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RESEARCH ARTICLE

A Chronological Narrative Review of AI Evolution in Dentistry

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ABSTRACT

Artificial intelligence (AI) has catalyzed a paradigm shift in dentistry, progressively transforming diagnostic accuracy, treatment planning and clinical work flows through advanced computational models, real-time image analysis, predictive analytics and autonomous robotic systems. This study presents a comprehensive chronological review of AI's integration into dental practice, delineating its evolution across five developmental stages. Early applications in the 1980s and 1990s were confined to rule-based expert systems and rudimentary CAD/CAM technologies, providing a nascent foundation for computational dentistry. The subsequent decade witnessed the adoption of machine learning (ML) with artificial neural networks (ANNs) surpassing human performance in caries detection. The proliferation of deep learning (DL) in the early 2010s marked a significant inflection point, as convolutional neural networks (CNNs) demonstrated superior precision in radiographic lesion detection, cephalometric landmarking and oral cancer screening. Between 2016 and 2020, AI achieved clinical validation, exemplified by FDA-cleared diagnostic systems and teledentistry applications, reinforcing its credibility for real-world deployment. The current era (2021–present) has expanded AI's role beyond imaging, introducing predictive analytics, natural language processing (NLP) for automated dental charting and AI-assisted robotic surgery with sub-millimetric precision. Despite these advancements, ethical concerns persist, particularly regarding dataset bias, regulatory oversight and algorithmic accountability. This study calls for the need for interdisciplinary collaboration between dental professionals, computer scientists and policymakers to optimize AI integration while ensuring ethical compliance and clinical reliability. Future research should prioritize AI model generalizability across diverse populations, regulatory standardization and the development of transparent, interpretable AI frameworks to enhance patient outcomes, optimize resource allocation and redefine precision-driven dental care in the digital age.

INTRODUCTION

Historically anchored in tactile dexterity and analog radiography, dentistry has undergone a sweeping digital transformation driven in large part by the integration of artificial intelligence (AI). Over the past four decades, AI has progressively redefined diagnostic precision, treatment planning and patient care to solidify its role as an indispensable pillar of contemporary dental practice (Schwendicke et al., 2020). Market projections by Grandview Research (2024) estimate that the global digital dentistry sector is sized at $6.8 billion in 2024 with an anticipated compound annual growth rate (CAGR) of 9.9% from 2025 to 2030. This surging growthunderscores the sector's increasing clinical relevance and commercial viability, particularly driven by the rapid expansion of AI applications in dentistry. Moreover, conventional dental workflows have long been criticized and hampered by diagnostic subjectivity and inter-clinician variability according to Shan et al. (2021). For example, radiographic detection of dental caries demonstrates inconsistency rates of 15–20% among practitioners, often leading to overdiagnosis, undertreatment or mismanagement of lesions (Liedke et al., 2014). Similarly, cephalometric landmark identification in orthodontic assessments is labor-intensive and error-prone, with interobserver discrepancies averaging 1.5–2.0 mm (Pittayapat et al., 2014). AI-driven automation has thus emerged as a corrective mechanismthat minimizes human error and standardizes diagnostic protocols, contributing to enhanced clinical decision-making through data-driven insights.

According to Ding et al.'s (2023) systematic review of dentistry literature, early AI applications in dentistry were largely rule-based expert systems in the 1980s which laid the conceptual groundwork for later advancements. However, it was the advent of machine learning (ML) and deep learning (DL) architectures that triggered a paradigm shift, enabling applications spanning from automated lesion detection to AI-assisted robotic surgery (Ding et al., 2023).Despite its widely recognized transformative potential among academics and practitioners, skepticism regarding AI adoption in clinical dentistry persists due to key challenges. Although contemporary algorithms for caries and periodontal disease detection now surpass 90% accuracy (Ferrara et al., 2025), concerns regarding dataset bias, algorithmic opacity and regulatory inertia remain significant (Kothandapani, 2025). A 2024 meta-analysis conducted by Rokhshad et al. (2024) found that over half of AI-based diagnostic models were trained on datasets from high-income countries, raising critical concerns about their generalizability to underrepresented populations. Moreover, the rapid commercialization of AI-powered dental tools such as Diagnocat, an FDA-approved platform for panoramic radiograph analysishas in some cases outpaced rigorous longitudinal validation, engendering ethical debates surrounding liability and accountability in cases of misdiagnosis (Schulze et al., 2024).

While prior studies have examined discrete AI applicationsfor instance, deep learning in oral cancer detection (Khanagar et al., 2021) or robotics in implantology (Neugarten, 2024), none have undertaken a holistic chronological analysis of AI's trajectory in dentistry in terms of its chronological evolution. Existing reviews often adopt a narrow focus, emphasizing either algorithmic advancements (e.g., convolutional neural networks) or specific subspecialties (e.g., orthodontic automation) without considering the influential factors in areas of technological evolution and clinical integration (Thurzo et al., 2022). This review addresses the aforementioned research gap by systematically reviewing AI's progression across five distinct developmental stagesranging, from early rudimentary expert systems to contemporary generative AI and autonomous robotics, delineating key historical milestones that have shaped modern dental practices to offer more comprehensive insights for the future of AI-driven advancements in dental applications. The review's novelty lies in its integrative chronological approach, revealing how foundational innovationsenabled later breakthroughs, discussing understudied areas and contextualizing AI within dentistry's broader digital transition. The aim of this chorological narrative review to offer clinicians and researchers a holistic roadmap for understanding AI's opportunities and risks.

