

ARTIFICIAL INTELLIGENCE-BASED EARLY DIAGNOSIS AND PERSONALIZED MANAGEMENT OF ORAL DISEASES THROUGH DIGITAL DENTISTRY

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Abstract

The integration of artificial intelligence (AI) into digital dentistry represents a transformative paradigm shift from reactive, symptom-driven intervention to proactive, personalized oral healthcare. This review synthesizes the current state of AI applications across the dental diagnostic and therapeutic continuum, examining algorithmic foundations, clinical performance benchmarks, regulatory landscapes, and implementation challenges. We systematically analyze discriminative deep learning architectures, including Convolutional Neural Networks and Vision Transformers, alongside generative AI models such as Generative Adversarial Networks and diffusion-based systems, and multimodal Large Language Models that synthesize imaging data with clinical text. Diagnostic performance metrics demonstrate that AI systems achieve sensitivities of 82–94% for caries detection, 79.5–100% for periodontal bone loss quantification, and up to 99.1% accuracy for oral squamous cell carcinoma identification, with specificity profiles exceeding 95% across multiple domains. In restorative workflows, generative AI reduces crown design time by up to fourfold while maintaining marginal gaps within 59–83 μm and occlusal deviations under 0.30 mm. Commercial translation is evidenced by dozens of FDA 510(k)-cleared platforms, predominantly concentrated in diagnostic radiology and implant planning. However, widespread clinical adoption faces persistent challenges, including algorithmic generalizability across diverse populations, data privacy concerns under HIPAA and GDPR frameworks, standardized reporting adherence, and the critical maintenance of clinician-in-the-loop oversight. This review underscores that while AI offers unprecedented opportunities for early diagnosis and personalized treatment optimization, successful implementation requires robust regulatory governance, transparent algorithmic reporting, and preservation of human clinical judgment at the center of patient care.

1. INTRODUCTION

Digital dentistry has undergone a fundamental transformation over the past three decades, evolving from isolated digital adaptations to a fully integrated, data-driven healthcare ecosystem (Revilla-León & Özcan, 2019). The initial

digitization wave focused on replacing analog methodologies with computer-aided alternatives, such as intraoral surface scanning (IOS) substituting elastomeric impressions, cone-beam computed tomography (CBCT) replacing complex two-dimensional projections, and computer-aided

design and manufacturing (CAD-CAM) streamlining indirect restorative fabrications (Patel et al., 2019). While these innovations successfully digitized geometric data, clinical interpretation, diagnostic reasoning, and treatment planning remained dependent on human expertise (Güth et al., 2013).

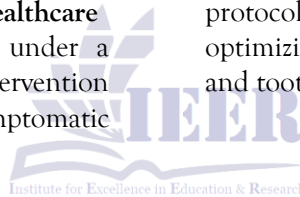
The integration of artificial intelligence (AI), specifically machine learning (ML) and deep learning (DL) algorithms, represents the second major evolutionary wave in digital oral healthcare. Modern digital dentistry couples' diagnostic hardware with computational systems capable of synthesizing multimodal patient data. By evaluating structural, clinical, and radiographic data, AI tools transition digital workflows from passive geometric storage systems to active clinical decision support systems (CDSS) (Bini et al., 2023).

1.2 The Paradigm Shift: From Reactive Intervention to AI-Driven Proactive Healthcare

Historically, oral healthcare operated under a reactive model wherein therapeutic intervention was initiated primarily after symptomatic

presentation or advanced structural destruction, such as cavitated carious lesions, severe alveolar bone resorption, or irreversible endodontic inflammation. This historical approach frequently required invasive restorative or surgical procedures, yielding higher long-term failure rates and increased financial expenditure (Dawood et al., 2015).

The integration of AI algorithms into digital dentistry accelerates a paradigm shift toward early, non-invasive diagnosis and personalized disease management. High-resolution image processing algorithms detect sub-clinical pathological alterations, including early enamel demineralization, subclinical interdental bone loss, and occult apical radiolucencies, prior to visual or tactile manifestation. Furthermore, by analyzing clinical risk parameters alongside structural imaging data, AI enables longitudinal risk stratification. This transitions patient management from standardized treatment protocols to personalized preventative regimens, optimizing long-term therapeutic predictability and tooth retention (Mangano et al., 2017).



