

Perceptions of undergraduate health professions students on the utilisation of artificial intelligence tools for teaching, learning and assessment: a cross-sectional questionnaire study at a health sciences university in southern India

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Abstract

Health professions students are adopting artificial intelligence (AI) tools ahead of formal curricular provision, yet evidence comes mainly from medical cohorts, leaving other health professions largely unexamined. We conducted a cross-sectional online questionnaire study among undergraduate students of a multi-faculty health sciences university in Belagavi, India, capturing demographics, prior AI exposure, twelve five-point Likert items and two open-ended questions; eleven items formed an overall perception score, analysed using non-parametric tests, multivariable regression and content analysis. Of 668 submissions, 612 consenting adults were analysed; 434 (70.9%) were women. Only 307 (50.2%) reported prior AI exposure, mostly ChatGPT. Agreement with individual statements ranged from 61.1% to 71.4%, disagreement never exceeded 7.5%, and 22.9–32.7% chose the neutral option on every item. The overall score was favourable but moderate (mean 3.71, standard deviation 0.72, on a 1–5 scale); trust in AI to grade assessments drew the lowest agreement (61.1%). Scores differed by discipline ($H = 35.25$, $p < 0.001$) but not by gender or year of study, and discipline was the only independent predictor; prior exposure was not ($B = 0.04$, 95% CI – 0.08 to 0.16). Free-text responses emphasised conceptual understanding as the main benefit and over-reliance as the main concern. Students held favourable but reserved views, with a large neutral middle better read as uncertainty from limited exposure than as ambivalence. Attitudes tracked professional programme rather than gender, seniority or exposure, supporting AI literacy as a shared, faculty-wide curricular component addressing verification of AI output and the limits of AI in assessment.

Introduction

Artificial intelligence (AI) has moved from the margins of health professions education to its everyday texture. Adaptive learning platforms, automated item generation, virtual patients and large language models are now used routinely by students, frequently without institutional sanction and almost always without formal instruction [1, 2]. The pace of adoption has outstripped the pace of curricular reform, and the resulting gap is not merely technical: students are making judgements about what AI is good for, what it can be trusted with, and where it should not be allowed, largely on their own [3].

The educational case for AI rests on plausible mechanisms. Adaptive systems can tailor content to an individual learner's demonstrated weaknesses; simulation and virtual patients can offer risk-free repetition of clinical reasoning; automated scoring can deliver feedback at a scale and speed that human tutors cannot match [4, 5]. Systematic reviews of AI in medical education report gains in efficiency and consistency alongside persistent uncertainty about fairness, transparency and data security [5, 6]. What these reviews cannot settle is whether students themselves accept the technology, because acceptance is the necessary condition for any of these mechanisms to operate.

Evidence on student perceptions has accumulated quickly but unevenly. Surveys of medical students in India, the Gulf states, Europe and Australia consistently describe a mixture of optimism about clinical applications and anxiety about the humanistic and ethical consequences of AI, coupled with very low

rates of formal training [7–11]. In a study of 325 medical students in Kerala, most viewed AI as an assistive rather than a substitutive technology, yet 91.4% reported no AI training within their curriculum and roughly three-quarters wanted structured teaching on the subject [7]. A cross-sectional needs assessment in Türkiye reached a similar conclusion and provided the item set on which several later studies were built [12]. A multi-country survey of health professions students across four Middle Eastern countries found that two-thirds rated their own AI knowledge as low [13].

Three limitations recur in this literature. First, it is dominated by undergraduate medical cohorts; nursing, physiotherapy, pharmacy, dentistry and the Indian systems of medicine appear far less often, and almost never in the same study, so the possibility that perceptions vary systematically between professional programmes has rarely been tested [14–16]. Second, most instruments ask about AI in clinical practice – diagnosis, imaging, job displacement – rather than about AI in the specific educational functions of teaching, learning and assessment, which are the functions students actually encounter as learners. Third, studies rarely separate perceptions of AI as a learning aid from perceptions of AI as an assessor, although these raise quite different questions of trust.

India's health professions education system is unusually well suited to addressing the first of these gaps. Health sciences universities routinely house medical, dental, nursing, pharmacy, physiotherapy and AYUSH (Ayurveda, Yoga and Naturopathy, Unani, Siddha and Homoeopathy) programmes on a shared campus, under a single regulatory umbrella, with a common digital infrastructure. Students in these programmes differ in their curricular traditions, their exposure to technology and their professional identities, yet they share an institutional environment. Such a setting allows perceptions to be compared across disciplines while holding the institution constant.

We therefore conducted a cross-sectional questionnaire study across the undergraduate programmes of one health sciences university in southern India. Our objectives were to describe students' perceptions of AI for teaching, learning and assessment; to determine the extent of prior exposure to AI tools and identify the tools in use; to examine whether perceptions varied by discipline, year of study, gender or prior exposure; and to characterise the benefits and concerns students articulated in their own words.

Materials and Methods

Study design and setting

This was a cross-sectional, questionnaire-based study conducted among undergraduate students enrolled in the constituent and affiliated colleges of a health sciences deemed-to-be-university in Belagavi, Karnataka, India. The university comprises colleges of medicine, dentistry, nursing, pharmacy, physiotherapy and homoeopathy on a shared campus. Data were collected between 29 September 2025 and 24 June 2026. Reporting follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement for cross-sectional studies [17] and the Checklist for Reporting Results of Internet E-Surveys (CHERRIES) where applicable [18].

Participants and sampling

Students aged 18 years or over and enrolled in any undergraduate health professions programme of the university were eligible. Postgraduate students, faculty and students of non-health disciplines were not eligible. A convenience sampling approach was used: the survey link was disseminated through official class and departmental groups on messaging platforms, with periodic reminders. Participation was voluntary and unincentivised. No a priori sample size was fixed; the intention was to obtain the widest possible coverage across programmes during the study window, and the achieved sample exceeds the 384 respondents required to estimate a population proportion of 50% with 5% absolute precision and 95% confidence.

Instrument

The instrument was a self-administered questionnaire delivered through an online forms platform. It opened with a participant information sheet and two explicit consent items, and was structured in four sections. The first collected demographic and academic details: name (optional), age, gender, college, year of study, and whether the respondent had any prior exposure to AI tools for teaching or learning, with a free-text field for those answering affirmatively to name the tools and their purpose.

