

Review

Not peer-reviewed version

Artificial Intelligence in Dental Education: A Scoping Review of Applications, Challenges, and Gaps

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Posted Date: 8 July 2025

doi: 10.20944/preprints202507.0693.v1

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Remiero

Artificial Intelligence in Dental Education: A Scoping Review of Applications, Challenges, and Gaps

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Abstract

Background/Objectives: This scoping review aims to map existing AI applications in dental education, in student learning, assessment, and diagnostic training, identifying key limitations and challenges. Methods: Following the Arksey and O'Malley framework and PRISMA-ScR guidelines, six databases were searched in March 2025 using combinations of the following search words: "dental education," "artificial intelligence," "machine learning," and "student assessment". Inclusion was limited to English-language empirical studies focused on dental student education. Of 547 identified studies, 17 met the inclusion criteria. They were categorized into four domains: (1) Preclinical Training, (2) AI in Clinical, Diagnostic Training, and Radiographic Interpretation, (3) AI as an Assessment Tool and Feedback System, and (4) AI in Content Generation for Dental Education. Results: AI has positively influenced various domains, enhancing procedural accuracy, diagnostic confidence, assessment efficiency, and content delivery. However, it struggles to assess nuanced competencies like dexterity and clinical judgment. The challenges faced include disparate definitions of AI, ethical and privacy concerns, model variability, and a deficiency of dental leadership in AI development. At present, most tools are engineered by computer scientists and may not align effectively with the priorities of dental education. Conclusion: AI holds significant potential to enhance dental education outcomes. However, to guarantee its relevance and reliability, it requires standard frameworks, ethical oversight, and clinician-led development. Future research should concentrate on implementing real-time AI-driven feedback systems during preclinical training and advocate for more precise definitions to support consistent AI application and evaluation in dental education.

Keywords: artificial intelligence; dental education; machine learning; simulation; assessment; AI-assisted learning

1. Introduction

Dental education is rapidly evolving to include new technologies that prepare students for modern clinical practice. Artificial intelligence (AI) has emerged as a transformative tool in health professions education, offering new approaches to teaching and decision-making. AI is broadly defined as the simulation of human intelligence by systems capable of perception, reasoning, learning, planning, and prediction.[1,2] In medical and dental education, AI applications such as radiographic analysis, diagnostic simulations, and automated assessments have demonstrated early promise. However, the systematic integration of AI into dental curricula remains underdeveloped. [3]

The adoption of AI in dental can enhance learning through personalized feedback and objective assessments. AI-powered systems may increase procedural accuracy, strengthen radiographic interpretation, and streamline grading processes. These innovations align with the shift toward competency-based, student-centred education.[3–5]

Despite its potential, AI implementation in dental education faces challenges including concerns about reliability, faculty readiness, and lack of standardized frameworks. [6,7] Furthermore, ethical concerns around data privacy, bias, and responsible AI use require attention within the educational context.[8–10] Many faculty members report limited AI knowledge and insufficient training, despite expressing positive attitudes toward AI integration. [7,11]

This scoping review aims to identify, summarize, and categorize existing applications of AI in dental education, with a focus on student learning, assessment, and diagnostic training. Additionally, it seeks to explore current limitations and challenges, providing insights to guide future research and support the responsible integration of AI into dental curricula.

To ensure consistency and clarity, this review adopts a standardized definition of AI as the simulation of human intelligence by machines capable of perception, reasoning, learning, planning, and prediction [2]. This definition aligns with established technological frameworks and distinguishes AI from other educational tools. AI research revived in 2006 with Hinton's deep learning model, enabling machines to learn autonomously[2]. This definition guided the review's evaluation of AI in dental education.

Virtual reality (VR) is an example of misclassification of AI in dental education research due to the lack of a standardized definition. While VR supports simulation, it lacks adaptive learning and autonomous decision-making key features of true AI [12]. Clearer definitions are needed to avoid such inaccuracies and ensure consistency in AI-focused studies.

2. Materials and Methods

This review followed the five-stage scoping framework proposed by Arksey and O'Malley[13], further refined by Peters et al[14], and This scoping review was conducted and reported in accordance with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) 2020 guidelines [15]. The review protocol was not registered. In line with standard scoping review methodology, no formal critical appraisal of included studies was performed, as the aim was to map the breadth of available literature rather than assess study quality.

However, two reviewers independently assessed each study for potential bias based on study design, sample size, outcome measures, and presence of control groups. Bias was categorized as low, moderate, or high to aid interpretation. Discrepancies were resolved by consensus, and ratings are presented in Table 1.

2.1. Research Question

Using the Population, Concept, and Context (PCC) framework[16], the guiding scoping question was: What are the applications, limitations, and challenges of artificial intelligence in dental education?

2.2. Search Strategy

PubMed, Web of Science, Cochrane Library, Google Scholar, Dentistry & Oral Sciences Source, and Embase, were searched in March 2025 using combinations of the following search words: "dental education," "artificial intelligence," "machine learning," and "student assessment". Included studies applied AI empirically in preclinical, clinical, or assessment-based dental education.

2.3. Eligibility Criteria

Inclusion:

- English-language empirical studies
- Direct evaluation of AI in teaching, feedback, or dental student assessments
 Exclusion:

- Opinion pieces or perception-based surveys
- Studies unrelated to AI or dental education
- Reports on AI solving exams or general curriculum reform
- Studies not directly related to the education of dental students or their teaching

A total of 547 records were identified through database searches. After removing 50 duplicates, 497 records were screened. Following the application of inclusion and exclusion criteria, 17 empirical studies were selected for inclusion in the review. Two reviewers assessed the full texts of all 497 articles. They reached agreement on excluding 480 studies due to reasons such as lack of empirical data, absence of focus on dental students, or classification as commentary or editorial pieces. The complete study selection process is illustrated in the PRISMA flow diagram (Figure 1). All studies that met the eligibility criteria during full-text assessment were included in the final synthesis.

