, 0.65]), whereas trust (2.95 [0.72]) and reliance (3.07 [0.74]) were moderate, and perceived impact was lowest (2.80 [0.57]), with concern about excessive reliance—particularly deskilling and weakened independent reasoning—endorsed as strongly as the perceived benefits. Item-level responses are given in **Table 2.**

Association between participant characteristics and Patterns of AI use

Regular AI use (at least weekly) was significantly associated with younger age, prior AI training, and higher self-rated AI knowledge, with a borderline association for gender; nationality, profession, qualification, workplace, and years of experience were not significantly associated **(Table 3)**.

Association between participant characteristics and domain scores

Higher reliance, trust, and more favorable attitudes were each significantly associated with younger age, fewer years of experience, prior AI training, and higher self-rated AI knowledge (all $P < .05$). Gender, nationality, profession, qualification, and workplace were not significantly associated with the domain scores **(Table 4).**

Predictors of high reliance on AI — multivariable logistic regression

High reliance on AI (mean reliance score ≥ 3.5) was reported by 150 participants (29.9%) and used as the binary outcome. After adjustment for all characteristics simultaneously, the independent predictors of high reliance were younger age, fewer years of experience, prior formal AI training, and higher self-rated AI knowledge; gender, nationality, profession, workplace, and qualification were not independent predictors (**Table 5**; model McFadden pseudo-$R^2 = 0.206$).

Table 1: Sociodemographic and professional characteristics of participants (n = 502)

Characteristic	Frequency	Percent (%)
Age group (years)		
<30	106	21.1
30–39	204	40.6
40–49	131	26.1

Characteristic	Frequency	Percent (%)
≥50	61	12.2
Gender		
Male	242	48.2
Female	260	51.8
Nationality		
Saudi	288	57.4
Non-Saudi	214	42.6
Profession		
Physician	133	26.5
Nurse	183	36.5
Pharmacist	61	12.2
Dentist	49	9.8
Allied health	76	15.1
Highest qualification		
Diploma	61	12.2
Bachelor's	230	45.8
Master's	110	21.9
Doctorate (PhD)	39	7.8
Board/Fellowship	62	12.4
Years of experience		
<5	156	31.1
5–10	148	29.5
11–15	105	20.9
>15	93	18.5
Current workplace		
MOH hospital	197	39.2
Other governmental	74	14.7
Private	124	24.7
Academic/University	57	11.4
Primary healthcare center	50	10.0
Prior formal AI/informatics training		
Yes	132	26.3
No	370	73.7
Self-rated AI knowledge		
Poor or less	72	14.3
Fair	156	31.1
Good	196	39.0
Excellent	78	15.5