The second and third sections comprised twelve statements rated on a five-point Likert scale from strongly disagree (1) to strongly agree (5). The items were adapted for the educational context of the present study from published instruments on AI in medical education, principally those of Civaner et al. [12] and the adaptation used by Jackson et al. [7], with wording modified to refer to teaching, learning and assessment rather than to clinical practice, and to be applicable across health professions rather than to medicine alone. The item set was reviewed for face and content validity by faculty members in medical education and community medicine and was piloted before deployment; pilot responses are not included in the analysis. The full instrument is provided as Online Resource 1.

The fourth section contained two open-ended questions: the benefits respondents saw in using AI in health professions education, and the concerns or challenges they foresaw. Neither was mandatory.

Scoring and derived variables

Eleven of the twelve Likert items were attitudinal statements about the value or acceptability of AI in education and were combined into an overall perception score, calculated as the arithmetic mean of the constituent item scores (range 1–5). No item required reverse coding. The twelfth item – that AI in education raises ethical concerns that must be addressed – is not a statement about the desirability of AI, and endorsing it does not indicate a negative attitude; it was therefore excluded from the composite and reported separately.

Three conceptual domains were specified a priori and each was scored as the mean of its items: teaching and learning (five items: engagement, conceptual understanding, comfort with AI-supplemented lectures, identification of individual learning needs, and virtual patients for clinical reasoning); assessment (three items: immediate personalised feedback, trust in fair objective grading, and reduction of workload with improved consistency); and readiness (three items: willingness to use AI learning tools, time management, and enthusiasm for AI integration). For descriptive purposes, a mean score of 3.5 or above was taken to indicate a favourable overall perception.

Free-text responses were entered verbatim, cleaned of non-informative entries (blank fields, single punctuation marks and one-word non-answers) and analysed by structured content analysis. A coding frame was developed inductively from a reading of the full response set, operationalised as keyword dictionaries, applied systematically to every response, and then verified by manual review; responses could be assigned to more than one category. Responses stating explicitly that the respondent had no concerns were counted separately rather than treated as missing.

Data management and statistical analysis

Responses were exported and analysed in Python 3 (pandas, SciPy and statsmodels). Age was extracted from free-text entries and values outside a plausible range for undergraduate study were treated as missing; one respondent who reported an age below 18 years was excluded from the analysis, since the ethics approval covered self-consenting adults only. Gender responses were harmonised across variant spellings, and college names, which had been entered as free text with considerable orthographic variation, were mapped to professional programmes by rule-based matching, with a residual category for entries too general to classify.

Categorical variables are summarised as frequencies and percentages and continuous variables as mean with standard deviation (SD) and median with interquartile range (IQR). Internal consistency was assessed using Cronbach's alpha with corrected item–total correlations. Because Likert-derived scores were markedly left-skewed, between-group comparisons used non-parametric tests: the Mann–Whitney U test for two groups, with the rank–biserial correlation as the effect size, and the Kruskal–Wallis H test for more than two groups, with pairwise Mann–Whitney tests and Bonferroni adjustment where the omnibus test was significant. Associations between categorical variables were tested with the chi-square test, and the relationship between age and perception score with Spearman's rank correlation.

Independent predictors of the overall perception score were identified using multivariable linear regression with heteroscedasticity-consistent (HC3) standard errors, entering discipline, year of study, gender, prior exposure and age; homoeopathy, the largest group, served as the reference discipline, and disciplines with fewer than 20 respondents were excluded from group comparisons and from the model. A prespecified sensitivity analysis repeated the principal comparisons after excluding respondents who selected the identical response option for all twelve items. A two-sided p value below 0.05 was taken as

statistically significant; no adjustment was made for multiplicity outside the post hoc discipline comparisons, and p values should be read as descriptive.

Ethical considerations

The study protocol was approved by the Jawaharlal Nehru Medical College Institutional Ethics Committee, KLE Academy of Higher Education and Research, Belagavi (Reference number MDC/JNMCIEC/323, dated 9 September 2025; Department of Health Research registration number EC/NEW/INST/2024/KA/0548). All participants read an online participant information sheet describing the purpose of the study, the absence of risk, the confidentiality of responses and the right to withdraw, and provided electronic informed consent through two explicit affirmations before any study item was displayed. Only respondents who affirmed both items were analysed. Provision of a name was optional, no identifying information is reported, and the dataset was de-identified before analysis.

Results

Participants

A total of 668 submissions were received. Of these, 43 respondents declined consent and a further 12 did not confirm that they had read the participant information sheet. One respondent who reported an age below 18 years was excluded, leaving 612 responses for analysis. There were no missing values on any Likert item.

Participant characteristics are shown in Table 1. The median age was 21 years (IQR 20–22; mean 21.3, SD 1.7; range 18–26), and 434 respondents (70.9%) were women. Homoeopathy students formed the largest group (232, 37.9%), followed by nursing (192, 31.4%), physiotherapy (108, 17.6%), pharmacy (42, 6.9%) and dentistry (24, 3.9%); three respondents (0.5%) were from Ayurveda and 11 (1.8%) gave a college name too general to classify. No respondent identified as an undergraduate medical (MBBS) student. Fourth-year students were over-represented (212, 34.6%) relative to other years.

Table 1
Characteristics of participating undergraduate health professions students

Characteristic	n	%
Age (years): mean (SD)	21.3 (1.7)	—
Age (years): median (IQR)	21 (20–22)	—
20 years or younger	198	32.4
21–22 years	268	43.8
23 years or older	144	23.5
Not reported or not interpretable	2	0.3
Gender		
Female	434	70.9
Male	178	29.1
Professional programme		
Homoeopathy	232	37.9
Nursing	192	31.4
Physiotherapy	108	17.6
Pharmacy	42	6.9
Dentistry	24	3.9
Ayurveda	3	0.5
Not classifiable from entry	11	1.8
Year of study		
First year	123	20.1
Second year	114	18.6
Third year	133	21.7
Fourth year	212	34.6
Final year or internship	30	4.9
Prior exposure to AI tools		
Yes	307	50.2
No	305	49.8

n = 612. AI artificial intelligence, IQR interquartile range, SD standard deviation. Percentages are of the total analysed sample and may not sum to 100 owing to rounding.

