Original Article

Knowledge, Attitude and Practice Towards Artificial Intelligence in Pharmaceutical Sciences Among Pharmacy Students and Graduates: A Cross-Sectional Study

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Background: Artificial intelligence (AI) is increasingly used in drug discovery, clinical research, and pharmacy practice. Little is known about how prepared pharmacy trainees and graduates are to use it. **Objective:** To assess knowledge, attitude, and practice (KAP) regarding AI in pharmaceutical sciences among pharmacy students and graduates, and to compare KAP across demographic and academic subgroups. **Methods:** We ran a cross-sectional online survey with a 16-item KAP questionnaire (5 knowledge, 6 attitude, 5 practice items). B.Pharm, M.Pharm, and Pharm.D students completed it, as did graduates working as faculty or in the pharmaceutical industry. Associations were tested with the chi-square test. Odds ratios (OR) with 95% confidence intervals (CI) were calculated for two-group comparisons. Significance was set at $p < 0.05$. **Results:** Of 327 responses, 306 were analysed (241 students, 65 graduates). Overall, 76.8% had heard of AI in pharmaceutical sciences, and 69.0% agreed it can be used in drug discovery. Only 56.5% reported using AI for pharmaceutical research and development (R&D). Gender and degree level (B.Pharm vs M.Pharm) were not associated with any KAP item. Students were more likely than graduates to use AI for R&D (60.2% vs 43.1%; OR 2.00, 95% CI 1.15–3.48; $p = 0.020$). They were also more likely to believe AI is more accurate than human experts (37.3% vs 15.4%; OR 3.28, 1.59–6.75; $p = 0.001$) and that AI will replace pharmacists (22.8% vs 9.2%; OR 2.91, 1.19–7.10; $p = 0.024$). Among students, later academic years showed higher agreement than the first year on three points: that AI supports drug discovery, that it will be widely used in the future, and that it should be taught. Use of AI for academic purposes followed the same pattern (all $p < 0.05$). **Conclusion:** Awareness of AI and attitudes towards it were favourable but cautious, while applied use lagged. Academic stage and student/graduate status were the main correlates of KAP. Gender and degree were not. Pharmacy curricula need structured, hands-on AI training, and graduates need the same through continuing education.

Key words: artificial intelligence, knowledge, attitudes, practice, pharmacy education, pharmaceutical sciences, drug discovery, cross-sectional studies.

AI is the branch of computer science that builds machines and software able to carry out tasks that normally need human intelligence, such as reasoning, learning, perception, and decision-making [1]. Its conceptual origins are usually traced to Turing's 1950 proposal of a test of machine intelligence [2]. The field was formally established at the 1956 Dartmouth Summer Research Project [3]. Cycles of enthusiasm and retrenchment, known as "AI winters", followed. Since the 1990s, AI has resurged on the back of very large datasets, greater computing power (notably graphics processing units) and advances in deep learning [4]. Machine learning (ML) is the part of AI that uses statistical methods to learn patterns from data instead of being explicitly programmed [5,6]. It is commonly divided into three types. Supervised learning covers classification and regression, for example, disease diagnosis and prediction of drug efficacy and ADMET properties. Unsupervised learning covers clustering and feature discovery, for example, identification of disease subtypes. Reinforcement learning is used for tasks such as de novo molecular design [7–10]. Deep learning (DL) is a subfield of ML built on multilayer artificial neural networks such as convolutional and recurrent networks. It has proved especially powerful with large experimental datasets [11,12]. These methods now appear across the pharmaceutical pipeline. Drug discovery is hard partly because chemical space is vast, at an estimated 10^{60} molecules [13]. Bringing a new drug to market

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also typically takes more than a decade and over US$2.5 billion [14]. AI has been applied to target identification and validation [15–17]. In one example, IBM Watson identified additional RNA-binding proteins linked to amyotrophic lateral sclerosis [18]. It has also been used in hit and lead discovery, where it can reduce the number of compounds that must be synthesised and tested [19,20], and in de novo molecular design [21,22], synthesis planning [23], and prediction of pharmacological properties, toxicity and drug–drug interactions [24–27]. Other applications include prediction of drug–target interactions and polypharmacology [28,29], drug repurposing [30,31], prediction of clinical-trial outcomes and patient recruitment [32,33], monitoring of dosing adherence [34,35], and omics-based biomarker discovery and personalised medicine [36,37].

Recent developments have sped this shift up. AlphaFold 3 predicts the structures of biomolecular complexes with high accuracy, which bears directly on target identification [38]. Conversational large language models such as ChatGPT have been adopted quickly in education, and surveys of pharmacy students' knowledge of these tools have followed [39]. Several reviews describe AI moving from a peripheral computational aid to a core driver of pharmaceutical discovery, development and clinical decision-making [40–43].

