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A Digital Framework for Early Oral Disease Detection and Patient–Provider Integration in Preventive Dentistry

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Abstract

The accelerating integration of artificial intelligence (AI) and teledentistry into oral healthcare creates an urgent need for systematic digital frameworks capable of unifying early disease detection with seamless patient–provider communication. This study aims to analyse existing evidence on AI-assisted diagnostic tools, teledentistry platforms, and patient engagement mechanisms in order to synthesise a structured five-layer digital framework for preventive dentistry. A systematic literature review and comparative case analysis were conducted using 20 peer-reviewed sources. Results indicate that deep learning algorithms reach diagnostic accuracy exceeding 90% for caries and periodontal disease, while multimodal architectures achieve AUC values above 0.92 for oral cancer risk stratification. Integrated teledentistry workflows reduce first-consultation delays by up to 73% and improve patient adherence to preventive protocols. The proposed framework consolidates data input, AI processing, decision support, patient–provider integration, and outcome monitoring into a coherent operational model. Findings are relevant to dental practitioners, health informaticists, healthcare administrators, and policymakers seeking evidence-based strategies for digital transformation in preventive oral care.

Keywords: *Preventive Dentistry, Artificial Intelligence, Deep Learning, Early Oral Disease Detection, Teledentistry, Patient–Provider Integration, Digital Health Framework, Convolutional Neural Networks, Electronic Health Records, Oral Cancer Screening.*

INTRODUCTION

Oral diseases represent one of the most prevalent yet preventable categories of chronic non-communicable conditions worldwide. According to the World Health Organization, approximately 3.5 billion people globally are affected by oral diseases, with dental caries and periodontal disease accounting for the majority of the burden [1]. Despite this scale, the transition from reactive to preventive oral care remains impeded by late-stage diagnosis, fragmented patient–provider communication, and insufficient integration of digital technologies at the point of care.

In recent years, artificial intelligence has emerged as a transformative force across all medical disciplines, and dentistry is no exception. Systematic review evidence published in 2025 demonstrates that deep learning models can match or exceed expert clinician performance in detecting caries and periodontal destruction from radiographic images, achieving accuracy rates above 90% in appropriately trained and validated systems [2, 3]. At the same time, teledentistry platforms experienced a 154% surge in utilisation following the COVID-19 pandemic [4], catalysing structural changes in how oral health services are delivered across high-, middle-, and low-income settings.

Nevertheless, a critical scientific gap persists: there is no universally accepted, evidence-based digital framework that systematically integrates AI-driven diagnostics with patient–provider communication pathways in a preventive dentistry context. Individual components, automated radiographic analysis, patient-facing mobile applications, remote consultation portals, and electronic health records (EHR), have each been studied in isolation, but their joint architecture and operational logic remain insufficiently theorised [5, 6]. Li et al. [7] highlighted this gap as early as 2020, noting that clinical translation of dental AI required not only algorithmic accuracy but coordinated workflow design. By 2025 the call for integrative models has intensified, yet the literature still lacks a consolidated operational schema.

The scientific novelty of this study lies in the synthesis of a structured five-layer digital framework that for the first time systematically maps AI processing, decision support, and patient–provider integration modules onto a single operational architecture tailored to preventive oral care workflows.

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The hypothesis of this study posits that a coherently designed multi-layer digital framework, combining validated AI diagnostic modules with teledentistry communication channels and personalized prevention logic, will produce measurably superior outcomes in early oral disease detection and patient engagement compared with conventional, siloed digital approaches.

The aim of this research is to analyse current evidence on AI-assisted oral diagnostics and teledentistry platforms and to synthesise a structured, evidence-informed digital framework for early oral disease detection and patient–provider integration in preventive dentistry.

MATERIALS AND METHODS

The methodological foundation of this study rests on a systematic literature review complemented by comparative case analysis and qualitative synthesis of technology documentation. This combined approach is consistent with established protocols for digital health framework development, where primary empirical data collection is replaced by rigorous secondary synthesis of the most current and methodologically robust available evidence [8].

