Journal of
Scientific Advances in Dentistry

REVO PUBLICATION

Original Research Article

Self-rated understanding versus objective knowledge of artificial intelligence among dental students: A single-institution cross-sectional pilot survey

Akash Raj Sharma[1], Kanchan Shukla[2], Pratiksha A Srivastava[1*], Chandrama Pratap[1], Gaurav Verma[3], Risabh Rana[3]

[1]Department of Prosthodontics and Crown & Bridge, Subharti Dental College and Hospital, Swami Vivekanand Subharti University, Meerut, Uttar Pradesh, India

[2]Private Practitioner, Meerut, Uttar Pradesh, India

[3]Subharti Dental College and Hospital, Swami Vivekanand Subharti University, Meerut, Uttar Pradesh, India

Abstract

Background: Dental students' self-perceived familiarity with artificial intelligence (AI) is often assumed to track their actual understanding, an assumption with direct implications for how dental curricula introduce AI content. This pilot study examined awareness, self-rated understanding, and objective knowledge of AI among dental students at a single, predominantly private dental institution, and tested whether self-rated understanding corresponded to objective knowledge.

Methods: A cross-sectional online survey using convenience sampling was conducted among dental students via Google Forms from 22 July to 3 August 2026. Of 94 responses, 92 were included after excluding one duplicate and one non-dental student. AI knowledge was assessed using three forced-choice items, with multiple selections scored as incorrect. Data were analysed using chi-square tests, independent t-tests, one-way ANOVA, and binary logistic regression in Python 3.

Results: Results: Among 92 respondents (mean age 22.9 ± 2.6 years; 72.8% female), 94.5% had heard of AI, and 93.5% currently used AI tools for academic work, mainly ChatGPT (69.6%). Self-rated understanding was Basic (20.5%), Moderate (38.6%), Good (28.4%), and Advanced (12.5%). The mean objective knowledge score was 1.43 ± 0.96 out of 3, with 18.5% answering none and 15.2% answering all three correctly. Self-rated understanding was not associated with objective knowledge (one-way ANOVA, $p = 0.82$). Gender, academic year, and age were not significant predictors. However, objective knowledge differed significantly by faculty guidance status ($p = 0.002$), with students reporting no formal guidance scoring higher on average than those receiving guidance.

Conclusion: In this single-institution pilot study, dental students' self-rated AI understanding did not reflect their actual knowledge, which was generally low across demographic and academic groups. These findings require validation through larger, multi-institutional studies using validated knowledge tools before making curriculum recommendations.

Keywords: Artificial intelligence, Dental students, Dental education, Knowledge assessment, Self-assessment, ChatGPT.

Received: 08-08-2026

Accepted: 18-10-2026

Published: 21-11-2026

***Corresponding author:** Pratiksha A Srivastava
Email: drpratikshaprostho@gmail.com

https://doi.org/10.65929/JSAD.2026.1.3.003

How to cite this article: Sharma AR, Shukla K, Srivastava PA, Pratap C, Verma G, Rana R. Self-rated understanding versus objective knowledge of artificial intelligence among dental students: A single-institution cross-sectional pilot survey. *J Sci Adv Dent*. 2026;1(3):94-102.

© 2026 The Author(s). Published by REVO Publication.

This is an Open Access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0) (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

1. Introduction

Artificial intelligence (AI) encompasses computer systems that operate like humans, in terms of learning, thinking and forming associations.[1] Its adoption in healthcare has been rapid, spanning from diagnostic imaging to clinical decision support.[2,3] Dentistry has seen similar progress; published reports highlight the use of AI for interpreting radiographic images, in orthodontic and prosthetic treatment planning, and in computer-aided design/computer-aided manufacturing (CAD-CAM).[4-7] Notably, there is a class of readily available, non-clinical, AI applications (chatbots) used by students for general tasks unrelated to learning Dentistry. These include

ChatGPT, Gemini, Claude, and similar large language model chatbots.[8]

Dental students represent a critical cohort, as it is they that will ultimately adopt and/or repurpose these technologies in their practice and further studies.[9] Hence, a growing body of cross-sectional surveys have examined dental (and medical) students' knowledge, awareness, attitudes, and practices (KAP) with regard to AI. A multinational study of dental students observed that whilst 76.2% agreed that they understood what AI is, only 34.7% could identify its application in dentistry and only 29.5% could correctly answer three factual knowledge questions about AI.[10] Another study among dental residents reported that only 58.3% knew the basic principles of AI.[11] A large knowledge, attitude, and practice survey among Indian dentists and students reported 63.5% overall awareness of AI, with gaps seen in awareness of different types and platforms.[12] Another cross-sectional study from South India of 208 undergraduates and postgraduates dental students found that 95.6% had heard of AI, but only 25.8% (vs 90.9% postgraduates) could identify its applications in dentistry.[13] Taken together, these reports highlight a consistent theme: that familiarity with the concept of AI far exceeds practical, verifiable knowledge of the technology.

