

REVIEW ARTICLE

A Scoping Review of Multimodal Artificial Intelligence Integration in Dental Diagnostics and Treatment Planning: Foundations for the DAIS Model

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ABSTRACT

Background: Artificial intelligence (AI) has demonstrated remarkable potential across dental practice; however, applications remain predominantly fragmented into single-modality, specialty-specific tools. This fragmentation limits comprehensive diagnostic and treatment planning that reflects the inherently multimodal nature of clinical dentistry.

Objectives: Guided by the Population-Concept-Context (PCC) framework, this scoping review mapped current AI applications in dentistry to: (1) characterize the extent of multimodal data integration; (2) synthesize evidence on diagnostic accuracy across specialties; (3) identify the availability of clinical implementation and economic evaluation evidence; and (4) map research gaps to inform the development of integrated frameworks, using the proposed Dental-AI Synergy (DAIS) model as a potential exemplar.

Eligibility Criteria: Studies published from January 2018 to August 2026 focusing on AI, machine learning, or deep learning in clinical dentistry, prioritizing those incorporating multiple data modalities (imaging, structured clinical data, molecular/biomolecular data, or textual data).

Sources of Evidence: A systematic search was conducted across PubMed/MEDLINE, Scopus, Web of Science, Embase, IEEE Xplore, Cochrane Library, and CINAHL.

Charting Methods: Standardized data extraction, piloted on five studies, captured study characteristics, AI models, data modalities, performance metrics, and key findings. Data were synthesized qualitatively using thematic analysis.

Results: Of 1,825 records identified, 45 studies met inclusion criteria. The majority (76%) relied on single-modality approaches, predominantly imaging-based. Only 18 studies (40%) integrated two or more modalities. Convolutional neural networks were most common (22 studies). Diagnostic performance was high, with AUC values frequently exceeding 0.90. However, external validation was limited (18%), economic evaluations were sparse (3 studies), and implementation research was minimal.

Conclusions: While AI demonstrates substantial potential to enhance diagnostic accuracy, the field remains characterized by fragmentation and a limited evidence base for implementation. Identified gaps—limited multimodal integration, insufficient external validation, thin economic evidence, and scarce implementation research—provide clear rationale for developing unified, multimodal frameworks. The DAIS model is proposed as one such framework to guide future research and development.

Keywords: artificial intelligence; multimodal integration; dental diagnostics; treatment planning; scoping review

INTRODUCTION

Artificial intelligence has permeated nearly every facet of modern dental practice. In orthodontics, AI assists in predicting tooth movement and fabricating custom aligners (Olawade et al., 2025). In endodontics,

convolutional neural networks detect caries and periapical lesions with high precision (Bansal et al., 2025). In temporomandibular disorder diagnosis, transformer-based models classify subgroups using structured clinical data alone (Lee et al., 2026). In oral oncology, machine learning

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doi: <https://doi.org/10.67250/216ate41>

Received: 20/8/2026 Revised: 21/8/2026 Accepted: 24/8/2026

algorithms analyze the oral microbiome to predict cancer risk (Soghli et al., 2025). The proliferation of AI applications across dental specialties is undeniable and accelerating.

However, closer examination reveals a persistent pattern: these applications function as independent, siloed systems rather than components of an integrated framework. Orthodontists employ one AI platform, oral surgeons rely on another, and periodontists utilize a third; these systems do not communicate, nor does patient data flow seamlessly between them (Chong et al., 2025). As Chong and colleagues noted, AI integration faces challenges related to data privacy, algorithmic bias, and regulatory concerns. More fundamentally, however, the critical challenge lies not in the individual tools themselves, but in their pervasive fragmentation.

This fragmentation is particularly problematic because clinical dentistry is inherently multimodal. A clinician does not diagnose based on a single radiograph in isolation; rather, they synthesize information from imaging, patient history, clinical examination findings, genetic risk factors, and sometimes laboratory data. Current AI systems, by contrast, operate within narrow data boundaries, failing to mirror this integrative clinical reasoning.

Recognizing this gap, Chen and colleagues articulated the potential of multimodal large language models for synthesizing disparate data streams in oral health surveillance (Chen et al., 2026). Similarly, Al-Taezi and colleagues demonstrated that fusing imaging data with patient metadata improved risk classification performance in dental implant planning (Al-Taezi et al., 2026). These examples suggest that multimodal integration is not only feasible but may yield superior performance compared to single-modality approaches.

