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AI-Driven Patient Engagement Ecosystems: Advancing Predictive Analytics and Personalised Care Through Multimodal Dental Data

Usman Tariq*
CEO and Co-Founder at Dental Assist Ai, USA

ABSTRACT

Fragmented dental information flows hinder the early detection of oral diseases and limit the personalisation of care, despite rapid progress in artificial intelligence and telehealth. The article outlines an AI-driven patient engagement ecosystem, grounded in multimodal dental data, that integrates imaging, electronic health records, demographic information, and patient-generated data from mobile and teledentistry channels. The aim is to align multimodal predictive analytics with continuous, personalised engagement at both individual and population levels. The study relies on an analytical synthesis of recent work on dental AI, public health–oriented predictive models, teledentistry platforms, and multimodal machine learning architectures. Dental AI Engagement Ecosystem (DAIE) connects curated dental datasets and fusion models with patient-facing services, including remote triage, conversational agents, risk-based recalls, and tailored behavioural support. Special attention is paid to vulnerable populations, the governance of data flows, and the explainability of predictions across clinical and home settings. The framework provides methodological and practical guidance for clinicians, health system managers, and digital health developers designing AI-ready dental care pathways.

Keywords: artificial intelligence, dentistry, multimodal data, patient engagement, teledentistry

1. INTRODUCTION

Oral diseases account for a substantial share of preventable health loss worldwide and often progress silently until advanced stages. At the same time, dental data remain highly fragmented across radiology systems, practice management software, public health registries, and emerging mobile applications. Discontinuity of information flows weakens risk stratification, complicates monitoring of long-term treatment outcomes and limits the use of behavioural insights for sustaining oral-health habits over time.

Artificial intelligence has produced convincing results in radiographic interpretation, automated documentation, and predictive planning in dentistry; however, these achievements are typically confined to single tasks or data streams. Without the explicit integration of multimodal datasets with patient-facing services, predictive models remain detached from everyday decision-making by patients, dentists, and public health planners. Teleconsultations, remote diagnostics, and conversational agents are already reshaping access to care, but their connection with structured predictive analytics and longitudinal oral health data remains poorly formalised.

The article aims to conceptualise an AI-driven patient engagement ecosystem in dentistry that integrates multimodal data, predictive models, and digital interaction channels across the entire care continuum. The first task consists of synthesising the current directions of AI development in dental clinical practice, dental public health, and teledentistry, with an emphasis on patient-centred applications. The second task focuses on generalising the structure of contemporary multimodal dental datasets and multimodal machine-learning pipelines

*Email: usman@dentalassist.ai

relevant for risk prediction and treatment personalisation. The third task formulates a system-level model that links these data and analytics capabilities to concrete engagement mechanisms for individual patients and population-level programs.

The novelty of this study lies in the Dental AI Engagement Ecosystem (DAIE), an original conceptual framework proposed by the author. Unlike prior studies that evaluate isolated AI applications in dentistry, DAIE connects multimodal predictive analytics, patient engagement channels, teledentistry workflows, and continuous learning mechanisms into a unified operational framework. The primary contribution of this study is the development of a unified conceptual architecture that integrates multimodal dental data, predictive analytics, conversational AI, teledentistry, and patient engagement mechanisms into a single continuously learning ecosystem.

To clarify the distinctive contributions of this study, the work:

• Introduces the Dental AI Engagement Ecosystem (DAIE) as the author's original conceptual model for linking multimodal dental datasets with clinical, telehealth, and home-care workflows.

• Synthesises recent literature on dental artificial intelligence, predictive public-health models, teledentistry, and conversational AI into a unified operational architecture centred on patient engagement.

• Defines a layered structure for DAIE, connecting data acquisition, multimodal fusion, prediction, patient-facing engagement, and governance mechanisms.

• Characterizes emerging multimodal dental imaging datasets from the viewpoint of continuous learning, patient-specific forecasting, and dental digital-twin construction.

• Describes deployment-oriented design principles for explainable, governance-aware, and interoperable implementation in dental clinics, teledentistry platforms, and public health programs.

2. MATERIALS AND METHODS

The article presents a narrative review based on a structured search and selection procedure. Electronic searches were performed in PubMed, Web of Science, Scopus, IEEE Xplore, and Google Scholar up to December 2025. Search strings combined dentistry and oral-health terms ("dentistry", "dental", "oral health", "caries", "periodontal", "implant"), artificial intelligence and prediction terms ("artificial intelligence", "machine learning", "deep learning", "predictive", "risk model", "forecast*", "decision support"), multimodal and fusion terms ("multimodal", "data fusion", "multisource", "multimodal learning", "transformer*"), and patient-facing or remote-care terms ("patient engagement", "teledentistry", "telehealth", "remote triage", "mobile health", "chatbot", "conversational agent", "EHR", "electronic health record", "CBCT", "panoramic", "periapical"). Reference lists of eligible papers and recent reviews were screened to capture additional records.