Another pertinent issue is students' perception of their own AI literacy. This is an important consideration, as the planning of an educational curriculum likely to influence students' choices with regard to adopting or avoiding AI tools depends on an accurate assessment of learners' self-perceived competence with the technology. Self-perceived competence, however, appears to be poorly correlated with objective measures of knowledge. Among healthcare students, self-reported knowledge of evidence-based terms showed only poor agreement (intraclass correlation 0.29) with objectively assessed knowledge; students' self-evaluations tended to be higher than their performance on open-ended questions.[14] Similarly, there was no positive correlation between self-perceived levels of competence and objectively assessed level of competence in clinical procedures amongst final year medical students (Spearman's rho − 0.12).[15] It remains to be established whether a similar discordance exists in relation to knowledge of AI, amongst dental students.

A particular concern in relation to chatbots is their documented tendency to make up information, including references, a phenomenon variously described as hallucination, fabrication, or confidence trickery.[16,17] Empirical validation of scientific references generated by ChatGPT indicated that 15.1% were completely fabricated, with an additional 9.3% containing errors.[18] Given that students are likely to use such chatbots for literature reviews, writing case presentations, and even for exam preparation,[10,19] it is important that they are aware of this limitation of the technology. This awareness, in turn, constitutes a form of verifiable knowledge.

This pilot study was undertaken to assess, amongst a convenience sample of dental students at a private dental institution, (i) awareness and self-perception of understanding of AI; (ii) objective knowledge of AI mechanisms and limitations ("hallucination", validation status); (iii) current use of AI tools, perceived barriers to use, and concerns; and (iv) association between self-perception of understanding and objective knowledge. Due to the convenience sampling method, this study is limited to exploratory/pilot observations, rather than generalizable conclusions, for the population of the institution in question. This caveat is discussed further in the Limitations section, following recommendations from a previous single-institution knowledge, attitude, and practice (KAP) survey on AI in dentistry, which warned against overstatement of applicability to the larger population of dental students.[13,19]

2. Methods

2.1. Study design and setting

This was a cross-sectional, online, self-administered survey of dental students. The report follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist for cross-sectional studies,[20] with deviations from the recommendations detailed in the Limitations section (particularly: use of convenience rather than probability sampling; inability to calculate the response rate). The survey was distributed as a link to Google Forms between 2 April and 3 August 2026 to dental students at a predominantly private dental college in northern UP region; a small number of respondents selected Government or Deemed university as their affiliation (Table 1). Informed consent was obtained electronically before respondents accessed the survey.

Eligible respondents comprised dental students studying for the Bachelor of Dental Surgery (BDS; all years of study), postgraduate/master's degrees (MDS), or internship. One respondent selected Dental Technician as their category and was excluded as ineligible. One further respondent was excluded due to duplication: the spreadsheet row contained the header information of the

questionnaire, not respondent data. The eligible analytical sample was therefore n = 92.

2.2. Sampling

Participants were recruited using a convenience/snowball sampling method: the link to the Google Forms survey was shared online. There was no sampling frame, no random selection, and therefore no way to calculate the response rate or to assess representativeness of the student body at large. No sample-size calculations were performed for this pilot study; this is a recognized limitation, detailed further in the Limitations section, and is a key difference from the KAP studies that utilized institutional class lists or invitation logs to generate a response rate.[13]

2.3. Data collection instrument

The questionnaire was developed for this pilot study by the investigators and administered via Google Forms. It comprised the following elements: demographic information (age, gender, year of study, institution type); awareness of AI and its applications in dentistry; self-reported levels of understanding of AI; current use of AI tools (frequency, purpose, platforms, time spent); three objective knowledge items (mechanism by which chatbots generate text, true/false statements on "hallucination" and validity of AI tools); perceived concerns and barriers to use; receipt of formal guidance on use of AI; and two free-text/response items.

