

Artificial Intelligence for Radiographic Caries Detection in Dental Education: A Narrative Review

Samandar S. Alikhodjaev, Nilufar Kh. Abdukhalimova, Sardorkhon G. Usmonov, Davron Kh. Sunnatov, Yasmina A. Bekmirzayeva, Ulugbek A. Khatamov*

Faculty of Dentistry, Kimyo International University in Tashkent, Tashkent, Uzbekistan

*Corresponding author: Ulugbek A. Khatamov, PhD, Associate Professor. E-mail: khatamovulugbek@yahoo.com

Article History	Abstract
Received: 14 th July, 2026 Accepted: 11 th August, 2026	Background: Radiographic caries detection is a core competency in undergraduate dentistry, yet both novices and experienced clinicians show limited sensitivity for early lesions and considerable inter-examiner variability. Deep learning-based systems now detect caries on intraoral radiographs with high accuracy, raising the question of how they should be used in teaching. Objective: To summarise current evidence on the diagnostic performance of artificial intelligence (AI) for radiographic caries detection and on its educational applications for dental students and faculty. Methods: Narrative review of literature indexed in PubMed/MEDLINE, Scopus, Europe PMC and Google Scholar from January 2015 to September 2026, supplemented by seminal earlier studies on radiographic caries diagnosis and examiner reliability. Results: Meta-analyses report pooled sensitivity and specificity of approximately 0.87 and 0.89 for AI on bitewing radiographs, with lower sensitivity for enamel than for dentine lesions and frequent high risk of bias. Randomised and controlled studies show that AI support increases clinicians' sensitivity for early lesions, sometimes at the cost of specificity and more invasive treatment decisions. In education, AI outperformed undergraduate students, AI-based training improved students' diagnostic metrics in controlled studies, and AI-assisted pre-annotation streamlined assessment development and increased unanimous instructor agreement from 73.3% to 86.7% in one pilot programme. The evidence is limited

	by small single-centre designs, reliance on commercial systems, short follow-up and heterogeneous reference standards. Conclusions: AI is a promising adjunct for feedback, assessment development and faculty calibration in caries-detection training, provided that students first develop independent interpretive skills and that curricula explicitly address automation bias. Multicentre studies, including studies in Central Asian dental schools, are needed.
Keywords: Artificial intelligence; deep learning; dental caries; bitewing radiography; dental education; faculty calibration; competency assessment	

1. Introduction

Dental caries remains the most prevalent noncommunicable disease worldwide. According to the World Health Organization, untreated caries of permanent teeth affects roughly two billion people, and caries of primary teeth more than half a billion children [1]. The global burden of untreated caries has changed little over recent decades despite advances in prevention [2,3]. Because carious lesions progress through stages, from reversible enamel demineralisation to cavitated dentine lesions, detection at an early stage allows non-invasive and micro-invasive management that preserves tooth structure and reduces the cost of care [4]. Conversely, late or inaccurate diagnosis can lead to pain, infection, tooth loss and more complex treatment.

Bitewing and periapical radiographs are indispensable adjuncts to visual-tactile examination, particularly for proximal surfaces that cannot be inspected directly. However, radiographic detection of caries is less reliable than is often assumed. Systematic reviews show that sensitivity for lesions confined to enamel is low, whereas specificity is comparatively high [5,6], and studies of examiner reliability have repeatedly demonstrated only moderate agreement between and within observers [7,8]. These limitations are amplified in undergraduate education, where students with little clinical experience must learn to recognise subtle radiolucencies while receiving feedback from instructors whose own diagnostic thresholds may differ.

Over the past decade, deep learning, in particular convolutional neural networks (CNNs), has transformed computer-aided analysis of dental radiographs. Early studies showed that CNNs could detect caries on periapical and bitewing images with accuracy approaching or exceeding that of dentists [9–11], and several systems are now commercially available. In medical radiology, AI has been proposed as a means of individualising feedback and supporting “precision education” [12]. Whether and how such tools should be integrated into dental curricula is, however, a different question from whether they are accurate.

The aim of this narrative review was to summarise current evidence on (i) the diagnostic performance of AI for radiographic caries detection, (ii) its effect on the diagnostic behaviour of clinicians, and (iii) its applications in teaching, assessment and faculty calibration, and to derive practical recommendations for dental schools, including those in which such tools are not yet in routine use.