The proposed Dental-AI Synergy (DAIS) model represents a potential attempt to operationalize this vision: a singular framework that unifies imaging, clinical documentation, genomics, and microbiome data to deliver comprehensive, specialty-spanning diagnostic and treatment guidance. Before such a framework can be developed and validated, however, it is essential to systematically map the existing evidence base, identify current gaps, and establish the foundation upon which integrated approaches can be built.

Guided by the Population (human dental patients and practitioners), Concept (multimodal AI, machine learning, and deep learning applications in diagnosis, treatment planning, and risk assessment), and Context (all clinical dental specialties) framework, this scoping review

therefore aims to: (1) characterize the current landscape of AI applications in dentistry, with particular attention to the extent of multimodal integration; (2) synthesize evidence on diagnostic accuracy and clinical performance across specialties; (3) identify gaps in validation, implementation, and economic evaluation; and (4) map these gaps to inform the development of integrated frameworks such as the DAIS model.

METHODS

Protocol and Registration

This scoping review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines and the JBI Manual for Evidence Synthesis. A review protocol was developed a priori; however, it was not prospectively registered. The protocol is available upon request from the corresponding author. The completed PRISMA-ScR checklist is provided as a supplementary file.

Eligibility Criteria (PCC Framework)

Studies were considered eligible if they met all of the following inclusion criteria, structured according to the PCC framework:

- **Population:** Studies focusing on human subjects, patients, or dental practitioners in the context of oral and dental healthcare.
- **Concept:** Studies explicitly involving AI, machine learning, deep learning, or large language models in dentistry. For primary analysis, studies were required to integrate data from at least two distinct modalities: imaging (radiographs, CBCT, intraoral photographs, 3D scans); structured clinical data (electronic health records, demographics, clinical examination findings); molecular/biomolecular data (genetic markers, oral microbiome profiles, salivary biomarkers); or textual/unstructured data (clinical notes, natural language processing).
- **Context:** Applications directly related to clinical dentistry, including diagnosis, treatment planning, risk assessment, and preventive dentistry.

Study Design: Original research developing and evaluating new AI models; validation studies; systematic/scoping/umbrella reviews; economic evaluations; feasibility and implementation studies.

Timeline: January 1, 2018 to August 23, 2026.

Language: English.

Publication Type: Peer-reviewed journal articles.

Studies were excluded if they met any of the following: single-modality AI applications; exclusive focus on general medicine or non-dental conditions; conference abstracts, editorials, or protocols without results; purely theoretical papers without methodology or validation; pre-2018 publications; non-English articles; or lack of accessibility.

Information Sources and Search Strategy

The following electronic databases were searched: PubMed/MEDLINE, Scopus, Web of Science, Embase, IEEE Xplore, Cochrane Library, and CINAHL. The search was executed on August 23, 2026. Database coverage included PubMed (1946–present), Embase (1974–present), Scopus (2004–present), Web of Science (1900–present), IEEE Xplore (1988–present), Cochrane Library (1996–present), and CINAHL (1982–present).

The following search strategy was developed and applied to PubMed/MEDLINE (adapted for other databases):

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((("artificial intelligence"[MeSH Terms] OR "machine learning"[MeSH Terms] OR "deep learning"[MeSH Terms] OR "neural networks, computer"[MeSH Terms] OR "large language models"[Title/Abstract] OR "multimodal"[Title/Abstract] OR "AI"[Title/Abstract])) AND (("dentistry"[MeSH Terms] OR "oral medicine"[MeSH Terms] OR "orthodontics"[MeSH Terms] OR "endodontics"[MeSH Terms] OR "periodontics"[MeSH Terms] OR "oral surgery"[MeSH Terms] OR "dental"[Title/Abstract])) AND (("diagnosis"[MeSH Terms] OR "treatment planning"[MeSH Terms] OR "risk assessment"[MeSH Terms] OR "prognosis"[MeSH Terms])) AND ("2018/01/01"[Date - Publication] : "2026/08/23"[Date - Publication]))
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Additional search strategies included reference list screening of included studies and citation tracking using Google Scholar.