2.4. Data cleaning and scoring rules

A number of data cleaning rules were applied to the raw data file, following inspection of the raw responses. Rules are detailed below, with rationale.

Single-choice item contamination: Several single-choice items (awareness of AI, self-reported understanding of AI, mechanism by which chatbots operate, and two true/false knowledge items) had multiple selections by respondents, indicating that checkboxes rather than radio buttons had been used by accident in the Google Forms interface. For the descriptive items (awareness, self-reported understanding), multi-selected items were coded as missing. For the three objective knowledge items, any response other than a clear selection of the correct option was coded as incorrect. This is a conservative approach, and this decision is explicitly stated so that the score is not artificially inflated compared to a missing response.

Free-text field errors: Two respondents provided their names rather than a numeric value in the age field. The records were considered missing for the purposes of age only; other fields were retained.

Attitude-statement matrix: The instrument contained a matrix of statements about AI, to which respondents could indicate their level of agreement on a scale from Strongly Disagree to Strongly Agree. In the exported data file this item appeared as a mixture of numbers, comma-separated lists, and free-text responses; it appears that the matrix format was not correctly recognized by Google Forms. As a result this item could not be analyzed and is excluded from this report. Consequently, findings on general attitudes to AI should be considered as not measured, rather than measured and negative.

2.5. Objective knowledge score

An objective knowledge score, out of 3, was calculated based on three items: correctly identifying the mechanism by which chatbots function; identifying "hallucination" as true; identifying the statement about equal validation of all AI tools as false. These items were scored as correct/incorrect according to clearly defined criteria, as per the Single-choice item contamination section. The score was then grouped into Poor (0 correct), Moderate (1–2 correct), and Good (3 correct).

2.6. Statistical analysis

Data were analyzed in Python 3 (pandas, SciPy, statsmodels). Descriptive statistics (frequencies, percentages, means, standard deviations) were computed for all variables. The associations between categorical variables were tested with the chi-square test; mean knowledge scores were compared between two groups using the independent-samples t-test and across more than two groups using one-way ANOVA. Binary logistic regression (outcome: Good objective knowledge versus not) was used to evaluate academic-year group, gender, and age as predictors, with year of study collapsed into three clinically meaningful groups (pre-clinical [1st–2nd year], clinical [3rd–final year], and intern/postgraduate) to preserve statistical power given the modest sample size. A p-value < 0.05 was considered statistically significant; because this was an exploratory, hypothesis-generating pilot analysis, p-values are reported descriptively and are not adjusted for multiple comparisons.

3. Results

3.1. Sample characteristics

Ninety-four responses were received; two were excluded (one duplicate header row entered as data, one ineligible

non-dental-student respondent), leaving an analytic sample of n = 92. Mean age was 22.9 ± 2.6 years (range 19–34; age unavailable for 2 respondents who entered their name instead of a numeric value). Sixty-seven respondents (72.8%) were female and 25 (27.2%) were male. By academic year: 2nd Year and Intern each accounted for 22 respondents (23.9% each), Final Year 17 (18.5%), 1st Year 15 (16.3%), and 3rd Year and PG each accounted for 8 (8.7% each). By institution type, 86 respondents (93.5%) identified their institution as Private, 4 (4.3%) as Deemed university, and 2 (2.2%) as Government — a distribution heavily skewed toward a single institution type, which limits the ability of this dataset to support any claim about institution-type differences (**Table 1**).

Table 1: Demographic characteristics of the analytic sample (n = 92

Variable	n	%
Age (years), mean ± SD (n = 90)	22.9 ± 2.6	—
Gender — Female	67	72.8
Gender — Male	25	27.2
Year — 1st Year	15	16.3
Year — 2nd Year	22	23.9
Year — 3rd Year	8	8.7
Year — Final Year	17	18.5
Year — Intern	22	23.9
Year — PG	8	8.7
Institution — Private	86	93.5
Institution — Deemed university	4	4.3
Institution — Government	2	2.2

3.2. Awareness and self-rated understanding

Of the 91 respondents with a valid (single-choice) answer to the awareness item, 86 (94.5%) reported having heard of AI in the context of education or dentistry; one response selecting both “yes” and “no” was treated as missing. Of the 88 respondents with a valid self-rated understanding response, 18 (20.5%) rated their understanding as Basic, 34 (38.6%) as Moderate, 25 (28.4%) as Good, and 11 (12.5%) as Advanced.