Prior exposure to AI tools

Almost exactly half the cohort – 307 respondents (50.2%) – reported any prior exposure to AI tools for teaching or learning. Exposure varied significantly by discipline (chi-square = 18.60, df = 4, $p < 0.001$), from 16/24 (66.7%) in dentistry and 106/192 (55.2%) in nursing to 16/42 (38.1%) in pharmacy and 38/108 (35.2%) in physiotherapy, and by year of study (chi-square = 17.52, df = 4, $p = 0.002$), rising from 48/123 (39.0%) in the first year to 127/212 (59.9%) in the fourth. Exposure did not differ by gender ($p = 0.694$).

Among the 307 students reporting exposure, 198 (64.5%) named at least one identifiable tool. ChatGPT dominated, named by 179 (58.3% of exposed students), followed by Google Gemini (43, 14.0%), Meta AI (12, 3.9%), Perplexity (9, 2.9%), and Claude and Canva (6 each, 2.0%). Named purposes clustered around explanation of concepts, doubt clearance, assignment preparation and case discussion. Purpose-built educational AI – adaptive question banks, virtual patients, simulation platforms – was almost entirely absent from the responses.

Item-level perceptions

Responses to individual items are shown in Table 2 and displayed in Fig. 1. The pattern is consistent across the instrument: agreement (agree or strongly agree) ranged narrowly from 374 (61.1%) to 437 (71.4%), disagreement never exceeded 46 respondents (7.5%), and between 140 (22.9%) and 200 (32.7%) selected the neutral midpoint on every item. Mean item scores clustered between 3.63 and 3.79, and the median response was agree for all twelve items.

Table 2
Item-level responses to the twelve Likert statements

Statement	SD n (%)	D n (%)	N n (%)	A n (%)	SA n (%)	Agree/SA n (%)	Mean (SD)
1. AI can make lectures more interactive and engaging	30 (4.9)	10 (1.6)	156 (25.5)	316 (51.6)	100 (16.3)	416 (68.0)	3.73 (0.92)
2. Integration of AI in teaching can improve conceptual understanding	27 (4.4)	13 (2.1)	140 (22.9)	342 (55.9)	90 (14.7)	432 (70.6)	3.74 (0.89)
3. I am comfortable with AI being used to deliver or supplement lectures	27 (4.4)	12 (2.0)	187 (30.6)	310 (50.7)	76 (12.4)	386 (63.1)	3.65 (0.88)
4. AI can help identify my individual learning needs and tailor content accordingly	20 (3.3)	15 (2.5)	167 (27.3)	343 (56.0)	67 (10.9)	410 (67.0)	3.69 (0.82)
5. I would like to use AI tools (adaptive quizzes, simulations) to enhance my learning	23 (3.8)	10 (1.6)	143 (23.4)	344 (56.2)	92 (15.0)	436 (71.2)	3.77 (0.86)
6. AI-based virtual patients or simulations can improve clinical decision-making skills	23 (3.8)	23 (3.8)	179 (29.2)	317 (51.8)	70 (11.4)	387 (63.2)	3.63 (0.87)
7. AI will help me in better time management	21 (3.4)	16 (2.6)	163 (26.6)	321 (52.5)	91 (14.9)	412 (67.3)	3.73 (0.87)
8. AI can provide immediate and personalised feedback on assessments	20 (3.3)	11 (1.8)	148 (24.2)	356 (58.2)	77 (12.6)	433 (70.8)	3.75 (0.82)
9. I trust AI to evaluate my performance fairly in objective assessments	18 (2.9)	20 (3.3)	200 (32.7)	302 (49.3)	72 (11.8)	374 (61.1)	3.64 (0.84)
10. AI can reduce student workload and improve consistency in performance	18 (2.9)	13 (2.1)	144 (23.5)	344 (56.2)	93 (15.2)	437 (71.4)	3.79 (0.83)
11. I am excited about the integration of AI in education	22 (3.6)	10 (1.6)	168 (27.5)	327 (53.4)	85 (13.9)	412 (67.3)	3.72 (0.85)
12. AI in education raises ethical concerns that must be addressed	20 (3.3)	9 (1.5)	193 (31.5)	329 (53.8)	61 (10.0)	390 (63.7)	3.66 (0.81)

n = 612. A agree, AI artificial intelligence, D disagree, N neutral, SA strongly agree, SD strongly disagree (in response columns) or standard deviation (in the final column). Items 1–11 contribute to the overall

perception score; item 12 is reported separately (see Methods).

The highest agreement was recorded for the propositions that AI can reduce student workload and improve consistency in performance (437, 71.4%) and that respondents would like to use AI tools such as adaptive quizzes and simulations (436, 71.2%). The lowest agreement, and the largest neutral fraction, attached to trusting AI to evaluate performance fairly in objective assessments (374, 61.1% agreement; 200, 32.7% neutral) – the only item on which students were asked to cede judgement rather than receive support. Comfort with AI delivering or supplementing lectures (386, 63.1%) and confidence that AI-based virtual patients improve clinical decision-making (387, 63.2%) were similarly restrained. Agreement that AI raises ethical concerns requiring attention was endorsed by 390 respondents (63.7%).

Domain and composite scores

Internal consistency of the eleven-item composite was very high (Cronbach's alpha 0.959; corrected item–total correlations 0.772 to 0.833), as was that of the three domains (teaching and learning 0.915; assessment 0.887; readiness 0.886). This magnitude is addressed in the sensitivity analysis and discussion below.

The overall perception score was favourable but moderate: mean 3.71 (SD 0.72), median 3.91 (IQR 3.36–4.00) on a 1–5 scale. Domain scores were closely comparable – teaching and learning 3.69 (SD 0.76), assessment 3.72 (SD 0.75) and readiness 3.74 (SD 0.78) – indicating no meaningful separation between how students viewed AI as a teaching aid, as an assessment aid and as something they were prepared to adopt. Overall, 425 respondents (69.4%) recorded a mean score of 3.5 or above.

Factors associated with perception

Univariable comparisons are presented in Table 3. Students with prior exposure to AI tools scored marginally higher overall than those without (median 3.91, IQR 3.45–4.00 versus 3.82, IQR 3.27–4.00; $U = 51,296$, $p = 0.039$; rank–biserial $r = 0.10$), and were more likely to record a favourable score (227/307, 73.9% versus 198/305, 64.9%; chi-square = 5.45, $p = 0.020$). The difference was confined to the teaching and learning domain ($p = 0.002$, $r = 0.15$) and was absent for assessment ($p = 0.372$) and readiness ($p = 0.213$). Neither gender ($p = 0.275$) nor year of study (Kruskal–Wallis $H = 4.70$, $df = 4$, $p = 0.320$) was associated with the overall score, and the correlation with age was negligible (Spearman's $\rho = 0.10$, $p = 0.015$).