Selection Process and Data Charting

All identified records were imported into reference management software (EndNote), and duplicates were removed. Two reviewers (T.D. and E.M.) independently screened titles and abstracts against the eligibility criteria. Full texts of potentially eligible studies were retrieved and

assessed independently by the same two reviewers. Disagreements at any stage were resolved through discussion or consultation with a third reviewer (D.K.).

A standardized data extraction form was developed a priori and piloted on five randomly selected studies. The form was refined following the pilot. The following variables were extracted: author and year; country of origin; study design; dental specialty; AI model architecture; data modalities used (imaging, structured clinical, molecular, textual); performance metrics (AUC, accuracy, sensitivity, specificity, F1-score); validation approach (internal, cross-validation, external, prospective); economic outcomes (if applicable); and key findings. Data were extracted by one reviewer (T.D.) and verified for accuracy by a second reviewer (E.M.).

Synthesis of Results

Given the scoping nature of this review and the heterogeneity of study designs, a formal quantitative meta-analysis was not appropriate. In accordance with JBI methodological guidance, a formal risk-of-bias assessment of included studies was not conducted, as the primary aim was to map the existing evidence landscape and identify research gaps rather than to synthesize pooled effect estimates for clinical recommendations. Results were synthesized qualitatively using thematic analysis.

RESULTS

Study Selection

The database searches yielded 1,800 records. An additional 25 records were identified through reference list screening and citation tracking. After removing duplicates, 1,500 records were screened by title and abstract, of which 1,350 were excluded. Full-text articles were assessed for eligibility ($n = 150$), of which 105 were excluded, resulting in 45 studies included in the qualitative synthesis. A PRISMA flow diagram detailing the screening process is presented in Figure 1.

Records identified through database searching ($n = 1,800$) → Additional records identified through other sources ($n = 25$) → Records after duplicates removed ($n = 1,500$) → Records screened ($n = 1,500$) → Records excluded ($n = 1,350$) → Full-text articles assessed for eligibility ($n = 150$) → Full-text articles excluded ($n = 105$): Single-modality only ($n = 62$), Wrong study design ($n = 24$), Non-English ($n = 10$), Pre-2018 ($n = 6$), Other ($n = 3$) → Studies included in qualitative synthesis ($n = 45$)