Awareness of specific AI tools (multiple selections permitted, n = 92) was highest for ChatGPT or similar chatbots (88.0%), followed by 3D treatment planning/CAD-CAM AI features (56.5%), AI-based diagnostic imaging software (44.6%), AI plagiarism/writing checkers (27.2%), and AI-based literature search tools (20.7%). The most commonly reported first source of learning about AI tools was self-exploration/internet (66.3%), followed by social media (46.7%), faculty/curriculum (31.5%), peers/seniors (30.4%), and conferences/workshops (19.6%); a subset of respondents selected more than one source despite the item's “tick one” instruction, another indicator of the checkbox-implementation issue noted in Methods.

3.3. Current use of AI tools

Eighty-six respondents (93.5%) reported currently using an AI tool for academic or learning purposes. Of those with a valid (single) frequency response (n = 86), 38.4% reported daily use, 45.3% a few times a week, 7.0% a few times a month, 8.1% rarely, and 1.2% never. Of those with a valid time-spent response (n = 89), 43.8% reported under 1 hour per week, 47.2% reported 1–3 hours, and 9.0% reported 4–7 hours. The platform reported as used most often (n = 92, normalized to primary platform mentioned) was ChatGPT (69.6%), followed by an unclear or multiple-platform response (12.0%), Gemini (6.5%), Claude (6.5%), no platform (3.3%), and Perplexity (2.2%). The most common reported purposes of use (multiple selections permitted, n = 92) were explaining difficult concepts (73.9%), exam/viva preparation (67.4%), summarizing textbook or journal content (63.1%, combining two near-duplicate response options), literature review/research writing (42.4%), clinical case discussion/differential diagnosis practice (37.0%), language and grammar correction (25.0%), case-presentation preparation (23.9%), and referencing/citation formatting (17.4%).

3.4. Objective Knowledge of AI

On the mechanism item, 33 of 92 respondents (35.9%) correctly and unambiguously identified that chatbots generate responses by predicting likely word sequences from training data. On the hallucination item, 59 of 92 (64.1%) correctly identified as True that AI-generated content can contain factual errors or fabricated references. On the validation item, 40 of 92 (43.5%) correctly identified as False the statement that all AI tools are equally validated for clinical/diagnostic decision-making in dentistry. The mean composite objective knowledge score was 1.43 ± 0.96 out of a maximum of 3. By category, 17 respondents (18.5%) scored Poor (0/3), 61 (66.3%) scored Moderate (1–2/3), and 14 (15.2%) scored Good (3/3) (**Table 2**).

Table 2: Objective AI knowledge item performance and composite score category (n = 92)

Item	n correct	%
Correctly heard of AI (valid responses, n = 91)	86	94.5
Correctly identifies chatbot text-generation mechanism	33	35.9
Correctly identifies hallucination risk as True	59	64.1
Correctly identifies "all AI tools equally validated" as False	40	43.5
Knowledge category — Poor (0/3)	17	18.5
Knowledge category — Moderate (1–2/3)	61	66.3
Knowledge category — Good (3/3)	14	15.2

Table 3: Objective knowledge category by gender and academic year (chi-square test)

Variable	Poor n (%)	Moderate n (%)	Good n (%)	p-value
Gender — Female (n=67)	14 (20.9)	43 (64.2)	10 (14.9)	0.62
Gender — Male (n=25)	3 (12.0)	18 (72.0)	4 (16.0)	
Year — 1st (n=15)	4 (26.7)	9 (60.0)	2 (13.3)	0.075
Year — 2nd (n=22)	6 (27.3)	11 (50.0)	5 (22.7)	
Year — 3rd (n=8)	1 (12.5)	4 (50.0)	3 (37.5)	
Year — Final (n=17)	1 (5.9)	16 (94.1)	0 (0.0)	
Year — Intern (n=22)	5 (22.7)	13 (59.1)	4 (18.2)	
Year — PG (n=8)	0 (0.0)	8 (100.0)	0 (0.0)	

3.5. Concordance between self-rated understanding and objective knowledge

Mean objective knowledge scores were roughly comparable across self-rated categories: Basic 1.39 ± 1.14, Moderate 1.50 ± 0.90, Good 1.28 ± 1.02, Advanced 1.55 ± 0.82 (one-way ANOVA, F = 0.31, p = 0.82); respondents who assessed themselves as "Good" were not objectively more knowledgeable than those who assessed themselves as "Basic" on average (and this applied to all categories). With the given sample size, this result cannot be used to confirm concordance between self-assessment and objective knowledge; rather, it must be noted that such concordance was not observed. This accords with previous studies reporting insufficient agreement between self-reported and objectively measured levels of knowledge in healthcare students in other areas of study.[14,15]