Table 3
Overall and domain perception scores by participant characteristics

Comparison	n	Mean (SD)	Median (IQR)	Test statistic	p value	Effect size
Overall score by prior exposure				U = 51,296	0.039	r = 0.10
Exposure: yes	307	3.74 (0.76)	3.91 (3.45–4.00)			
Exposure: no	305	3.68 (0.69)	3.82 (3.27–4.00)			
Teaching and learning domain by prior exposure				U = 53,615	0.002	r = 0.15
Exposure: yes	307	3.74 (0.80)	4.00 (3.50–4.00)			
Exposure: no	305	3.64 (0.72)	3.80 (3.20–4.00)			
Assessment domain by prior exposure				U = 48,700	0.372	r = 0.04
Exposure: yes	307	3.73 (0.80)	4.00 (3.33–4.00)			
Exposure: no	305	3.72 (0.70)	4.00 (3.33–4.00)			
Readiness domain by prior exposure				U = 49,440	0.213	r = 0.06
Exposure: yes	307	3.75 (0.80)	4.00 (3.33–4.00)			
Exposure: no	305	3.73 (0.76)	4.00 (3.33–4.00)			
Overall score by gender				U = 36,470	0.275	r = 0.06
Female	434	3.75 (0.66)	3.91 (3.36–4.00)			
Male	178	3.62 (0.86)	3.82 (3.27–4.00)			
Overall score by year of study				H = 4.70, df = 4	0.320	—
First year	123	3.70 (0.56)	3.82 (3.32–4.00)			
Second year	114	3.76 (0.76)	3.82 (3.55–4.09)			

Comparison	n	Mean (SD)	Median (IQR)	Test statistic	p value	Effect size
Third year	133	3.67 (0.85)	3.82 (3.00–4.00)			
Fourth year	212	3.71 (0.71)	3.91 (3.36–4.00)			
Final year or internship	30	3.80 (0.70)	4.00 (3.43–4.09)			
Overall score by professional programme				H = 35.25, df = 4	< 0.001	—
Homoeopathy	232	3.86 (0.76)	4.00 (3.64–4.18)			
Dentistry	24	3.83 (0.53)	3.82 (3.64–4.02)			
Pharmacy	42	3.72 (0.64)	3.91 (3.55–4.00)			
Physiotherapy	108	3.59 (0.77)	3.64 (3.09–4.00)			
Nursing	192	3.59 (0.67)	3.73 (3.27–4.00)			

n = 612. AI artificial intelligence, df degrees of freedom, H Kruskal–Wallis test statistic, IQR interquartile range, SD standard deviation, U Mann–Whitney test statistic. Scores range from 1 to 5, with higher values indicating a more favourable perception. Effect size r is the rank–biserial correlation. Programmes with fewer than 20 respondents were excluded from the between-programme comparison. Post hoc pairwise testing with Bonferroni adjustment: homoeopathy versus nursing, adjusted $p < 0.001$, $r = 0.31$; homoeopathy versus physiotherapy, adjusted $p < 0.001$, $r = 0.27$; all other contrasts, adjusted $p > 0.05$.

Discipline, by contrast, was strongly associated with perception (Kruskal–Wallis $H = 35.25$, $df = 4$, $p < 0.001$; Fig. 2). Homoeopathy students recorded the highest mean score (3.86), followed by dentistry (3.83) and pharmacy (3.72), with nursing (3.59) and physiotherapy (3.59) lowest. In post hoc pairwise testing with Bonferroni adjustment, homoeopathy differed significantly from nursing (adjusted $p < 0.001$, $r = 0.31$) and from physiotherapy (adjusted $p < 0.001$, $r = 0.27$); no other pairwise contrast reached significance.

In the multivariable model ($n = 597$; Table 4), discipline was the only independent predictor. Relative to homoeopathy, nursing students scored 0.26 points lower (95% CI – 0.40 to – 0.12, $p < 0.001$) and physiotherapy students 0.26 points lower (95% CI – 0.45 to – 0.07, $p = 0.007$). The univariable association with prior exposure did not survive adjustment ($B = 0.04$, 95% CI – 0.08 to 0.16, $p = 0.478$), consistent

with confounding by discipline, since exposure and perception both varied by programme. Female gender showed a non-significant positive association ($B = 0.13$, 95% CI – 0.01 to 0.28, $p = 0.074$), and neither age nor year of study contributed. The model explained little of the variance in perception (R-squared 0.038; adjusted R-squared 0.020), indicating that measured demographic and exposure characteristics account for only a small fraction of the between-student differences.

Table 4
Multivariable linear regression model of the overall perception score

Predictor	B	95% CI	p value	
Intercept	3.57	2.61 to 4.53	< 0.001	
Professional programme (reference: homoeopathy)				
Nursing	–0.26	–0.40 to – 0.12	< 0.001	*
Physiotherapy	–0.26	–0.45 to – 0.07	0.007	*
Pharmacy	–0.11	–0.34 to 0.11	0.325	
Dentistry	–0.02	–0.27 to 0.22	0.842	
Year of study (reference: first year)				
Second year	–0.02	–0.21 to 0.16	0.819	
Third year	–0.06	–0.25 to 0.14	0.566	
Fourth year	–0.08	–0.25 to 0.09	0.369	
Final year or internship	–0.15	–0.48 to 0.18	0.377	
Prior exposure to AI tools (reference: no)	0.04	–0.08 to 0.16	0.478	
Female gender (reference: male)	0.13	–0.01 to 0.28	0.074	
Age (per year)	0.01	–0.04 to 0.06	0.663	

$n = 597$. AI artificial intelligence, B unstandardised regression coefficient, CI confidence interval. Heteroscedasticity-consistent (HC3) standard errors. Model R-squared 0.038; adjusted R-squared 0.020; $F = 1.83$, $p = 0.046$. Fifteen respondents were excluded from the model owing to missing age or an unclassifiable programme. *Statistically significant at $p < 0.05$.