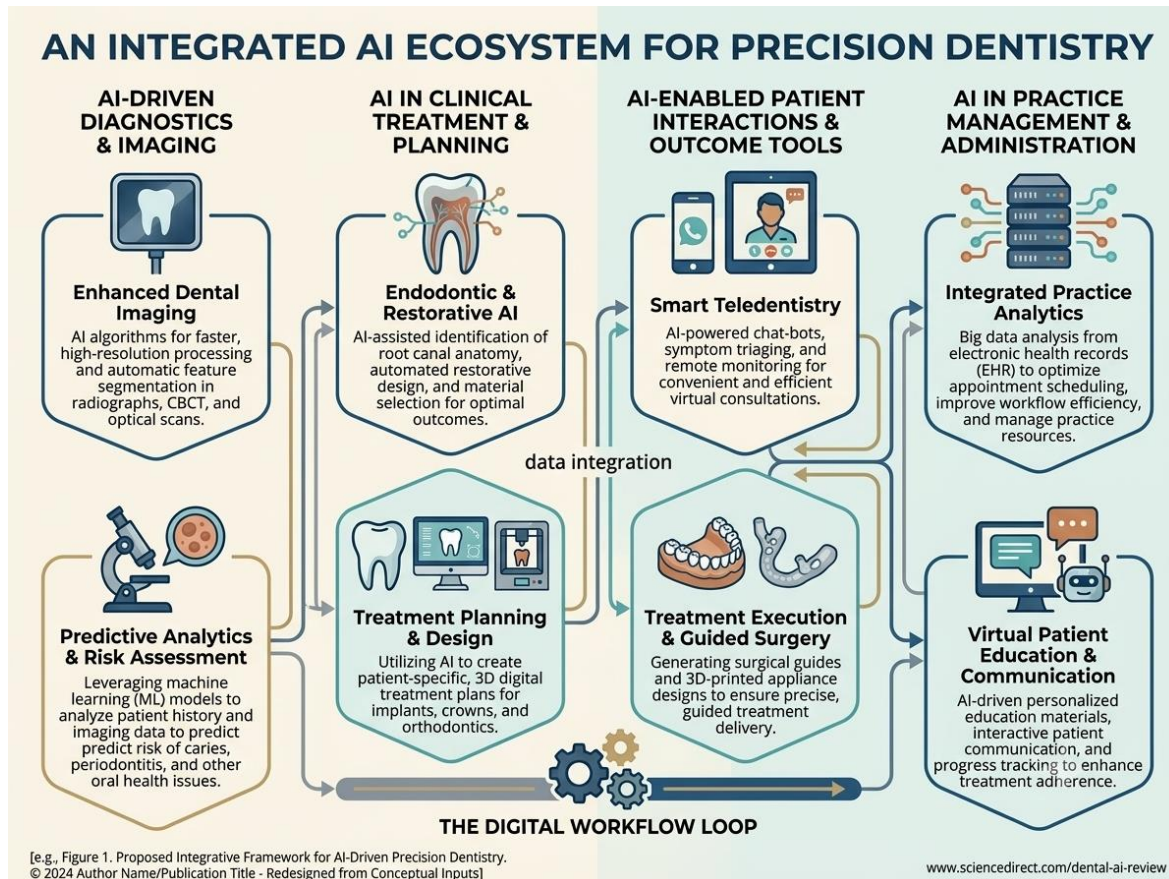


Figure 1. An integrated AI ecosystem and digital workflow loop for precision dentistry.

2. Technological Foundations and Algorithmic Frameworks

2.1 Imaging Modalities and Data Integration

The clinical performance of dental AI platforms is fundamentally constrained by the data modalities utilized for training and inference. Contemporary digital dentistry relies on a multi-tiered array of imaging modalities, each exhibiting distinct spatial resolutions, noise characteristics, and dimensional dimensions (Joda et al., 2019). Two-dimensional intraoral bitewings and periapical radiographs offer superior spatial resolution, serving as the gold standard for proximal caries detection and early marginal bone evaluation, whereas panoramic radiographs provide a broad maxillofacial overview that is advantageous for developmental assessments but limited by anatomical superposition (Miyazaki et al., 2009). In contrast, cone-beam computed tomography provides isotropic three-dimensional voxels,

eliminating anatomical overlap and allowing volumetric evaluation of complex endodontic anatomy, furcation defects, and peri-implant bone geometry. Supplementing these radiographic modalities, optical intraoral scanners capture high-density surface meshes of crown morphology and soft tissue contours, while extraoral stereophotogrammetry captures facial landmarks for orthognathic and facial aesthetic integration (Goodacre et al., 2018).