3.6. Demographic and academic-year associations with knowledge

Objective knowledge did not differ significantly between genders (mean 1.68 ± [male] vs. 1.34 [female]; independent t-test, t = 1.56, p = 0.13) or academic years (one-way ANOVA, p = 0.55; mean ranged from 1.24 in Final Year to 2.00 in 3rd Year, n=8). Knowledge category (Poor/Moderate/Good) was not associated with gender (chi-square, p = 0.62) or academic year (chi-square, p = 0.075), with borderline results in the latter case (Table 3). Using binary logistic regression with Good objective knowledge as the dependent variable and year group, gender, and age as predictors produced no significant results overall (likelihood-ratio p = 0.89; pseudo-R^2 = 0.014), with none of the individual predictors reaching significance. This suggests that in this sample, no demographic or academic-year-related factors were significantly associated with objective AI knowledge.

3.7. Faculty guidance

Thirty-eight respondents (41.3%) reported having received formal faculty/institutional guidance on ethical and effective AI use, 35 (38.0%) reported no such guidance, and 19 (20.7%) were not sure. Mean objective knowledge score differed significantly across these groups (one-way ANOVA, p = 0.002): No-guidance 1.83 ± 1.04, Yes-guidance 1.34 ± 0.75, Not-sure 0.89 ± 0.94. This is a counterintuitive direction, students who reported receiving no formal guidance scored highest, not lowest. We report this finding without a causal interpretation; plausible non-causal explanations are self-selection (students who are already self-taught and AI-engaged may both perceive less need for, or recall of, formal guidance, and score higher on independently-acquired knowledge), a single-item, non-validated measure of "guidance" that may capture recall or salience rather than guidance quality or dose, and the cross-sectional design's inability to establish temporal or causal order. This

finding is discussed further below and should not be read as evidence that faculty guidance is counterproductive.

3.8. Concerns and barriers

The most frequently selected top concern about AI in dental education (multiple selections permitted, n = 92) was over-dependence reducing independent critical thinking (55.4%), closely followed by accuracy/reliability of information (54.3%), risk of plagiarism/academic dishonesty (37.0%), data privacy (32.6%), lack of faculty guidance on proper use (23.9%), and cost of premium tools (18.5%). The most frequently selected barriers to greater AI use (multiple selections permitted, n = 92) were lack of training on how to use AI tools (58.7%), lack of awareness of available tools (34.8%), cost (23.9%), institutional/faculty restrictions (20.7%), internet/ device access issues (13.0%), and no barriers reported (16.3%).

3.9. Data not analyzable

As specified in Methods, the seven-statement attitude Likert matrix (intended to capture agreement with statements about AI's academic and clinical value, trustworthiness, and effect on independent thinking) could not be reliably scored owing to a form-implementation error and is not reported quantitatively. Two open-ended free-text items (perceived educational value of AI; desired content of an AI training session) yielded qualitative responses that were reviewed but not formally coded for this pilot analysis; representative themes included using AI to clarify difficult concepts, assistance with case presentations and CAD-CAM-related coursework, and a expressed desire for training on how to verify AI output against textbooks and identify unreliable information.

4. Discussion

In this single-institution pilot sample, nearly all dental students had heard of AI and reported currently using an AI tool, chiefly ChatGPT, for academic work, echoing the near-universal term-level awareness reported in other dental-student KAP surveys (94.5% here versus 95.6% in a South Indian sample of 208 students[13] and 95% among undergraduates in a multinational survey.)[10] However, awareness did not translate into strong objective knowledge: the mean composite score was 1.43 out of 3, and only 15.2% of respondents answered all three objective items correctly. This awareness–knowledge gap parallels the multinational dental-student survey, in which 76.2% of respondents agreed they "understood what AI entails" yet only 29.5% answered all three factual knowledge items correctly,[10] and the dental-resident survey in which only 58.3% knew basic AI principles despite presumably higher clinical exposure than undergraduates.[11]