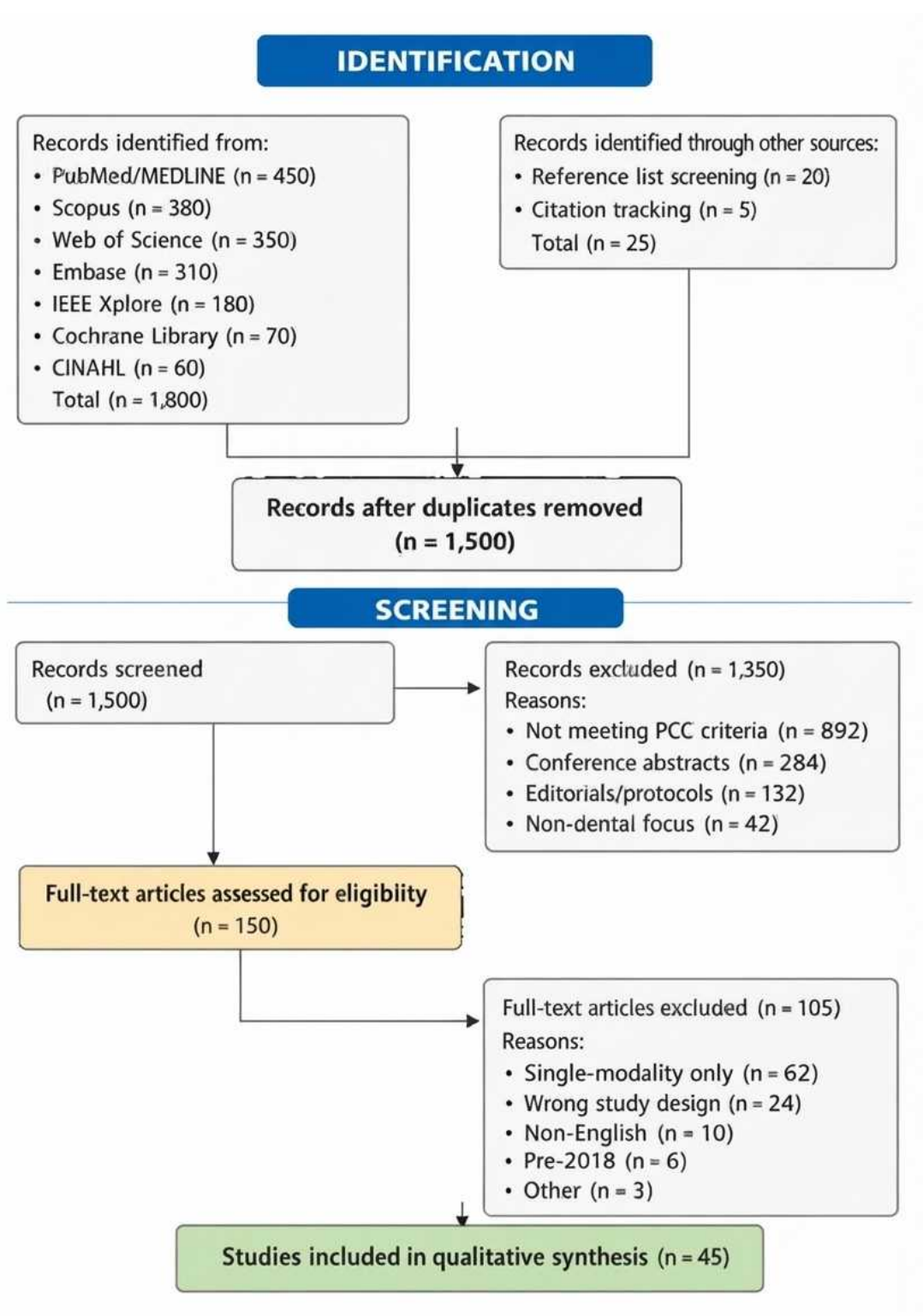


FIGURE 1: PRISMA 2020 flow diagram detailing the study selection process for this scoping review.

From: Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* 2021;372:n71.

Characteristics of Included Studies

The characteristics of the 45 included studies are summarized in **Table 1**. Studies were published between 2018 and 2026, with a clear increasing trend over time. Geographically, studies originated from Asia (n = 15), Europe (n = 14), North America (n = 8), the Middle East (n = 4), Africa (n = 2), and Australia/Oceania (n = 2).

By study design, original research developing and evaluating new AI models comprised the largest category (n = 18, 40%), followed by systematic/scoping/umbrella reviews (n = 12, 26.7%), narrative reviews (n = 6, 13.3%), economic evaluations (n = 3, 6.7%), bibliometric analyses (n = 2, 4.4%), feasibility/implementation studies (n = 2, 4.4%), and perspective/ethics articles (n = 2, 4.4%).

Across dental specialties, oral medicine/pathology/oncology had the most studies (n = 8), followed by orthodontics (n = 6), oral surgery/implantology (n = 6), general/multidisciplinary dentistry (n = 5), endodontics/conservative dentistry (n = 5), periodontics (n = 4), public health/surveillance (n = 4), TMD/orofacial pain (n = 2), forensic odontology (n = 2), and ethics/implementation (n = 3).

Convolutional neural networks were the most commonly employed AI architecture (n = 22 studies), followed by traditional machine learning methods (n = 10), tabular transformers (n = 8), and multimodal large language models (n = 5).

Multimodal Integration

A central finding is the limited extent of multimodal integration. As shown in **Table 2**, imaging data were the most frequently employed modality, appearing in 34 of 45 studies (76%). Structured clinical data were used in 20 studies (44%). Molecular or biomolecular data appeared in 9 studies (20%). Textual or unstructured data were used in 5 studies (11%).

Only 18 studies (40%) integrated two or more data modalities. The most common combination was imaging plus clinical data (n = 12). Imaging plus genetic or biomarker data appeared in 5 studies. Clinical data plus microbiome data appeared in 4 studies. Imaging plus clinical plus genetic/microbiome data (true multimodal integration) appeared in 6 studies. Clinical data plus textual data using NLP or LLMs appeared in 3 studies.