2.4. Data Charting and Synthesis

Data were extracted from the included studies using a structured Excel-based data charting form developed by the review team. The author extracted that data and presented it to the review team with key information from each study, including author, year, country, aim, design, sample size, AI domain classification, key findings, limitations, and bias risk. Discrepancies between reviewers were resolved through discussion and consensus. all necessary information was available in the published reports. No data transformations or conversions were required. All data were extracted as reported in the original studies and summarized descriptively. Missing numerical details were not imputed, and all synthesis was based on the available published information. Results of individual studies were tabulated in a structured summary table (Table 1), organized by domain, with key information including study aim, design, strengths, limitations, findings, conclusions, and bias risk rating. This table was developed to support thematic synthesis and comparison across domains. A descriptive, narrative synthesis was used to summarize and categorize findings across the included studies. This approach was chosen due to the heterogeneity of study designs, AI applications, and outcome measures, which precluded quantitative synthesis. Thematic grouping by domain allowed for structured comparison and identification of trends, challenges, and research gaps. No statistical meta-analysis was performed. No statistical methods were used to explore heterogeneity among study results, such as subgroup analysis or meta-regression, as this scoping review aimed to map the scope of evidence rather than quantify effects across comparable studies. No sensitivity analyses were conducted, as the aim of this scoping review was to map the breadth of existing literature rather than evaluate the robustness of effect estimates through quantitative synthesis. Risk of bias due to missing results or selective reporting was not formally assessed, as this scoping review did not involve outcome-level synthesis or effect estimation. Certainty in the body of evidence was not assessed, as this review aimed to map the scope and characteristics of existing literature rather than evaluate the strength of evidence for specific outcomes.

Extracted data were categorized into four domains based on thematic analysis of the included studies. As no standardized classification framework existed for AI in dental education, we developed our own domain structure Two reviewers independently reviewed each study's objectives, methods, and outcomes, and allocated them to the most relevant domain through consensus. Where studies overlapped multiple domains, classification was based on the dominant theme. This ensured consistency in synthesis and interpretation across domains.

- 1-Preclinical training[18,19]
- 2-AI in Clinical, Diagnostic Training, and Radiographic Interpretation.[20–29]
- 3-AI as an Assessment Tool and Feedback System[30–32]
- 4-AI in Content Generation for Dental Education[33,34]

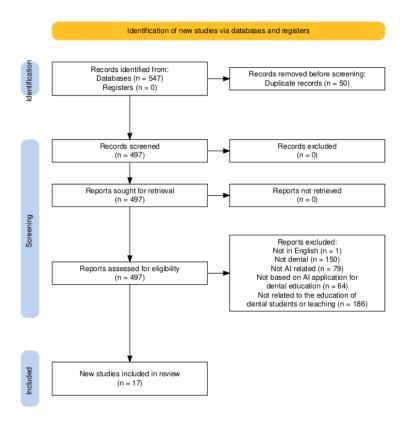


Figure 1. PRISMA flow diagram[17] for the scoping review process performed.

3. Results

Seventeen peer-reviewed studies met the inclusion criteria. They were published between 2022 and 2025. Findings are summarized by domain:

3.1. AI in Preclinical Training

AI simulation platforms improved procedural accuracy, student confidence, and feedback quality. However, no study included real-time feedback on operative procedures such as cavity preparation, highlighting a current research gap. The two included studies in this domain used quasi-experimental and observational designs with moderate risk of bias. Both relied on self-reported student perceptions and had relatively small sample sizes. Despite positive findings, limited generalizability and lack of objective outcome measures reduce certainty.

3.2. AI in Clinical, Diagnostic Training, and Radiographic Interpretation

AI has shown strong potential in dental education by improving diagnostic accuracy and supporting clinical decision-making. Tools like chatbots and image analysis systems enhance pattern recognition and often outperform student assessments. However, limitations in context, ethics, and the need for human oversight mean AI should support not replace clinical judgment. This domain included the largest group of studies, with varied designs including randomized trials and comparative analyses. Risk of bias ranged from moderate to low. Studies with expert benchmarks and objective diagnostic outcomes showed stronger methodology, while those using perception-only data or small samples had higher bias risk.

3.3. AI as an Assessment Tool and Feedback System

AI is used in dental education for automated grading and real-time feedback, enhancing efficiency and reducing bias. It supports personalized learning by identifying student weaknesses and offering adaptive guidance. However, AI struggles with evaluating complex, subjective responses and lacks the depth needed for holistic clinical judgment. Ethical concerns, lack of standardization, and student over-reliance highlight the need for faculty oversight and careful

integration. Studies in this domain explored AI-generated feedback and grading but primarily relied on small samples and student self-reporting. They were judged to have moderate risk of bias due to limited outcome validation, short study duration, and potential novelty bias.

3.4. AI in Content Generation

AI is being used to generate educational content in dental education, including case studies, quizzes, and interactive modules, enhancing efficiency and accessibility. Studies show AI tools can support self-directed learning and improve information retrieval compared to general models. However, faculty oversight is needed to validate accuracy and ensure content meets accreditation standards. Key challenges include potential bias, limited nuance in complex cases, and ensuring student engagement. Both studies in this domain were early-stage or pilot evaluations of AI-generated educational content. Risk of bias was rated as moderate due to limited external validation, absence of student outcome assessment, and potential inconsistencies in AI-generated material.

3.5. Key Findings

AI plays a significant role in enhancing various aspects of dental education. In preclinical training, AI has been shown to improve learning outcomes by supporting decision-making and boosting student confidence. It also enhances diagnostic training, particularly in radiographic interpretation, by supporting more accurate and consistent image analysis. automated grading to improve efficiency, though it often lacks human-like feedback for deeper learning.