2. METHODS

This narrative review adhered to a structured, methodologically rigorous search and synthesis framework as per Ferrari (2015) to ensure transparency and scholarly integrity. A comprehensive literature search was conducted across PubMed, Scopus, Web of Science and IEEE Xplore, targeting peer-reviewed articles, systematic reviews, meta-analyses, clinical trials and seminal reports published between 1980 and 2025. Given the rapidly evolving nature of artificial intelligence (AI) advancements in recent years, the search strategy was designed to encompass a broad yet clinically relevant spectrum of studies spanning five key developmental stages, each representing a distinct era of AI integration into dental practice. Stage 1 (1980s–1990s) introduced rule-based expert systems and early CAD/CAM technology with MYCIN-inspired diagnostics (Abbey, 1987) and the first chairside milling system, CEREC® (Mörmann et al., 1989), laying the groundwork for digital dentistry. Stage 2 (2000–2010) saw machine learning (ML) emerge in radiographic diagnostics as ANNs outperformed dentists in caries detection (Devito et al., 2008), while CAD/CAM advancements like CEREC 3D (Otto & De Nisco, 2002) enabled single-visit restorations. Stage 3 (2011–2015) ushered in deep learning (DL) with CNNs achieving expert-level accuracy in radiographic lesion detection (Hiraiwa et al., 2019) and early oral cancer screening (Fu et al., 2020), while cephalometric landmarking became automated (Lindner et al., 2015). Stage 4 (2016–2020) focused on clinical validation and regulatory approvals, as Diagnocat's AI gained FDA clearance (Schwendicke et al., 2019), CBCT-based AI models enhanced implant planning (Bayrakdar et al., 2021) and teledentistry applications demonstrated accurate remote triage (Etai et al., 2016). Stage 5 (2021–Present) expanded AI's role into predictive analytics, NLP-based automated charting (Patel et al., 2023), generative AI for synthetic imaging (Mehandru et al., 2021), and AI-assisted robotic surgery with

Yomi® achieving sub-millimetric implant precision (Neugarten et al., 2024), marking the transition towards autonomous, AI-driven dental care.

To maximize the retrieval of pertinent literature, search queries employed a combination of MeSH terms, free-text keywords and Boolean operators (“AND,” “OR”). Core search terms included various permutations of “artificial intelligence,” “machine learning,” and “dentistry”, further refined with discipline-specific terms such as “caries detection,” “orthodontic prediction,” “robotic surgery,” “deep learning-assisted diagnostics,” “computer-aided detection,” “convolutional neural networks,” “natural language processing,” “teledentistry AI,” “image segmentation,” and “predictive analytics in dentistry.” These refinements enabled the identification of studies addressing AI-driven diagnostic accuracy and treatment planning optimizations. Inclusion criteria prioritized methodologically rigorous studies with clearly reported accuracy, sensitivity, specificity and external validation metric as high-impact investigations and FDA approved AI applications were retained and prioritised, while non-English studies, non-validated prototypes, opinion pieces and commercially biased white papers were excluded. Grey literature such as patents and conference proceedings were selectively included for historical context, particularly regarding pioneering CAD/CAM systems like CEREC® (Mörmann et al., 1989). Extracted data were structured into three analytical dimensions: (1) Technological innovation, evaluating algorithm types (e.g., “convolutional neural networks,” “natural language processing”), dataset properties, and performance benchmarks; (2) Clinical impact, measuring diagnostic precision, workflow efficiency and patient outcomes, particularly through AI-human comparative studies (e.g., Hiraiwa et al., 2019); and (3) Limitations and challenges including algorithmic bias, dataset representativeness and regulatory constraints. Despite the review’s broad scope, inherent limitations persist including a geographic skew favoring high-income nations and the underrepresentation of pediatric and geriatric applications in AI-driven dentistry.

Stage 1: Early foundations (1980s-1990s)

Rule-based systems and computational diagnostics

The 1980s and 1990s marked the emergence of foundational digital technologies in dentistry, primarily focused on the development of rule-based expert systems and the emergence of computer-aided design/computer-aided manufacturing (CAD/CAM) technology (Carrillo-Perez et al., 2022). Although constrained by static algorithms, limited data availability and hardware inefficiencies, Dobrazski et al. (2020) argue that these early developments laid the conceptual groundwork for AI’s eventual integration into mainstream dental practice. For example, expert systems introduced decision-support frameworks aimed at reducing diagnostic subjectivity while CAD/CAM innovations redefined the precision and efficiency of restorative dentistry (Rehak & Howard, 1985). Stanford’s MYCIN rule (Figure 1, Clancey, 1983, p222), represented a pioneering expert system for infection diagnosis and was increasingly adapted into dental caries risk assessment, demonstrating an early attempt to introduce probabilistic reasoning into diagnostic workflows (Stheeman et al., 1992). Building on MYCIN’s foundational work, Abbey (1987)) introduced one of the earliest PC-based expert systems for oral diagnosis allowing clinicians to input patient information, which was then processed through a fixed knowledge base to generate probable diagnoses and management recommendations. It was found that the system was highly effectively when evaluating periapical radiolucencies and lesions at the apex of a tooth via offering differential diagnoses and treatment options based on radiographic characteristics and clinical findings.