Synthesizing these disparate data streams into unified spatial coordinates presents a significant computational challenge. Advanced AI frameworks employ multi-modal registration networks that align optical surface meshes with volumetric CBCT data and two-dimensional radiographic projections. This multi-modal fusion establishes a comprehensive digital twin of the patient's stomatognathic system, allowing algorithms to cross-reference hard-tissue

radiographic density with soft-tissue contours and dynamic occlusal paths (Chen et al., 2020).

2.2 Machine Learning, Deep Learning, and Discriminative Models

Classical machine learning approaches in dental diagnostics relied heavily on handcrafted feature extraction, such as edge detection operators and gray-level co-occurrence matrices, paired with shallow classifiers including Support Vector Machines (SVM), Random Forests, or Backpropagation Neural Networks (BPNN). These early models exhibited limited generalizability when exposed to variations in image contrast, exposure artifacts, or complex anatomical anomalies (Ahmed et al., 2021).

Deep learning architectures, specifically Convolutional Neural Networks (CNNs), transformed the field by learning hierarchical feature representations directly from raw pixel arrays. Fully Convolutional Networks and specialized architectures such as U-Net, Feature Pyramid Networks (FPN), and Mask R-CNN perform semantic and instance segmentation of anatomical structures including individual tooth boundaries, pulp chambers, and mandibular canals as well as pathological lesions (Schwendicke et al., 2020). More recently, Vision Transformers (ViT) have been introduced to model global contextual relationships across full-arch radiographs, improving the classification of subtle conditions such as furcation involvement and early root fractures where broader anatomical context is required (Khanagar et al., 2021).

2.3 The Generative AI Frontier: GANs, Diffusion Models, and Multimodal LLMs

While discriminative models focus on classification, segmentation, and object detection, Generative Artificial Intelligence (GenAI) models learn underlying data distributions to synthesize novel, high-fidelity biological and physical outputs. Generative Adversarial Networks (GANs) and diffusion-based architectures, trained on massive anatomical libraries, generate patient-specific, biomechanically sound restorative crown geometries (Joda et al., 2023). Rather than relying on static anatomical dental libraries, these generative models compute missing tooth structures by evaluating contralateral morphology, adjacent tooth wear patterns, and functional dynamic occlusion. Furthermore, generative architectures facilitate synthetic data augmentation, generating high-variance, anonymized radiographic training sets to balance rare pathological representations in diagnostic datasets (Hung et al., 2020).

In parallel, multimodal Large Language Models (LLMs) and cross-attention vision transformers process unstructured clinical notes, patient medical histories, and diagnostic imaging outputs simultaneously. These models assist clinicians by formulating differential diagnostic summaries, generating tailored patient communication materials, and screening for complex mucosal and jaw pathologies by integrating textual patient risk factors with clinical imagery (AlSaad et al., 2024).

Table 1: Comparative Analysis of Algorithmic Architectures in Digital Dentistry.

Architectural Category	Representative Models	Core Mechanism	Primary Dental Modalities	Key Strengths	Primary Limitations
Classical Machine Learning [cite: 7, 14]	SVM, Random Forest, BPNN	Handcrafted feature extraction paired with supervised decision bounds	2D Radiographs, Tabular clinical data	Low computational requirements; highly interpretable	Poor performance on noisy images; limited spatial abstraction

Discriminative Deep Learning [cite: 1, 9, 10, 14]	CNNs (ResNet, VGG), U-Net, Mask R-CNN, Vision Transformers	Hierarchical spatial feature learning via convolutional kernels and self-attention	2D/3D Radiographs, CBCT, Intraoral photos	High accuracy in object detection, segmentation, and disease classification	Requires large annotated datasets; vulnerable to distribution shifts
Generative AI (GenAI) [cite: 5, 6]	GANs, Diffusion Models, Autoregressive Models	Estimation of probability distributions to synthesize novel 3D biological mesh structures	3D IOS scans, CBCT volume meshes	Synthesizes custom, biomechanically optimized crown designs; data augmentation	High computational intensity; risk of unrealistic anatomical hallucination
Multimodal LLMs [cite: 5, 16]	GPT-4 Vision, LLaMA-derived multimodal architectures	Cross-attention mechanisms linking natural language with visual tokens	Intraoral photos, Textual clinical records	Synthesizes multi-source records; generates patient explanations	Risk of linguistic hallucination; inconsistent diagnostic standardization