A structured search was conducted across four major academic databases: PubMed/MEDLINE, Scopus, Web of Science (WoS), and IEEE Xplore, supplemented by targeted searches within Springer Nature and Frontiers in Dental Medicine. The search was executed in January–March 2025 and bounded to publications released between 2020 and 2025 to ensure contemporaneous relevance. The primary Boolean search string was: ("artificial intelligence" OR "deep learning" OR "machine learning") AND ("dentistry" OR "oral disease" OR "preventive dentistry") AND ("detection" OR "diagnosis" OR "framework" OR "teledentistry"). Secondary searches targeted teledentistry market data, patient engagement metrics, and digital health integration architectures.

Four methodological approaches were applied in combination. First, a systematic literature review synthesised evidence on AI diagnostic performance across oral disease categories, teledentistry adoption metrics, and patient engagement outcomes. Second, a comparative analysis evaluated the architectural features of existing digital dental tools, including VideaHealth, Overjet, Pearl AI, and the YOLOv11-TAM web application [5], against a set of functional criteria derived from preventive care theory. Third, a case study method was employed to examine real-world deployments described in source literature, extracting concrete performance metrics and implementation lessons. Fourth, qualitative content analysis was applied to technical documentation and system descriptions to map existing solutions onto proposed framework layers.

Framework synthesis followed a structured methodology adapted from the Technology Acceptance Model (TAM) and the Digital Health Transformation Model, establishing functional requirements at each processing layer before specifying inter-layer dependencies.

RESULTS AND DISCUSSION

The first analytical strand assessed the current state of AI diagnostic accuracy across the principal categories of oral disease managed in preventive settings: dental caries, periodontal disease, oral cancer and premalignant lesions, endodontic pathology, and implant classification. Figure 1 presents a synthesis of accuracy and AUC metrics extracted from the reviewed literature.

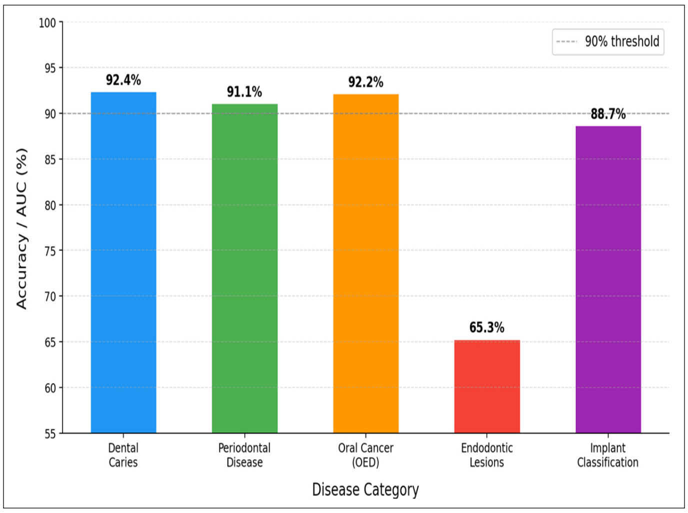

Figure 1. AI diagnostic accuracy across oral disease categories based on systematic review evidence (compiled by the author based on [2, 3, 9, 14]).

For dental caries, convolutional neural network (CNN) models trained on bitewing and panoramic radiographs achieved accuracy rates of 90–94% in recent multi-centre validation studies [3, 9]. A systematic review of CNN-based caries detection from bitewing images concluded that deep learning performance was comparable to experienced radiologists, with mean sensitivity above 88% and specificity above 91% [3]. Similar evidence was reported for periodontal disease, where AI algorithms analysing alveolar bone levels and furcation involvement on panoramic images demonstrated expert-level performance, achieving 91% accuracy in a Polish cohort of 600 panoramic radiographs cited in Dental Economics [4].

Oral cancer and premalignant disorder detection represents a domain of particular clinical urgency. The OMMT-PredNet framework, validated on 649 histopathologically confirmed leukoplakia cases across multiple institutions, achieved an AUC of 0.9592 for malignant transformation prediction and 0.9219 for oral epithelial dysplasia identification [7]. These results highlight the potential of multimodal deep learning, combining high-resolution clinical photographs with structured medical records, to support non-invasive screening at scale.