For the pharmacy profession, this raises a question of preparedness. Graduates will be expected to understand what AI can and cannot do, to judge AI-generated outputs critically and to use such tools responsibly in R&D, industry, dispensing or clinical care. KAP surveys are widely used to describe what a population knows about a subject, how it feels about it, and whether those views turn into behaviour [44–47]. They can therefore show where educational effort is most needed.

Recent studies of pharmacy populations show a consistent pattern. A multinational study of 875 pharmacy students and faculty members from six Middle Eastern and North African countries found moderate overall knowledge (mean score 42.3 ± 21.8 out of 100). Students scored higher than faculty, and 96.2% believed AI could improve patient care [44]. Among Japanese pharmacy students, familiarity with general terms such as "machine learning" was far greater than with technical terms such as "natural language processing" [39]. A study of medicine and pharmacy students in Jordan and Palestine found limited conceptual understanding that varied with academic year and prior exposure to informatics coursework [45]. An international multicentre survey reported minimal formal AI content in pharmacy curricula despite largely positive attitudes [48]. A US national survey found high self-reported familiarity among students, along with a need for structured curricular content among both students and faculty [49].

Studies of practising pharmacists report favourable attitudes towards AI but concerns about data privacy, accountability and preparedness [46]. They also report infrastructural, financial and training barriers [50] and limited real-world use despite reasonable awareness [47,51]. Few studies have examined pharmacy students and graduates together in a single cohort with a focused KAP instrument on AI in pharmaceutical sciences, and data from India are scarce. We therefore conducted a cross-sectional study with three aims: (i) to compare KAP regarding AI in pharmaceutical sciences across demographic characteristics (age, gender, educational qualification and occupation); (ii) to compare KAP among students across academic years; and (iii) to compare KAP between pharmacy students and graduates.

2. METHODS

2.1 Study design and setting

This was a cross-sectional, questionnaire-based KAP survey, an established design for assessing AI readiness in pharmacy populations. Data were collected between 10th August 2026 and 20th August 2026 through an online form (Google Forms) circulated by email to pharmacy students and professionals.

2.2 Participants

Eligible participants were students enrolled in B.Pharm, M.Pharm, or Pharm.D programmes, and graduates holding one of these degrees who worked as faculty in pharmacy colleges or in the pharmaceutical industry. We excluded D.Pharm students because of their limited involvement in drug discovery and clinical research. We also excluded students from other scientific disciplines and questionnaires that were less than half completed. Participants were recruited by convenience sampling. The sample size was calculated with the Raosoft calculator at a 95% confidence level and an assumed response distribution of 50%, which gave a target of 306 respondents.

2.3 Study instrument

We developed a structured, validated, closed-ended questionnaire for the study (Supplementary File 1). It had five demographic items (age group, gender, qualification, occupation, and for students, academic year) and 16 KAP items. The five knowledge items covered awareness of AI in pharmaceutical sciences, its use in drug discovery and design, its role in clinical trials, the need for specific skills to use AI tools, and self-rated ability to identify AI applications.

The six attitude items covered expected future use, willingness to incorporate AI professionally, AI replacing pharmacists, AI being more accurate than human experts, AI revolutionising pharmacy sciences, and teaching AI to all pharmacy students. The five practice items covered use of AI for academic purposes, for writing research articles and for pharmaceutical R&D, attendance at an AI seminar or workshop, and reading articles on AI in pharmacy. Responses were Yes/No or Agree/Neutral/Disagree.

2.4 Variables and statistical analysis

The independent variables were age group, gender, educational qualification, occupation, academic year (students only), and student/graduate status. The dependent variables were the responses to each KAP item. Categorical data are given as frequencies and percentages. Percentages in the tables refer to the positive response (Yes or Agree) within each subgroup. We tested associations between each item and each grouping variable with the chi-square test of independence. For two-group comparisons, we calculated odds ratios with 95% CIs (positive response, first-named group versus second). A two-sided p-value < 0.05 was considered statistically significant. No adjustment was made for multiple comparisons.

3. RESULTS

3.1 Participants

We received 327 responses. Twenty-one did not meet the inclusion criteria, which left 306 respondents for analysis (241 students and 65 graduates). Most respondents were aged 20–25 years (66.7%), and the sample was balanced by gender (51.0% male). The large majority held or were pursuing a B.Pharm (91.5%). Fourth-year students were the largest student group (33.6% of students). Faculty (n = 7) and respondents aged above 30 years (n = 2) were very small groups (Table 1).