3. AI-Based Early Diagnosis of Oral Diseases

3.1 Cariology and Early Demineralization Detection

Dental caries remains one of the most prevalent chronic conditions globally. Conventional detection methods, including visual-tactile inspection and manual radiographic review, exhibit substantial inter-observer variability and limited sensitivity for sub-surface enamel demineralization where early proximal lesions are frequently obscured by adjacent sound enamel. AI algorithms trained on bitewing and periapical radiographs detect subtle attenuation changes corresponding to localized mineral loss. Evaluated across extensive multi-center datasets, deep learning models achieve overall caries detection sensitivities ranging from 82% to 94.15% and specificities up to 99% (Alquassier, 2023).

A critical diagnostic distinction exists between early enamel lesions and advanced dentinal lesions. For instance, clinical evaluations of commercial platforms such as the Overjet Caries Assist module indicate an average sensitivity of 0.69 for shallow enamel lesions, compared to 0.91 for lesions extending into dentin, while

maintaining specificities of 0.99 and 0.98, respectively (Ismail, 2004). This performance gradient reflects an intentional tuning threshold within commercial models: prioritizing high specificity in early enamel lesions minimizes false positives, thereby preventing unnecessary operative preparation of remineralizable enamel structures (Anil et al., 2023).

The diagnostic processing pipeline operates by ingesting raw bitewing or periapical radiographs, applying spatial normalization algorithms to adjust contrast variations, and feeding pixel arrays into convolutional neural networks such as U-Net or ResNet architectures. The output generates highlighted overlays denoting lesion boundaries alongside depth estimates, empowering clinicians to recommend non-invasive remineralization therapies or minimally invasive restorations. In educational settings, integrating such AI caries modules into student diagnostic workflows has been demonstrated to improve diagnostic accuracy by 43% to 46% (Farooq, 2022).

3.2 Periodontology: Bone Loss Quantification, Staging, and Risk Assessment

Periodontal disease progression involves complex osteo-immunological interactions resulting in the irreversible loss of alveolar supporting bone. Traditional diagnostic protocols depend on manual periodontal probing and manual radiographic measurement of the distance between the cemento-enamel junction (CEJ) and the alveolar bone crest (ABC), processes susceptible to probing force variations, angle distortions, and measurement inaccuracies (Mu et al., 2026).

Deep learning segmentation frameworks automate periodontal diagnostic workflows by segmenting tooth structures, CEJs, ABCs, and defect morphologies across bitewing, periapical, and panoramic radiographs, as well as CBCT volumes. AI systems achieve diagnostic accuracies of 85% to 92% for overall periodontal status evaluation, with reported sensitivities ranging between 0.795 and 1.00 and specificities between 0.73 and 1.00 (Tonetti et al., 2018).

The choice of imaging modality significantly influences algorithmic performance. Two-dimensional panoramic radiographs present lower sensitivity and specificity due to spatial distortion and anatomical superposition, whereas three-dimensional CBCT-based deep learning systems achieve superior volumetric assessment with diagnostic accuracies reaching up to 0.91. Beyond bone level measurement, specialized multi-task CNNs and Vision Transformers successfully classify complex infrabony defects, furcation involvements (Grades I-III), and soft-tissue parameters such as gingival inflammation and calculus deposition directly from intraoral photographic data (Güner et al., 2026).

3.3 Endodontics, TMJ Disorders, and Oral Pathology

Endodontic diagnosis hinges on the accurate identification of periapical radiolucencies, complex root canal morphology, and vertical root fractures. CNN-based models applied to CBCT volumes demonstrate superior performance in identifying subtle periapical bone destruction compared to 2D intraoral radiographs, successfully isolating early apical periodontitis before cortical bone plate perforation occurs (Schwendicke et al., 2020).

In temporomandibular joint (TMJ) diagnostics, deep neural networks applied to panoramic radiographs achieve an overall diagnostic accuracy of 0.78, a sensitivity of 0.73, and a specificity of 0.82 in screening for TMJ osteoarthritis (TMJOA) structural deformities, offering an accessible triage tool for general practices lacking direct access to MRI or specialized maxillofacial radiologists (Kang et al., 2023).