Studies were eligible when they: (1) addressed dentistry or oral-health services; (2) used or explicitly modelled multimodal inputs (imaging combined with structured records, demographics, text, behavioural logs, mobile or telehealth streams); (3) reported predictive analytics, risk stratification, or decision support intended for care planning, recall scheduling, triage, or prevention targeting; (4) linked analytics to patient engagement workflows (remote triage, personalised recalls, reminders, coaching modules, chatbots, teledentistry platforms, home monitoring); (5) were peer-reviewed original articles, dataset or benchmark papers, validation studies, implementation/pilot reports, or systematic reviews/meta-analyses; and (6) were published in English between 2020 and 2025. Editorials and narrative opinions without extractable methods, single-case reports without quantitative outcomes, studies confined to one modality without integration, and papers without a patient-facing or workflow linkage were excluded.

After duplicate removal, titles and abstracts were screened against the criteria above. Full texts were then evaluated for alignment with the review aim of connecting multimodal dental data, predictive modelling, and engagement channels (teledentistry, mobile applications, conversational agents, risk-based recalls, and remote triage). The final evidence base comprised 32 peer-reviewed sources covering multimodal dental datasets, fusion architectures, risk prediction use cases, and deployment pathways for engagement-oriented digital dental care.

The database search returned a total of 612 records (PubMed: n = 160, Web of Science: n = 120, Scopus: n = 140, IEEE Xplore: n = 62, Google Scholar: n = 130). After removal of 188 duplicates, 424 titles and abstracts underwent screening. Screening excluded 356 records for irrelevance to dentistry, absence of multimodal integration, or non-research formats. Sixty-eight full-text reports were assessed for eligibility. Thirty-six full texts were excluded for the following reasons: single-modality designs without fusion (n = 12), no explicit engagement or workflow pathway (n = 10), descriptive AI reports lacking predictive or decision-support outcomes (n = 7), insufficient methodological detail or non-extractable results (n = 7). The remaining 32 studies formed the final evidence base. The identification and selection pathway is summarised in a PRISMA 2020 flow diagram (Fig. 1).