Sensitivity analysis

Two hundred and seven respondents (33.8%) selected the identical response option for all twelve items, most commonly agree (116) or neutral (50). Excluding them ($n = 405$) reduced the alpha of the composite from 0.959 to 0.910 but left the substantive findings unchanged: the overall mean score was 3.72 (SD 0.60), the difference by prior exposure remained of similar size and significance (3.76 versus 3.68, $p = 0.046$), and the difference by discipline persisted (Kruskal–Wallis $H = 22.88$, $p < 0.001$). The very

high alpha in the full sample is therefore best interpreted as reflecting undifferentiated responding by a substantial minority rather than as evidence of a well-discriminating unidimensional scale.

Perceived benefits and concerns in students' own words

A substantive answer on benefits was provided by 510 respondents (83.3%) and on concerns by 388 (63.4%); a further 114 respondents (18.6%) stated explicitly that they foresaw no concerns at all. Coded categories are shown in Table 5 and Fig. 3.

Table 5
Content analysis of free-text responses on perceived benefits and concerns

Category	n	% of substantive responses
Perceived benefits (510 substantive responses; 83.3%)		
Improved conceptual understanding and clarity	196	38.4
Rapid and convenient access to information	100	19.6
Enhanced clinical and diagnostic reasoning	75	14.7
Time saving and efficiency	67	13.1
Visual, simulation and virtual patient learning	37	7.3
Personalised and self-paced learning	34	6.7
Support for assessment, feedback and revision	29	5.7
Reduced workload and study burden	24	4.7
Support for research and academic writing	14	2.7
Perceived concerns (388 substantive responses; 63.4%)		
Over-reliance and loss of critical thinking	66	17.0
Inaccurate, outdated or misleading information	55	14.2
Data privacy and security risks	54	13.9
Erosion of human interaction and the teacher's role	36	9.3
Access, cost and technical barriers	26	6.7
Academic dishonesty, plagiarism and ethics	20	5.2
Displacement of future employment	18	4.6
Bias, lack of transparency and accountability	15	3.9
Increased screen time and eye strain	7	1.8
Loss of practical and clinical skills	6	1.5
Limited coverage of system-specific knowledge	2	0.5

n = 612. Categories are not mutually exclusive; a single response could be assigned to more than one category, so percentages sum to more than 100. Denominators are the number of respondents providing a substantive answer to each question. A further 114 respondents (18.6%) stated explicitly that they foresaw no concerns.

Benefits were dominated by a single theme. Improved conceptual understanding and clarity of learning accounted for 196 responses (38.4%), twice as many as the next category, rapid and convenient access to information (100, 19.6%). Enhanced clinical and diagnostic reasoning (75, 14.7%) and time saving (67, 13.1%) followed. Categories corresponding to the pedagogical affordances most often invoked in the literature were comparatively rare: visual, simulation and virtual patient learning was mentioned by 37 respondents (7.3%), personalised or self-paced learning by 34 (6.7%), and support for assessment, feedback and revision by 29 (5.7%). Students were, in short, describing AI as a better explanation engine rather than as an adaptive tutor.

Concerns were more dispersed. Over-reliance with a consequent loss of independent and critical thinking was the most frequently raised (66, 17.0%), followed by inaccurate, outdated or misleading output (55, 14.2%) and data privacy and security (54, 13.9%). Erosion of human interaction and of the teacher's role was raised by 36 respondents (9.3%), access, cost and connectivity barriers by 26 (6.7%), academic dishonesty and plagiarism by 20 (5.2%), displacement of future employment by 18 (4.6%), and algorithmic bias or lack of transparency by 15 (3.9%). Notably, loss of practical and clinical skills, a prominent concern in the medical education literature, was raised by only six respondents (1.5%), and only two mentioned that AI tools cover their own system of medicine poorly.

Discussion

Across 612 undergraduate students spanning six health professions programmes at a single Indian health sciences university, perceptions of AI for teaching, learning and assessment were favourable but distinctly reserved. Agreement with individual propositions never exceeded 72%, outright disagreement was rare, and roughly a quarter to a third of respondents sat on the neutral midpoint of every item. Half the cohort had no prior exposure to AI tools at all. Attitudes varied significantly by professional programme but not by gender, seniority or age, and discipline remained the only independent predictor after adjustment.

A large neutral middle, not genuine ambivalence

The most striking feature of these data is not the level of agreement but the size of the neutral category, which was remarkably stable across items with quite different content. Neutrality on a Likert item can mean indifference, genuine balance, or absence of a basis for judgement. The third interpretation fits best here: half the sample reported no exposure to AI tools, the highest neutral fraction attached to the item requiring the most specific knowledge – trusting AI to grade objective assessments – and free-text answers described AI in general terms of explanation and convenience rather than in terms of specific educational functions. Students appear to be withholding judgement on a technology they have not yet used in any structured way. This reading is consistent with the repeated finding that low AI knowledge coexists with broadly positive general attitudes [7, 12, 13], and it has a practical implication: this population is unlikely to resist AI literacy teaching, but neither can it be assumed to arrive with usable prior knowledge.

Trust in AI as an assessor is the weakest link

Students were readier to accept AI that supports learning than AI that judges them. The item on trusting AI to evaluate performance fairly in objective assessments attracted the lowest agreement and the largest neutral fraction, while the item on reduced workload and improved consistency — AI as a labour-saving aid — attracted the highest. The gap is modest in absolute terms but conceptually important, since it is precisely in automated scoring and item generation that institutions are most likely to deploy AI first, on grounds of efficiency. Concerns about fairness, transparency and accountability in AI-mediated assessment are well documented in the wider literature [5, 6, 19], and our data indicate that students share them. Any institutional move towards AI-supported assessment will require explicit disclosure of where AI is used, what human oversight exists, and how a contested outcome can be appealed.

Discipline matters more than exposure

The association between prior exposure and more favourable perceptions, evident in univariable analysis, disappeared once discipline was accounted for. Because exposure itself varied nearly two-fold between programmes, the apparent effect of individual familiarity was substantially an effect of the programme the student belonged to. This finding qualifies a common assumption in this literature — that attitudes will improve as individual exposure accumulates — and matches the observation from a curricular intervention study that structured teaching, rather than incidental use, shifts attitudes [20]. It suggests that the relevant unit of intervention is the programme, not the individual student.