In oral oncology, early detection of Oral Squamous Cell Carcinoma (OSCC) is vital for improving patient survival rates. Deep learning architectures including pre-trained transfer learning ensembles such as VGG16, InceptionV3, and ResNet applied to histopathological images achieve diagnostic accuracies up to 99.1%, sensitivities of 99.5%, and specificities of 99.6% (AUC = 0.9952) in distinguishing normal oral mucosa from malignant transformation (Das et al., 2022). Furthermore, multimodal LLM systems and photographic classification models are emerging as frontline screening tools, demonstrating high diagnostic sensitivity for differentiating benign leukoplakia from erythroplakia and dysplastic malignant mucosal lesions (Ariji et al., 2024).

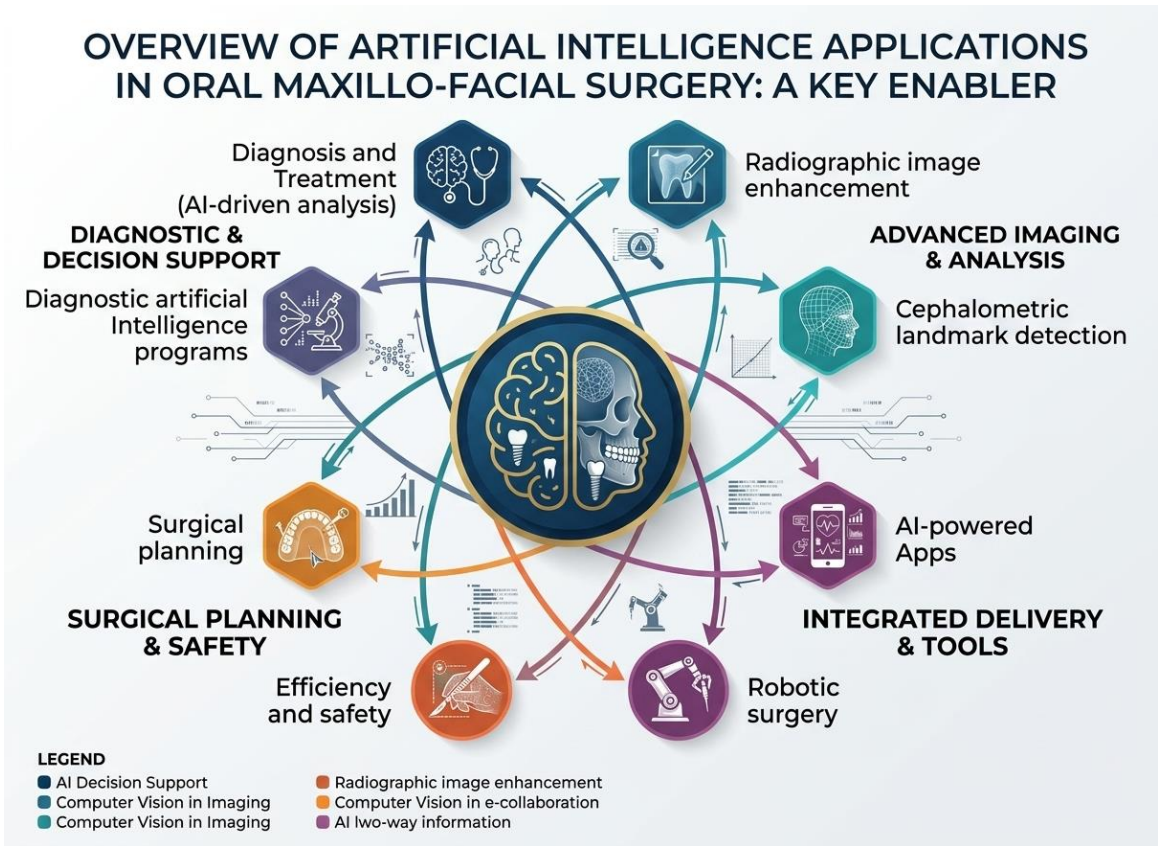


Figure 2. Overview of artificial intelligence applications and modalities in oral and maxillofacial surgery.

Table 2: Diagnostic Performance Benchmarks of Artificial Intelligence Models Across Oral Diseases.