2. Methods

This narrative review was based on a literature search of PubMed/MEDLINE, Scopus, Europe PMC and Google Scholar for English-language publications from January 2015 to September 2026. Search terms combined “artificial intelligence”, “deep learning”, “convolutional neural network” or “machine learning” with “dental caries”, “caries detection”, “bitewing” or “intraoral radiograph”, and with “dental education”, “dental students”, “calibration” or “assessment”. Reference lists of relevant systematic reviews were hand-searched, and seminal earlier studies on radiographic caries diagnosis and examiner reliability were added.

Studies were included if they reported the diagnostic performance of AI for caries detection, the effect of AI support on human examiners, or the use of AI in dental education. Given the heterogeneity of study designs, outcomes and AI systems, findings were synthesised thematically rather than pooled, and no formal risk-of-bias assessment was performed. One university thesis reporting student-level outcomes [13] was included as grey literature because the faculty-level results of the same programme were subsequently published in a peer-reviewed journal.

3. The diagnostic challenge of radiographic caries detection

3.1. Accuracy of human examiners

Radiographic caries detection depends on recognising a small loss of mineral against a background of overlapping anatomy. The meta-analysis by Schwendicke et al. found that radiographs detect advanced dentine lesions reasonably well but miss a large proportion of lesions confined to enamel [5]. A later meta-analysis of proximal caries diagnostics reported in vitro areas under the receiver operating characteristic curve of 0.55–0.82 for bitewing detection of any caries, compared with 0.81–0.92 for dentine caries, and noted that few available studies had a low risk of bias [6]. The gap is also evident in practice-like conditions: in the ADEPT study, general dentists working without AI assistance identified only 44.3% of enamel-only proximal lesions [14]. Because enamel lesions are precisely those amenable to remineralisation, low sensitivity at this stage undermines minimally invasive care.

3.2. Sources of error and variability

Several perceptual phenomena contribute to diagnostic errors. Cervical burnout and the Mach band effect can mimic radiolucencies near the cemento-enamel junction and the enamel–dentine junction, respectively, and are classic causes of false-positive diagnoses [15]. Overlapping contacts, suboptimal projection geometry, image noise and existing restorations further obscure lesions. Examiner fatigue and differences in training and diagnostic thresholds produce inconsistency,

and classic reliability studies documented only moderate inter-observer agreement for bitewing interpretation [7,8]. For learners, this variability has a further consequence: when supervising clinicians disagree, students receive conflicting feedback, which slows the formation of stable diagnostic criteria and can undermine their confidence.

4. Diagnostic performance of artificial intelligence

Applications of deep learning to radiographic caries detection emerged in 2017–2018 [9,16]. Lee et al. trained a CNN on periapical radiographs and reported high diagnostic accuracy for premolars and molars [9]. Cantu et al. showed that a deep learning model detected caries lesions of different radiographic extension on bitewings with higher sensitivity than individual dentists, particularly for early lesions [11]. Subsequent work extended these approaches to the detection of early lesions on bitewings [10], to single-shot detectors that identify interproximal, occlusal and secondary caries in one pass [17], and to comparisons with junior dentists [18].

Systematic reviews broadly confirm these findings while emphasising methodological weaknesses. Albano et al. reviewed 20 studies and concluded that AI models show good diagnostic performance and may become an important aid in caries detection [19]. Ammar and Kühnisch, analysing studies on bitewing radiographs, reported a pooled sensitivity of 0.87 and a pooled specificity of 0.89; sensitivity was lower for enamel caries (0.71) than for dentine caries (0.84), and in the three studies that compared models with dentists, the models consistently achieved a higher average sensitivity [20]. However, most included studies had an unclear or high risk of bias and lacked external validation [20]. AI-based detection has also been explored on intraoral photographs [21] and compared with clinical examination [22], suggesting that its role may extend beyond radiographs.

4.1. Effect of AI on clinicians

High standalone accuracy does not guarantee better decisions by the human user. In a cluster-randomised crossover trial, Mertens et al. found that AI support increased dentists' sensitivity for enamel caries but did not markedly improve detection of dentine lesions, and that it was associated with more invasive treatment decisions [23]. In the ADEPT study, dentists assisted by AI detected 75.8% of enamel-only proximal lesions, compared with 44.3% without assistance, at the cost of an 11% decrease in specificity [14]. Economic modelling suggests that AI-supported detection may nevertheless be cost-effective, mainly because fewer lesions remain undetected [24]. Together, these studies show that AI shifts the balance between sensitivity and specificity and that its benefit depends on how clinicians translate detections into management decisions — a point of direct relevance to teaching.