Why homoeopathy students should hold the most favourable views, and nursing and physiotherapy students the least, cannot be determined from these data, and we resist post hoc explanation. Plausible contributors include differences in curricular workload and timetabling, in the availability of digital infrastructure across colleges, in the degree to which each programme's assessment rewards recall versus procedural skill, and in local faculty attitudes to educational technology. Nursing and physiotherapy curricula are heavily weighted towards supervised psychomotor and interpersonal competence, for which current text-based AI tools offer little; the modest scores in these groups may reflect an accurate appraisal of limited relevance rather than generalised scepticism. Comparable multi-programme data are scarce, but a multi-country survey of medical, nursing, physiotherapy and nutrition students similarly reported low self-rated AI knowledge with variation between programmes [13], and reviews in nursing describe moderately positive attitudes tempered by anxiety [15, 16]. This is a hypothesis-generating finding that warrants replication across institutions before it is used to justify differential curricular provision.

What students want AI for, and what worries them

The free-text data qualify the Likert findings in a useful way. Students overwhelmingly described AI as a tool for understanding concepts and obtaining quick answers; the affordances that dominate the academic literature — adaptive learning paths, virtual patients, automated formative feedback — barely

featured. The named tools tell the same story: general-purpose conversational assistants, led by ChatGPT, with purpose-built educational AI almost entirely absent. Students are therefore forming their view of AI in education from consumer chatbots rather than from educational technology, which places a particular onus on curricula to teach verification, source appraisal and appropriate task selection.

Their concerns were correspondingly well judged. Over-reliance and the erosion of independent thinking headed the list, ahead of factual inaccuracy and data privacy — a hierarchy that mirrors the risks that most concern educators [19, 21]. That 18.6% of respondents volunteered that they foresaw no concerns whatsoever is itself informative and points in the same direction as the neutral responses: a sizeable minority has not yet engaged with the question closely enough to identify risks. The near-absence of concern about loss of practical and clinical skills (1.5%) contrasts with the medical education literature, where deskilling is a recurrent theme [7, 21], and may reflect the fact that these students encounter AI in their study time rather than in clinical placements.

Implications for curriculum and policy

Three implications follow. First, AI literacy should be introduced as a shared, faculty-wide component of undergraduate health professions curricula rather than as a discipline-specific elective; the between-programme differences we observed argue for a common floor of provision, delivered so that programmes with the least exposure are not left furthest behind. Second, teaching should target the gap our data reveal most clearly — students use general-purpose chatbots as explanation engines, so instruction should concentrate on verifying output against authoritative sources, recognising fabrication, and understanding what these tools cannot do — rather than on abstract accounts of machine learning. Third, institutions should establish and publish policy on AI in assessment before deploying it, covering permitted student use, disclosure requirements, and the extent and nature of human oversight where AI contributes to scoring. Student trust on this point is the most fragile finding in our data and the easiest to lose.

Strengths and limitations

The principal strength of this study is its breadth: 612 students drawn from six undergraduate health professions programmes within a single university, which allows between-discipline comparison while holding the institution, regulatory environment and digital infrastructure constant. Analysis was conducted on the raw response data, item-level distributions are reported in full, and a prespecified sensitivity analysis addresses response-style bias. Quantitative findings are triangulated against free-text responses from a large majority of the cohort.

Several limitations qualify the findings. Convenience sampling through class messaging groups, together with voluntary participation, admits self-selection bias; students already interested in AI may be over-represented, which would bias perception scores upward. Because the denominator of students reached by the survey link is not known, a response rate cannot be calculated, and the distribution across programmes and years is uneven — fourth-year students are over-represented and no undergraduate

medical (MBBS) student responded, so the findings should not be generalised to medical undergraduates. Prior exposure was self-reported and undefined, so it captures self-perceived familiarity rather than any measured competence. The instrument, although adapted from published sources and reviewed for content validity, was not formally validated in this population and has not undergone factor analysis; the domain structure is conceptual rather than empirically derived, and the near-identical domain scores may indicate that students did not distinguish between them. The very high internal consistency, together with the finding that a third of respondents answered identically to all twelve items, indicates acquiescence and straight-lining that inflate reliability estimates, although the sensitivity analysis showed the main comparisons to be robust. Free-text responses were typically brief, so the content analysis quantifies the salience of themes rather than exploring them in depth; a qualitative study with interviews or focus groups would be better suited to the latter. Data collection extended across nine months, during which the AI tools available to students changed. Finally, the design is cross-sectional and single-centre, so no causal inference is possible and generalisability beyond comparable Indian health sciences universities is uncertain.

Conclusions

Undergraduate health professions students at an Indian health sciences university held broadly favourable but reserved views of AI in teaching, learning and assessment, with a large and consistent neutral middle that reflects limited exposure rather than considered ambivalence. Half had never used an AI tool for learning, and those who had were using general-purpose chatbots as explanation engines rather than purpose-built educational technology. Perceptions tracked professional programme rather than gender, seniority or self-reported exposure, and trust in AI as an assessor was the weakest point in an otherwise positive picture. These findings support introducing AI literacy as a common, faculty-wide element of undergraduate curricula, focused on verification and appropriate use, and accompanied by explicit institutional policy on the use of AI in assessment. Multi-institutional studies with probability sampling and validated instruments are needed to establish whether the between-discipline differences observed here are a general feature of health professions education.

Declarations

Ethics approval

This study was performed in line with the principles of the Declaration of Helsinki and the National Ethical Guidelines for Biomedical and Health Research Involving Human Participants of the Indian Council of Medical Research. Approval was granted by the Jawaharlal Nehru Medical College Institutional Ethics Committee, KLE Academy of Higher Education and Research, Belagavi, Karnataka, India (Reference number MDC/JNMCIEC/323, dated 9 September 2025; Department of Health Research registration number EC/NEW/INST/2024/KA/0548).

Consent to participate

Informed consent was obtained electronically from all individual participants included in the study before any study item was displayed. Only respondents aged 18 years or over who confirmed that they had read the participant information sheet and who explicitly consented to participate were included.

Consent to publish

Not applicable. The manuscript contains no identifying information about any individual participant.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

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Data availability

The de-identified dataset generated and analysed during the present study, together with the analysis code, is available from the corresponding author on reasonable request. The dataset is not publicly archived because participants consented on the basis that their responses would be held confidentially by the research team. The survey instrument is provided as Online Resource 1.

Declaration of Generative AI Use

[Authors to verify and customise before submission.] A large language model (Anthropic Claude) was used to assist with statistical analysis of the de-identified response dataset, with preparation of tables and figures, and with language editing and structuring of the manuscript draft. All analyses were specified by the authors, all outputs were checked against the source data by the authors, and all interpretation, conclusions and final wording are the authors' own. The authors take full responsibility for the content and integrity of the work.