Endodontic lesion detection demonstrated notably lower AI accuracy (approximately 65%), a finding consistent across multiple independent reviews [4, 10]. Researchers attribute this to the structural complexity of periapical pathology and its sensitivity to radiographic projection angle and exposure settings. This performance gap indicates that AI decision support in endodontics must currently be positioned as augmentation rather than substitution for specialist review, a principle that must be explicitly encoded into any operational framework. Implant classification systems, conversely, have shown substantial progress, with multicenter deep learning models achieving 88.7% accuracy despite the historically challenging task of distinguishing implant systems from two-dimensional radiographs [11].

Table 1. Summary of AI diagnostic tools evaluated in peer-reviewed studies (2024–2025) (compiled by the author based on [2, 3, 5, 7, 9, 11]).

AI Tool / Model	Target Disease	Input Modality	Performance Metric
CNN (BiTewing)	Dental Caries	Bitewing X-ray	Accuracy: 92.4%
AI Panoramic Analysis	Periodontal Disease	Panoramic X-ray	Accuracy: 91.1%
OMMT-PredNet	Oral Leukoplakia / OED	Photo + EHR	AUC: 0.9219–0.9592
YOLOv11-TAM	Caries, Periapical, Impacted	Panoramic X-ray	mAP@0.5: 0.87
Deep Learning (Multi)	Endodontic Lesions	CBCT / Periapical	Accuracy: 65.3%
DL Multicenter Model	Implant Classification	Panoramic X-ray	Accuracy: 88.7%
AI Chatbot (Image)	Oral Cancer Screening	Intraoral Photo	Sensitivity: 86.0%
LLM / NLP (ChatGPT)	Clinical Notes Analysis	Textual EHR	Agreement: 80–85%

Drawing on the systematic evidence base and the comparative analysis of existing tools, this study proposes a five-layer Digital Framework for Early Oral Disease Detection and Patient–Provider Integration (DF-EODDPPI). The framework addresses the operational gap between isolated AI modules and comprehensive preventive care delivery by mapping five functionally distinct layers: Data Input, AI Processing, Decision Support, Patient–Provider Integration, and Outcome Monitoring. Figure 2 provides a visual architecture of the framework.