3.6. Identified Gaps

Several key gaps remain in the integration of AI within dental education. There is a lack of research on AI's role in real-time procedural assessment, such as evaluating restorative cavity preparation or restoration accuracy, leaving its potential in preclinical feedback, interactive clinical training and preclinical student assessments underexplored. Additionally, AI models designed for interactive, case-based diagnostic reasoning are still underdeveloped. Current AI grading systems also fall short in providing contextual, human-like feedback, which is essential for supporting meaningful learning and reflective practice.

3.7. Challenges

Across the reviewed studies, several key challenges to integrating AI into dental education were identified. A major concern is the inconsistent application of AI definitions, highlighting the need for clearer terminology and guidelines. over-reliance on AI poses risks, as it cannot replace the critical thinking and clinical judgment fundamental to dentistry. Ethical and privacy issues arise from patient data use, demanding strong governance frameworks. Successful integration further depends on faculty training and institutional support. Progress is additionally limited by the lack of dental leadership in AI development, as most models are created by computer scientists, reducing alignment with dental education priorities such as preclinical skills training.

Table 1. Summary of Included Studies Categorized by AI Domain in Dental Education.

Category of AI domain classified by this scoping review		'Aim	Design	Strengths	Limitations	Findings	Scoping review conclusions
AI in Preclinical Training	Choi et al. (2023), Australia[18]	evaluate an interactive AI	dObservationa study; 79 fourth-year dental students participated,	l Development and implementation of a novel AI assessment system	Only 44 out of 79 participants completed the post-survey (55.7%)	Students found the AI feedback system helpful for identifying and correcting errors	feedback system was positively received and



		performance in endodontic access cavity preparation and provide immediate feedback.	completed the	Real-time, eindividualized feedback for skill refinement Use of a structured Likert-scale survey to gather student feedback	objective skill performance measure Single-center study limits	satisfaction was reported for system usability and self- directed learning support Most students preferred combining AI feedback with instructor feedback	preparation. However, further validation is required using objective outcome measures and control groups. Bias Risk: Moderate due to reliance on self- reported outcomes, and incomplete survey responses.
AI in Preclinical Training	Mahrous et al., 2023 USA[18]	using traditional methods versus the AiDental AI and game- based learning	Quasi- experimental study; two- group comparison s(AI-game group vs. control	assessment of practical exam Integration of AI and gamified learning Direct evaluation of student	intervention, n = 37 control) Short intervention period (2 weeks before testing) Survey-based	The AiDental group outperformed the control group in RPD design accuracy and completeness (statistically significant simprovement). Survey results indicated positive student perception,	The integration of AI and game-based learning improved short-term performance in RPD design and was well-received by students. However, the short duration and reliance on a single institution limit generalizability. Bias Risk: Moderate due to the short intervention period, absence of long-term outcomes, and reliance on self-reported perceptions.
AI in Clinical, Diagnostic Training, and Radiographic Interpretatio n	2024	To evaluate the feasibility and effectiveness of an AI-powered chatbot for improving patient historytaking skills among dental	Pilot observational study using a single cohort of third-year dental students interacting with an AI chatbot for simulated history-taking.	High engagement: 100% student participation with the chatbot compared to 2/13 in traditional tutorials Realistic simulation using GPT-3.5-based patient responses Scalability and accessibility for repetitive practice	post performance measures Subjective	chatbot Staff supported the tool's educational value and	The chatbot was positively received and showed promise as a supplementary tool for dental education. However, due to the small sample size and lack of control group, findings must be interpreted cautiously. Bias Risk: High, due to subjective measures, small sample, and lack of comparative



AI in Clinical, Diagnostic Training, and Radiographic e et al., 2024, Interpretatio n	To explore how artificial intelligence (AI) can be integrated into endodontic education and identify both its potential benefits and limitations.	Scoping review of 35 relevant studies, conducted through electronic and grey literature search across databases including MEDLINE, Web of Science, and Cochrane Library up to December 2023.	applications into	selection bias due to broad inclusion criteria and lack of systematic review methodology.	assessment, preclinical training, advanced simulation, real-time guidance, autonomous robotics, progress tracking and	AI holds promise to revolutionize endodontic education through personalized learning, diagnostic assistance, and simulation- based training. However, educators must acknowledge its current limitations and ensure its responsible implementation. Bias risk: Moderate due to lack of critical appraisal of included studies and variability in evidence quality across reviewed articles.
AI in Clinical, Diagnostic Ayan et al., Training, and 2024, Radiographic Turkey [22] Interpretatio n	To assess the diagnostic performance of dental students in identifying proximal caries lesions before and after training with an AI-based deep learning application.	study involving pre-	Use of a validated deep learning algorithm (YOLO – You Only Look Once tailored for caries detection. Expert-labeled dataset (1,200 radiographs) ensures strong ground truth reliability. Comparative pre- and post-intervention design increases internal validity.	Small participant sample size (n = 40 dental students). Only one institution involved, limiting generalizability Increased post- test labeling time in AI- trained group may indicate increased complexity or cognitive load.	significant improvement in accuracy, sensitivity, specificity, and F1 scores (p < 0.05). No significant difference in precision score. Labeling time increased in the AI-trained group.	the educational benefit suggests that AI can serve as a valuable tool for radiographic