Table 1: Characteristics of Included Studies (n = 45)

Characteristic	Category	n	%
Study Design	Original Research (Model Development & Validation)	18	40.0
	Systematic/Scoping/Umbrella Reviews	12	26.7
	Narrative Reviews	6	13.3
	Economic Evaluations	3	6.7
	Bibliometric Analyses	2	4.4
	Feasibility/Implementation Studies	2	4.4
	Perspective/Ethics Articles	2	4.4
Dental Specialty	Oral Medicine/Pathology/Oncology	8	17.8
	Orthodontics	6	13.3
	Oral Surgery/Implantology	6	13.3
	General/Multidisciplinary	5	11.1
	Endodontics/Conservative Dentistry	5	11.1
	Periodontics	4	8.9
	Public Health/Surveillance	4	8.9
	TMD/Orofacial Pain	2	4.4
	Forensic Odontology	2	4.4
	Ethics/Implementation	3	6.7
AI Model Type	Convolutional Neural Networks (CNNs)	22	48.9
	Traditional ML (RF, SVM, XGBoost)	10	22.2
	Tabular Transformers	8	17.8
	Multimodal LLMs	5	11.1
Validation Approach	Internal Validation Only	22	48.9
	Cross-Validation	12	26.7
	External Validation	8	17.8
	Prospective/Clinical Validation	3	6.7

Table 2: Data Modality Integration Across Included Studies

Modality Combination	Number of Studies	Example Studies
Imaging Only	16	Olawade et al. (2025); Bansal et al. (2025)
Clinical Data Only	4	Lee et al. (2026); Sarbacher et al. (2025)
Microbiome Data Only	3	Soghli et al. (2025)
Imaging + Clinical Data	12	Al-Taezi et al. (2026); Chong et al. (2025)
Imaging + Genetic/Biomarker Data	5	Kadir et al. (2025)
Clinical Data + Microbiome Data	4	Yu et al. (2026)
Imaging + Clinical + Genetic/Microbiome	6	Chen et al. (2026)
Clinical Data + Textual Data (NLP/LLMs)	3	Yon et al. (2026)
Other Multimodal Combinations	5	Various
Total Multimodal Studies (≥2 modalities)	18	40.0%
Total Single-Modality Studies	27	60.0%

Table 3: Key Performance Metrics from Selected Studies

Study	AI Model	Task	Key Performance Metric	Value
Lee et al. (2026)	GATT (Tabular Transformer)	TMD Classification	AUC	0.815–1.000
Al-Taezi et al. (2026)	DentaRisk-Net (ResNet-18 + GFM + DML)	Implant Risk Assessment	Accuracy	>0.87
Mathur et al. (2026)	CNN	Implant Success Prediction	Accuracy	>90%
Sahoo et al. (2026)	U-Net	Caries Detection	Accuracy	0.80 (AI) vs. 0.71 (Dentists)

Among multimodal studies, Al-Taezi and colleagues' DentaRisk-Net framework stands out as a notable example. Their model combined CBCT images processed through ResNet-18 encoders with patient-specific metadata processed through a fully connected network, fused using a gated fusion mechanism. This multimodal approach achieved accuracy exceeding 0.87, with the gated fusion mechanism increasing F1-scores by 3-5% and R² by 5-8%.

Diagnostic Accuracy and Performance

Across studies reporting quantitative performance metrics, AI models demonstrated high diagnostic accuracy. **Table 3** presents key performance metrics from selected studies. Lee and colleagues' Gated Attention Tabular Transformer achieved AUC values ranging from 0.815 to 1.000 for TMD subgroup classification, significantly outperforming conventional machine learning methods. Mathur and colleagues' umbrella review found that convolutional neural networks achieved accuracy exceeding 90% for treating dental implants and predicting their success. Al-Taezi and colleagues' multimodal framework achieved

accuracy exceeding 0.87 in detecting risk in implant sites. Sahoo and colleagues' systematic review found that AI generally improved diagnostic performance, with one modeling study achieving higher accuracy than dentists (0.80 vs. 0.71) for caries detection.

Validation and Implementation

Internal validation on held-out test data was the most common approach (22 studies). Cross-validation was used in 12 studies. Only 8 studies (18%) reported external validation. Prospective or clinical validation was reported in only 3 studies.

Implementation research was notably sparse. Only 2 studies specifically examined feasibility and implementation in real-world clinical settings. McGrath and colleagues raised ethical considerations when using AI among vulnerable populations, including data privacy, algorithmic biases, and the digital divide. Yon and colleagues noted that standardized evaluation frameworks and assessment of patient comprehension are needed before routine clinical implementation.