5. Artificial intelligence in caries-detection education

5.1. Comparing AI with students

Several studies have benchmarked AI against undergraduate students. Bahadir et al. compared fourth- and final-year students with an AI application on panoramic radiographs and found that the AI identified caries and fillings significantly more accurately [25]. At the UCLA School of Dentistry, the Second Opinion® platform (Pearl Inc., Los Angeles, CA, USA) was compared with two consecutive cohorts of second-year students taking a radiographic caries-detection examination; the AI achieved a sensitivity of 89.5% and an accuracy of 93.6%, exceeding both cohorts [13]. Such comparisons establish that an AI tool can serve as a credible reference for learners, but they do not by themselves show that students learn more when using it.

5.2. AI-supported training

Controlled studies have begun to address this question (Table 1). Ayan et al. randomised 40 students into a group trained with a CNN-based application and a control group; after training, the AI-trained group had significantly higher accuracy, sensitivity, specificity and F1 scores, although the time students needed to label images increased [26]. Schropp et al. examined students' AI-assisted assessment of proximal caries on bitewing radiographs [27]. In a randomised trial by Rampf et al., fourth-year students who received elaborated feedback improved their radiographic diagnostic competence more than those who received knowledge-of-results feedback; an AI system evaluated in parallel showed almost perfect diagnostic performance, and the authors suggested that AI could be an alternative to expert labelling of teaching radiographs [28]. Caldwell et al. found that a commercial AI-based training module improved the radiographic caries diagnosis of first- and third-year students [29]. Outside cariology, the combination of AI with game-based learning has been explored in prosthodontic education [30], indicating wider interest in AI-supported instruction.

A common mechanism across these studies is immediate and consistent feedback. Traditionally, students wait for instructors to review their interpretations, sometimes for days. An AI system returns its interpretation instantly and applies the same criteria to every image, allowing students to compare their own reading with a stable reference, examine discrepancies and repeat practice at their own pace. Used in this way, AI does not provide answers to be memorised but generates disagreements that can be discussed — which is where diagnostic reasoning is learned.

Table 1. Selected studies on artificial intelligence in caries-detection education

Study	Setting and participants	AI system	Educational use	Main findings
Ayan et al., 2024 [26]	Turkey; 40 dental	YOLO-based CNN trained on	AI-based training application	Trained group had higher accuracy, sensitivity,

Study	Setting and participants	AI system	Educational use	Main findings
	students, randomised	1,000 bitewings		specificity and F1 score after training ($p < 0.05$); labelling time increased
Rampf et al., 2024 [28]	Germany; fourth-year students, randomised trial	dentalXrai Pro 3.0	Feedback methods; AI as candidate reference labeller	Elaborated feedback improved diagnostic competence; AI showed almost perfect performance
Bahadir et al., 2025 [25]	Turkey; fourth- and final-year students	AI application on panoramic radiographs	Comparison of students with AI	AI more accurate than students for caries and fillings ($p < 0.05$)
Ji, 2025 [13]	USA (UCLA); second-year cohorts, $n = 86$ and $n = 80$	Second Opinion®	Benchmarking; AI-assisted examination development; mandatory self-assessment	AI sensitivity 89.5%, accuracy 93.6%; cohort 2 accuracy 40.4% → 61.7%; first-attempt pass rate 96.25% vs 55.8%
Caldwell et al., 2026 [29]	USA; 82 first- and third-year students	Overjet Caries Assist with training module	Pre/post training with AI module	Training module improved students' radiographic caries diagnosis
Ji et al., 2026 [31]	USA (UCLA); 4 instructors	Second Opinion®	Instructor calibration and case selection	High baseline performance (>91%); modest non-significant gains; more unanimous agreement, mainly for E0 and D1/D2

CNN, convolutional neural network; E0, sound surface; D1/D2, early-to-moderate dentine lesion.