AI in Clinical, Diagnostic Training, and 2024, Radiographic USA[23] Interpretatio	To evaluate (1) the efficiency and accuracy o dental students performing full-mouth radiograph mounting with and without Al assistance, and (2) student perceptions of AI's usefulness in dental education.	experimental study with two student groups: manual vs AI- assisted radiograph mounting. Pre- and post- study surveys	perceptions) outcome measures. Random allocation of 40 participants	Small sample size (n = 40 dental students). Single institution study. AI assistance led to reduced accuracy, suggesting issues with over-reliance or automation. No long-term assessment of retention or skill transfer.	AI-assisted group completed radiograph mounting significantly faster (p < 0.05). However, the AI-assisted group demonstrated significantly lower accuracy than the manual group n(p < 0.01). Student confidence and perceptions of AI did not differ significantly between groups, before or after the intervention.	While AI assistance improved efficiency, it negatively impacted accuracy, indicating that premature automation may hinder skill development in novice learners. Students maintained neutral perceptions toward AI, highlighting the need for careful integration of AI tools in early dental education. Bias Risk: Moderate due to small sample size, lack of blinding, and single-site scope.
AI in Clinical, Prakash et Diagnostic al., 2024, Training, and India[24] Radiographic Interpretatio n	To develop and evaluate DentQA, a GPT3.5-based dental semantic search engine aimed at improving information retrieval for dental students, while addressing issues like hallucination, bias, and misinformation.	Tool development and validation study using both non- human (BLEU score) and human performance metrics, including accuracy, hallucination rate, and user satisfaction.	(human evaluation) performance assessments. Tailored specifically to dental education content. Compared directly to GPT3.5 baseline	Total of 4 human evaluators only and 200 questions evaluated. Lack of real- world classroom or clinical implementatior . Evaluations limited to document- based Q&A rather than broader clinical decision- making tasks.	reduced hallucinations (p = 0.026). Demonstrated consistent performance across question types (X² = 13.0378, p = 0.012). BLEU Unigram score of 0.85 confirmed linguistic	DentQA provides a promising AI- based solution for reliable and efficient information retrieval in dental education. Its reduced hallucination rate and consistent performance across question types support its potential as a domain-specific educational tool. Further testing in real academic settings is recommended. Bias Risk: Moderate due to ea limited number of evaluators and absence of practical deployment data.

AI in Clinical, Diagnostic Training, and al., 2024, Radiographic Oman[25] Interpretatio	To compare the diagnostic accuracy of dental students (junior and senior cohorts) with that of a modified ChatGPT-4 model in endodontic assessments related to pulpal and apical conditions, and to explore the potential role of AI in supporting dental education.	Comparative sobservational study using seven standardised clinical scenarios. Diagnostic accuracy was measured for junior and senior dental students l versus	Included a large student sample (n = 109). Included junior (n = 54) and senior (n = 55) groups for subgroup analysis. Used gold-standard expert assessments for accuracy comparisons. Applied robust statistical analysis (Kruskal-Wallis and Dwass-Steel Critchlow-Fligner tests). Clearly delineated performance metrics for AI vs students.	limited to sever predefined cases may not generalize across broader clinical complexity. No evaluation of long-term retention or educational impact post-AI exposure. Does not assess-student reasoning or process—only final answer accuracy.	(79.7%) and juniors (77.0%). Median diagnostic accuracy: ChatGPT = 100%, Seniors = 85.7%, Juniors = 82.1%. Statistically significant difference between ChatGPT and both student groups (p < 0.001). No statistically significant difference	as an educational support tool, particularly for reinforcing diagnostic standards. However, caution is advised
						due to robust sample size, expert-defined gold standard, and appropriate statistical testing.
AI in Clinical, Diagnostic Training, and 2024, Radiographic Germany[26] n	To assess the impact of two feedback methods elaborated Feedback (eF) and Knowledge of Results (KOR) on radiographic diagnostic competencies in dental students, and to evaluate the	receive either eF or KOR while interpreting 16 virtual radiological cases over 8	design with two intervention arms. Use of real radiographic cases and multiple	Some outcomes showed no significant differences between groups. Short duration (8 weeks) may not reflect long term learning retention. No detailed	receiving elaborated feedback (eF) performed significantly better than those receiving only knowledge of results (KOR	ecategories ocompared to basic feedback. The AI system demonstrated near-perfect