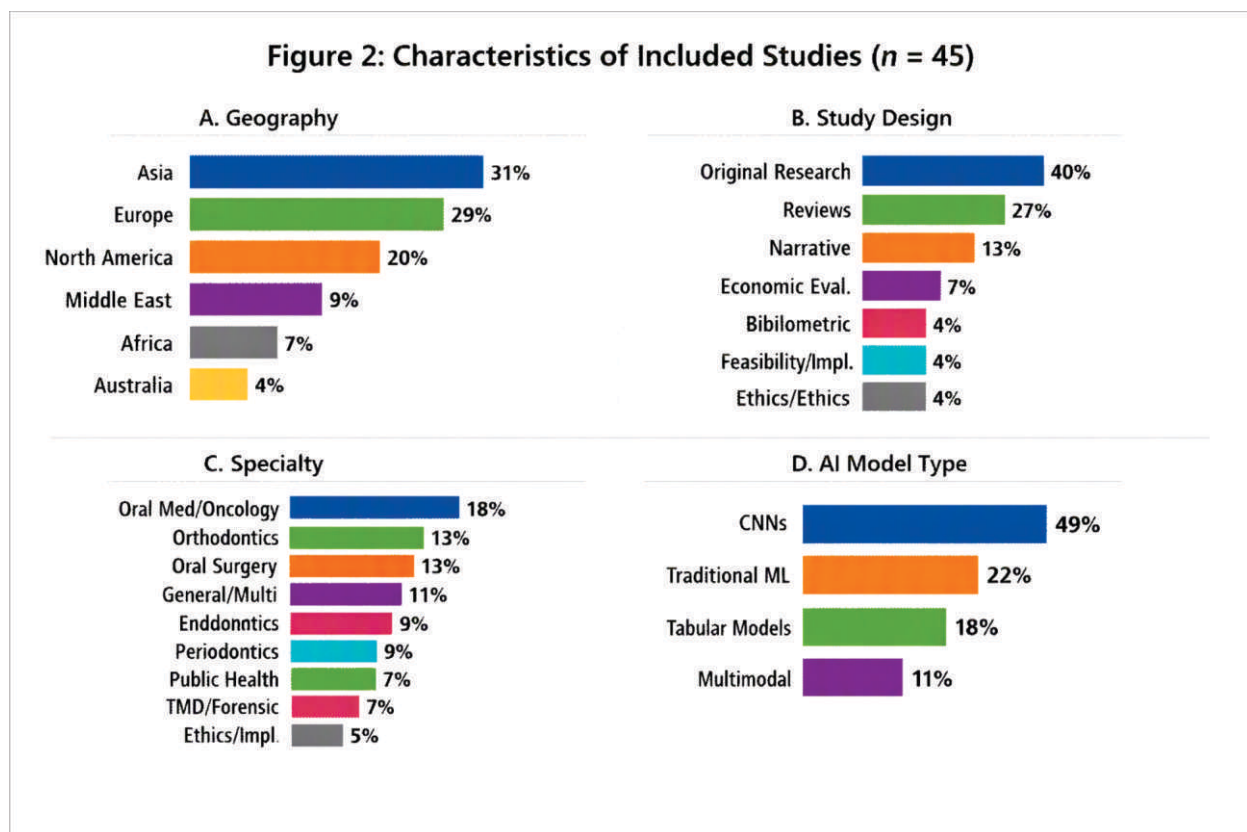


Figure 2: Characteristics of Included Studies

Economic Evaluation

Economic evidence was thin. Only 3 studies conducted economic evaluations of AI in dentistry, all in German dental care settings evaluating AI-assisted detection of caries. Three model-based evaluations reported lower costs and greater tooth-retention outcomes with AI than conventional assessment. However, one randomized trial found that AI-supported assessment increased sensitivity but was associated with more invasive treatment decisions, resulting in similar costs and identical mean tooth retention.

Thematic Synthesis

Theme 1: Single-Modality Dominance. The field is characterized by predominance of single-modality approaches, with imaging-based applications most common. This fragmentation across specialties represents a fundamental limitation that motivates the development of integrated frameworks.