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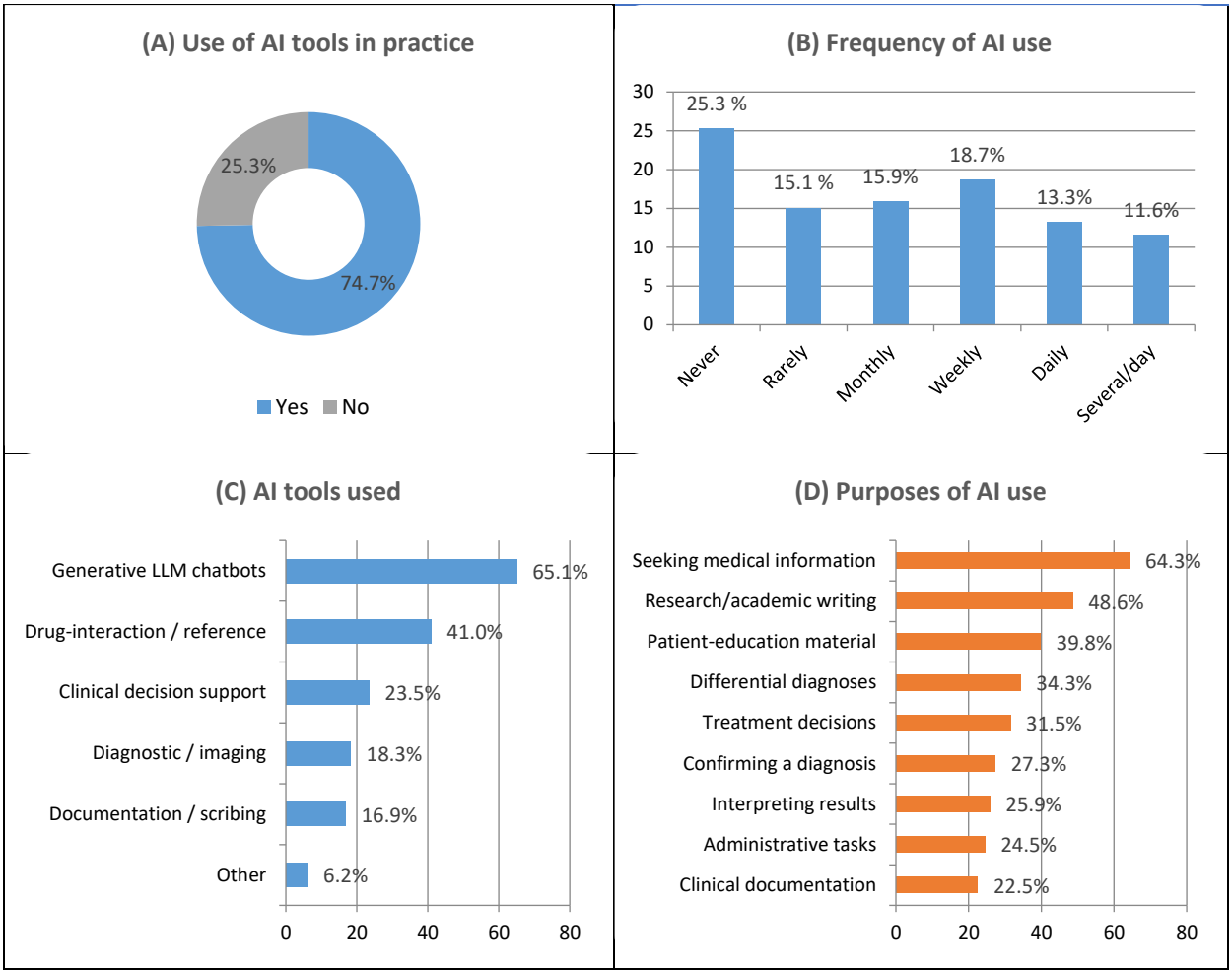


Figure 1: Patterns of artificial intelligence use among participants (n = 502). (A) Proportion using AI tools in practice; (B) frequency of AI use; (C) AI tools used; (D) purposes of AI use.

Table 2: Trust, attitudes, reliance, and perceived impact item-level responses and domain scores (n = 502)

Items and Domains	Mean ± SD*	Agree/ Strongly Agree (%)
Trust in AI (6 items)	**2.95 ± 0.72**	
I trust the information provided by AI tools.	3.42 ± 1.00	45.2
AI tools are a reliable source of clinical information.	3.35 ± 0.97	43.2
I am confident in the accuracy of AI-generated outputs.	3.28 ± 0.96	41.2
AI tools generally provide consistent results.	3.20 ± 0.98	37.1
I am cautious/wary about acting on AI recommendations. (R)	3.76 ± 0.86	63.7
AI systems can sometimes be misleading or deceptive. (R)	3.78 ± 0.85	62.4
General attitudes towards AI (8 items)	**3.41 ± 0.65**	
AI will improve the overall quality of healthcare.	3.88 ± 0.91	67.5
AI can help solve many clinical and health-system problems.	3.84 ± 0.89	67.1
AI makes my professional work more efficient.	3.84 ± 0.89	65.9
I am interested in using AI in my practice.	3.93 ± 0.88	70.3
I find the use of AI in healthcare threatening. (R)	2.75 ± 0.87	17.7
AI could be used to harm patients. (R)	2.57 ± 0.84	13.5
I am concerned about the risks of AI in clinical care. (R)	3.44 ± 0.88	47.8