Author contributions

SJK conceived and designed the study, obtained ethical approval, supervised data collection and wrote the first draft of the manuscript. JN contributed to study design and critically revised the manuscript for important intellectual content. SKD designed the analysis plan, performed the statistical analysis and interpretation, critically revised the manuscript for scientific accuracy, and coordinated submission as corresponding author. [Contributions of additional co-authors to be inserted.] All authors commented on previous versions of the manuscript, and all authors read and approved the final manuscript.

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Figures

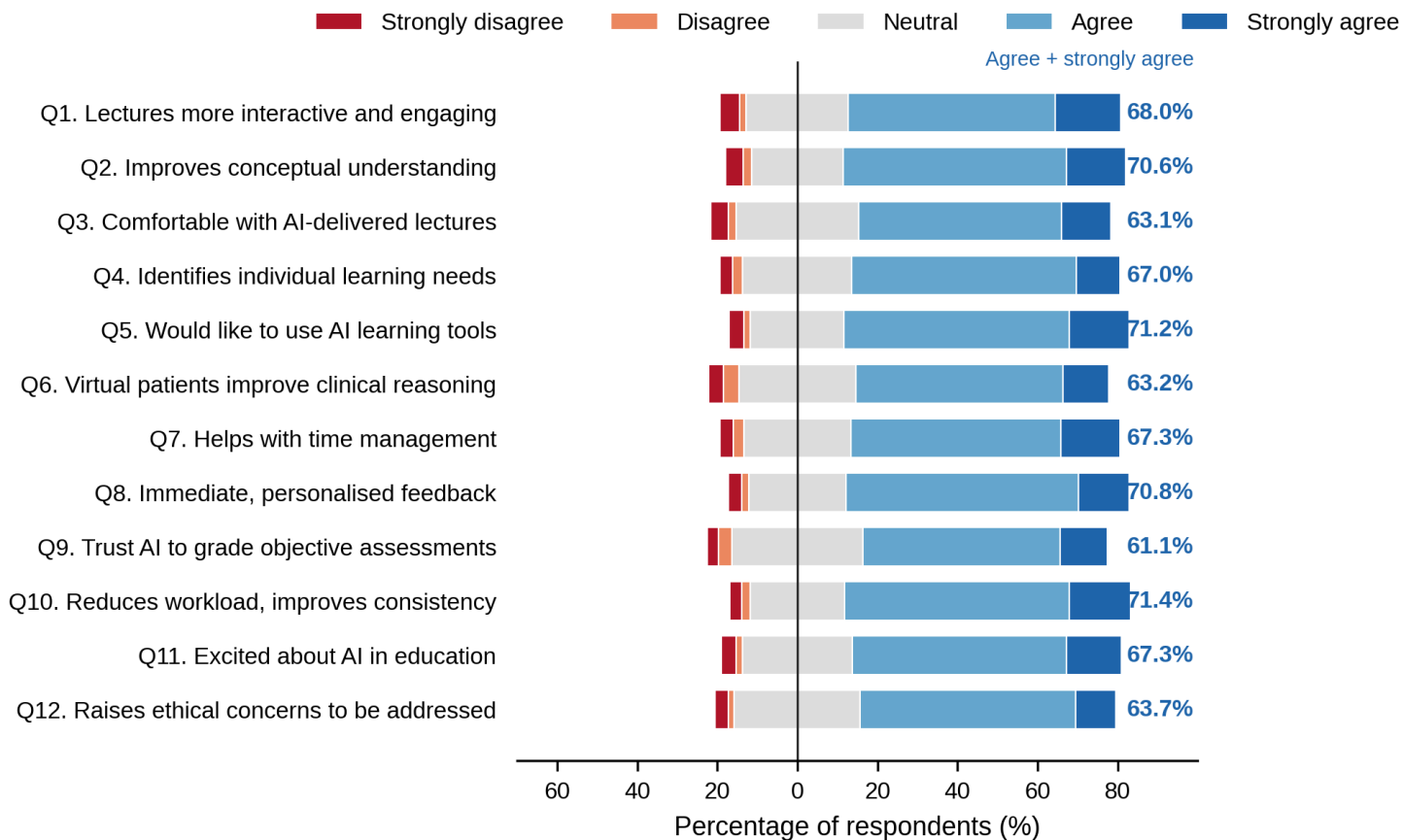


Figure 1

Distribution of responses to the twelve five-point Likert statements (n = 612). Bars are centred on the neutral category. The percentage to the right of each bar is the combined agree and strongly agree proportion. Item numbers correspond to those in Table 2