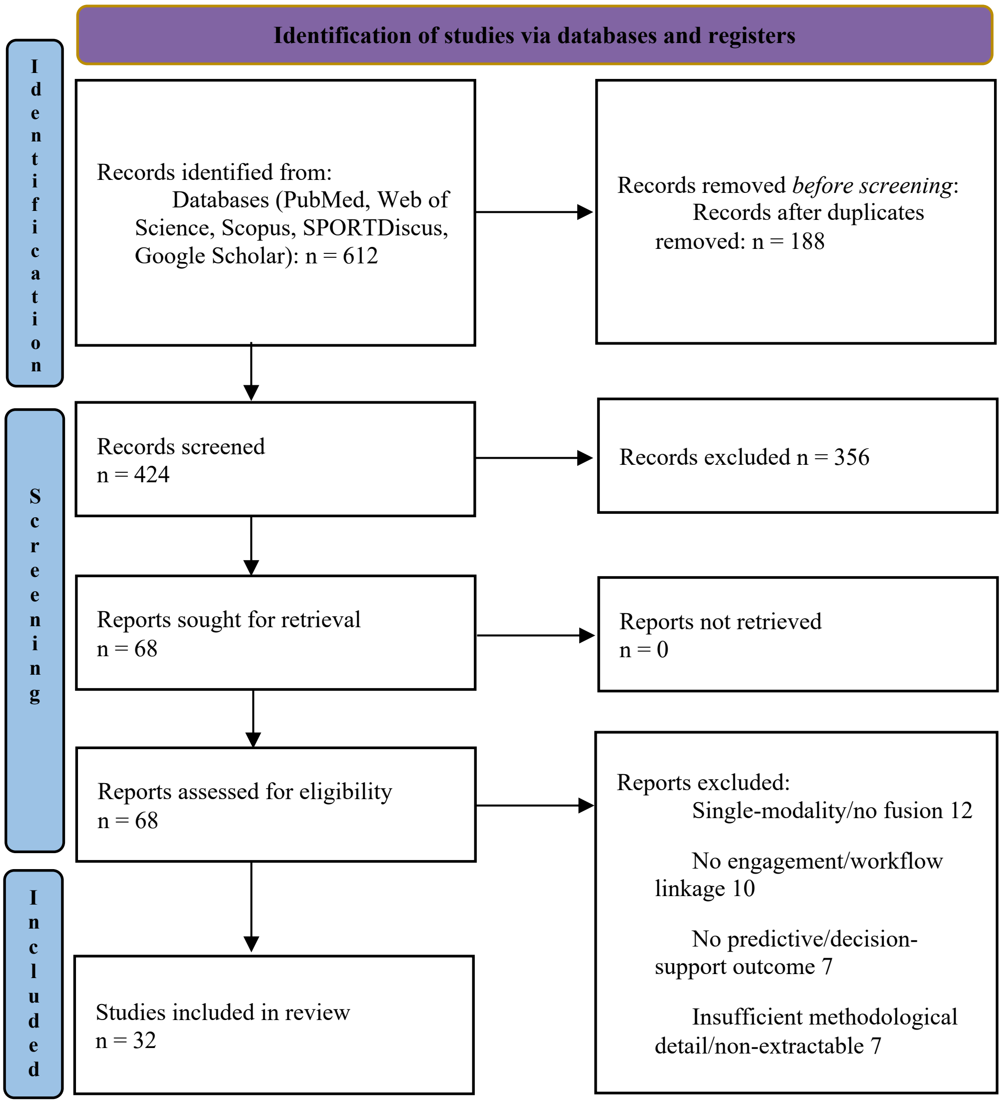

Figure 1. Flow of study identification, screening, eligibility assessment and inclusion (adapted from PRISMA 2020).

From each included study, the following information was extracted: publication type and design; clinical or public-health setting; population and data origin; modalities and data structure (imaging, structured records, demographics, text, behavioural or remote streams); prediction targets and time horizon; modelling approach and fusion strategy; validation scheme and reported metrics; delivery channel (teleconsultation, mobile app, chatbot, dashboards, recall systems); and governance elements (privacy, consent handling, interpretability, bias/equity considerations).

Methodological appraisal was conducted using design-matched tools: PROBAST for prediction models, QUADAS-2 for diagnostic accuracy studies, and AMSTAR 2 for systematic reviews/meta-analyses. Appraisal outcomes informed weighting during narrative synthesis; no paper was removed solely on appraisal results. Given heterogeneity in modalities, endpoints, and evaluation protocols, meta-analytic pooling was not undertaken. Studies were organised into thematic groups covering (1) multimodal dental data resources, (2) fusion and modelling pipelines, (3) engagement and teledentistry delivery mechanisms, and (4) governance, explainability, and equity constraints, enabling an integrated description of an AI-driven patient engagement ecosystem in dentistry.

3. RESULTS

The integration of predictive analytics with patient engagement in dentistry requires a layered ecosystem that links data infrastructure, analytic pipelines, and interaction channels (Table 1).

Table 1: Visual summary of the Dental AI Engagement Ecosystem (DAIE)

Ecosystem Layer	Technologies	Outcomes
Data Layer	CBCT, panoramic radiographs, periapical radiographs, EHR, practice management systems, mobile data, teledentistry inputs	Structured multimodal data collection and longitudinal patient profiling
AI Layer	Multimodal fusion, transformer-based encoders, prediction models, calibration modules, uncertainty estimation	Risk stratification, early disease detection, treatment forecasting, recall prioritisation
Engagement Layer	Chatbots, teledentistry platforms, mobile applications, risk dashboards, tailored reminders	Patient interaction, behavioural support, remote triage, treatment acceptance
Governance Layer	Privacy controls, consent management, explainability, bias monitoring, audit logs	Trust, compliance, clinical accountability, equitable deployment

At the data layer, the reviewed works show a gradual transition from isolated radiographs or administrative records to structured multimodal repositories. Araidy [1] documents how early AI studies relied almost exclusively on single-modality radiographic datasets. In contrast, more recent work incorporates clinical variables, periodontal indices, and follow-up information to enhance prognosis and treatment planning. Bamashmous [2] extends this trajectory to dental public health, where epidemiological registries, sociodemographic variables, and service utilisation data support predictive models for caries burden, screening needs, and allocation of preventive programs.

Multimodal dental datasets, as described by Huang [5] and Wang [10], form the structural foundation of such an ecosystem. Huang's dataset includes 169 patients and three commonly used radiographic modalities—cone-beam CT, panoramic radiographs and periapical radiographs—collected under unified protocols and enriched with labels reflecting diverse oral conditions. Wang's STS-Tooth dataset adds scale and dense annotation, comprising 4,000 panoramic images, 148,400 CBCT scans, 900 pixel-level masks for scenic photos, and 8,800 annotated CBCT scans tailored for semi-supervised tooth segmentation. These resources demonstrate how carefully curated imaging data can be organised to support cross-modal feature learning and downstream tasks such as 3D reconstruction or lesion localisation.

Figure 2 summarises the conceptual architecture of the patient engagement ecosystem derived from these datasets and the broader literature. The lower layer aggregates imaging modalities (CBCT, panoramic and periapical radiographs), structured clinical records, demographic variables and patient-generated data streams from mobile applications and teleconsultation platforms. The intermediate layer hosts multimodal learning pipelines inspired by the fusion strategies described by Krones [7]: feature-level integration of imaging and tabular data, late fusion of decision scores, and transformer-based architectures capable of handling image-text combinations. The upper layer exposes predictions and recommendations to patients and clinicians through teledentistry systems, chatbots, risk dashboards and decision-support interfaces.