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Items and Domains	Mean ± SD*	Agree/ Strongly Agree (%)
AI may reduce the human element of patient care. (R)	3.48 ± 0.89	47.8
Reliance on AI for decision-making (7 items)	**3.07 ± 0.74**	
I rely on AI tools when making clinical decisions.	3.42 ± 0.99	46.0
I often accept AI recommendations without independently verifying them.	3.06 ± 0.99	29.9
When an AI tool disagrees with my judgement, I tend to change my decision to match the AI.	2.93 ± 0.97	27.3
I would feel less confident making clinical decisions without AI support.	3.36 ± 0.97	42.4
I depend on AI tools to look up information I would previously have recalled from memory.	3.55 ± 0.95	52.6
I use AI as my first source of information before consulting guidelines or colleagues.	3.20 ± 0.99	38.2
I verify AI-generated information against trusted sources before acting on it. (R)	4.03 ± 0.79	77.5
Perceived impact on practice and quality of care (7 items)	**2.80 ± 0.57**	
Using AI has improved the quality of my clinical decisions.	3.57 ± 0.86	53.0
Using AI has improved my efficiency and time management.	3.70 ± 0.89	59.0
Using AI has improved my access to up-to-date medical knowledge.	3.75 ± 0.90	64.7
I am concerned that excessive reliance on AI could erode my clinical skills (deskilling). (R)	3.93 ± 0.78	72.1
Excessive reliance on AI could weaken my independent clinical reasoning. (R)	3.83 ± 0.78	67.7
Excessive reliance on AI could negatively affect the clinician–patient relationship. (R)	3.69 ± 0.80	61.2
Uncritical reliance on AI could negatively affect patient safety. (R)	3.94 ± 0.80	71.7

SD, standard deviation. Domain means are computed after recoding reverse-scored (R) items; item means shown are raw. (R) = reverse-scored item.

Table 3: Association between participant characteristics and Patterns of AI Use (at least weekly)

Characteristic	n	Regular users, n (%)	χ^2	P value
Age group (years)			**18.84**	**<.001**
<30	106	63 (59.4)		
30–39	204	91 (44.6)		
40–49	131	42 (32.1)		
≥50	61	23 (37.7)		
Gender			**3.98**	**.046**
Male	242	94 (38.8)		
Female	260	125 (48.1)		
Nationality			**0.15**	.697
Saudi	288	123 (42.7)		
Non-Saudi	214	96 (44.9)		
Profession			**2.44**	.655
Physician	133	57 (42.9)		
Nurse	183	83 (45.4)		
Pharmacist	61	25 (41.0)		

Characteristic	n	Regular users, n (%)	χ^2	P value
Dentist	49	25 (51.0)		
Allied health	76	29 (38.2)		
Highest qualification			**6.53**	.163
Diploma	61	30 (49.2)		
Bachelor's	230	104 (45.2)		
Master's	110	52 (47.3)		
Doctorate (PhD)	39	13 (33.3)		
Board/Fellowship	62	20 (32.3)		
Years of experience			**7.35**	.061
<5	156	81 (51.9)		
5–10	148	63 (42.6)		
11–15	105	38 (36.2)		
>15	93	37 (39.8)		
Current workplace			**2.98**	.561
MOH hospital	197	87 (44.2)		
Other governmental	74	27 (36.5)		
Private	124	54 (43.5)		
Academic/University	57	25 (43.9)		
Primary healthcare center	50	26 (52.0)		
Prior formal AI/informatics training			**18.28**	**<.001**
Yes	132	79 (59.8)		
No	370	140 (37.8)		
Self-rated AI knowledge			**12.55**	**.006**
Poor or less	72	23 (31.9)		
Fair	156	62 (39.7)		
Good	196	88 (44.9)		
Excellent	78	46 (59.0)		

χ^2 = Pearson chi-square test. Regular use = AI tools used weekly or more often. Bold P values indicate statistical significance (P < .05).

Table 4: Mean domain scores (mean ± SD) by participant characteristics (n=502)

Characteristic	Trust	Attitudes	Reliance	Perceived impact
Age group (years)	*P* = **<.001**	*P* = **<.001**	*P* = **<.001**	*P* = **<.001**
<30	3.29 ± 0.63	3.71 ± 0.54	3.44 ± 0.65	3.07 ± 0.52
30–39	3.01 ± 0.71	3.47 ± 0.60	3.14 ± 0.71	2.87 ± 0.56
40–49	2.69 ± 0.71	3.14 ± 0.66	2.75 ± 0.75	2.56 ± 0.56
≥50	2.75 ± 0.65	3.24 ± 0.67	2.88 ± 0.67	2.65 ± 0.49
Gender	*P* = .239	*P* = .178	*P* = .236	*P* = .204
Male	2.91 ± 0.74	3.37 ± 0.67	3.03 ± 0.76	2.77 ± 0.58