diagnostic

Student

(accuracy,

10 of 20

indicating

interacted with Detecting

	alagnostic	diagnostic	(accuracy,	AL or foodback	_	strong potential
	accuracy of an AI system	-	sensitivity,	AI or feedback	_	strong potential as an alternative
	(dentalXrai Pro	-		No explicit	accuracy, p	to expert-
	3.0) as a	and	Inclusion of AI	control group	= .011; ↑	generated
	potential	compared,	system	without	sensitivity, p	feedback in
	educational	and the	benchmarking	feedback or AI	= .003; ↑ AUC, p	
	aid.	performance	with near-perfec	t to isolate	= .001)	settings.
		of the AI	reported	effects.	Assessing	However, the
		system was	performance.		periapical	limited
		independentl	Statistical		image quality	specificity in
		y evaluated	comparisons		(p = .031)	enamel caries AI
		on the same	conducted with		No significant	•
		tasks.	appropriate tests		differences	(0.074) warrants
			(Welch's t-test,		between groups	
			ROC analysis).		were found for	-
					tasks.	The randomized
					The AI system	design and
					(dentalXrai Pro	
					3.0) showed	support the
					near-perfect	study's
					diagnostic	reliability.
					performance:	Bias Risk: Low
					Enamel caries:	due to
					Accuracy	randomized
					96.4%,	controlled
					Sensitivity	design, clear
					85.7%,	metrics, and
						direct AI-human
						comparison with
					Accuracy 98.8%,	transparent
					Sensitivity	reporting.
					94.1%,	
						,
					Specificity 100%	'n
					Specificity 100% Overall:	o
					Overall:	0
						0
					Overall: Accuracy	o
					Overall: Accuracy 97.6%,	ò
					Overall: Accuracy 97.6%, Sensitivity	ò
					Overall: Accuracy 97.6%, Sensitivity 95.8%,	o
					Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3%	
	To investing		Included by the		Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall	The study
	To investigate		Included both		Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for	The study demonstrates
	whether		medical	Tast_ratest	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying	The study demonstrates that GANs can
	whether synthetic		medical professionals	Test-retest Ireliability was	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic	The study demonstrates that GANs can generate highly
	whether synthetic panoramic		medical professionals (n=54) and denta	lreliability was	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was	The study demonstrates that GANs can generate highly realistic
	whether synthetic panoramic radiographs		medical professionals	lreliability was low (Cohen's	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%;	The study demonstrates that GANs can generate highly realistic panoramic
	whether synthetic panoramic		medical professionals (n=54) and denta students (n=33).	lreliability was low (Cohen's kappa = 0.23).	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was	The study demonstrates that GANs can generate highly realistic
AI in	whether synthetic panoramic radiographs (syPRs),	Experimental	medical professionals (n=54) and denta students (n=33). Used a	lreliability was low (Cohen's	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was	The study demonstrates that GANs can generate highly realistic panoramic radiographs that
Clinical,	whether synthetic panoramic radiographs (syPRs), generated	Experimental study with	medical professionals (n=54) and denta students (n=33). Used a controlled	lreliability was low (Cohen's kappa = 0.23). Sample size	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%.	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often
Clinical, Diagnostic Schoenhof et	whether synthetic panoramic radiographs (syPRs), generated using GANs	-	medical professionals (n=54) and denta students (n=33). Used a controlled number of real	lreliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87),	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals:	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl
Clinical, Diagnostic Schoenhof et Training, and al., 2024,	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2- ADA), can be reliably	study with	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic	lreliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87),	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%,	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany (27)	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2- ADA), can be reliably	study with survey and	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control	lreliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%,	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany[27]	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2- ADA), can be reliably distinguished from real	study with survey and test-retest	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation	lreliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33).	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students:	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany (27)	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2- ADA), can be reliably distinguished from real radiographs	study with survey and test-retest reliability	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation accuracy,	Ireliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33). Study used a	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students: sensitivity	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have educational and
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany[27]	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2- ADA), can be reliably distinguished from real radiographs and evaluate	study with survey and test-retest reliability	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation accuracy, perceived image	Ireliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33). Study used a limited set of	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students: sensitivity 75.5%,	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have educational and research value
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany[27]	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2- ADA), can be reliably distinguished from real radiographs and evaluate their potential	study with survey and test-retest reliability evaluation.	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation accuracy, perceived image quality, and item	Ireliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33). Study used a limited set of images for	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students: sensitivity 75.5%, specificity	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have educational and research value without privacy
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany[27]	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2-ADA), can be reliably distinguished from real radiographs and evaluate their potential use in teaching.	study with survey and test-retest reliability evaluation.	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation accuracy, perceived image quality, and item agreement.	Ireliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33). Study used a limited set of images for evaluation (45	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students: sensitivity 75.5%, specificity 82.7%.	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have educational and research value without privacy concerns.
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany[27]	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2-ADA), can be reliably distinguished from real radiographs and evaluate their potential use in teaching, research, and	study with survey and test-retest reliability evaluation.	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation accuracy, perceived image quality, and item agreement. Included test-	Ireliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33). Study used a limited set of images for	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students: sensitivity 75.5%, specificity 82.7%. Median image	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have educational and research value without privacy concerns. Bias Risk:
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany[27]	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2-ADA), can be reliably distinguished from real radiographs and evaluate their potential use in teaching, research, and clinical	study with survey and test-retest reliability evaluation.	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation accuracy, perceived image quality, and item agreement. Included test-retest reliability	Ireliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33). Study used a limited set of images for evaluation (45	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students: sensitivity 75.5%, specificity 82.7%. Median image quality score:	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have educational and research value without privacy concerns. Bias Risk: Moderate due to
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany[27]	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2-ADA), can be reliably distinguished from real radiographs and evaluate their potential use in teaching, research, and	study with survey and test-retest reliability evaluation.	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation accuracy, perceived image quality, and item agreement. Included test-	Ireliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33). Study used a limited set of images for evaluation (45	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students: sensitivity 75.5%, specificity 82.7%. Median image quality score: 6/10.	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have educational and research value without privacy concerns. Bias Risk: Moderate due to small sample
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany[27]	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2-ADA), can be reliably distinguished from real radiographs and evaluate their potential use in teaching, research, and clinical	study with survey and test-retest reliability evaluation.	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation accuracy, perceived image quality, and item agreement. Included test-retest reliability	Ireliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33). Study used a limited set of images for evaluation (45	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students: sensitivity 75.5%, specificity 82.7%. Median image quality score: 6/10. Median rating	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have educational and research value without privacy concerns. Bias Risk: Moderate due to small sample size, low retest
Clinical, Diagnostic Training, and al., 2024, Radiographic Germany[27]	whether synthetic panoramic radiographs (syPRs), generated using GANs (StyleGAN2-ADA), can be reliably distinguished from real radiographs and evaluate their potential use in teaching, research, and clinical	study with survey and test-retest reliability evaluation.	medical professionals (n=54) and denta students (n=33). Used a controlled number of real (20), synthetic (20), and control (5) PRs. Assessed image interpretation accuracy, perceived image quality, and item agreement. Included test-retest reliability	Ireliability was low (Cohen's kappa = 0.23). Sample size modest (total n=87), particularly within student subgroup (n=33). Study used a limited set of images for evaluation (45	Overall: Accuracy 97.6%, Sensitivity 95.8%, Specificity 98.3% Overall sensitivity for identifying synthetic images was 78.2%; specificity was 82.5%. Professionals: sensitivity 79.9%, specificity 82.3%. Students: sensitivity 75.5%, specificity 82.7%. Median image quality score: 6/10.	The study demonstrates that GANs can generate highly realistic panoramic radiographs that are often indistinguishabl e from real ones by professionals and students. These synthetic images have educational and research value without privacy concerns. Bias Risk: Moderate due to small sample