The more notable finding in this dataset is not the low knowledge score itself but its lack of association with self-rated understanding. Students who rated their own understanding as "Good" or "Advanced" scored no higher, on average, than those who rated themselves "Basic" ($p = 0.82$). This is consistent with evidence from outside dentistry that self-report and objectively assessed knowledge or competence can be poorly correlated: healthcare students' self-reported knowledge of evidence-based practice terminology showed only poor agreement with open-ended assessment (ICC = 0.29),[14] and final-year medical students' self-perceived clinical competence was not positively correlated with objectively observed competence.[15] If this pattern replicates in a larger sample, it has a direct practical implication: surveys or curriculum needs-assessments that rely solely on students' self-rated AI competence risk substantially misjudging where instructional effort is actually needed, since the students who feel most confident are not necessarily the students who know the most.

A specific and arguably higher-stakes knowledge gap concerns AI "hallucination." Only 64.1% of respondents correctly identified that AI-generated content can contain fabricated references, and, more strikingly, only 35.9% correctly identified how chatbots generate text in the first place (i.e., by predicting likely token sequences rather than retrieving verified facts from a database). This distinction is not academic: empirical audits of AI-generated references in biomedical writing have found substantial fabrication rates, for example, 15.1% of ChatGPT-generated references in one stem-cell-research audit were entirely fictitious and a further 9.3% were erroneous,[18] and multiple case reports and editorials have documented convincing but non-existent citations generated by general-purpose chatbots.[16,17] Given that 42.4% of respondents in this sample reported using AI tools for literature review or research writing, and 67.4% for exam/viva preparation, a substantial minority of students may be using AI output, including fabricated references or plausible-sounding but incorrect clinical claims, without the conceptual grounding needed to critically evaluate it.

Neither gender, academic year, nor age was a significant predictor of objective knowledge in this sample, in bivariate or multivariable analysis. This null result contrasts with some larger dental-student KAP surveys that found academic level to be a significant

predictor of knowledge (e.g., postgraduate students scoring higher than undergraduates, $p<0.01$, in a 208-respondent South Indian sample.)[13] Several explanations are possible and cannot be distinguished with this dataset: this sample may be genuinely more homogeneous in AI knowledge across year groups than larger, more diverse samples; the sample may simply be underpowered to detect a real but modest year effect (the year × knowledge-category association here was borderline, $p = 0.075$, suggesting a true effect cannot be excluded); or the three-item knowledge measure used here, chosen for brevity rather than validated breadth, may not capture the same knowledge domains as longer, validated instruments used elsewhere.[13]

The finding that objective knowledge was highest among students reporting no formal faculty guidance (mean 1.83) and lowest among those unsure whether they had received guidance (mean 0.89) warrants caution rather than a curriculum-reform narrative. It is tempting, but not justified by this design, to read this as evidence that faculty guidance is ineffective or counterproductive. A cross-sectional, single-item, non-validated measure of "guidance" cannot establish what form that guidance took, how recently it occurred, or whether the association is confounded by unmeasured factors such as self-directed learning tendency, which could independently drive both lower engagement with formal guidance and stronger self-taught objective knowledge. We report this result because it is a real feature of the data that should not be omitted, but we explicitly decline to draw a policy conclusion from it; disentangling this relationship would require a study specifically designed for that purpose, ideally with a validated, multi-item measure of guidance dose and content.

Reported concerns and barriers were broadly consistent with prior literature: over-dependence on AI reducing independent critical thinking and concerns about accuracy/reliability of AI output were the two most frequently cited concerns, and lack of training was the most frequently cited barrier to greater use. These patterns mirror barriers reported in broader healthcare-education contexts[21] and suggest that, if AI literacy content were to be developed at this institution, students themselves would likely engage with it, since lack of training rather than lack of interest was the dominant barrier.