Characteristic	Trust	Attitudes	Reliance	Perceived impact
Female	2.99 ± 0.70	3.45 ± 0.62	3.11 ± 0.72	2.83 ± 0.56
Nationality	*P* = .632	*P* = .564	*P* = .172	*P* = .449
Saudi	2.94 ± 0.70	3.39 ± 0.64	3.03 ± 0.71	2.79 ± 0.56
Non-Saudi	2.97 ± 0.75	3.43 ± 0.66	3.12 ± 0.78	2.83 ± 0.59
Profession	*P* = .112	*P* = .128	*P* = .092	*P* = .081
Physician	3.01 ± 0.70	3.45 ± 0.64	3.13 ± 0.74	2.84 ± 0.56
Nurse	2.84 ± 0.71	3.32 ± 0.65	2.96 ± 0.73	2.72 ± 0.55
Pharmacist	3.02 ± 0.74	3.49 ± 0.65	3.15 ± 0.78	2.88 ± 0.63
Dentist	3.08 ± 0.82	3.54 ± 0.73	3.23 ± 0.82	2.94 ± 0.64
Allied health	2.99 ± 0.66	3.39 ± 0.58	3.07 ± 0.67	2.79 ± 0.52
Highest qualification	*P* = .063	*P* = .229	*P* = .318	*P* = .298
Diploma	2.71 ± 0.73	3.24 ± 0.69	2.96 ± 0.76	2.68 ± 0.64
Bachelor's	2.96 ± 0.73	3.40 ± 0.66	3.05 ± 0.76	2.79 ± 0.58
Master's	3.03 ± 0.70	3.48 ± 0.64	3.19 ± 0.75	2.88 ± 0.55
Doctorate (PhD)	2.93 ± 0.72	3.41 ± 0.62	3.01 ± 0.73	2.82 ± 0.65
Board/Fellowship	3.03 ± 0.70	3.45 ± 0.57	3.06 ± 0.66	2.82 ± 0.45
Years of experience	*P* = **.003**	*P* = **<.001**	*P* = **.002**	*P* = **<.001**
<5	3.12 ± 0.74	3.58 ± 0.60	3.24 ± 0.76	2.95 ± 0.54
5–10	2.94 ± 0.68	3.39 ± 0.58	3.06 ± 0.67	2.79 ± 0.54
11–15	2.83 ± 0.71	3.29 ± 0.68	2.95 ± 0.75	2.71 ± 0.56
>15	2.84 ± 0.72	3.28 ± 0.73	2.93 ± 0.78	2.69 ± 0.64
Current workplace	*P* = .651	*P* = .648	*P* = .846	*P* = .568
MOH hospital	2.96 ± 0.72	3.43 ± 0.65	3.07 ± 0.76	2.83 ± 0.56
Other governmental	2.94 ± 0.80	3.36 ± 0.67	3.03 ± 0.77	2.75 ± 0.56
Private	3.01 ± 0.68	3.42 ± 0.63	3.09 ± 0.72	2.82 ± 0.58
Academic/University	2.84 ± 0.70	3.31 ± 0.69	3.01 ± 0.77	2.71 ± 0.60
Primary healthcare center	2.91 ± 0.74	3.47 ± 0.62	3.16 ± 0.68	2.86 ± 0.55
Prior formal AI/informatics training	*P* = **<.001**	*P* = **<.001**	*P* = **<.001**	*P* = **<.001**
Yes	3.34 ± 0.73	3.73 ± 0.64	3.48 ± 0.72	3.09 ± 0.60
No	2.81 ± 0.66	3.29 ± 0.61	2.92 ± 0.69	2.70 ± 0.52
Self-rated AI knowledge	*P* = **<.001**	*P* = **<.001**	*P* = **<.001**	*P* = **<.001**
Poor or less	2.56 ± 0.62	3.04 ± 0.56	2.67 ± 0.67	2.53 ± 0.53
Fair	2.83 ± 0.68	3.27 ± 0.63	2.92 ± 0.68	2.70 ± 0.53
Good	3.08 ± 0.71	3.53 ± 0.63	3.21 ± 0.75	2.90 ± 0.57
Excellent	3.23 ± 0.73	3.73 ± 0.57	3.41 ± 0.70	3.01 ± 0.56

Values are mean ± SD of the five-point domain score. p-values are from one-way ANOVA (≥ 3 groups) or independent-samples t-test (2 groups), shown on each characteristic's row. Bold = P < .05.