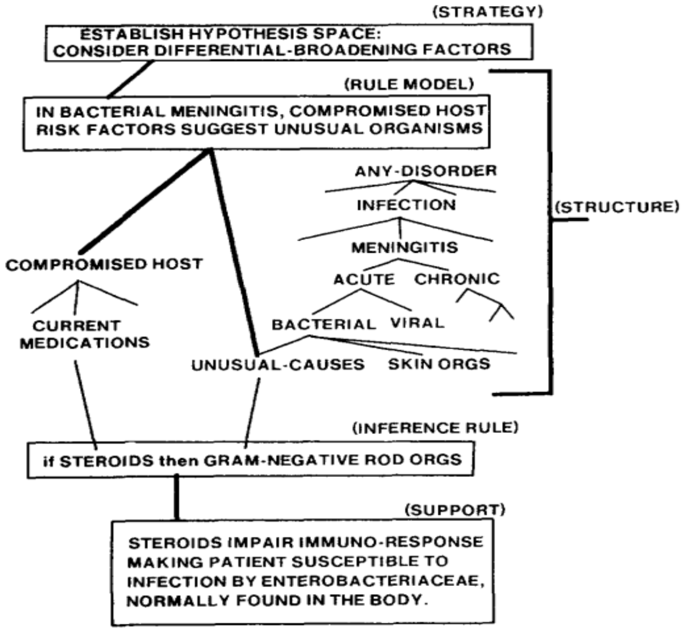

Figure 1: Knowledge for indexing, justifying and invoking a MYCIN rule (Clancy, 1983, p222)

Parallel advancements were made in orthodontic digital applications as Sims-Williams et al. (1987) developed an early expert system designed to assist general dentists with limited orthodontic training in treatment planning for malocclusions. This rule-based system functioned as a decision-support tool, guiding practitioners through the management of cases such as lower arch crowding through systematically analyzing occlusal features and recommending appropriate interventions. By 1991, the system had evolved to recognize and classify Class II Division 1 malocclusions and determine suitability for removable appliance therapy (Hammond & Freer, 1997). However, two fundamental challenges emerged, first, encoding a patient's occlusal characteristics in a structured, computer-readable format, and second, translating an orthodontist'sclinical judgment into rigid "if-then" rules. A critical evaluation of these early expert systems was conducted by Stheeman et al. (1992) and their findings illustrated the stark contrast between digital expert systems advancements in medicine and their slower adoption in dentistry. Between 1984 and 1991, only two peer-reviewed studies on dental expert systems were published, compared to more than 600 in digital medical research. This discrepancy was attributed to multiple factors including the relatively smaller research community in dental informatics, the lack of standardized digital dental datasets and the profession's skepticism toward digital-assisted diagnostics. Stheeman et al. (1992) proposed criteria for evaluating dental expert systems, emphasizing that for such tools to be integrated into routine practice, they needed to be rigorously tested, validated and refined through clinical trials.

Early CAD/ CAM technology in dentistry

In the late 1980s, dentistry was revolutionized by CAD/CAM (computer-aided design/computer-aided manufacturing) technology which automated the design and fabrication of dental restorations. Early pioneers laid the groundwork for digital workflows that enabled efficient production of crowns, inlays and other prostheses.Duret et al. (1988) were widely recognized as the progenitors of dental CAD/CAM, developing one of the first systems capable of digitizing tooth preparations and milling restorations. As early as 1971, Duret et al. (1988) experimented with an optical scanner to capture three-dimensional images of prepared teeth and by 1983, they successfully produced the first CAD/CAM crown andin a dramatic live demonstration at the 1985 French Dental Association meeting, Duret et al. (1988) captured an optical impression of a tooth and machined a full crown in under an hour (Figure 2). Concurrently, Swiss dentist Dr. Mörmann introduced CEREC in the mid-1980s as the first commercially successful chairside CAD/CAM system (Figure 3, Mormann & Curilovic, 1991). CEREC, an acronym for CEramic REConstruction, ingeniously merged a custom optical scanner with a computer-controlled milling unit to fabricate ceramic inlays and onlays directly within the dental office. Mörmann et al. (1989) achieved the world's first chairside restoration in a single appointment in 1985, utilizing a porcelain inlay milled on the spot, they study also documented 13 CEREC-milled ceramic inlays that functioned successfully for three years, albeit with challenges such as a steep learning curve and initial fit issues.