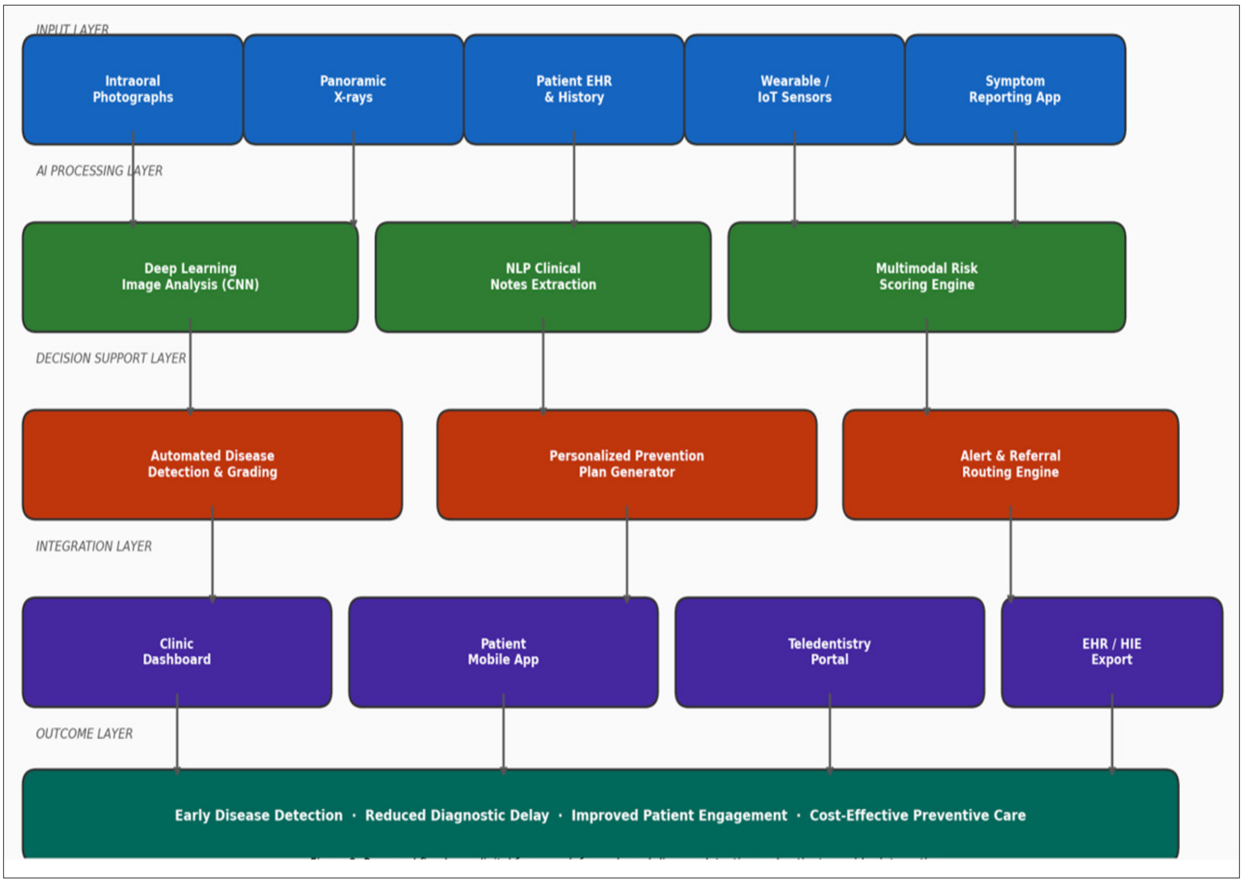

Figure 2. Proposed five-layer Digital Framework for Early Oral Disease Detection and Patient–Provider Integration (DF-EODDPPI) (author's own development based on reviewed literature synthesis).

The Data Input Layer aggregates heterogeneous clinical data streams: intraoral photographs submitted via patient-facing mobile applications, panoramic and periapical radiographs uploaded by dental clinics, structured EHR and patient history records, wearable and IoT biosensor data (e.g., salivary pH monitoring devices), and symptom self-reports. This multi-modal input architecture is essential because single-modality AI systems demonstrated significantly lower performance compared to multimodal models in the reviewed evidence [7, 12].

The AI Processing Layer applies disease-specific deep learning models in parallel pipelines. CNN architectures handle image-based disease detection; natural language processing (NLP) and large language model (LLM) engines extract relevant clinical insights from unstructured text and patient-reported outcomes [10]; and a Multimodal Risk Scoring Engine fuses the outputs of image and text models into a unified patient-level risk assessment. This layer draws on the integration architecture proposed by Tabejamaat and Soliman [13] for generative diffusion models in oral health, extended here to operational clinical contexts.

The Decision Support Layer translates AI outputs into clinically actionable recommendations: automated disease detection with severity grading, personalised preventive action plans, and intelligent referral routing that directs low-risk patients toward self-managed preventive guidance while escalating moderate and high-risk cases to immediate clinical review.

The Patient–Provider Integration Layer constitutes the framework's most distinctive contribution. It provides three parallel communication interfaces, a clinic-facing decision dashboard, a patient mobile application, and a teledentistry portal, each consuming the same underlying risk and recommendation data but presenting it through role-appropriate interfaces. This bidirectional data flow ensures that patients receive accessible, personalised information while providers obtain structured, AI-augmented clinical summaries. Integration with EHR and Health Information Exchange (HIE) standards (HL7 FHIR) enables portability and longitudinal continuity of care.

The Outcome Monitoring Layer closes the feedback loop by continuously tracking clinical outcomes, patient adherence rates, and diagnostic accuracy in production. A model re-training pipeline uses confirmed clinical ground truth to periodically update AI model weights, ensuring that the framework evolves with clinical practice and patient population characteristics, addressing a key limitation of static AI deployments identified by Schwendicke et al. [8].