Diagnostic Domain	Primary Imaging / Data Modality	Specific Diagnostic Task	Sensitivity Range	Specificity Range	Overall Accuracy / Performance Metric
Cariology	Bitewing & Periapical Radiographs	Enamel & Dentinal Caries Detection	0.69 – 0.941	0.98 – 0.99	Accuracy: 82.0% – 94.0%
Periodontology	PA / Panoramic / CBCT	Bone Loss Measurement & Staging	0.795 – 1.00	0.73 – 1.00	Accuracy: 85.0% – 92.0% (CBCT up to 0.91)
Endodontics	CBCT vs. 2D Radiographs	Periapical Radiolucency Detection	0.86 – 0.98	0.88 – 0.96	AUC > 0.88
TMJ Pathology	Panoramic Radiographs (OPG)	TMJ Osteoarthritis Screening	0.73	0.82	Accuracy: 0.78
Oral Oncology (OSCC)	Histopathological Images	Malignant Transformation Diagnostic	0.983 – 0.995	0.950 – 0.996	Accuracy: 96.6% – 99.1% (AUC: 0.995)

4. Personalized Management and Restorative Workflows

4.1 AI-Guided Treatment Planning and Digital Smile Design

Personalized treatment planning requires integrating static anatomical features with patient expectations and dynamic biomechanical requirements. Advanced Digital Smile Design (DSD) environments incorporate intraoral surface meshes, 3D facial scans, and digital dynamic articulators into unified virtual patients (Warin et al., 2023).

Automated landmark identification models, such as WebCeph, Audax, and WeDoCeph, process 2D and 3D cephalometric radiographs to rapidly detect skeletal and soft-tissue reference points. While these systems demonstrate high radial error compliance within established limits (≤ 1.5 mm for lateral projections), recent validation studies reveal that automated software can exhibit systematic overestimation in key sagittal and vertical orthodontic parameters, such as the ANB angle and FMA, necessitating clinician oversight during orthognathic and orthodontic treatment design (Lee et al., 2020).

4.2 Computer-Aided Design and Prosthodontic Rehabilitation

Traditional CAD design workflows rely heavily on manual technician expertise, utilizing generic digital tooth libraries and static virtual wax-ups. This manual approach often introduces design variability, requiring time-consuming intraoral occlusal and proximal adjustments during crown seating (Kühnisch et al., 2023).

Generative AI models synthesize highly customized, patient-specific restorative morphologies. Trained on vast datasets of healthy dentitions, GenAI algorithms evaluate adjacent contact points, antagonist occlusal topography, and masticatory motion paths to generate functional crown geometries (Orhan et al., 2020). Recent evaluations demonstrate that AI-designed crowns maintain morphological and occlusal deviations within clinically acceptable thresholds (0.18 to 0.30 mm) and achieve internal marginal

gaps ranging between 59 and 83 μ m. This degree of fit matches or exceeds conventional manual CAD design while accelerating overall design time by up to fourfold (Fu et al., 2024).

The digital fabrication workflow begins with the acquisition of high-density intraoral surface scans and CBCT registration volumes, which are transferred to a Generative AI CAD engine. Using GANs or diffusion networks, the engine generates an initial restoration mesh optimized for occlusion and contact tightness. For complex full-arch fixed reconstructions, advanced optimization algorithms such as Particle Swarm Optimization (PSO) and Bi-evolutionary Structural Optimization (BESO) are utilized to engineer full-arch framework geometries (Sesma et al., 2026). These algorithmic approaches redistribute stress concentrations across sub-framework components under simulated masticatory forces, minimizing long-term ceramic chipping and framework fracture prior to additive 3D printing or subtractive CAM milling (Sowmiya et al., 2026).

4.3 Implantology, Surgical Navigation, and Prognostic Outcome Modeling

Surgical implant planning demands sub-millimeter precision to avoid critical neurovascular structures, such as the inferior alveolar nerve and maxillary sinus cavities, while ensuring prosthetically driven implant positioning. AI systems applied to fused CBCT and intraoral mesh datasets achieve performance accuracies of 90% to 99.5% in identifying optimal implant placement sites, selecting appropriate fixture dimensions, and generating custom surgical drilling guides (Pozza et al., 2026).

In addition to diagnostic and surgical execution support, AI algorithms demonstrate predictive capabilities in prognostic outcome modeling. Machine learning classification and regression models evaluating patient systemic risk parameters, such as smoking status, diabetes, and bone density metrics, alongside local biomechanical variables predict long-term implant survival and peri-implantitis risks with accuracies exceeding 90% (Górski, 2025).