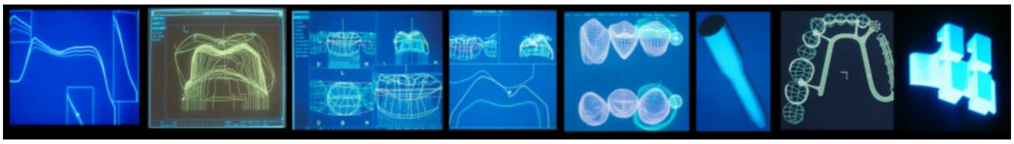

Figure 2: World's first commercial dental CAD/CAM – Duret system

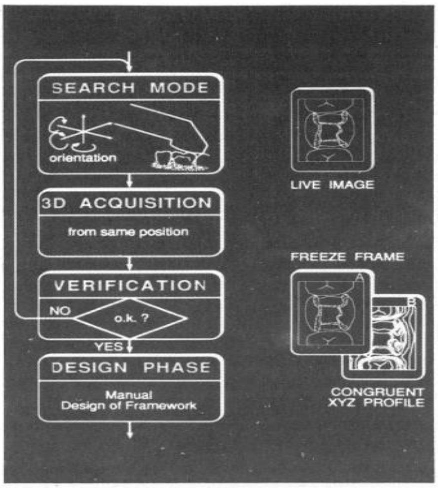

Figure 3: Flow diagram of the CEREC optical impression method (Mormann & Curilovic, 1991)

At the University of Minnesota, Rekow et al. (1991) developed an alternative CAD/CAM system employing digital imaging and five-axis milling. Unlike CEREC's intraoral video capture, Rekow et al. (1991) used a series of high-resolution photographs and scans to compute a restoration design, which was then milled from ceramic or composite blocks. Although the Minnesota system did not reach commercial success, it provided valuable insights into digital impression techniques and computerized fabrication that influenced subsequent simulation software.In Sweden, Persson et al. (1995) pioneered the Procera system in the 1980s focusing initially on high-precision ceramic copings for crowns. Their innovative process involved scanning stone dies to design a coping that was milled from alumina ceramic and later veneered with porcelain. Moreover, Persson et al. (1995) expanded CAD/CAM to create composite veneered restorations through integrating a milled substructure with esthetic layering. Procera, which debuted commercially in the late 1980s (later adopted by Nobel Biocare as "NobelProcera"), demonstrated that centralized production-center networks could broaden the impact of CAD/CAM beyond chairside use (Örtorp et al., 2009). These early studies confirmed that Procera-fabricated cores exhibited excellent fit and strength, thereby reinforcing how digital fabrication could enhance both consistency and quality in lab-fabricated prostheses. Collectively, these pioneering efforts in the 1980s-90s transformed dental prosthetics, proving that CAD/CAM technology could fabricate common restorations (inlays, onlays, crowns, etc.) with sufficient accuracy for clinical use and laid the foundation to today's widespread use of intraoral scanners, design software and milling/3D printing systems that are now integral to dental practice.

Stage 2: Rapid digitalization of dentistry (2000-2010)

CAD/CAM in prosthodontics

Early 2000s research validated chairside CAD/CAM systems like CEREC® for fabricating crowns, inlays and onlays as increasing number of studies demonstrated improvements in digital impression captureand automated milling during this decade. A ten-year clinical study of CEREC CAD/CAM inlays Otto & De Nisco (2002)found 90.4% survival rate with only ~8–11% needing replacement (mostly due to ceramic fractures. An even longer follow-up by Otto & Schneider (2008) reported an 88.7% success rate at 17 years for first-generation CEREC I ceramic inlays/onlays as a "very respectable" outcome comparable to gold standards, achieving high patient satisfaction with CAD/CAM restorations. The mid-2000s saw stronger ceramics for CAD/CAM aslithium disilicate (e.g. IPS e.max CAD) was introduced as a chairside millable ceramic offering high strength and esthetics. A 2-year clinical evaluation by Fasbinder et al. (2010) on 62 e-max CAD crowns (milled with CEREC 3) reported zero fractures or chipping and excellent margins (over 92% rated "Alfa"/ideal). Other researchers like Reich et al. (2010) and Poticnny & Kilm (2010) concluded these monolithic lithium-disilicate crowns performed well in function, supporting their effectiveness for all-ceramic restorations as newer CAD/CAM materials could achieve similar success to traditional porcelains.

Digital impression-taking also became feasible in this era, replacing physical molds as systems like CEREC 3/Bluecam and Lava COS (circa 2008–2009) introduced optical scanners to capture 3D tooth geometry(Seelbach et al., 2010). Early evaluations by Bindl & Mormann (2005) found that CAD/CAM crown copings produced via digital scans had marginal fit in the 20–40 µm range, on par with conventional techniques. In their study, all-ceramic CAD/CAM crowns showed similar or smaller gap dimensions compared to traditional pressed or cast crowns indicating that digital workflows could achieve clinically acceptable (often <120 µm) accuracy giving confidence that intraoral scanning and CAD design did not compromise restorative precision. As CAD/CAM software automated much of the restoration design process (proposing crown anatomy from a tooth library), milling devices were guided by these computer-generated models asprotocols improved to minimize human error in tool-path planning and occlusal adjustment. The CEREC 3 unit split the scanner/design module from the milling unit for efficiency and newer software iterations were found to optimize machining parameters which allowed dentists to complete restorations start-to-finish in a single visit.The advancement of CEREC systems in the early 21st century saw the development of major innovations, as evidential in the CEREC 3D, CEREC 3 bio-generic inlay proposals, CEREC MC XL, CEREC AC, CEREC Bluecam and CEREC SW 3.8 bio-generic crown systems as shown in Figure 4 (Sirona, 2020).