					related importance: 7/10. 11 out of 14 radiographic items showed agreement with expected interpretation.	subjective evaluation metrics.
AI in Clinical, Diagnostic Schropp et Training, and al., 2023, Radiographic Denmark[28] Interpretatio n	dental students' ability to detect enamel-only proximal caries in bitewing radiographs and to assess	Randomized controlled study with two assessment sessions and reference-standard comparison.	Random allocation of 74 dental students to control and test groups. Use of validated software (AssistDent®). Two-session longitudinal structure allowed for measuring learning progression. Consideration of radiographic overlap as a variable influencing accuracy.	Only enamelonly caries assessed; may not generalize to more advanced lesions. Somewhat limited by moderate sample size (n=74). AI assistance was only used in the first session	Session 1: No significant difference in positive agreement between control (48%) and test (42%) groups (p = .08). Test group had higher negative agreement (86% vs. 80%, p = .02). Session 2: No significant difference between groups. Within-group improvement: Test group improved in positive agreement over time (p < .001); control group improved in negative agreement (p < .001). Tooth overlap occurred in 38% of surfaces and significantly reduced diagnostic agreement (p < .001)	not significantly improve students' diagnostic performance in detecting enamel-only proximal caries. However, both groups showed improvement over time. Tooth overlap negatively affected diagnostic accuracy regardless of AI use. Bias Risk: Low due to randomized design, adequate student sample, objective outcome
AI in Clinical, Diagnostic Suárez et Training, and al., 2022, Radiographic Spain [29] Interpretatio n	students' satisfaction and perceived usefulness after interacting with an AI- powered chatbot	study using a satisfaction survey following several weeks of interaction with the AI virtual patient.	Large and representative sample (n = 193, surpassing minimum of 169). Inclusion of students in two clinical years (4th and 5th year), allowing comparisons across experience levels. Gender-balanced data reporting.	design limits inference on causality or elongitudinal impact.	satisfaction with the AI chatbot (mean score 4.36/5). Fifth-year students rated	The AI-based virtual patient chatbot was well-received by students and viewed as a useful supplement for diagnostic training. It provided a cost-effective, space-saving educational solution that promotes

				Integration of real student	perception rather than	through the chatbot	engagement through natural
				interaction with an AI tool over several weeks, enhancing ecological validity.	objective diagnostic skill gain.	interaction gave higher satisfaction ratings. Positive student perception supports the tool's potential value for repeated diagnostic practice in a safe environment.	processing. Bias Risk: Moderate due to self-reported, perception-only data and
AI as an Assessment Tool and Feedback System	Kavadella et al., 2024, Cyprus [30]	radiology module using a mixed-methods approach.	learning task between two groups: one using ChatGPT and the other using traditional internet-based research. Data collection included aknowledge sexam scores and thematic analysis of student feedback.	comparison of examination scores provides objective outcome data.	reducing generalizability Short-term evaluation; no long-term retention or application assessment. Potential novelty bias influencing students' enthusiasm for AI use. Single- institution study, limiting external applicability.	interface, broad knowledge access. Limitations identified: need for refined prompts, generic or inaccurate information, inability to provide visuals. Students expressed readiness to adopt ChatGPT in education, clinical practice, and research with appropriate guidance.	ChatGPT enhanced students' performance in knowledge assessments and was positively received for its utility and adaptability in dental education. Students demonstrated critical awareness of its limitations and used it creatively. Bias Risk: Moderate due to short study duration, institution-specific sample, and self-reported feedback, although objective performance data strengthens credibility
AI as an Assessment Tool and Feedback System		feedback provided by an	study analyzing 194 student responses to two histology questions. Feedback from	Large sample size (n = 194) enhances reliability. Use of both student perception and expert evaluation provides	not generalize to other areas of dentistry. Limited to one	ffeedback for one question; AI scored	ChatGPT-4 demonstrated effectiveness in providing clear and constructive feedback, performing comparably or better than human tutors

dental	and human	multidimensiona	a Potential bias ir	second and	based on expert
students'	tutors was	l insight.	student	overall scores.	analysis. Student
histology	assessed	Standardized	preferences due	Students	preferences
assignments.	using a	rubric ensures	to familiarity	perceived no	leaned toward
	standardized	consistency	with human	significant	human feedback
	rubric.	across	feedback.	difference in	due to emotional
	Students	assessments.		understanding,	comfort, not
	rated	Expert-blinded		critical	quality.
	feedback on	review of		thinking,	Bias Risk:
	five	feedback		relevance, or	Moderate while
	dimensions,	enhances		clarity, but	expert
	and an expert	objectivity.		preferred	validation
	reviewed 40			human	strengthens
	randomly			feedback for	findings, the
	selected			comfort.	emotional bias
	feedback			Expert	in student
	samples.			evaluation	responses and
				showed AI was	single-discipline
				superior in	scope limit
				mistake	broader
				identification,	generalization.
				clarity (P	
				< .001), and	
				$suggestions \ for \\$	
				improvement (I	

< .001).

ChatGPT ChatGPT's responded inability to Exploratory accurately to process imagestudy using most Broad based questions knowledgeassessment limits independentl based question coverage with 50 generalizability y constructed types (MCQs, To explore the customto clinical questions SAQs, SEQs, accuracy of developed items scenarios true/false, fillspanning 5 ChatGPT in across multiple Only the free in-the-blank) common responding to formats version of assessment ChatGPT various Realistic ChatGPT was formats struggled with AI as an healthcare integration of AI tested Ali et al., (MCQs, image-based Assessment education use in student- Lack of 2024, SAQs, SEQs, questions and Tool and assessment assigned tasks benchmarking true/false, fill-Qatar[32] critical Feedback formats and Addresses both against student appraisal tasks in-the-blank) System discuss its formative (e.g., or educator implications for and several Generated feedback reports)performance undergraduate academic reflective and and summative Critical writing tasks. research dental (e.g., MCQs) appraisal Each format responses were education. assessment types outputs from included 10 mostly **Explores** ChatGPT were satisfactory items. ChatGPT was qualitative and found to be Word count weaker quantitative used to limitations performance noted with the attempt all questions. free version

strong potential in supporting healthcare and dental education through accurate responses to diverse assessment types. However, its limitations in processing visual data and critical reasoning tasks highlight the need for educators to redesign assessments and learning approaches to integrate AI responsibly.