Table 3: Applications, Technical Benchmarks, and Workflow Impacts of AI in Prosthodontics and Implantology.

Clinical Domain	Algorithmic Approach	Technical Performance Benchmark	Primary Workflow Impact
Cephalometric Analysis [cite: 11, 18]	Landmark Detection Neural Networks	MRE ≤ 1.5 mm (Lateral); overestimation bias observed in ANB/FMA	Automated orthodontic treatment planning and facial profiling
Monolithic Crown CAD [cite: 5, 6]	GenAI (GANs, Diffusion Networks)	Internal gap: 59-83 μ m; occlusal deviation: 0.18-0.30 mm	4x reduction in total design time; reduced intraoral adjustment
Full-Arch Framework Optimization [cite: 6]	Particle Swarm Optimization (PSO), BESO	Finite element stress concentration reduction	Enhances structural integrity; prevents ceramic chipping
Implant Surgical Planning [cite: 6]	CNN 3D Segmentation & Spatial Mapping	Site identification & drilling protocol accuracy: 90.0% - 99.5%	Prosthetically guided surgical execution; nerve avoidance
Prognostic Survival Modeling [cite: 6]	Supervised Machine Learning / Regression	Risk prediction accuracy for implant retention: >90.0%	Stratifies patient maintenance intervals; mitigates peri-implantitis

5. Translational Landscape, Commercial Integration, and FDA Regulatory Framework

5.1 FDA 510(k) Approvals and Commercial Ecosystem

The transition of academic AI algorithms into commercial clinical workflows requires strict regulatory clearance to ensure safety, efficacy, and software dependability. In the United States, the Food and Drug Administration (FDA) regulates most dental AI software functions as Medical Devices containing Software (SiMD) or Software as a Medical Device (SaMD). The majority of commercial approvals are granted through the 510(k) Premarket Notification pathway, requiring demonstration of substantial equivalence to an established predicate device, with a small fraction

pursuing De Novo classification (Warraich et al., 2025).

Dozens of distinct AI/ML-based dental devices have received official FDA 510(k) clearances. The market is geographically concentrated, with nearly half of all cleared devices originating from the United States (46.15%), followed by South Korea (9.61%), Canada (5.76%), and Israel. Oral radiology and diagnostic assistance account for the largest functional segment (~48% of cleared devices), led by platforms such as Overjet, Pearl Second Opinion, Diagnocat, VideaAI, and Denti.AI Detect. Implantology and regenerative planning tools comprise approximately 32% of clearances (Pantanowitz et al., 2024).

Table 4: Representative FDA-Cleared Dental AI Commercial Platforms and Clinical Indications.

Developer / System	Primary Indication / Clinical Focus	Target Modality	Key Regulatory & Technical Outcomes
Overjet, Inc. (Caries / Calculus / Dental / Charting Assist)	Caries & calculus detection, bone level quantification, automated charting	Intraoral bitewings, PA radiographs	4 distinct clearances; Enamel/dentin sensitivity: 0.69/0.91; Specificity: ~0.98-0.99

Pearl (Second Opinion)	Comprehensive pathology identification (caries, calculus, margin integrity, periapical lesions)	2D Intraoral & Panoramic radiographs	510(k) clearance; multi-pathology real-time detection overlay
Diagnocat Inc. (Diagnocat)	Volumetric anatomical segmentation and pathology detection	CBCT volumes & 2D Radiographs	Standalone cloud platform; 3D tooth segmentation and bone defect mapping
Denti.AI (Denti.AI Detect / Auto-Chart)	Pathology identification, bone loss measurement, auto-charting	Bitewing, PA, Panoramic radiographs	wAFROC AUC: 0.737; Tooth numbering accuracy: 85.9%; Restoration sensitivity: high
Ewoosoft Co., Ltd. (Ez3D-i Platform)	3D Volumetric rendering, canal tracking, implant planning	CBCT volumes	6 distinct approvals targeting 3D anatomical segmentation and surgical planning
Better Diagnostics (BDCA v1.0)	Proximal and occlusal caries detection	Bitewing & PA radiographs	Bitewing sensitivity: 89.2%, specificity: 99.5%; reader study showed significant clinician improvement

6. Regulatory Standards, Ethical Governance, and Implementation Challenges

6.1 Standardized Reporting Frameworks

The rapid expansion of medical AI has highlighted the necessity for standardized reporting guidelines to ensure methodological transparency, reproducibility, and clinical safety. Unclear reporting in literature impairs systematic meta-analysis and masks underlying risks of bias. Standardized guidelines such as STARD-AI (Standards for Reporting Diagnostic Accuracy Studies-AI) and TRIPOD-AI (Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis-AI) require researchers to detail sample selection protocols, reference standard definitions, missing data handling, and demographic distribution shifts (Patel et al., 2019).