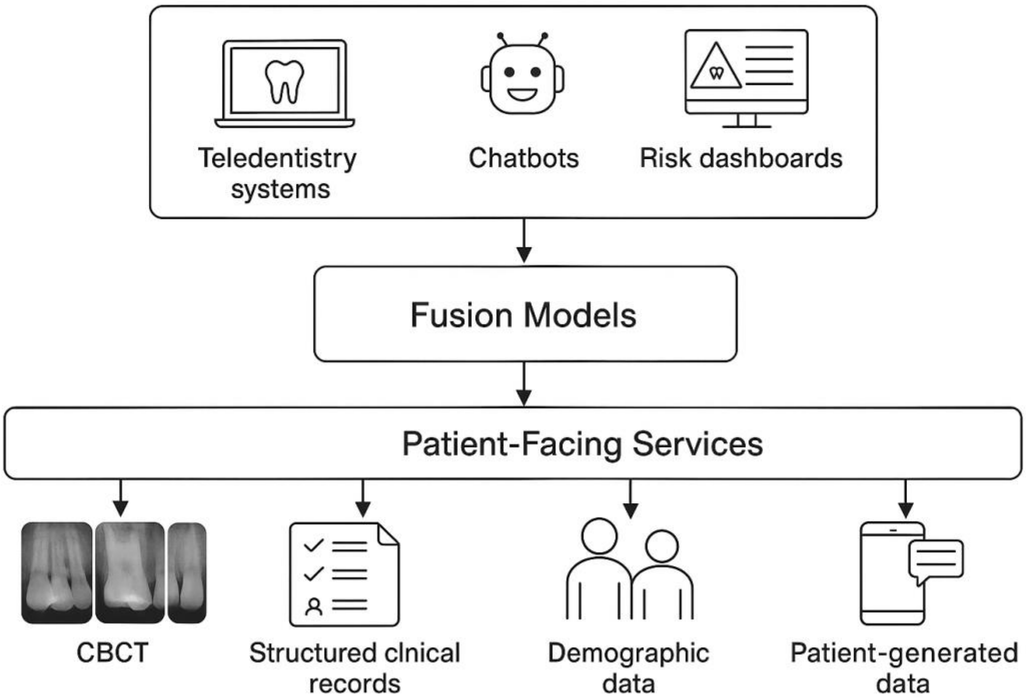

Figure 2. Author's Proposed AI-Driven Dental Engagement Ecosystem (DAIE): conceptual architecture integrating multimodal dental datasets, fusion models, and patient-facing services

DAIE relies on a structured pipeline that transforms heterogeneous dental data streams into actionable predictions and engagement events. The pipeline connects acquisition systems in clinics and public health settings with mobile and teledentistry applications, multimodal learning components, and patient-facing services driven by predictive analytics.

At the ingestion stage, imaging studies (CBCT, panoramic, and periapical radiographs), structured clinical records, sociodemographic variables, and patient-generated content from mobile applications or teleconsultation platforms are integrated into a unified data layer. Each source passes through modality-specific quality control procedures, including integrity checks, harmonisation of acquisition parameters, de-identification, and mapping to shared terminologies for diagnoses, procedures, and anatomical regions. Time stamps from clinics and remote channels undergo alignment into longitudinal patient timelines that support repeated risk estimation.

The feature-extraction stage transforms raw inputs into latent representations suited for fusion. Convolutional or transformer-based encoders process radiographic images and CBCT volumes, while gradient-boosted trees or feedforward networks embed tabular variables and scores derived from questionnaires. Text encoders convert brief clinical notes or structured symptom descriptions into dense vectors. Inspired by recent work on multimodal healthcare models and transformer architectures, shared embedding spaces are constructed for imaging and non-imaging data, allowing downstream components to treat heterogeneous signals as coordinated views of the same clinical situation [7, 11, 12].

At the fusion stage, intermediate representations from multiple modalities enter a joint module that aggregates information across channels and visits. Attention mechanisms weigh signals from imaging, clinical records, demographics, and patient-generated streams according to their relevance for each prediction task, while gating units or learned masks handle missing or low-quality modalities without discarding complete cases. The fusion block outputs task-specific embeddings for outcomes such as caries progression, implant failure, periodontal deterioration, or non-attendance at recalls.

The prediction stage attaches lightweight task heads to fused embeddings. Logistic or survival models estimate event probabilities over predefined horizons, whereas regression heads estimate continuous quantities, such as expected treatment duration. Calibration layers and uncertainty estimates adjust raw scores to ensure that decision thresholds align with clinical risk tolerance and public health priorities. Outputs feed both individual-level actions (such as recall scheduling, behavioural recommendations, and triage decisions) and population-level dashboards that guide the planning of screening programs.

The final delivery stage links predictive outputs to engagement channels. For each patient, a decision engine maps risk profiles and uncertainty estimates to specific interventions: automated reminders, chatbot conversations with tailored explanations of findings, referral prompts, or targeted educational modules. At the population level, aggregated scores inform campaign design for communities with high disease burdens. Logging services record every prediction and follow-up action, enabling periodic retraining and monitoring of model drift.