Table 1. Demographic characteristics of the respondents (N = 306)

Characteristic	Category	n (%)
Age group (years)	Below 20	91 (29.7)
	20–25	204 (66.7)
	25–30	9 (2.9)
	Above 30	2 (0.7)
Gender	Male	156 (51.0)
	Female	150 (49.0)
Qualification	B.Pharm	280 (91.5)
	M.Pharm	26 (8.5)
Occupation	Student	241 (78.8)
	Faculty	7 (2.3)
	Pharmaceutical industry	25 (8.2)
	Not employed	10 (3.3)
	Others	23 (7.5)
Academic year (students, n=241)	First	67 (27.8)
	Second	46 (19.1)
	Third	47 (19.5)
	Fourth	81 (33.6)
Student/graduate status	Students	241 (78.8)
	Graduates	65 (21.2)

Percentages are of the total sample except academic year, which is of students.

3.2 Overall knowledge, attitude and practice

Overall, 76.8% of respondents had heard of AI use in pharmaceutical sciences, and 69.0% agreed that AI can be used in drug discovery and design. Fewer agreed that AI can assist in clinical trials (53.3%), and 62.4% felt able to identify AI applications in pharmaceutical sciences (Table 2). Attitudes were favourable. A total of 78.1% expected AI to be widely used in the future, 67.6% were willing to incorporate it into their profession, and 65.0% supported teaching AI to all pharmacy students. Only 19.9% believed AI will replace pharmacists, and 32.7% believed it to be more accurate than human experts. Practice was lower. A total of 73.2% had used AI for academic purposes and 60.8% for writing research articles. Only 56.5% used it for pharmaceutical R&D, 50.0% had attended an AI seminar or workshop, and 48.7% had read an article on AI in pharmacy.

3.3 Students compared with graduates

Knowledge did not differ significantly between students and graduates. Students more often felt able to identify AI applications (65.1% vs 52.3%; p = 0.080), but that difference did not reach significance. Three attitude items differed. Students were more likely to believe that AI will replace pharmacists, that AI is more accurate than human experts, and that AI will revolutionise pharmacy sciences. Students also reported greater use of AI for pharmaceutical R&D (60.2% vs 43.1%; OR 2.00, 95% CI 1.15–3.48; p = 0.020). Use of AI for academic purposes was higher among students but did not reach significance (75.9% vs 63.1%; p = 0.055) (Table 2).

3.4 Students across academic years

Among students, six items differed significantly by academic year (Table 3). Later years showed higher agreement than the first year on four points: that AI can be used in drug discovery and design, that AI use requires advanced skills, that AI will be widely used in the V future, and that AI should be taught to all students. The same held for the use of AI for academic purposes and for having read an article on AI in pharmacy. The trends were not strictly linear. Second- and third-year students often reported levels similar to or higher than fourth-year students. Use of AI for pharmaceutical R&D was of borderline significance (52.2%, 60.9%, 51.1% and 71.6% from first to fourth year; p = 0.050).

3.5 Age, gender, qualification and occupation

Age group was associated with having heard of AI in pharmaceutical sciences (p = 0.019) and with self-rated ability to identify AI applications (p = 0.0002). It was not associated with any attitude or practice item. The two oldest age groups contained only 9 and 2 respondents, so these results need cautious reading. No knowledge, attitude, or practice item differed significantly by gender (all p > 0.05) or between B.Pharm and M.Pharm respondents (all p > 0.05). Occupation was associated with agreement that AI is more accurate than human experts (p = 0.012), which was highest among students (37.3%) and lowest among those not employed (0%). It was

also associated with use of AI for academic purposes (p = 0.029), use for pharmaceutical R&D (p = 0.008), and attendance at AI seminars or workshops (p = 0.023). Faculty reported the highest engagement on each practice item, but this group had only seven respondents (Table 4).

Table 2. Knowledge, attitude and practice regarding AI in pharmaceutical sciences: overall and students versus graduates