ChatGPT shows

Bias Risk:
Moderate
customdesigned
questions ensure
targeted
evaluation, but
lack of
comparative
analysis with
human
responses and
reliance on only

text-based
questions limits
generalizability.

AI in Content Generation for the Dental Field	Aldukhail et al, 2024, Saudi Arabia[33]	To evaluate and compare the performance of two large language models ChatGPT 3.5 and Google Bard in the context of dental education and research support.	two reviewers. Scoring was based on pre- defined metrics and analysed using	Direct head-to-head comparisor of two major LLMs in a dental education context Multi-domain evaluation covering exercises, simulations, literature critique, and tool generation Use of blind reviewers and statistical analysis to reduce subjective bias Practical relevance for educators seeking to integrate LLMs in curriculum design	were tested, excluding newer or alternative models Evaluation was based on a limited number of prompts (n=7), which may not generalise across broader contexts Reviewer subjectivity, despite blinding, could still influence scoring outcomes The study does not evaluate student learning outcomes	simulations, and assessment tools with higher clarity, accuracy, and specificity Google Bard showed strength in retrieving real research articles and critiquing them effectively Statistically significant differences (p ≤ 0.05) were found in scores	Bard can support dental education through simulation, content creation, and literature analysis. However, each model has distinct strengths and weaknesses, and critical judgment is essential when incorporating them into educational practice. Bias Risk: Moderate while the methodology includes blinding and structured
AI in Conten Generation for the Dental Field	t Katebzad et al,2024, USA[34]	To evaluate whether publicly available generative AI platforms can develop high-quality, standardized, and clinically relevant simulated pediatric denta cases for use in predoctoral education, including OSCE-style assessments.	study using standardized prompts across three de-identified AI platforms to generate pediatric dental cases on three lthemes. AI-	blinded, board-certified examiners Introduces a novel rubric (AI-SMART) for systematic quality assessment Proof-of-concept	generalizability Control cases scored significantly higher, indicating AI limitations in clinical accuracy and OSCE formulation Some AI- generated answers	0.44) and readability (p = 0.15) between AI and control cases Investigator-generated cases scored significantly higher in OSCE quality (p < 0.001) and answer	prompt engineering are

Pilot	by two	engineering in	guidelines (e.g.,	AI platforms	integrating AI in
comparative	masked,	dental education	AAPD)	were efficient ir	case-based
study using	board-		AI-SMART tool	producing	learning, though
standardized	certified		is not yet	interdisciplinar	further
prompts across	s evaluators		validated and	y cases, but	validation and
three de-	using the AI-		requires further	required	broader testing
identified AI	SMART		research	manual review	are needed.
platforms to	rubric.		Study did not	and correction	Bias Risk:
generate	Statistical		assess student	Some AI-	Moderate due
pediatric denta	ılanalysis		learning	generated	to Using of
cases on three	included		outcomes or	OSCE answers	blinded
themes. AI-	ANOVA and		implementation	were incorrect	evaluators and
generated case	sBonferroni		feasibility	or overly	statistical rigor
were compared	d correction.			simplistic	adds reliability,
to investigator-	-			Highlighted the	but the tool used
generated				importance of	for scoring (AI-
(control) cases				standardized	SMART) is
by two				prompt design	unvalidated,
masked, board	-			for effective AI	and results are
certified				use in	based on a pilot
evaluators				education	sample.
using the AI-					
SMART rubric					
Statistical					
analysis					
included					
ANOVA and					
Bonferroni					
correction.					

4. Discussion

This review confirms that AI holds promise in dental education, but highlights two major gaps limiting progress: the absence of a standardized definition of AI and the lack of clinician-led model development. Many studies misclassify tools like virtual reality as AI due to unclear definitions, undermining consistency across the field. Additionally, most AI tools are developed by computer scientists with minimal dental input, resulting in limited clinical relevance. By introducing a domain-based classification, this review offers a structured foundation that can help guide future studies toward more practical, targeted, and clinically meaningful AI applications in dental education.

4.1. AI in Preclinical Training

AI applications in this domain focus on skill development, simulation-based learning, and automated feedback systems to support students before they engage in direct patient care. Several studies have demonstrated AI's effectiveness in improving procedural accuracy, reinforcing learning outcomes, and providing individualized feedback.[18,19] However, challenges remain in standardizing AI-driven training, ensuring reliability, and integrating AI assessments into competency-based education frameworks.

AI-driven simulation platforms have enhanced interactive preclinical training by providing structured, self-directed learning. Mahrous et al.[19] found that students using AI-generated feedback for prosthodontic design achieved higher accuracy than those with traditional instruction. Choi et al.[18] found AI useful in evaluating endodontic access cavity preparations. However, AI still struggles with assessing nuanced skills like hand dexterity, which require human oversight.

In the view of this scoping review's authors, while AI offers measurable benefits in preclinical training, several challenges merit attention. While effective at assessing objective metrics like cavity depth, AI struggles with subjective skills such as dexterity and technique. Its accuracy depends on the quality and diversity of training datasetsany bias or limitation reduces reliability. Integrating AI into curricula also requires faculty training, infrastructure, and alignment. Moreover, excessive

reliance on AI may hinder students' development of self-assessment and critical thinking skills essential for clinical reasoning and growth.

4.2. AI in Clinical and Diagnostic Training and Radiographic Interpretation

AI is increasingly used in dental education to support clinical and diagnostic training, especially in radiographic interpretation and case-based reasoning. Studies by Qutieshat et al.[25], Rampf et al[26], and Schropp et al. [28] show that AI can improve diagnostic accuracy and standardize image interpretation, often outperforming student assessments in detecting caries, pulp, and periodontal pathologies. Similarly Or et al.[20] reported improved diagnostic confidence from students using an AI chatbot for history-taking These tools support real-time decision-making and diagnostic consistency, but over-reliance, ethical issues, and limited adaptability remain key barriers.