Figure 4: CEREC innovations in the late 20th and early 21st century (Sirona, 2020)

Machine learning (ML) in radiographic diagnostics

The 2000s produced some of the first studies applying machine learning to dental radiographs for diagnosis as researchers began experimenting with algorithms (primarily artificial neural networks) to detect common dental diseases like caries and periodontal bone loss on X-rays. One pioneering effort was by Kositbowornchai et al. (2006), who trained an artificial neural network to identify simulated occlusal caries in digital radiographic images, confirming that an ANN could be taught to interpret features of decay versus sound tooth structure, essentially prototyping an AI-based caries detector. Building on these initial discoveries, Devito et al. (2008) developed a multilayer perceptron model for proximal caries on bitewing radiographs via a trial with 160 tooth radiographs (validated against actual tooth sections). It found that the neural network outperformed human dentists in detecting lesions with the best dentist achieved an ROC AUC of 0.717, whereas the trained ANN reached 0.884, demonstrating improved diagnostic accuracy by 39%. Application of ML to assess periodontal status also begin in this period, asresearchers explored using radiographic features (bone levels) and patient risk factors to train models that classify periodontitis severity. For example, a pilot study by Shankarapillai et al. (2010) employed two ANN models to predict periodontal risk, inputting clinical parameters and radiographic bone loss data with the aim to distinguish high-risk patients.Although data on accuracy were limited (small sample), the study proved feasibility. Early ML diagnostic studies also reported promising accuracy for their era, achieving sensitivity and specificity in the 80–90% range for detecting pathologies in controlled settings (Economopoulos et al., 2008).

More importantly, these early studies introduced rigorous metrics like ROC curves, precision/recallinto dental diagnostics (Poulter, 2008; Horst, 2010), establishing baselines against which newer AI algorithms would be compared.Introducing ML-based analysis into diagnostics aimed to reduce observer variability as Olsen et al. (2009) argue that traditional radiographic diagnosis can be inconsistent as different clinicians might miss a lesion or grade bone loss differently. Early AI systems showed potential to standardize this, as ML-based diagnostic tools apply uniform decision-making criteria across all cases to achieve standardized analysis independent of human variability. A study by Carmody et al. (2008) demonstrated this principle through evaluating a machine classification system trained to analyze periapical radiographs. The system utilized gaze-tracking data to determine key image regions for classification, creating a more targeted and effective feature selection process. The results revealed that while human observers achieved an accuracy of only 57% in classifying periapical disease severity, the machine learning classifier outperformed them with an accuracy of 84%. Carmody et al.'s (2008) study further highlighted the superiority of using gaze-selected sampling techniques over conventional random selection methods. With a χ^2 value of 0.78 for gaze-guided selection compared to 0.69 and 0.68 for random sampling techniques, supporting that machine learning algorithms can effectively extract and prioritize diagnostically relevant features that human observers may overlook, asevidenced by the precise fixation locations identified through ML (Figure 5, Carmody et al., 2008, p1244).

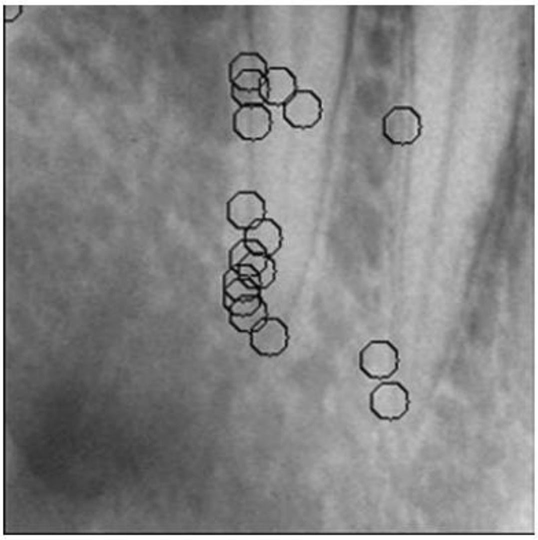

Figure 5: ML-driven analysis of fixation-based digital imaging diagnostics (Carmody et al., 2008, p1244)

Stage 3: Deep learning revolution (2011-2015)

CNN-driven diagnostic breakthroughs

The early 2010s marked the advent of deep convolutional neural networks (CNNs) in medical imaging and dentistry began embracing this revolution by the mid-2010s. CNNs excel at automatically learning image features (edges, shapes, patterns) through layered filters, supporting complex tasks like image classification, lesion detection and segmentation according to Rodrigues et al.'s (2021) literature review. Moreover, Athiwaratkun & Kang (2015) found that CNNs (e.g. AlexNet) dramatically outperformed previous algorithms in general image recognition, paving the way for AI-driven dental diagnostics. A key theme in 2011–2015 was applying deep learning to early oral cancer detection. Oral cancers (especially oral squamous cell carcinoma) often present as lesions on the mucosa, and early identification greatly improves prognosis. Initial studies by Brito et al. (2012) trained CNNs on clinical photos of oral mucosal lesions, facilitating automated screening in primary care or remote settings through using transfer learning on proven architectures (e.g. Inception-ResNet or ResNet-101), these models could classify lesions as "suspicious" vs "normal" with notable accuracy. Contrast-enhanced computed tomography (CECT) was found to demonstrate high diagnostic accuracy in detecting cervical lymph node metastasis in oral squamous cell carcinoma (OSQCC). Using nodal size (≥1 cm) and central nodal necrosis (CNN) as primary radiological criteria, CECT achieved 88% accuracy, 92% sensitivity and 84% specificity in staging histopathologically confirmed metastatic nodes (Pandeswhar et al., 2013). The presence of CNN correlated significantly with metastatic involvement, emphasizing its role as a key imaging marker.