5. Limitations

1. Single, predominantly private institution. 93.5% of respondents identified their institution type as Private; findings cannot be generalized to students at government or other private/deemed institutions, or to other regions, without independent replication.
2. Non-probability, convenience sampling. Participants were recruited via a shared online link rather than a defined sampling frame or randomization procedure. A response rate cannot be calculated, and the possibility of self-selection bias (e.g., AI-interested or AI-skeptical students being more likely to respond) cannot be excluded.
3. Modest sample size without a priori power calculation. No formal sample-size calculation was performed for this pilot survey. The borderline year × knowledge association ($p = 0.075$) and several small subgroup cell counts (e.g., $n = 8$ in the 3rd-year and PG strata) indicate the study may be underpowered to detect real, moderate-sized subgroup differences; null findings for gender, year, and age should be read as inconclusive rather than as evidence of no true difference.
4. Unvalidated, brief knowledge instrument. The objective knowledge score was derived from only three items, developed for this pilot survey without a prior content-validity panel, pilot testing for comprehension, or a formal reliability analysis (e.g., Cronbach's alpha for a 3-item forced-choice scale would in any case be of limited interpretive value). The score should be treated as a coarse, exploratory indicator rather than a validated measure of AI literacy.
5. Instrument implementation errors. Several items intended as single-choice were implemented as multi-select in the underlying online form, producing contaminated responses that required conservative scoring rules (detailed in Methods). The seven-item attitude Likert matrix could not be scored at all and was excluded from analysis in its entirety; this study therefore provides no quantitative evidence on general attitudes toward AI or curriculum inclusion, a gap that should be corrected with a properly implemented grid item in any follow-up study.
6. Cross-sectional design. No causal or directional inferences can be drawn, including for the counterintuitive faculty-guidance finding discussed above.
7. Self-report and social-desirability bias. Current-use, frequency, and concern items were entirely self-reported and were not independently verified.
8. No ethics-approval or informed-consent detail confirmed at the time of writing. These fields are placeholders pending confirmation by the study

authors and must be completed with the actual institutional approval before submission.

6. Conclusion

In this single-institution pilot survey, dental students reported widespread awareness and use of AI tools, chiefly generic chatbots, but demonstrated modest and unevenly distributed objective knowledge of how those tools work and where their outputs can be unreliable. Self-rated understanding of AI showed no measurable relationship with objective knowledge in this sample, a pattern consistent with self-report/objective-knowledge discordance reported in other healthcare-student populations, and one with direct relevance to how future AI-curriculum needs assessments should be designed: they should not rely on self-rated confidence alone. Given the convenience-sampled, single-institution design and the modest, non-validated knowledge instrument used here, these findings should be treated as hypothesis-generating rather than as a basis for curriculum policy. A larger, multi-institutional study using a validated, psychometrically tested AI-literacy instrument, ideally paired with an objective assessment of AI-output evaluation skill (for example, asking students to identify a fabricated citation embedded in AI-generated text), is warranted before firm educational recommendations can be made.

Author Contributions

Dr Akash Raj Sharma: Conceptualization, data curation, formal analysis, methodology, writing — original draft. Dr Kanchan Shukla: data collection, writing — review and editing. Dr Pratiksha A Srivastava: data curation, formal analysis, methodology. Dr Manjulika Tyagi: supervision, methodology review, writing — review and editing. Dr Chandrama Pratap: writing, review and editing**.** All authors approved the final manuscript.

List of Abbreviations

AI: Artificial Intelligence
ANOVA: Analysis of Variance
BDS: Bachelor of Dental Surgery
CAD-CAM: Computer-Aided Design and Computer-Aided Manufacturing
ICC: Intraclass Correlation Coefficient
KAP: Knowledge, Attitudes, and Practices
MDS: Master of Dental Surgery
PG: Postgraduate
SD: Standard Deviation
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

Ethics Approval and Consent to Participate

Not Required.

Financial Support and Sponsorship

None.

Conflicts of Interest

None.

Data Availability Statement

The cleaned, de-identified dataset and analysis code generated for this study are available from the corresponding author upon reasonable request.