AI shows strong potential in radiographic interpretation, improving students' ability to detect caries and other pathologies. Studies by Rampf et al.[26] and Qutieshat et al.[25] found AI-enhanced diagnostic tools outperformed or matched student performance, especially in early enamel caries and endodontic cases. However, Schropp et al. [28] highlighted concerns about AI model generalizability across systems, recommending AI as a supportive not stand-alone tool. Additionally, Suárez et al. [29] found AI chatbots improve students' diagnostic reasoning, though Qutieshat et al. [25] emphasized AI's lack of clinical intuition, underscoring the continued need for human oversight.

In the view of the scoping review authors, while AI offers clear benefits in enhancing diagnostic skills, key challenges remain. There is a risk of students becoming overly reliant on AI, potentially diminishing their clinical reasoning and independent judgment. Ethical concerns around accountability also arise if AI-generated errors impact patient safety. Moreover, variability across AI models underscores the need for standardization and regulatory oversight in dental education.

4.3. AI as an Assessment Tool and Feedback System

AI is increasingly used in dental education for automated grading and real-time feedback, improving efficiency, reducing bias, and enhancing learning through personalized responses [31]. However, challenges remain, including difficulty evaluating complex answers, risks of student overreliance, and concerns about transparency and bias.

AI-driven grading systems in dental education offer consistent and scalable assessment, improving efficiency and reducing variability[31]. However, students found AI feedback lacking in depth for open-ended and case-based tasks[32].

AI assessment tools provide real-time feedback that helps students self-correct and adapt. [31]. In clinical skill evaluations, AI has improved performance by analyzing procedural accuracy and providing iterative feedback [18] However, proper calibration and faculty oversight are essential to prevent reinforcement of incorrect techniques.

In the view of the scoping review authors, while AI enhances assessment efficiency and consistency, key challenges persist. Students may become overly reliant on AI, potentially weakening their critical thinking. Current models struggle with nuanced evaluations involving communication and ethics. Additionally, privacy concerns and the lack of standardization across platforms limit broader integration into dental education.

4.4. AI in Content Generation for the Dental Education

AI is increasingly used in dental education to generate case-based materials, automated questions, and structured content. Tools like natural language processing and machine learning support the creation of curricular resources and adaptive learning modules[32,33]. These tools enhance efficiency and accessibility, but challenges persist around validating content, meeting accreditation standards, and avoiding bias.

AI has been used to create structured learning materials like case studies and assessments, enhancing diagnostic training and self-directed learning [34]. AI-powered search tools also outperform general models in retrieving accurate, relevant dental education resources[33].

AI has been used to automate the creation of MCQs and interactive assessments, helping generate quizzes aligned with key learning objectives [34]. This reduces faculty workload while supporting adaptive student practice.

In the view of the scoping review authors, despite its efficiency, AI-generated content in dental education presents key challenges. It requires careful review for accuracy and relevance, as limited training datasets may introduce bias. Content must also align with accreditation standards and competency frameworks, while remaining engaging enough to promote meaningful student learning and participation.

The advancement of this field is hindered by the absence of a standardized definition of AI within dental research, coupled with a notable shortage of input from dentists with AI expertise in the development of relevant platforms. Addressing these challenges through clinician-led AI research and the formulation of clearer definitions will significantly enhance the quality and relevance of future studies, paving the way for a more effective incorporation of AI in dental education.

4.5. Limitations

This review followed a rigorous PRISMA-ScR methodology; however, some relevant studies may have been missed due to database restrictions or keyword limitations [15] Many included studies had methodological constraints such as small sample sizes, unvalidated instruments, and limited generalizability [18,19,31] Furthermore, a reliance on student self-reported data introduces potential bias due to recall or social desirability factors [30]. Few studies explored faculty or curriculum designer perspectives, revealing a gap in understanding institutional readiness for AI integration [20,21,28]. Some methodological limitations should be acknowledged. The review was not registered in a protocol registry, and although multiple databases were searched, the inclusion was limited to English-language publications, which may have excluded relevant non-English studies. Additionally, no formal critical appraisal tool was used, and data extraction and bias assessment were conducted manually, which may introduce subjective interpretation despite independent review by two authors.

5. Conclusions

AI holds significant potential to enhance dental education, particularly in preclinical assessments where students develop foundational clinical skills. Its integration can support real-time feedback, improve diagnostic training, and personalize learning. However, current research remains limited, especially in evaluating core tasks such as restorative cavity preparation. To ensure AI's relevance and reliability, future research should focus on developing clinically meaningful, real-time assessment tools led by dental educators. Clear definitions of AI, standardized classification frameworks, and robust ethical oversight are essential to support consistent evaluation and safe implementation. At the institutional and policy level, integration of validated AI systems should be accompanied by clear governance structures, while educators should ensure that AI complements rather than replaces human oversight and judgment in student learning.

Author Contributions: Dr. Mohammed El-Hakim, Prof Robert Anthonappa, and A/Prof Amr Fawzy made the following contributions to this article "Conceptualization, Mohammed El-Hakim; methodology, Mohammed El-Hakim.; investigation, Mohammed El-Hakim.; writing—original draft preparation, Mohammed El-Hakim.; writing—review and editing, Mohammed El-Hakim, Robert Anthonappa, and Amr Fawz.; Data curation, Mohammed El-Hakim.; supervision, Robert Anthonappa, and Amr Fawzy.; project administration, Mohammed El-Hakim. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement: All data generated or analyzed during this scoping review are publicly available and included within the published manuscript. This includes extracted study data, classification domains, and risk of bias assessments. No additional datasets or code were used or generated beyond what is presented in the review

Acknowledgments: This research was supported by an Australian Government Research Training Program (RTP) Scholarship.

Conflicts of Interest: "The authors declare no conflicts of interest."

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