Item (positive response)	Overall n (%) N=306	Students n (%) N=241	Graduates n (%) N=65	OR (95% CI)	p value
Knowledge					
K1. Heard of AI use in pharmaceutical sciences	235 (76.8)	184 (76.3)	51 (78.5)	0.89 (0.46–1.72)	0.847
K2. AI can be used in drug discovery/design	211 (69.0)	166 (68.9)	45 (69.2)	0.98 (0.54–1.78)	1.000
K3. AI can assist in clinical trials	163 (53.3)	133 (55.2)	30 (46.2)	1.44 (0.83–2.49)	0.248
K4. Using AI tools requires advanced skills	209 (68.3)	168 (69.7)	41 (63.1)	1.35 (0.76–2.39)	0.385
K5. Can identify AI applications	191 (62.4)	157 (65.1)	34 (52.3)	1.70 (0.98–2.97)	0.080
Attitude					
A1. AI will have wide future use	239 (78.1)	191 (79.3)	48 (73.8)	1.35 (0.72–2.55)	0.443
A2. Willing to incorporate AI	207 (67.6)	169 (70.1)	38 (58.5)	1.67 (0.95–2.94)	0.102
A3. AI will replace a pharmacist	61 (19.9)	55 (22.8)	6 (9.2)	2.91 (1.19–7.10)	**0.024**
A4. AI is more accurate than human experts	100 (32.7)	90 (37.3)	10 (15.4)	3.28 (1.59–6.75)	**0.001**
A5. AI will revolutionise pharmacy sciences	164 (53.6)	137 (56.8)	27 (41.5)	1.85 (1.06–3.23)	**0.040**
A6. All students should be taught AI	199 (65.0)	161 (66.8)	38 (58.5)	1.43 (0.82–2.51)	0.269
Practice					
P1. Used AI for academic purposes	224 (73.2)	183 (75.9)	41 (63.1)	1.85 (1.03–3.31)	0.055
P2. Used AI in writing research articles	186 (60.8)	152 (63.1)	34 (52.3)	1.56 (0.90–2.71)	0.152
P3. Uses AI for pharmaceutical R&D	173 (56.5)	145 (60.2)	28 (43.1)	2.00 (1.15–3.48)	**0.020**
P4. Attended AI seminar/workshop	153 (50.0)	126 (52.3)	27 (41.5)	1.54 (0.89–2.68)	0.162
P5. Read an article on AI in pharmacy	149 (48.7)	120 (49.8)	29 (44.6)	1.23 (0.71–2.14)	0.548

OR = odds ratio (students vs graduates); CI = confidence interval; R&D = research and development. p values from chi-square test; bold indicates p < 0.05.

Table 3. Items showing significant variation across academic years among students (n = 241)

Item (positive response)	Year 1 (n=67) %	Year 2 (n=46) %	Year 3 (n=47) %	Year 4 (n=81) %	p value
K2. AI can be used in drug discovery/design	52.2	80.4	68.1	76.5	0.013
K4. Using AI tools requires advanced skills	58.2	76.1	59.6	81.5	0.037
A1. AI will have wide future use	67.2	82.6	87.2	82.7	0.046
A6. All students should be taught AI	50.7	78.3	68.1	72.8	0.033
P1. Used AI for academic purposes	62.7	82.6	87.2	76.5	0.013
P5. Read an article on AI in pharmacy	44.8	47.8	38.3	61.7	0.049

p values from chi-square test across the four academic years. The remaining 10 knowledge, attitude, and practice items did not differ significantly.

Table 4. Statistically significant associations with age group and occupation

Grouping variable	Item	Highest / lowest subgroup (%)	p value
Age group	K1. Heard of AI in pharmaceutical sciences	25–30 y: 88.9 / Below 20: 65.9	0.019
Age group	K5. Can identify AI applications	Below 20: 69.2 / Above 30: 0	0.0002
Occupation	A4. AI more accurate than human experts	Students: 37.3 / Not employed: 0	0.012
Occupation	P1. Used AI for academic purposes	Faculty: 100 / Not employed: 50	0.029
Occupation	P3. Uses AI for pharmaceutical R&D	Faculty: 85.7 / Not employed: 30	0.008
Occupation	P4. Attended AI seminar/workshop	Faculty: 85.7 / Industry: 24	0.023

Faculty n = 7; respondents above 30 years n = 2; not employed n = 10. Percentages for these groups are unstable.

DISCUSSION

In this survey of 306 pharmacy students and graduates, awareness of AI in pharmaceutical sciences and belief in its future importance were high. Attitudes were favourable but cautious. Practical use in pharmaceutical R&D and structured exposure (workshops, reading) were noticeably lower. Academic year and student/graduate status were the main correlates of KAP. Gender and degree level showed no association with any of the 16 items.

Awareness was high, but fewer respondents recognised AI's role in clinical trials or could identify specific applications. Familiarity with AI as a general concept therefore seems to exceed understanding of where it fits in the drug-development pipeline. This agrees with the moderate knowledge scores among pharmacy students and faculty in the Middle East and North Africa [44]. It also agrees with the limited conceptual understanding among medicine and pharmacy students in Jordan and Palestine [45] and with the observation that pharmacy students know general AI terms far better than technical ones [39]. We measured knowledge with self-rated agreement items and not a scored test. Our figures probably reflect perceived knowledge more than demonstrated knowledge.