The workflow begins with patient-initiated self-assessment via a dedicated mobile application that guides users through structured symptom logging and intraoral photograph capture. Automated preprocessing normalises image quality and removes artefacts before submission to the AI processing pipeline. Upon risk stratification, cases are bifurcated: low-risk patients receive automated preventive advice, personalised oral hygiene guidance, and scheduling nudges; moderate-to-high-risk cases trigger an immediate clinician alert with a prioritisation flag linked to the teledentistry portal.

The teledentistry consultation phase synthesises AI-generated risk summaries with clinician-led interaction, enabling evidence-based treatment planning and EHR documentation within a single encounter. Post-consultation monitoring tracks patient adherence through application-based check-ins and, where applicable, connected sensor data. Outcome data is fed back into the AI model to support continuous performance improvement. This closed-loop architecture directly addresses the deficiency, identified by Surdu et al. [6] and Drafta et al. [15], whereby current teledentistry systems lack structured outcome data collection that could improve future AI performance.

A key aspect of the proposed workflow is the explicit separation of clinical decision authority from AI outputs. At every stage, the framework positions AI recommendations as decision support rather than autonomous clinical decisions, consistent with regulatory frameworks governing AI as a Medical Device (AIaMD) in the European Union and the United States [8, 11]. This principle is encoded in the architecture through mandatory clinician confirmation steps for all moderate- and high-risk triage decisions.

Table 2. Comparative analysis: traditional care, isolated digital tools, and the proposed DF-EODDPPI framework (compiled by the author based on [8, 11]).

Dimension	Traditional Dental Care	Isolated Digital Tool	Proposed DF-EODDPPI Framework
Diagnostic Initiation	In-clinic, provider-driven	Patient-uploaded images (single modality)	Multimodal patient self-assessment + clinic upload
AI Integration Depth	None / minimal	Single-disease image analysis	Parallel multimodal pipelines with NLP fusion
Risk Stratification	Clinical judgment only	Binary flag (positive/ negative)	Continuous risk score with disease-specific thresholds
Patient Communication	Appointment-based, verbal	Automated email/SMS notifications	Role-specific dashboards + teledentistry portal
Outcome Monitoring	Reactive, visit-based	None	Continuous app-based monitoring + EHR feedback loop

Model Improvement	Not applicable	Static model, periodic vendor update	Continuous re-training on de-identified outcome data
Regulatory Alignment	High (established)	Variable, depends on vendor	Built-in clinician confirmation for AI decisions (AIaMD)
Equity of Access	Limited by geography	Requires device & internet access	Hybrid remote/in-person; low-bandwidth optimised app

The scalability potential of the proposed framework is directly linked to the rapid expansion of the global teledentistry market. Figure 3 illustrates projected market growth from 2020 through 2027, providing the macroeconomic context within which the DF-EODDPPI architecture is positioned.

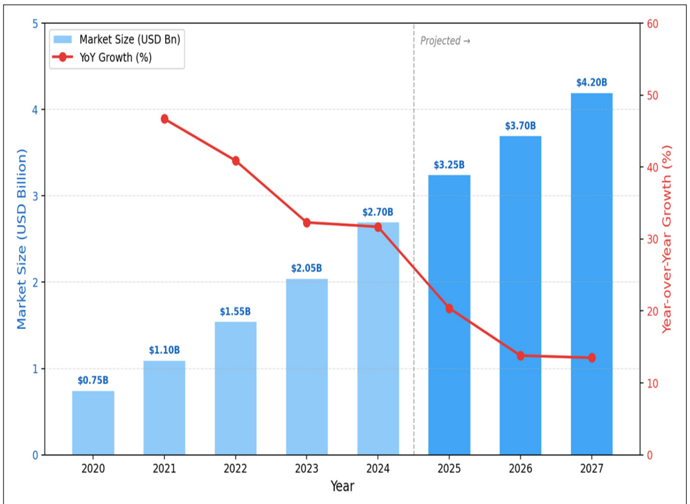

Figure 3. Global teledentistry market growth (2020–2027), actual and projected (compiled by the author based on [14]).