In operational terms, the pipeline can be described as a sequence of stages:

1) Data acquisition and secure ingestion from imaging systems, practice management software, public-health registries, and mobile or teleconsultation platforms.
2) Standardisation, de-identification, and temporal alignment into longitudinal patient and population datasets.
3) Modality-specific feature extraction for images, tabular variables, text fragments, and time series.
4) Multimodal fusion with attention-based handling of heterogeneous and partially missing inputs.
5) Task-specific prediction, calibration, and risk stratification at individual and population scales.
6) Routing of predictions into patient engagement workflows, dashboards for clinicians and managers, and feedback logs that support continuous evaluation and updates.

The diagram organises the pipeline into four horizontal tiers (Figure 3).

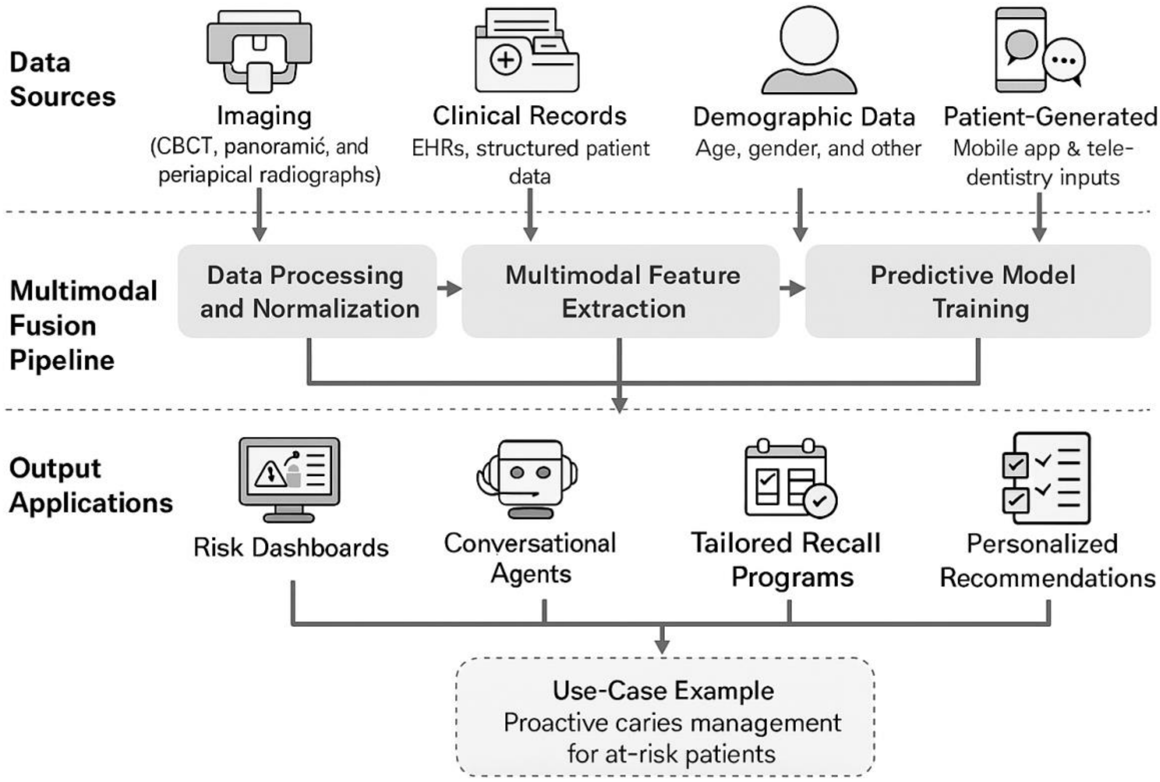

Figure 3. Author's Proposed Multimodal Fusion and Predictive Engagement Pipeline within DAIE

The framework presented in Figures 2 and 3 represents the author's proposed model for integrating multimodal dental datasets, predictive analytics, conversational AI, and patient engagement services into a continuously learning dental care ecosystem. DAIE translates heterogeneous clinical, imaging, behavioural, and telehealth inputs into operational engagement actions, including risk-based recall, remote triage, tailored counselling, patient education, and population-level prevention planning.

Predictive analytics capabilities within this architecture already appear in several strands of the literature. Bamashmous [2] reports applications where deep-learning models derived from panoramic radiographs support automated caries detection, identification of impacted teeth, and surveillance of periodontal bone loss, with diagnostic performance patterns consistent with the evidence synthesised in recent systematic evaluation studies [14]. Liu [8] discusses the use of AI for predictive planning, for example, forecasting orthodontic treatment duration or implant survival based on combined imaging and clinical data, framing these tasks as regression or survival-analysis problems. Araidy [1] highlights risk-score models for peri-implantitis or caries progression that learn from longitudinal check-up data. At the same time, public-health-oriented applications incorporate environmental and behavioural variables to identify high-risk communities.