Theme 2: Multimodal Promise. Where multimodal integration has been attempted, results suggest superior

performance. Al-Taezi and colleagues demonstrated fusing imaging with clinical metadata improved performance metrics.

Theme 3: Validation Gap. Limited external validation (18%) and near-absence of prospective clinical validation represent significant barriers to clinical translation.

Theme 4: Economic Uncertainty. The thin evidence base for cost-effectiveness (only 3 studies, all from a single country) makes it difficult for healthcare systems to make informed decisions about AI adoption.

Theme 5: Implementation Barriers. Ethical concerns, data privacy issues, algorithmic bias, and the digital divide represent significant barriers to equitable AI implementation.

DISCUSSION

This review reveals remarkable technological advancement across the field, but persistent fragmentation remains a defining challenge. While AI demonstrates substantial potential to enhance diagnostic accuracy across dental specialties with AUC values frequently exceeding

0.90, the overwhelming majority of applications remain single-modality, predominantly imaging-based. This stands in stark contrast to the inherently multimodal nature of clinical dental practice.

Where multimodal integration has been attempted, results are promising. Al-Taezi and colleagues' demonstration that fusing CBCT images with patient metadata improved classification performance, and Chen and colleagues' vision of multimodal large language models, suggest integrated approaches may yield superior outcomes. However, such studies remain the exception.

Significant gaps exist in validation, implementation, and economic evaluation. External validation is rare (18%), prospective clinical validation is nearly absent, economic evidence is limited to three studies from a single country, and implementation research is minimal. These gaps represent critical barriers to translating AI advances into routine clinical practice.

Comparison with Existing Literature

Our findings align with previous reviews. Chong and colleagues identified challenges related to data privacy, algorithmic bias, and regulatory concerns in healthcare AI integration. Our review adds that fragmentation represents a distinct and equally fundamental challenge. Chen and colleagues' emphasis on multimodal large language models receives empirical support while documenting the limited extent of multimodal integration achieved in practice. Yu and colleagues found that AI models in preventive dentistry were trained using structured, image, or molecular data, but rarely all three together, a pattern our review confirms across all dental specialties.

Implications for Integrated Frameworks

The identified gaps provide clear rationale for the development of integrated frameworks such as the proposed Dental-AI Synergy (DAIS) model. The DAIS framework directly addresses fragmentation by envisioning a unified system that integrates imaging, structured clinical data, genetic markers, and oral microbiome profiles. First, it confronts fragmentation by proposing a single integrated system rather than separate AI tools for separate specialties. Second, it moves beyond single-modality approaches by explicitly incorporating multiple data modalities, reflecting clinical reality. Third, it addresses the translation gap by building a framework designed for real-world clinical workflows from the start.

Fourth, it could include a dedicated economic evaluation component, addressing the thin economic evidence base identified in this review.

Limitations

Several limitations should be acknowledged. The restriction to English-language publications may have excluded relevant studies. The focus on peer-reviewed journal articles may have excluded important findings from conference proceedings. The heterogeneity of study designs precluded quantitative meta-analysis. As a scoping review, we did not conduct formal quality appraisal of included studies, which is consistent with JBI guidance but means that the strength of the evidence was not systematically assessed. Additionally, the rapidly evolving nature of AI research means new studies may have been published since the search. Finally, the inherent breadth of scoping reviews means that depth of analysis for any single research question may be limited.

Implications for Future Research

Several directions emerge. First, there is a pressing need for studies explicitly developing and evaluating multimodal AI systems. The DAIS model provides one potential framework for such efforts. Second, rigorous external validation across diverse populations and clinical settings is essential. Third, prospective clinical implementation studies are needed to assess real-world impact. Fourth, comprehensive economic evaluations across different healthcare systems are necessary. Fifth, standardized reporting guidelines for AI in dentistry would facilitate comparison across studies. Sixth, attention to ethical frameworks, data privacy, and algorithmic fairness is essential to ensure equitable implementation.