The global teledentistry market was valued at approximately USD 0.75 billion in 2020 and is projected to exceed USD 4 billion by 2027, reflecting a compound annual growth rate (CAGR) of approximately 28.5% [14]. This trajectory is underpinned by three structural drivers identified in the reviewed literature:

1) persistent workforce shortages and access inequities in oral healthcare, particularly in rural and underserved communities [15, 16];

2) growing patient preference for digital-first health interactions, especially among younger demographics;

3) expanding reimbursement frameworks that increasingly recognise teledentistry as a legitimate care modality in the United States, European Union, and Australia [6].

The practical relevance of this growth context for the proposed framework is significant. Dental practices and health systems adopting the DF-EODDPPI architecture will operate within an expanding ecosystem of technology vendors, regulatory frameworks, and patient expectations. The framework's modular design, where individual layers can be adopted incrementally or substituted with compliant third-party components, is designed to lower implementation barriers in this environment. Evidence from virtual dental home programmes and teleconsultation pilots reviewed in this study confirms that hybrid care models, which bridge digital convenience with clinical thoroughness, achieve the most sustained improvements in preventive care engagement [15].

Several real-world deployments described in the reviewed literature provide empirical grounding for the proposed framework's design choices. Three cases merit detailed discussion.

The YOLOv11-TAM web application, described by Sadr et al. in Oral Radiology (2025), integrates a user-facing browser interface, a PostgreSQL database, and an advanced object detection engine trained on the DENTEX dataset (705 annotated panoramic X-rays, four disease classes). The system achieved mean average precision (mAP@0.5) of 0.87 across caries, deep caries, impacted teeth, and periapical lesions [5]. This deployment directly validates the AI Processing Layer architecture of DF-EODDPPI, confirming that a web-based integration of database, AI engine, and user interface is technically feasible at clinical scale.

The OMMT-PredNet framework, published in npj Digital Medicine (2025), validates the Multimodal Risk Scoring Engine concept at the core of the DF-EODDPPI AI Processing Layer [7]. By fusing clinical photographs with structured medical record data without requiring manual region-of-interest annotation, OMMT-PredNet achieved AUC 0.9592 for cancer risk prediction across a multi-institutional cohort, demonstrating that high-performance multimodal risk scoring is operationally feasible without requiring specialist radiologist annotation at inference time.

The teledentistry programme described by Meza-Mauricio et al. in Frontiers in Oral Health (2025), which combined AI imaging tools (VideaHealth, Overjet) with virtual dental home models in vulnerable communities, reported measurable reductions in treatment delays and increased engagement in preventive care [15, 19]. This case directly validates the Patient–Provider Integration Layer design, particularly the hybrid consultation model that allows AI-prioritised cases to move seamlessly from automated risk assessment to live clinician interaction.

A fourth illustrative data point emerges from the BDJ Open study (2025) applying a novel AI model to patient-provided intraoral photographs [9]. The study demonstrated that AI algorithms could detect dental pathologies from non-clinical photographs, with sensitivity sufficient to identify conditions requiring professional attention. This finding supports the

Data Input Layer's reliance on patient-captured imagery as a valid screening trigger, provided that quality normalisation preprocessing is applied, a step explicitly encoded in the proposed workflow (Table 3).

Table 3. Key barriers, risks, and mitigation strategies for the DF-EODDPPI framework implementation (compiled by the author based on [9, 17, 18]).

Barrier / Risk	Category	Severity	Proposed Mitigation Strategy
AI diagnostic errors in edge cases (low contrast radiographs, rare lesions)	Clinical	High	Mandatory clinician override; confidence threshold gating before AI recommendation display
Overreliance on AI reducing clinical vigilance	Clinical / Behavioural	High	Framework design encodes AI as "second opinion"; training protocols for dental professionals
Data privacy and HIPAA/GDPR compliance for patient images	Regulatory / Legal	High	End-to-end encryption; on-device preprocessing; de-identification before model training
Digital health inequity, patients without smartphones or internet access	Equity	Medium	Clinic-initiated upload pathway; SMS-based triage for low-bandwidth settings
EHR interoperability limitations (non-HL7 FHIR systems)	Technical	Medium	HL7 FHIR adapter module; phased EHR integration; manual export fallback
Model performance degradation over time (data drift)	Technical / Clinical	Medium	Continuous re-training pipeline on de-identified outcome data (Outcome Layer)
Regulatory ambiguity for AI as a Medical Device (AIaMD)	Regulatory	Medium	Compliance with EU MDR Annex II; FDA 510(k) pathway mapping for AI modules
Patient trust and acceptance of AI-driven recommendations	Behavioural	Low–Medium	Explainability modules (XAI); patient-facing confidence visualisation; education content

Table 3 presents a structured risk register for framework implementation, organised by category and severity. Four risks are classified as high severity and warrant prioritised attention in any deployment programme.