Krones [7] describes multimodal fusion workflows that are directly transferable to dental use cases, including joint representation learning for imaging and electronic health records, attention mechanisms that dynamically weigh modalities, and training strategies that handle missing data. Within DAIE, these approaches support risk stratification at both individual and population levels. For example, an individual's combined CBCT features, periodontal indices, and self-reported behaviours can feed a model predicting the probability of implant failure over a specified horizon. At the same time, aggregated outputs across a catchment area inform the planning of targeted recall campaigns or fluoride-varnish programs.

Patient-facing engagement mechanisms outpace simple reminders and appointment scheduling when AI is embedded across channels. Surdu [9] documents teledentistry platforms that support remote consultations with AI-assisted image triage and decision support, enabling dentists to prioritise urgent cases, validate preliminary findings, and reduce diagnostic delays. Kaushik [6] describes scenarios in which computer-vision algorithms applied to smartphone images pre-classify cases before synchronous video visits, while automated scheduling modules organise follow-up visits and referrals. Danesh [3] emphasises mobile applications and AI-mediated guidance tailored to vulnerable populations, including children, older adults and people living in remote regions, where limited chairside capacity necessitates digital triage and education strategies.

Conversational agents and chatbots add another layer of engagement. Surdu [9] reports AI-driven virtual assistants that answer common questions, remind patients of hygiene routines and explain post-operative instructions in accessible language. Liu [8] discusses how such tools can be coupled with real-time documentation and workflow automation, guiding patients through symptom reporting while simultaneously populating clinical records. Evidence from controlled evaluations of large-language-model outputs in oral health counselling tasks indicates variable clinical reliability, which supports the requirement for professional verification before chatbot responses are delivered to patients [23]. When linked to multimodal predictive models, these interfaces can provide personalised risk messages, adapt educational content to behavioural profiles and propose individualised recall intervals or home-monitoring tasks.

At the system level, the literature illustrates both the potential and constraints of emerging ecosystems. Bamashmous [2] stresses that AI-driven surveillance supports more precise targeting of preventive programs and efficient resource allocation in dental public health, yet raises questions about data privacy, consent and equity when large-scale registries and imaging archives are integrated. Erol [4] emphasises that digital-twin frameworks in dentistry necessitate continuous feedback loops between clinical events and virtual models, thereby driving infrastructure requirements for interoperability, cybersecurity, and governance. Liu [8] identifies interpretability, regulatory fragmentation, and clinician training as key barriers to integration, while Araidy [1] and Kaushik [6] highlight the uneven quality of datasets, limited external validation, and potential bias in AI models deployed through telehealth channels and clinician training as key barriers to integration [17; 28]. These observations highlight that the success of AI-driven patient engagement ecosystems depends not only on technical capability but also on the alignment of data governance, ethical frameworks, and practice-level workflows.

4. DISCUSSION

The synthesised ecosystem demonstrates that multimodal dental datasets are structural backbones for continuous learning cycles that link clinical encounters, remote monitoring, and public health interventions. Huang's dataset [5] exemplifies a carefully designed imaging repository where standardised acquisition protocols, multiple modalities and clinically meaningful labels facilitate robust benchmarking of diagnostic and segmentation models. Wang's STS-Tooth dataset [10] extends this logic by offering large-scale, densely annotated imaging suitable for semi-supervised learning, which is crucial for settings where manual labelling of CBCT slices is prohibitively expensive. When such datasets are embedded into an engagement ecosystem, they underpin not only improved radiological accuracy but also downstream patient interactions, from automated explanations of radiographic findings to simulations of alternative treatment plans [30].

The comparison in Table 2 illustrates complementary design philosophies. Huang et al. [5] prioritise diversity of imaging modalities and clinical conditions, enabling cross-modal translation and multimodal reconstruction of dental structures. Wang et al. [10] emphasise scale and annotation density, which are crucial for training data-hungry deep networks and exploring semi-supervised strategies that combine labelled and unlabelled scans.

Table 2: Characteristics of selected multimodal dental imaging datasets relevant for AI-driven engagement ecosystems [5; 10]

Dataset/reference	Patients	Modalities included	Primary AI focus
Multimodal dental dataset by Huang et al.	169	Cone-beam CT, panoramic radiographs, periapical radiographs	Image segmentation, image translation, and diagnostic support for diverse oral conditions
STS-Tooth dataset by Wang et al.	Large-scale sample including 4,000 panoramic images and 148,400 CBCT scans	Panoramic X-ray (PXI) and CBCT with 900 PXI masks and 8,800 annotated CBCT scans	Semi-supervised tooth segmentation and benchmarking of segmentation algorithms

From the perspective of patient engagement ecosystems, such datasets form the basis for explainable radiology tools that provide patients with consistent visualisations across modalities, support longitudinal tracking of structural changes, and inform digital twin representations of the oral cavity. A dental digital twin is a continuously updated virtual representation of a patient's oral condition that synchronises imaging, clinical records, behavioural data, and treatment history to support forecasting, simulation, and personalised intervention planning. Within DAIE, the digital twin updates after each radiographic examination, treatment procedure, mobile check-in, or teleconsultation. Its value lies in comparing projected and observed changes in caries progression, periodontal status, implant stability, orthodontic movement, and adherence-related outcomes.