Additionally, variations in nodal densities were associated with primary tumor differentiation, suggesting that CNN detection alone may not be sufficient in cases of low-grade tumors, indicating that nodes smaller than 1 cm may require adjunct techniquessuch as ultrasound-guided fine needle aspiration, to improve diagnostic precision (Pandeswhar et al., 2013). A study by Warin et al. (2011) collected clinical oral photographs between 2009 and 2018 at a n oral and maxillofacial surgery centre, employing DenseNet-121 for classification and reported a sensitivity of 98.75% and a specificity of 100%. These findings confirm that CNN models can identify visually subtle malignant changes (such as irregular texture or color patterns) that might elude less experienced clinicians. Beyond standard photographs, researchers also explored CNN analysis of cytology and histology images of oral lesions. For example, convolutional models were trained on oral cytology slides and shown to accurately classify dysplastic vs normal cells as shown in Figure 6 (Lee, 2014, p33). Similarly, CNNs have been applied to high-resolution microendoscopy (HRME) and confocal endomicroscopy images of oral tissue, offering real-time optical biopsy with reported high accuracies (Abbaci et al., 2014). The common theme here lies in that deep learning (even in its infancy around 2015) started to augment clinicians' ability to detect oral cancers early, identifying suspicious regions on images (sometimes with heatmaps to indicate where the network "sees" a potential tumor), CNN systems can serve as decision support, leading to earlier biopsies or referrals.

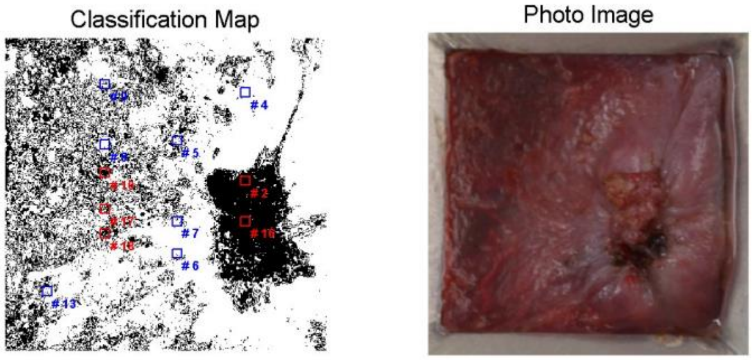

Figure 6: Classification of dysplastic and the actual tissue image of tissues (Lee, 2014, p33)

Cephalometric landmark identification with CNNs

In orthodontics and craniofacial analysis, identifying anatomical landmarks on lateral cephalometric radiographs is essential for diagnosis and treatment planning, traditionally involving tedious manual tracing by orthodontists (Sener et al., 2018). The period around 2014–2015 saw the start of automating this process with AI and CNNs soon became the leading approach, overcoming the challenge of automatic cephalometric landmark detection was initially tackled with classical machine learning. For example, the IEEE ISBI 2014 and 2015 cephalometric challenges benchmarked algorithms on locating standard cranial landmarks, as top performers commonly used techniques like random forests rather than deep networks (LeCun et al., 2015). While those models achieved moderate accuracy, a drawback was their complexity and lack of transparency, combining many decision trees made it hard to interpret how a landmark position was determined (LeCun et al., 2015). Alternatively, CNN-based solutions dramatically improved cephalometric analysis as deep networks could learn the subtle anatomical features around each landmark point (such as incisor tips, condyles, orbitale, etc.) from large annotated datasets, achieving 75–80% success detection within 2 mm error for 19 key landmarks which is typically considered the threshold for clinical acceptability (Figure 7, Hwang et al., 2021). This level of precision was unprecedented as it meant that automated ceph tracings were feasible, potentially saving orthodontists significant time. Through producing consistent landmark identification, CNN systems also removed inter-observer variability inherent in manual tracings (Vasamsetti et al, 2015). The best-performing models in this domain often used multi-stage CNNs or cascaded networks (first roughly locating the skull outline, then refining landmark positions), augmented with techniques like heatmap regression or even Bayesian CNNs for uncertainty estimation (Mohamed, 2014).