5.3. Assessment development and faculty calibration

A less discussed application concerns the faculty side of teaching. Building a valid image bank for competency assessment traditionally requires a course director to select radiographs and several experienced examiners to reach consensus — a labour-intensive process that must be repeated whenever the bank is refreshed. The UCLA programme illustrates how AI can support this process [13,31]. Candidate radiographs were pre-annotated by Second Opinion®, screened by a radiology resident and an experienced radiologist, and then classified independently by four instructors; only lesions on which at least three of the four instructors agreed ($\geq 75\%$) were retained for the examination [13]. Because AI accelerated the construction of a new examination, the previous year's examination could be reused as a mandatory, examination-equivalent self-assessment for the next cohort. Students' accuracy rose from 40.4% on the self-assessment to 61.7% on the examination, and the first-attempt pass rate reached 96.25%, compared with 55.8% in the preceding cohort [13]. These results should be interpreted cautiously because examination content and preparatory requirements differed between cohorts; nevertheless, they suggest that AI-enabled assessment development can make high-fidelity formative practice feasible.

The same programme examined the effect of AI annotations on the instructors themselves [31]. Baseline instructor performance was high, with group mean metrics exceeding 91%, and AI-assisted interpretation produced only modest, non-significant improvements. More notably, the proportion of unanimous (4/4) agreement increased from 73.3% without AI to 86.7% with AI annotations [13], with the largest gains for sound surfaces (E0) and early-to-moderate dentine lesions (D1/D2) [31]. In the thesis data, unanimous agreement for D1/D2 lesions rose from 72.7% to 95.5% and for E0 surfaces from 62.5% to 87.5%, whereas agreement on enamel lesions (E1/E2) and deep dentine lesions (D3) changed little [13]. Better agreement among instructors matters educationally because it reduces the contradictory feedback that confuses learners. At the same time, a small proportion of cases moved from unanimous agreement to an evenly split decision after AI annotations were shown [13], a reminder that AI can introduce as well as resolve uncertainty.

6. Risks: automation bias and deskilling

The pedagogical value of AI depends on preserving, not replacing, students' interpretive reasoning. Automation bias — the tendency to accept algorithmic output uncritically — is a particular concern for novices, who lack the experience needed to recognise AI errors. AI systems may produce false positives in the cervical region or beneath restorations and false negatives when lesions are small, overlapped or imaged with artefacts. Eye-tracking data illustrate how AI changes visual behaviour: in a randomised trial, dentists using AI annotations noticed lesions and restorations faster, but their visual search was less systematic, with fewer tooth-by-tooth

transitions [32]. For a learner, a systematic search strategy is itself a competence to be acquired, and premature exposure to AI overlays could hinder its development.

Clinical trials further show that AI support can increase the number of invasive treatment decisions and decrease specificity [14,23]. Caries detection should therefore be taught together with lesion-activity assessment and minimally invasive management, so that an additional detection does not automatically become an additional restoration. Other concerns include dependence on commercial vendors, data privacy when radiographs are processed in the cloud, unequal access between institutions, and the absence of evidence that gains in simulated examinations translate into better clinical performance.

7. Limitations of the current evidence

Most educational studies are single-centre, involve small cohorts, use one commercial system and one imaging device, and measure short-term outcomes on curated image sets from which poor-quality radiographs were excluded [13,26,29,31]. Reference standards range from single-expert labels to faculty consensus, and few studies use histological or clinical validation, even though estimates of AI performance depend strongly on the chosen reference [20]. Some investigations were conducted by teams with links to the developers of the software studied [14]. Outcomes such as long-term retention, transfer to clinical practice, treatment decisions and patient outcomes remain largely unexamined. Finally, almost all available evidence comes from North America, Western Europe and Turkey; data from Central Asia, including Uzbekistan, are absent.

8. Practical recommendations for curriculum integration

Based on the evidence reviewed, we propose a staged approach to integrating AI into caries-detection training (Table 2). First, students should learn radiographic anatomy, caries pathogenesis, a lesion classification system (for example, the ADA Caries Classification System or ICCMS) and a systematic search pattern without AI. Second, AI should be introduced as a feedback tool only after the student has recorded an independent interpretation (“read first, then compare”), so that discrepancies become learning events rather than answers to copy. Third, discrepancy analysis should be structured: students explain why their reading differed from the AI output and from the faculty reference, including in cases deliberately chosen because the AI is wrong. Fourth, faculty can use AI pre-annotation to build and refresh assessment image banks and to calibrate instructors, while expert consensus remains the reference standard. Fifth, programmes should evaluate outcomes beyond test scores, including diagnostic thresholds, treatment decisions and students’ attitudes toward AI.