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Table 5: Crude and adjusted odds ratios for high reliance on AI (reliance score ≥ 3.5)

Characteristic	Crude OR (95% CI)	p	Adjusted OR (95% CI)	p
Age group (years)				
<30 (ref)	1.00 (reference)		1.00 (reference)	
30–39	0.45 (0.28–0.73)	**.001**	**0.45 (0.26–0.77)**	**.003**
40–49	0.26 (0.15–0.45)	**<.001**	**0.24 (0.13–0.44)**	**<.001**
≥50	0.38 (0.19–0.73)	**.004**	**0.26 (0.12–0.55)**	**<.001**
Gender				
Male (ref)	1.00 (reference)		1.00 (reference)	
Female	1.27 (0.87–1.85)	.223	1.16 (0.75–1.80)	.496
Nationality				
Saudi (ref)	1.00 (reference)		1.00 (reference)	
Non-Saudi	1.52 (1.04–2.23)	**.031**	1.37 (0.89–2.11)	.159
Profession				
Physician (ref)	1.00 (reference)		1.00 (reference)	
Nurse	0.83 (0.51–1.34)	.441	0.69 (0.40–1.19)	.184
Pharmacist	1.53 (0.83–2.82)	.178	1.50 (0.75–3.00)	.251
Dentist	1.61 (0.84–3.11)	.154	1.06 (0.50–2.26)	.879
Allied health	0.86 (0.47–1.58)	.620	0.89 (0.45–1.74)	.728
Highest qualification				
Diploma (ref)	1.00 (reference)		1.00 (reference)	
Bachelor's	1.40 (0.75–2.58)	.288	1.40 (0.71–2.76)	.336
Master's	1.85 (0.95–3.59)	.070	2.06 (0.98–4.32)	.057
Doctorate (PhD)	1.32 (0.56–3.09)	.530	1.34 (0.51–3.53)	.557
Board/Fellowship	1.59 (0.76–3.36)	.221	1.70 (0.74–3.92)	.210
Years of experience				
<5 (ref)	1.00 (reference)		1.00 (reference)	
5–10	0.64 (0.40–1.03)	.064	0.69 (0.41–1.19)	.181
11–15	0.42 (0.24–0.74)	**.002**	**0.39 (0.21–0.73)**	**.003**
>15	0.52 (0.30–0.91)	**.021**	**0.44 (0.24–0.82)**	**.010**
Current workplace				
MOH hospital (ref)	1.00 (reference)		1.00 (reference)	
Other governmental	0.97 (0.55–1.71)	.914	1.12 (0.59–2.14)	.732
Private	0.97 (0.60–1.57)	.913	1.10 (0.64–1.91)	.729
Academic/University	0.82 (0.43–1.57)	.555	0.80 (0.39–1.68)	.559
Primary healthcare center	1.07 (0.56–2.05)	.830	1.15 (0.55–2.38)	.709
Prior formal AI/informatics training				
Yes (ref)	1.00 (reference)		1.00 (reference)	
No	0.30 (0.20–0.46)	**<.001**	**0.22 (0.13–0.35)**	**<.001**
Self-rated AI knowledge				

Characteristic	Crude OR (95% CI)	p	Adjusted OR (95% CI)	p
Poor or less (ref)	1.00 (reference)		1.00 (reference)	
Fair	1.76 (0.86–3.61)	.123	1.99 (0.93–4.30)	.078
Good	3.65 (1.85–7.21)	**<.001**	**4.18 (2.01–8.68)**	**<.001**
Excellent	5.24 (2.47–11.09)	**<.001**	**6.07 (2.68–13.73)**	**<.001**

OR = odds ratio; CI = confidence interval. Outcome = high reliance (mean reliance score ≥ 3.5). Adjusted ORs are from a single multivariable model containing all listed characteristics. Bold = P < .05.