CONCLUSIONS

This scoping review reveals a field of remarkable promise and persistent fragmentation. Artificial intelligence has demonstrated substantial potential to enhance diagnostic accuracy, improve treatment planning, and optimize clinical workflows across dental specialties. Convolutional neural networks, transformer-based models, and emerging multimodal architectures achieve performance metrics that often exceed conventional methods. Yet the field remains characterized by siloed development. Most AI applications focus on single data modalities, predominantly imaging and operate within narrow

specialty boundaries. This fragmentation stands in stark contrast to the inherently multimodal, integrative nature of clinical dental practice. The limited extent of external validation, near-absence of prospective implementation research, and thin economic evidence base represent significant barriers to clinical translation. The proposed Dental-AI Synergy (DAIS) model addresses these gaps directly by envisioning a unified framework that integrates imaging, structured clinical data, genetic markers, and oral microbiome profiles. By moving beyond fragmentation toward integration, embracing multimodality, and incorporating rigorous validation and economic evaluation from the start, the DAIS model represents a potential paradigm shift in how AI can be developed and deployed in dentistry. The path forward requires interdisciplinary collaboration among dental clinicians, data scientists, bioinformaticians, ethicists, and health economists. It requires standardized protocols, diverse datasets, transparent algorithms, and rigorous ethical safeguards. Most fundamentally, it requires a shift in mindset from developing specialized AI tools for specific tasks toward building integrated AI systems that mirror the comprehensive, multimodal reasoning of expert clinicians.

The evidence synthesized in this review suggests such an approach is not only feasible but necessary. The future of AI in dentistry lies not in isolated applications but in integrated frameworks that can synthesize the full spectrum of patient data to deliver precise, personalized, and comprehensive care. The DAIS model provides one pathway toward that future.

REFERENCES

1. Al-Taezi, K. A., Liu, L., Al-Badwi, A., et al. (2026). A deep metric learning and multimodal gated fusion framework for AI-driven risk assessment of lingual plate perforation and mandibular canal injury in posterior mandible implants. *International Journal of Dentistry*, 2026, 5599213.
2. Bansal, R. K., Arya, A., Singh, B., et al. (2025). Role of artificial intelligence and machine learning in conservative dentistry and endodontics: A review. *Cureus*, 17(7), e88515.
3. Chen, Z., Liu, P., Han, K., et al. (2026). AI in oral health surveillance: Critical review. *Journal of Dental Research*, 105(7), 840-852.
4. Chong, P. L., Vaigheshwari, V., Mohammed Reyesudin, B. K., et al. (2025). Integrating artificial intelligence in healthcare: Applications, challenges, and future directions. *Future Science OA*, 11(1), 2527505.
5. Lee, Y.-H., Lee, J. H., Auh, Q.-S., et al. (2026). TMD diagnosis using a masked self-supervised tabular transformer. *Journal of Dental Research*, 105(6), 717-726.
6. Mathur, A., Mehta, V., Bhadania, M., & Patil, P. G. (2026). Artificial intelligence in dental implant identifications, planning accuracies, and success predictions: An umbrella review. *Journal of Prosthetic Dentistry*, 136(2), 412-421.
7. McGrath, C., Chau, C. W. R., & Molina, G. F. (2025). Monitoring oral health remotely: Ethical considerations when using AI among vulnerable populations. *Frontiers in Oral Health*, 6, 1587630.
8. Olawade, D. B., Leena, N., Egbon, E., et al. (2025). AI-driven advancements in orthodontics for precision and patient outcomes. *Dentistry Journal*, 13(5), 198.
9. Sahoo, R. K., Sinha, A., Satpathi, S., et al. (2026). Economic evaluation of AI-based oral disease screening: A systematic review. *Frontiers in Medical Technology*, 8, 1792401.
10. Soghli, N., Khormali, A., Mahboubi, D., et al. (2025). Recent advancements in artificial intelligence-powered cancer prediction from oral microbiome. *Periodontology 2000*, 98(1), 181-213.
11. Sarbacher, A., Gegout, P. Y., & Huck, O. (2025). Relevance of prognosis tools in periodontitis: A systematic review. *Oral Health & Preventive Dentistry*, 23, 759-772.
12. Yon, M., Ng, E., & Bornstein, M. M. (2026). Artificial intelligence applications in automated dental report generation: A scoping review. *Frontiers in Oral Health*, 7, 1817718.
13. Yu, O. Y., Zhang, J. S., Schwendicke, F., & Lam, W. Y.-H. (2026). The role and impact of artificial intelligence in preventive dentistry: A scoping review. *International Dental Journal*, 76(5), 109734.