Table 2. Proposed staged framework for integrating AI into caries-detection training

Stage	Educational goal	Role of AI	Safeguard
1. Foundations	Radiographic anatomy, caries pathogenesis, lesion classification, systematic search pattern	None	Independent interpretive competence before exposure to AI
2. Guided practice	Calibration of diagnostic thresholds through repeated practice	Immediate feedback after the student's own reading	Student records an interpretation before viewing AI output
3. Discrepancy analysis	Critical appraisal and diagnostic reasoning	"Second opinion", including cases with known AI errors	Written justification; faculty review of contested cases
4. Assessment and calibration	Reliable, regularly refreshed competency assessment	Pre-annotation of image banks; instructor calibration	Expert consensus (e.g., $\geq 75\%$ agreement) as reference standard
5. Programme evaluation	Continuous quality improvement	Analysis of student performance by lesion category	Outcomes include treatment decisions and attitudes, not only test scores

For dental schools in Uzbekistan and other countries where AI tools are not yet widely used, practical issues include licensing costs, compatibility with locally used sensors and image formats, data-protection requirements for transmitting patient images, and the language of the user interface. Locally collected, anonymised radiographs annotated by calibrated faculty would allow external validation of commercial systems on the local population and imaging equipment before educational deployment.

9. Directions for future research

Priorities include multicentre randomised studies comparing AI-supported and conventional training against clinically validated reference standards; longitudinal follow-up of students into their clinical years; analyses stratified by lesion depth and image quality, including difficult cases with artefacts and anatomical overlap; measurement of interpretation time; comparisons of learners at different levels of experience; and qualitative research on the trust that students and instructors place

in AI. Educational research in Central Asian dental schools would add evidence from settings that are currently unrepresented.

10. Conclusions

AI systems detect caries on intraoral radiographs with accuracy comparable to or exceeding that of dentists and consistently outperform undergraduate students, although the quality of the underlying evidence is limited. In education, AI offers immediate and consistent feedback, can accelerate the development of competency assessments and may improve agreement among instructors. Its benefits are greatest when it complements, rather than replaces, structured teaching of interpretive skills: students should learn to read radiographs independently before using AI, and curricula should explicitly address automation bias, diagnostic thresholds and minimally invasive management. Carefully designed multicentre studies are needed to establish whether AI-supported training improves clinical performance and patient care.

Declarations

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References

1. World Health Organization. Global oral health status report: towards universal health coverage for oral health by 2030. Geneva: World Health Organization; 2022.
2. Kassebaum NJ, Bernabé E, Dahiya M, et al. Global burden of untreated caries: a systematic review and metaregression. J Dent Res. 2015;94(5):650-8.
3. Bagramian RA, Garcia-Godoy F, Volpe AR. The global increase in dental caries. A pending public health crisis. Am J Dent. 2009;22(1):3-8.
4. Featherstone JD. The science and practice of caries prevention. J Am Dent Assoc. 2000;131(7):887-99.
5. Schwendicke F, Tzschoppe M, Paris S. Radiographic caries detection: a systematic review and meta-analysis. J Dent. 2015;43(8):924-33.
6. Kapor S, Rankovic MJ, Khazaei Y, et al. Systematic review and meta-analysis of diagnostic studies of proximal surface caries. Clin Oral Investig. 2021;25(11):6069-79. doi:10.1007/s00784-021-04113-1