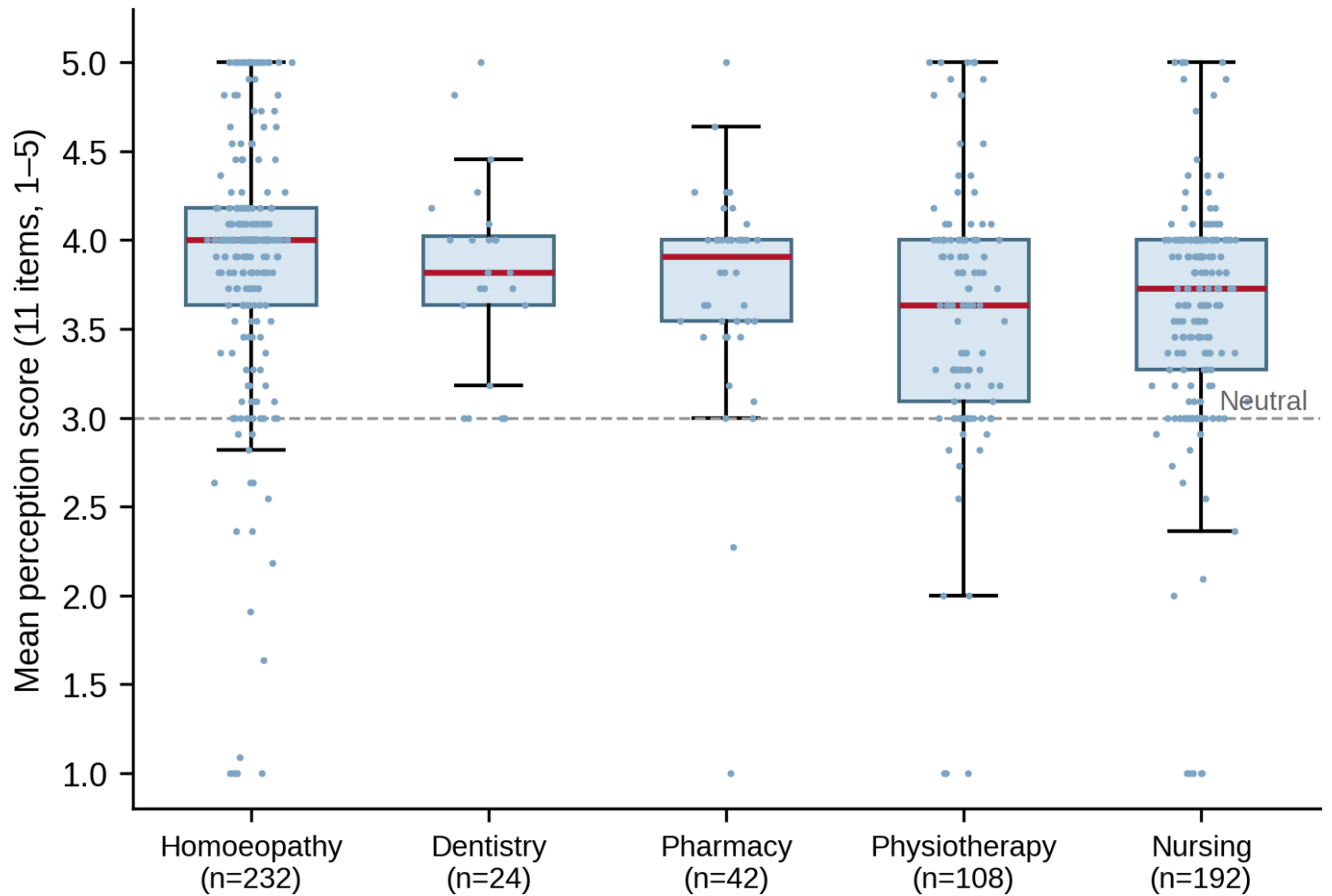


Figure 2

Overall perception score by professional programme. Boxes show the median and interquartile range, with whiskers extending to 1.5 times the interquartile range; individual respondents are overlaid as jittered points. The dashed line marks the neutral value of 3. Programmes with fewer than 20 respondents are not shown. Kruskal–Wallis $H = 35.25$, $df = 4$, $p < 0.001$

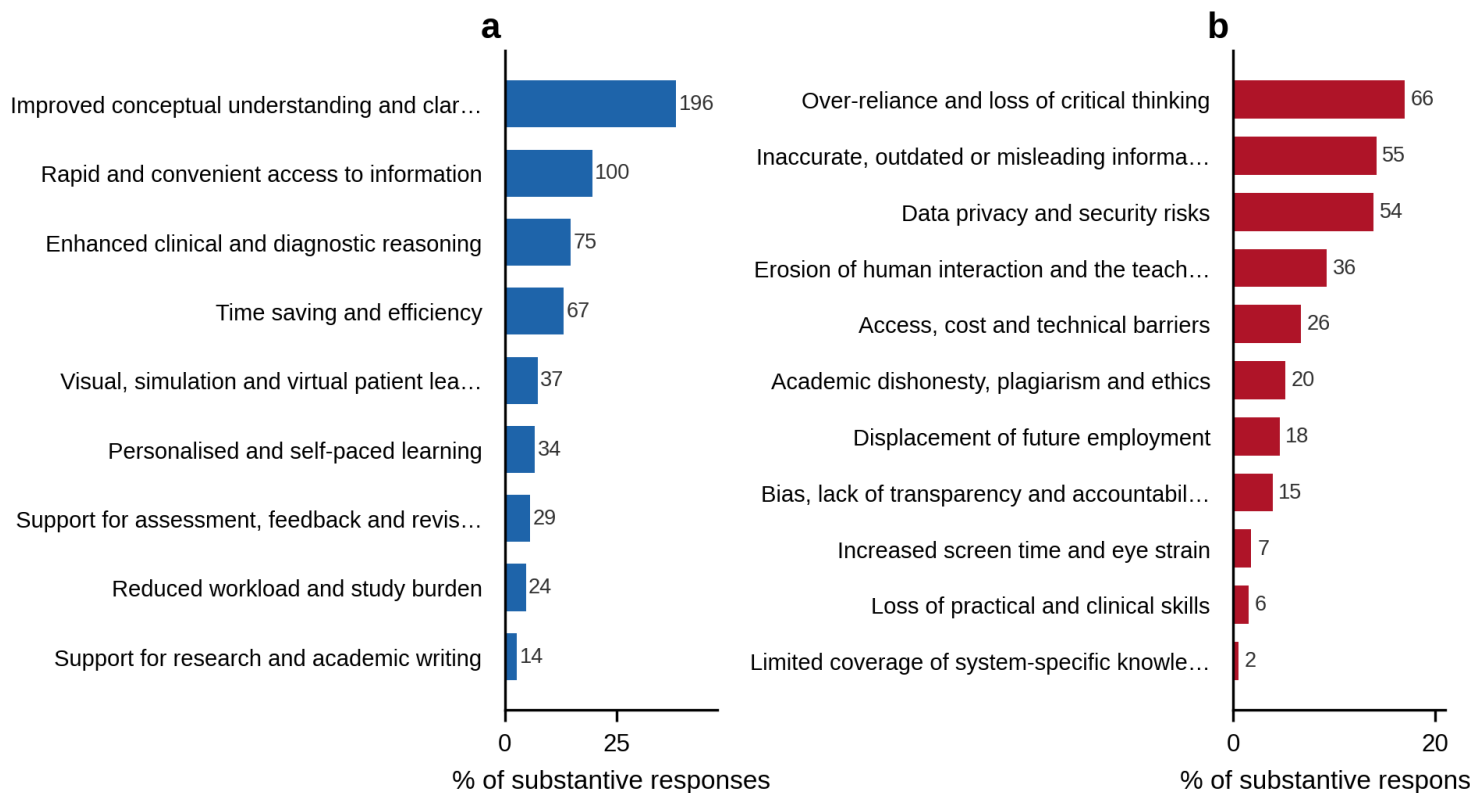


Figure 3

Categories identified by content analysis of free-text responses on the perceived benefits (a) and perceived concerns (b) of artificial intelligence in health professions education. Percentages are of respondents providing a substantive answer to each question; counts are shown beside each bar. Categories are not mutually exclusive

Supplementary Files

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