DISCUSSION

In this national cross-sectional study of 502 healthcare professionals in Saudi Arabia, the use of AI-based tools was common, yet measured reliance on AI for clinical decision-making was only moderate. Attitudes toward AI were favorable but coexisted with substantial concern that excessive reliance could erode clinical skills and compromise patient safety. High reliance was concentrated among younger and less experienced professionals and among those with prior AI training and higher self-rated AI knowledge, whereas gender, nationality, profession, workplace, and qualification were not independent predictors. To our knowledge, this is among the first studies to quantify reliance—rather than attitudes alone—among healthcare professionals in the region.

The proportion of professionals using AI tools (74.7%) and the predominance of generative LLMs are consistent with recent surveys documenting rapid adoption across diverse settings, including postgraduate residents in Oman (18), general practitioners in the United Kingdom (19), and newly graduated interns (20), as well as earlier Saudi and international reports (5-7). The observation that most users relied on AI for only a limited share of their weekly information needs suggests that, at present, these tools supplement rather than replace established sources, echoing evidence that clinicians and the public increasingly consult LLM-based tools as a first, but not sole, source of information (8).

A central finding is the dissociation between favorable attitudes and more moderate reliance, which supports the conceptual distinction between endorsing a technology and depending on its output. This distinction is clinically important because reliance, not attitude, is the behavior through which automation bias operates—the tendency to excessively trust automated recommendations and to discount contradictory evidence (10,11). Reassuringly, verification of AI output against trusted sources was the most strongly endorsed reliance item, indicating that most respondents retained a checking behavior that mitigates automation bias. Nonetheless, a sizeable minority (29.9%) met the threshold for high reliance, a group in whom the balance between the demonstrated benefits of AI-assisted reasoning (9) and its risks warrants particular attention.

Concern about deskilling and weakened independent reasoning was endorsed as strongly as the perceived benefits of AI, and respondents also recognized potential harm to the clinician–patient relationship. These findings mirror conceptual and empirical work cautioning that habitual delegation of cognitive tasks may erode clinical expertise and that AI introduced into the consultation can affect patient trust (12,21). Because person-centered care depends on communication, empathy, and trust, safeguarding these dimensions should be an explicit objective of any AI-integration strategy rather than an afterthought.

The independent association of high reliance with younger age and fewer years of experience is consistent with greater digital fluency among early-career professionals, who may also be more vulnerable to skill erosion before their own expertise is consolidated. The association with prior AI training and higher self-rated AI knowledge is double-edged: training plausibly increases both competent use and dependence, and self-rated knowledge is a subjective measure that may diverge from objective competence. These findings argue for training that deliberately pairs facility in using AI with instruction in its limitations, verification, and the preservation of independent reasoning, in line with validated frameworks for medical AI readiness (22).

At the system level, the findings are relevant to Saudi Arabia's national AI agenda under Vision 2030 and the National Strategy for Data and Artificial Intelligence (1,2). As AI tools become embedded in routine care, institutional governance—clear usage policies, verification requirements, human-in-the-loop safeguards, and attention to data privacy—will be needed to realize benefits while protecting clinical competence and patient safety. The concentration of high reliance in identifiable subgroups offers a practical target for such measures.

This study has limitations. The cross-sectional design precludes causal inference about the relationship between reliance and its correlates. Convenience sampling and the online mode may have favored professionals who are more engaged with technology, potentially overstating adoption and limiting generalizability. Reliance and knowledge were self-reported and therefore subject to social-desirability and self-assessment biases; self-rated AI knowledge in particular is not a substitute for objective evaluation. Finally, the study was conducted in a single country, and the findings should be confirmed in other settings and, ideally, with longitudinal and performance-based designs.

CONCLUSION

In this national survey, healthcare professionals in Saudi Arabia reported widespread but largely supplementary use of AI, with moderate reliance for clinical decision-making. Favorable attitudes coexisted with strong concern about deskilling and patient safety, and high reliance was concentrated among younger, less experienced professionals and those with prior AI training and higher self-rated AI knowledge. These findings support targeted AI-literacy training, explicit verification safeguards, and institutional governance that preserve independent clinical judgment and the clinician–patient relationship as AI is integrated into practice.

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