References

1. Russell S, Norvig P. Artificial Intelligence: A Modern Approach. 4th ed. Pearson; 2020.
2. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med*. 2019;25(1):44–56. https://doi.org/10.1038/s41591-018-0300-7
3. Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. *Nat Med*. 2022;28(1):31–8. https://doi.org/10.1038/s41591-021-01614-0
4. Schwendicke F, Samek W, Krois J. Artificial Intelligence in Dentistry: Chances and Challenges. *J Dent Res*. 2020;99(7):769–74. https://doi.org/10.1177/0022034520915714
5. Khanagar SB, Al-Ehaideb A, Maganur PC, Vishwanathaiah S, Patil S, Baeshen HA, et al. Developments, application, and performance of artificial intelligence in dentistry - A systematic review. *J Dent Sci*. 2021;16(1):508–22. https://doi.org/10.1016/j.jds.2020.06.019
6. Joda T, Bornstein MM, Jung RE, Ferrari M, Waltimo T, Zitzmann NU. Recent Trends and Future Direction of Dental Research in the Digital Era. *Int J Environ Res Public Health*. 2020;17(6):1987. https://doi.org/10.3390/ijerph17061987
7. Al Hendi KD, Alyami MH, Alkahtany M, Dwivedi A, Alsaqour HG. Artificial intelligence in prosthodontics. *Bioinformation*. 2024;20(3):238–42. https://doi.org/10.6026/973206300200238
8. Uribe SE, Maldupa I, Schwendicke F. Integrating Generative AI in Dental Education: A Scoping Review of Current Practices and Recommendations. *Eur J Dent Educ*. 2025;29(2):341–55. https://doi.org/10.1111/eje.13074
9. Kumar V. Reimagining oral health: The new era of AI in dentistry. *J Orofac Health Sci*. 2026;13(1):43–4.
10. Kavadella A, Uribe SE, da Silva MAD, Schwendicke F, Tichý A, Jacobs R, et al. Dental students' knowledge, perceptions, and educational needs regarding artificial intelligence: a multinational cross-sectional survey. *BMC Med Educ*. 2026;26(1):401. https://doi.org/10.1186/s12909-026-08699-6
11. Ali F, Ikram F, Masood Z, Ghandhi D, Sukhia RH. Knowledge and awareness of dental residents regarding the applications of artificial intelligence for diagnosis and

treatment planning- a cross-sectional survey. *BMC Oral Health*. 2026;26(1):368. https://doi.org/10.1186/s12903-026-07712-0

12. Kalaimani G, Sivapathasundharam B, Chockalingam RM, Karthick P. Evaluation of Knowledge, Attitude, and Practice (KAP) of Artificial Intelligence Among Dentists and Dental Students: A Cross-Sectional Online Survey. *Cureus*. 2023;15(9):e44656. https://doi.org/10.7759/cureus.44656
13. Usha GV, Nadar B, Almalki S, Bhagat TV, Gowdar IM. Knowledge, Attitudes, and Practices of Artificial Intelligence in Dentistry: a cross-sectional survey. *F1000Research*. 2025;14:1314. https://doi.org/10.12688/f1000research.173028.1
14. Snibsøer AK, Ciliska D, Yost J, Graverholt B, Nortvedt MW, Riise T, Espehaug B. Self-reported and objectively assessed knowledge of evidence-based practice terminology among healthcare students: a cross-sectional study. *PLoS One*. 2018;13(7):e0200313. https://doi.org/10.1371/journal.pone.0200313
15. Katowa-Mukwato P, Banda S. Self-perceived versus objectively measured competence in performing clinical practical procedures by final year medical students. *Int J Med Educ*. 2016;7:122-129. https://doi.org/10.5116/ijme.5709.2a7e
16. Goddard J. Hallucinations in ChatGPT: A Cautionary Tale for Biomedical Researchers. *Am J Med*. 2023;136(11):1059–60. https://doi.org/10.1016/j.amjmed.2023.06.012
17. Alkaissi H, McFarlane SI. Artificial Hallucinations in ChatGPT: Implications in Scientific Writing. *Cureus*. 2023;15(2):e35179. https://doi.org/10.7759/cureus.35179
18. Sharun K, Banu SA, Pawde AM, Kumar R, Akash S, Dhama K, Pal A. ChatGPT and artificial hallucinations in stem cell research: assessing the accuracy of generated references — a preliminary study. Ann Med Surg (Lond). 2023;85(10):5275–8. https://doi.org/10.1097/MS9.0000000000001228
19. Elchaghaby M, Wahby R. Knowledge, attitudes, and perceptions of a group of Egyptian dental students toward artificial intelligence: a cross-sectional study. *BMC Oral Health*. 2025;25(1):11. https://doi.org/10.1186/s12903-024-05282-7
20. von Elm E, Altman DG, Egger M, Pocock SJ, Gøtzsche PC, Vandenbroucke JP; STROBE Initiative. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: guidelines for reporting observational studies. *J Clin Epidemiol*. 2008;61(4):344–9. https://doi.org/10.1016/j.jclinepi.2007.11.008
21. Ahmed MI, Spooner B, Isherwood J, Lane M, Orrock E, Dennison A. A Systematic Review of the Barriers to the Implementation of Artificial Intelligence in Healthcare. *Cureus*. 2023;15(10):e46454. https://doi.org/10.7759/cureus.46454