In diagnostic imaging, the updated CLAIM 2024 (Checklist for Artificial Intelligence in Medical Imaging) framework mandates explicit transparency regarding neural network code accessibility, data partition splits (ensuring complete separation between training, validation, and test sets at the patient level), and uncertainty quantification (Güth et al., 2013). Furthermore, the ITU/WHO Focus Group on AI for Health (FG-AI4H Dental Subgroup) established a consensus-based 31-item checklist specifically

tailored to dental diagnostic and digital dentistry studies. This framework provides benchmark protocols for dataset curation, ground-truth annotation by multi-expert panels, and multi-center validation requirements (Khanagar et al., 2021).

6.2 Data Privacy, Algorithmic Transparency, and Clinical Autonomy Levels

Integrating AI into routine clinical workflows introduces complex ethical, legal, and operational challenges. Dental radiographs and 3D intraoral scans constitute Protected Health Information (PHI), while facial scans used in Digital Smile Design and stereophotogrammetry contain biometric identifiers capable of rendering patient re-identification possible even after radiographic header de-identification (Farooq, 2022). Compliance with regulatory frameworks, such as HIPAA and GDPR, mandates encrypted data pipeline protocols and federated learning models that train algorithms across decentralized institutional servers without transferring raw patient files (Anil et al., 2023).

The integration of AI exists along a defined continuum of clinical autonomy. At Level 1, software provides basic supportive utilities such as image enhancement and spatial measurements. At Level 2 (Advisory Mode), real-time diagnostic

overlays display bounding boxes around carious lesions or bone loss areas, operating under a strict "clinician-in-the-loop" model where the practitioner evaluates AI suggestions prior to formulating a definitive treatment plan. Level 3 represents delegated execution within defined boundaries, such as automated generative crown synthesis or self-executing bracket placement algorithms (Alquassier, 2023).

As AI systems transition toward Level 3 execution, accountability models evolve. If an AI system generates a misaligned occlusal surface or fails to identify an aggressive osteolytic lesion, legal liability becomes shared among the treating clinician, the healthcare institution, and the software developer. Maintaining a strict clinician-in-the-loop framework remains the gold standard, ensuring that professional human judgment remains central to patient care decisions (Hung et al., 2020).

Conclusion

The convergence of artificial intelligence and digital dentistry heralds a new epoch in oral healthcare, characterized by early, non-invasive diagnosis and personalized therapeutic protocols.

As this comprehensive review demonstrates, AI algorithms have matured from experimental proof-of-concept systems to clinically deployable tools with demonstrable diagnostic accuracy and workflow efficiency improvements across cariology, periodontology, endodontics, oral pathology, and prosthodontic rehabilitation. Deep learning architectures now consistently match or exceed human expert performance in specific pattern recognition tasks, while generative models are revolutionizing restorative design through patient-specific, biomechanically optimized morphologies. The translation of these academic innovations into commercial platforms, evidenced by the expanding portfolio of FDA-cleared AI devices, signals growing clinical acceptance and regulatory maturity. However, the path to universal adoption requires navigating substantial challenges: algorithmic biases arising from training datasets lacking demographic diversity, the imperative for standardized reporting

frameworks such as STARD-AI and CLAIM 2024 to ensure methodological transparency, robust data privacy protections for protected health information and biometric identifiers, and the ethical governance of AI systems as they transition toward higher levels of clinical autonomy. The ultimate success of AI in dentistry hinges not on replacing human expertise but on augmenting it maintaining the clinician-in-the-loop paradigm ensures that computational power serves as an adjunct to, rather than a substitute for, professional judgment. Looking forward, the development of federated learning architectures, explainable AI systems, and seamless integration with electronic health records will be crucial for realizing the full potential of precision oral healthcare. As these technologies continue to evolve, interdisciplinary collaboration among clinicians, data scientists, regulatory bodies, and patients will be essential to ensure that AI-driven dentistry fulfills its promise of improved diagnostic accuracy, personalized treatment outcomes, and ultimately, enhanced patient quality of life.

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