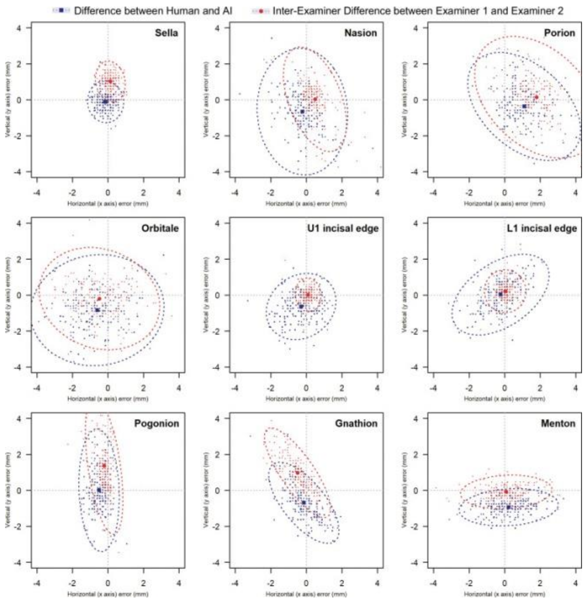

Figure 7: Scatter plots with 95% confidence ellipses for cephalometric landmark detection errors (Hwang et al., 2021)

Dataset augmentation and synthetic data generation

A recurring challenge in applying deep learning to dentistry (circa 2011–2015) was the limited availability of large, labeled dental image datasets, unlike general computer vision (which has millions of labeled images), dental AI researchers often had only a few hundred or thousand radiographs or clinical photos for training, sometimes from homogeneous patient groups (Okada et al., 2015). To overcome this data scarcity and improve model generalizability, a variety of dataset augmentation strategies were developed through generative augmentation with generative adversarial networks (GANs).Initially introduced by Goodfellow (2014) as a class of machine learning framework for approaching generative AI, two neural networks contest with each other in the form of a zero-sum game where gains from on agent is another agent's loss, allowing the model to learn in an unsupervised manner as shown in Figure 8.According to Nazareth-Arya (2015), GANs can learn the distribution of real images and produce synthetic images that are statistically similar to the originals, aiding the generation of artificial dental data to address class imbalances or enrich rare cases.Nazareth-Arya (2015) applied the StyleGAN2 model generating periapical X-rays of C-shaped root canals, a relatively uncommon anatomic variant, to augment a training set. The fake images passed a "visual Turing test" where oral radiologists struggled to tell them apart from genuine radiographs. When these GAN-generated images were added to the training data, the CNN's classification performance for detecting that root canal shape improved notably compared to training on real images alone, proving that GAN-based augmentation can fill in the gaps for under-represented cases (e.g. uncommon pathologies or anatomies) and mitigate dataset bias.

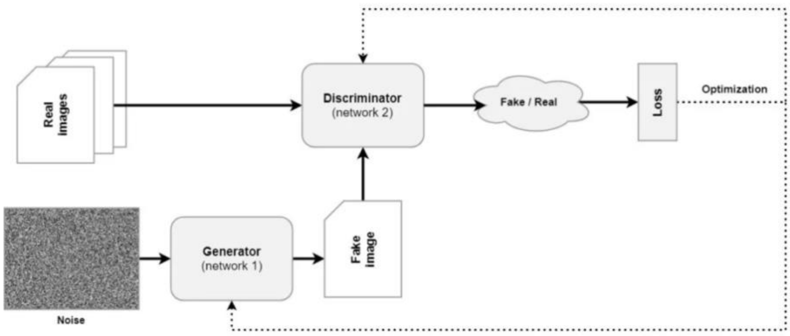

Figure 8: The process of GANs (Goodfellow, 2014)

Stage 4: Clinical validation &commercialization (2016–2020)

Diagnostic AI validation (lesions, caries and impactions)

AI in dentistry progressed from research to clinical use between 2016 and 2020 with early regulatory clearances enabling real-world deployment (Schwendicke et al., 2020). For example, an AI diagnostic imaging system later known as Diagnocat was developed in 2018 and performed near-expert radiographic detection performance especially in conditions having multifactorial etiolog (Figure 9, Mudrak, 2019). A study by Ezhoy et al. (2021) reported the AI's sensitivity (~0.924) in identifying dental pathologies on 3D scans was comparable to that of oral radiologists (~0.932), confirming that AI tools could automatically detect common conditions (e.g. caries, periapical lesions, impacted teeth) on panoramic and CBCT images with high accuracy. A literature review by Issa et al. (2023) found that many pee-reviewed studies conducted between 2016 and 2020 evaluated AI accuracy for detecting dental diseases, often reporting performance on par with experienced dentists. For periapical radiolucencies (endodontic lesions), early deep learning models achieved sensitivities around 86–92% and specificities around 84–97% in identifying apical pathology (Issa et al., 2023).

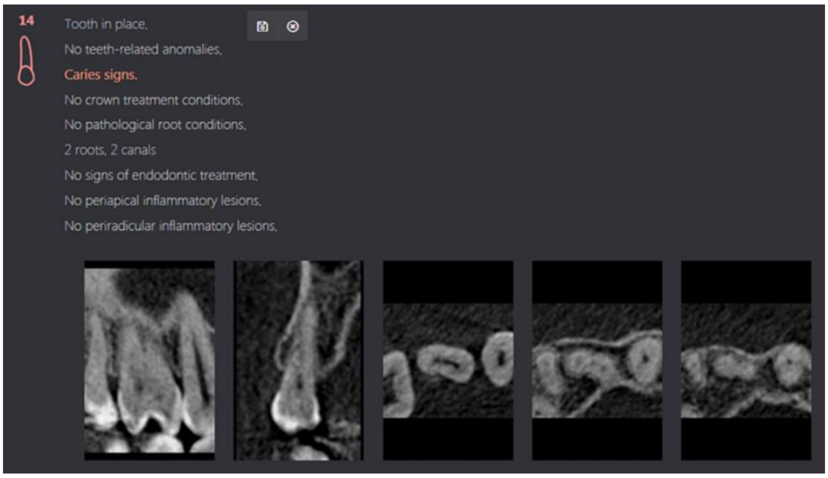

Figure 9: Example of AI diagnoses on Diagnocat (Mudrak, 2019)