While imaging datasets anchor the data layer, sustained engagement depends on how AI-enabled services reach patients through routine digital channels. Teledentistry research indicates that remote consultations, pre-visit image uploads, AI-assisted triage, and integrated scheduling can shorten diagnostic pathways and improve continuity of follow-up under defined imaging-quality and workflow conditions [6; 9; 18; 19; 22]. COVID-era studies remain relevant as evidence of rapid implementation, but within DAIE they illustrate triage-first pathways, asynchronous image review, and remote follow-up protocols that can be adapted beyond emergency pandemic conditions [16; 20; 21; 24–27]. Danesh [3] further supports the use of mobile guidance and tailored digital interventions for vulnerable groups, where geography, language, literacy, or limited chairside capacity restrict access to continuous preventive care.

These observations can be summarised through functional categories of engagement, grounded in the reviewed sources. The functions in Table 3 show how multimodal data support increasingly fine-grained personalisation of engagement.

Table 3: AI-enabled patient engagement functions in contemporary digital dental care [1; 2; 4–7; 9; 10; 27]

Function	Description	Dominant data inputs
Remote triage and risk screening	Pre-visit assessment of symptoms and uploaded images to classify urgency, guide self-care, and prioritise appointments	Smartphone photographs, panoramic photos, brief symptom questionnaires, demographic data
AI-assisted teleconsultation support	Real-time or asynchronous decision support during teleconsultations, including automated annotations on radiographs and structured summaries	Live video, radiographic images, electronic records
Conversational guidance and education	Chatbots and virtual assistants delivering oral-hygiene coaching, postoperative instructions and motivational messages	Text and voice interactions, prior visit history, and simple behavioural logs
Predictive recall and preventive targeting	Dynamic adjustment of recall intervals and preventive interventions based on multimodal risk scores at the individual and population level	Combined imaging features, clinical indices, sociodemographic and behavioural data
Digital-twin-based treatment simulation	Iterative simulation of treatment options and long-term outcomes using virtual models synchronised with new data.	Multimodal imaging, longitudinal treatment records, and patient-generated data

Consider an adult patient with recent implant placement in a rural setting, enrolled in a practice that uses DAIE. After surgery, the clinic obtains CBCT and panoramic radiographs, which are incorporated into the multimodal dataset alongside baseline periodontal indices, systemic health information, and sociodemographic variables. At discharge, the patient is instructed to install a mobile application that supports periodic symptom check-ins and guided smartphone photographs of the peri-implant region [29].

During follow-up, the mobile application prompts the patient to upload photographs and complete short questionnaires on discomfort, bleeding, and hygiene routines. The predictive pipeline merges these data with baseline imaging features and clinical records to estimate the probability of peri-implantitis over specified horizons. Elevated risk triggers an automated message offering a fast-track teleconsultation slot, while moderate risk leads to intensified coaching through chatbot interactions that reinforce hygiene instructions and monitor adherence. Aggregated risk scores from multiple patients inform the planning of outreach campaigns for communities with a high incidence of peri-implant complications, illustrating how continuous multimodal data flows into both individual and population-level interventions.

Risk-based recall strategies build on population-level predictive analytics described by Bamashmous [2], where AI models quantify disease probabilities and identify communities that benefit most from targeted preventive campaigns. Digital-twin applications outlined by Erol [4] rely on continuous synchronisation between virtual models and real-world events, which presupposes structured capture of imaging, procedural details and behavioural adherence through mobile and telehealth channels.

Ethical and organisational dimensions permeate the entire ecosystem. Liu [8] emphasises that the integration of AI in dental care raises concerns over algorithmic bias, data privacy, and the opacity of decision logic, urging a shift toward explainable models and interoperable standards. Bamashmous [2] and Danesh [3] emphasise that predictive analytics and teledentistry risk exacerbating inequities if data from vulnerable groups remains underrepresented or if digital services fail to account for connectivity and literacy constraints. Patient-facing surveys conducted during the coronavirus pandemic reported broad acceptance of remote dental contacts and high perceived value of rapid professional feedback, supporting the feasibility of engagement-focused telecare workflows [15]. Krones [7] notes that multimodal fusion frameworks necessitate careful handling of missingness and domain shifts across care settings to prevent misleading predictions when one modality is absent or degraded.

At the same time, the reviewed works expose gaps that motivate further development of AI-driven engagement ecosystems. Most dental AI studies focus on model performance metrics, leaving it uncertain how predictive tools alter adherence, disease trajectories or patient experience. Araidy [1] highlights the scarcity of prospective validation and real-world implementation reports. Teledentistry studies compiled by Surdu [9] and Kaushik [6] often treat AI components as supplementary aids. Liu [8] advocates for stronger collaboration among AI developers, clinicians, and regulators to transform proof-of-concept models into trustworthy tools that are embedded in everyday practice. Addressing these gaps requires rigorous ecosystem-level evaluation frameworks that track not only diagnostic accuracy but engagement, equity and long-term oral-health gains.