7. Valachovic RW, Douglass CW, Berkey CS, et al. Examiner reliability in dental radiography. *J Dent Res.* 1986;65(3):432-6.
8. Langlais RP, et al. Interpretation of bitewing radiographs: application of the kappa statistic to determine rater agreements. *Oral Surg Oral Med Oral Pathol.* 1987;64(6):751-6.
9. Lee JH, Kim DH, Jeong SN, Choi SH. Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. *J Dent.* 2018;77:106-11.
10. Lee S, Oh SI, Jo J, et al. Deep learning for early dental caries detection in bitewing radiographs. *Sci Rep.* 2021;11(1):16807.
11. Cantu AG, Gehrung S, Krois J, et al. Detecting caries lesions of different radiographic extension on bitewings using deep learning. *J Dent.* 2020;100:103425.
12. Duong MT, Rauschecker AM, Rudie JD, et al. Artificial intelligence for precision education in radiology. *Br J Radiol.* 2019;92(1103):20190389.
13. Ji S. Harnessing artificial intelligence for caries detection: a new paradigm in dental education [thesis]. Los Angeles (CA): University of California, Los Angeles; 2025. Available from: <https://escholarship.org/uc/item/3865t5p4>
14. Devlin H, Williams T, Graham J, Ashley M. The ADEPT study: a comparative study of dentists' ability to detect enamel-only proximal caries in bitewing radiographs with and without the use of AssistDent artificial intelligence software. *Br Dent J.* 2021;231(8):481-5.
15. Berry HM Jr. Cervical burnout and Mach band: two shadows of doubt in radiologic interpretation of carious lesions. *J Am Dent Assoc.* 1983;106(5):622-5.
16. Srivastava MM, Kumar P, Pradhan L, Varadarajan S. Detection of tooth caries in bitewing radiographs using deep learning. *arXiv:1711.07312 [Preprint].* 2017.
17. Karakuş R, Öziç MÜ, Tassoker M. AI-assisted detection of interproximal, occlusal, and secondary caries on bite-wing radiographs: a single-shot deep learning approach. *J Imaging Inform Med.* 2024;37(6):3146-59.
18. Liu Y, et al. Artificial intelligence for caries detection: a novel diagnostic tool using deep learning algorithms. *Oral Radiol.* 2024;40(3):375-84.
19. Albano D, Galiano V, Basile M, et al. Artificial intelligence for radiographic imaging detection of caries lesions: a systematic review. *BMC Oral Health.* 2024;24(1):274. doi:10.1186/s12903-024-04046-7
20. Ammar N, Kühnisch J. Diagnostic performance of artificial intelligence-aided caries detection on bitewing radiographs: a systematic review and meta-analysis. *Jpn Dent Sci Rev.* 2024;60:128-36. doi:10.1016/j.jdsr.2024.02.001
21. Adnan N, et al. Developing an AI-based application for caries index detection on intraoral photographs. *Sci Rep.* 2024;14(1):26752.

22. Alam MK, Alanazi NH, Alazmi MS, Nagarajappa AK. AI-based detection of dental caries: comparative analysis with clinical examination. *J Pharm Bioallied Sci.* 2024;16(Suppl 1):S580-2. doi:10.4103/jpbs.jpbs_872_23
23. Mertens S, Krois J, Cantu AG, Arsiwala LT, Schwendicke F. Artificial intelligence for caries detection: randomized trial. *J Dent.* 2021;115:103849. doi:10.1016/j.jdent.2021.103849
24. Schwendicke F, Rossi JG, Göstemeyer G, et al. Cost-effectiveness of artificial intelligence for proximal caries detection. *J Dent Res.* 2021;100(4):369-76. doi:10.1177/0022034520972335
25. Bahadir HS, et al. Comparison of diagnoses made by dentistry students and by artificial intelligence dentists. *J Dent Educ.* 2025;89(7):1165-73.
26. Ayan E, Bayraktar Y, Celik C, Ayhan B. Dental student application of artificial intelligence technology in detecting proximal caries lesions. *J Dent Educ.* 2024;88(4):490-500. doi:10.1002/jdd.13437
27. Schropp L, Sørensen APS, Devlin H, et al. Use of artificial intelligence software in dental education: a study on assisted proximal caries assessment in bitewing radiographs. *Eur J Dent Educ.* 2024;28(2):490-6.
28. Rampf S, Gehrig H, Möltner A, Fischer MR, Schwendicke F, Huth KC. Radiographical diagnostic competences of dental students using various feedback methods and integrating an artificial intelligence application—a randomized clinical trial. *Eur J Dent Educ.* 2024;28(4):925-37.
29. Caldwell J, Parekh K, Crowther B, et al. Performance evaluation of AI-based caries detection technology and its educational training module: a dual-phase investigation. *Front Dent Med.* 2026;6:1741855. doi:10.3389/fdmed.2025.1741855
30. Mahrous A, et al. The use of artificial intelligence and game-based learning in removable partial denture design: a comparative study. *J Dent Educ.* 2023;87(8):1188-99.
31. Ji S, Daly L, Shah K, Bhoopathi V, Mallya SM. Artificial intelligence in dental education: a pilot study of caries detection accuracy and instructor agreement. *J Dent Educ.* 2026;90(9):1342-9. doi:10.1002/jdd.70126
32. Arsiwala-Scheppach LT, Castner NJ, Rohrer C, et al. Impact of artificial intelligence on dentists' gaze during caries detection: a randomized controlled trial. *J Dent.* 2024;140:104793.