Attitudes were largely positive. Support for teaching AI to all pharmacy students (65.0%) was strong, which echoes calls from pharmacy educators for structured curricular integration [48,49]. Only about one in five respondents thought AI would replace pharmacists, and fewer than one in three thought it more accurate than human experts. This fits a view of AI as a supportive technology and not a substitute. Similar mixtures of enthusiasm and concern about accuracy, accountability, data privacy and professional role have been described among pharmacy students and pharmacists [44,46,50].

The gap between attitude and practice is a recurrent finding. Studies of practising pharmacists report limited use of AI-based tools despite reasonable awareness, and they attribute this to inadequate infrastructure, training and institutional support [47,50,51]. Intensive use of computational tools such as virtual screening and QSAR modelling is described mainly among specialised drug-discovery researchers [12,52]. This fits our finding that structured exposure was much less common than casual use. Most respondents had used AI for academic tasks, yet only about half had attended a workshop or read an article on AI in pharmacy. Our practice items captured use of general-purpose AI tools and not domain-specific platforms. The reported 56.5% use in pharmaceutical R&D should therefore be read as self-reported exposure and not as evidence of advanced computational drug-discovery skills.

Students were more likely than graduates to endorse AI's accuracy, its potential to revolutionise pharmacy and its replacement of pharmacists, and to use it in R&D. One plausible explanation is that current students have grown up with generative AI as part of their learning environment. Graduates formed their professional views earlier and may have less access to training after graduation. The lower workshop attendance among graduates and non-employed respondents supports this. Students' stronger endorsement of replacement and superior accuracy may also reflect less exposure to AI's limits in professional practice. Greater AI exposure among younger cohorts has likewise been proposed to explain why pharmacy students outscored faculty in a multinational study [44].

These interpretations are speculative, because the design cannot separate cohort, career-stage, and selection effects. Within students, higher agreement in later years on several items is consistent with cumulative exposure through coursework and projects. The non-linear pattern argues against a simple dose–response relationship, since second- and third-year students often scored similarly to fourth-year students.

Our findings fit the picture from other regions. Studies from the Middle East and North Africa report moderate knowledge, high enthusiasm, and limited structured training [44–46]. US data show high familiarity but persistent gaps in formal curricular content [49]. An international multicentre study reports minimal AI content in pharmacy curricula despite positive attitudes [48]. The knowledge–practice gap therefore looks widespread and not specific to one healthcare system, although data from India remain limited.

Gender and degree showed no differences. AI awareness and attitudes do not appear to be stratified by these characteristics in this population, so educational interventions may be better targeted by stage of training than by demographic group. Our findings support introducing AI literacy early and progressively in the pharmacy curriculum. Formal AI content is still minimal in many programmes [48], and at the time of a recent US survey, accrediting bodies had not yet added explicit AI competencies to pharmacy education standards [49]. Hands-on components would help, for example, critical appraisal of AI outputs, basic ML concepts, and cheminformatics or pharmacovigilance applications. Continuing professional development for graduates, particularly those outside academic or industrial settings, would help turn favourable attitudes into competent use.

Strengths and limitations

The study included both students and graduates in one cohort and reported effect sizes with confidence intervals. Several limitations apply. First, the cross-sectional design precludes causal inference. Second, recruitment was by an online link circulated to selected institutions. The sample is not representative, and self-selection bias is likely. Graduates were fewer than students (n = 65 vs 241), and several subgroups (faculty, M.Pharm, respondents above 30 years) were very

small. This makes estimates imprecise and chi-square approximations unreliable. Third, all data were self-reported and may be affected by social desirability. Fourth, the instrument used single binary or three-point items without a composite score, and its validity and reliability were/were not formally assessed. Fifth, roughly 90 comparisons were performed without correction for multiple testing. Borderline findings (p-values close to 0.05) may be chance findings and should be treated as hypothesis-generating.

CONCLUSION

Pharmacy students and graduates in this study were aware of AI. They saw it as important for the future of pharmaceutical sciences and regarded it mainly as a complement to professional judgement. Applied use and structured exposure lagged. Academic stage and student/graduate status distinguished knowledge, attitudes and practice. Gender and degree level did not. Progressive, hands-on AI training within pharmacy curricula, together with continuing education for graduates, may help turn favourable attitudes into competent and responsible use. Larger, probability-based and multi-institutional studies with validated, scored instruments are needed to confirm these findings.

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