Evaluation of DAIE should combine clinical, behavioural, operational, and equity metrics. At the patient level, assessment should track engagement rates, recall adherence, treatment acceptance, completion of recommended follow-up, and patient-reported clarity of AI-supported communication. At the clinical level, evaluation should examine early disease detection, risk-score calibration, false-positive and false-negative triage rates, reduction in missed appointments, chairside time saved, and referral appropriateness. At the population level, equity indicators should compare model performance, service uptake, and follow-up completion across age, language, socioeconomic status, rurality, disability, and digital-access groups.

5. PRACTICAL IMPLICATIONS

For dental clinics, DAIE supports risk-based scheduling, earlier identification of high-risk patients, and more consistent follow-up after treatment. Predictive outputs can be converted into recall intervals, triage categories, and chairside visual explanations that help clinicians discuss risks and treatment options with patients.

For dental software vendors, the framework creates a modular roadmap for integrating AI services into practice management systems, radiology workstations, appointment platforms, and patient portals. Priority should be given to secure APIs, DICOM-compatible imaging exchange, structured EHR connectors, audit logs, and configurable dashboards for clinical and administrative users.

For AI developers, DAIE defines concrete technical requirements: multimodal training pipelines, handling missing modalities, calibrated predictions, explainable outputs, subgroup performance monitoring, and post-deployment feedback loops for learning. These requirements shift development from single-task model accuracy toward clinically usable engagement workflows.

For public health agencies, aggregated risk scores can support targeted prevention campaigns, allocate screening resources, identify underserved groups, and monitor oral health inequalities. DAIE can connect individual-level care with population-level prevention by transforming routine dental data into actionable surveillance indicators.

For teledentistry providers, the framework supports pre-consultation image upload, conversational intake, risk-guided escalation, post-treatment follow-up, and structured handoff to in-person services. This improves continuity between remote and chairside care while preserving professional oversight over AI-supported recommendations.

6. LIMITATIONS

This study has several limitations. First, the narrative review design supports conceptual integration but does not provide pooled effect estimates. Second, meta-analysis was not performed because the included studies differed in modalities, endpoints, model architectures, validation protocols, and engagement outcomes. Third, the evidence base remains heterogeneous, combining dataset papers, diagnostic studies, public-health analyses, teledentistry reviews, and implementation reports. Fourth, many dental AI studies still rely on retrospective datasets, limited external validation, and short observation periods. Finally, prospective ecosystem-level validation remains scarce, especially for longitudinal outcomes such as recall adherence, treatment acceptance, disease progression, patient experience, and equity effects.

7. FUTURE RESEARCH DIRECTIONS

Future research should move from conceptual modelling toward prospective validation of DAIE in real-world dental settings. Federated learning deserves special attention because it allows multi-site model training without centralising identifiable patient data. This direction is especially relevant for dental clinics that use different practice management systems, radiology platforms, and national data-governance rules.

AI governance frameworks in dentistry require further development, including consent models, audit standards, explainability requirements, and procedures for detecting bias across demographic and socioeconomic groups. Dental digital twins should be tested as longitudinal tools for simulating disease progression, treatment alternatives, and adherence-sensitive outcomes. Multimodal foundation models trained on imaging, structured records, clinical text, and patient-generated data could provide a broader technical base for risk prediction and personalised engagement.

Longitudinal ecosystem validation should measure recall adherence, treatment acceptance, missed appointments, early disease detection, patient understanding, clinician workload, and equity indicators. Explainable AI methods should be embedded into patient-facing and clinician-facing interfaces so that predictive outputs remain interpretable, contestable, and clinically traceable.

8. CONCLUSION

From a deployment architecture perspective, DAIE should be implemented as a modular service layer connected to practice management systems, radiology workstations, teledentistry platforms, and mobile applications through secure APIs. DICOM-compatible imaging exchange, structured EHR connectors, terminology mapping, and event-driven messaging allow CBCT volumes, panoramic radiographs, treatment records, symptom forms, and appointment events to enter the analytic layer without disrupting existing clinical workflows. Real-time analytics services can return calibrated risk scores during image review, virtual intake, or teleconsultation, while batch pipelines can retrain models and audit performance over longer intervals.

Cloud deployment can support scalable storage, inference, monitoring, and multi-site model updates, provided that the security architecture is designed around encryption at rest and in transit, identity and access management, consent logging, audit trails, network segmentation, and backup policies. In clinics with stricter data-sovereignty requirements, hybrid deployment can keep identifiable records within local systems while sending de-identified features or model parameters to shared learning services. These architectural decisions determine whether predictive engagement remains technically reliable, clinically traceable, and acceptable for regulated dental environments.

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