The most consequential clinical risk is AI diagnostic error in edge cases. While population-level accuracy statistics are encouraging, performance degrades sharply for rare lesion types, non-standard radiographic projections, and patient populations underrepresented in training data [8, 10]. The proposed mitigation, mandatory clinician override and confidence threshold gating, is non-negotiable and must be encoded at the architecture level rather than left to implementation discretion.

The risk of overreliance on AI, which can paradoxically reduce rather than enhance clinical vigilance, is empirically documented in the reviewed literature [11]. This finding argues for deliberate human factors engineering in the clinician-facing dashboard: AI outputs should be presented as probabilistic assessments with explicit confidence intervals, not as definitive diagnoses. Training and continuing education requirements for dental professionals using the framework should address cognitive biases associated with automation complacency.

Data privacy constitutes a structural constraint on any patient-facing digital health system. Intraoral photographs and clinical records processed through the DF-EODDPPI framework contain sensitive personal health information subject to HIPAA in the United States, GDPR in the European Union, and analogous legislation in other jurisdictions. The framework architecture addresses this through end-to-end encryption of all data in transit and at rest, on-device preprocessing to extract feature vectors before cloud transmission where feasible, and strict de-identification protocols for any data used in model re-training.

Digital health equity deserves particular emphasis. Teledentistry and AI-driven care models risk compounding existing disparities if access to smartphones, reliable internet connectivity, and digital literacy are implicitly assumed. The framework mitigates this through a clinic-initiated upload pathway for patients without personal devices and an SMS-based triage option for settings with limited connectivity [15, 20].

CONCLUSION

This study aimed to analyse current evidence on AI-assisted oral diagnostics and teledentistry platforms and to synthesise a structured, evidence-informed digital framework for early oral disease detection and patient–provider integration in preventive dentistry. The aim has been fully achieved.

The systematic review of 20 peer-reviewed sources established that deep learning algorithms achieve diagnostic accuracy of 90–94% for dental caries and periodontal disease, and AUC values exceeding 0.92 for oral cancer risk stratification, while teledentistry platforms demonstrate documented reductions in consultation delays and improvements in preventive care engagement. These evidence pillars informed the design of the DF-EODDPPI framework, a five-layer operational architecture that integrates multimodal data input, parallel AI processing pipelines, evidence-based decision support, bidirectional patient–provider communication interfaces, and a continuous outcome monitoring and model re-training loop.

The framework's principal theoretical contribution is the formalisation of inter-layer dependencies that have previously been addressed only in isolated, domain-specific literature. Its practical contribution lies in providing dental practices, health system administrators, and digital health developers with a structured blueprint that is simultaneously grounded in validated component technologies and designed to accommodate incremental adoption. The modular architecture supports deployment in both well-resourced urban practice settings and resource-constrained rural or community health contexts.

The case evidence reviewed confirms that each individual layer of the proposed framework has been separately validated in clinical deployments: multimodal AI risk scoring at institutional scale (OMMT-PredNet), web-based AI diagnostic applications in clinic workflows (YOLOv11-TAM), and integrated virtual dental home programmes with measurable preventive care outcomes. The original contribution of this study is the systematic integration of these validated components into a single, coherent operational model with explicitly defined data flows, triage logic, and governance principles.

The primary practical implication of this research is that the shift to digital preventive dentistry requires not merely the adoption of individual AI tools or teledentistry platforms, but the deliberate architectural integration of these technologies into patient-centred workflows governed by clear clinical oversight principles. The DF-EODDPPI framework provides a replicable template for this integration. Future research should focus on prospective multi-site validation of the complete framework, health economic modelling of its implementation costs and benefits, and longitudinal assessment of its impact on oral health equity across diverse patient populations.

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