A study by Ekert et al. (2019) applied a CNN to panoramic X-rays for apical lesion detection, yielding an AUC up to 0.89 and specificity ~87%, approaching the diagnostic capability of specialists. In dental caries detection, AI systems likewise consistently showed strong performance as studies reported sensitivity ranges roughly 63%–92% and specificity 61%–100% for detecting carious lesions on radiographs, as Megalan & Kalpalath (2020) applied CNN model for proximal caries on bitewings reached about 90% accuracy with >90% sensitivity. AI has also been validated in recognizing impacted teeth on imaging, as evidential in Orhan et al's (2020) study that applied AI model Diagnocat toanalyze 153 periapical lesions and achieved a 92.8% detection reliability, successfully identifying 142 of 153 lesions (Pandeswhar et al., 2013). The system effectively localized lesions to the maxilla, mandible or specific teeth with only one misidentified tooth. Furthermore, volumetric measurements performed by the AI were statistically comparable to manual segmentation ($p > 0.05$), suggesting its potential for automated lesion assessment. These findings reinforce AI's capability to provide clinically reliable periapical lesion detection and measurement, especially its integration into CBCT workflows for enhanced diagnostic consistency and efficiency with performance on par with human analysis. AI-based lesion evaluation offers a promising tool for streamlining radiographic interpretation in endodontics and oral radiology, matching human-level diagnostic performance in dentistry and that collaboration (AI + dentist) is found to yield the best outcomes (Joda et al., 2020).

AI in implant planning and teledentistry

Between 2016 and 2020, AI applications in implantology often applied CBCT imaging to enhance surgical precision as deep learning models were developed to automatically segment anatomical structures, including teeth, alveolar bone and neurovascular pathways to achieve more precise preoperative assessment (Rios et al., 2017; Hung et al., 2020). A study by Sorkhabi & Khajeh (2019) found that 3D convolutional neural networks (CNNs) achieved up to 95% precision in classifying alveolar bone density, providing strong predictive insights into primary stability and osseointegration potential. Sorkhabi & Khajeh's (2019) findings suggest that AI can help evaluate implant sites (e.g. predicting bone quality or primary stability) before surgery, aiding the automation of implant measurement and planning to measure available bone height/thickness at edentulous sites and detected anatomical constraints like the mandibular nerve canal, as results showed no significant difference between the AI's measurements and experts' manual measurements in most regions (e.g. maxillary premolar/molar sites). Bayrakdar et al. (2021) tested data collected in 2020 tomeasure alveolar ridge height and width using Diagnocat AI with comparable accuracy to a radiologist in many regions.In their trial with 75 CBCT scans (508 implant sites), there was no significant difference between AI and expert measurements of bone height in several jaw regions (e.g. mandibular premolars, maxillary premolars/molars, p>0.05),suggesting the AI's linear measurements for implant length selection were as reliable as a human in those areas (Figure 10). However, the AI's bone thickness (width) estimates still differed significantly from manual values in all tested regions (p<0.001), indicating room for improvement in cross-sectional measurements, especially in detecting about mandibular canals, sinuses/fossae and missing-tooth sites of which moderate success rates of 72%, 66% and 95% were recorded respectively (Bayrakdaar et al., 2021).

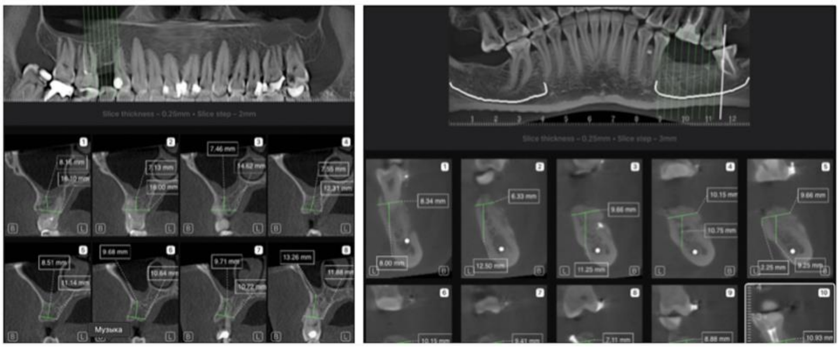

Figure 10: Implant report created using AI (Bayrakdar et al., 2021)

The rise of smartphones to capture dental images has aided the development of remote AI diagnosis systems, as Zhang et al. (2020) proposed a real-time early childhood caries (ECC) detection system using a deep learning model on photos taken by parents' smartphones. A multistage CNN app was developed to analyze pictures of children's teeth for cavities (Figure 11). The model's ROC curve indicated performance not far from that of dentists, detecting most cavities (mAP ~30–47% under strict criteria using a lightweight SSD-MobileNet network in comparison to the 77% sensitivity level of pediatric dentists. A systematic review on teledentistry for caries detection performed by Etai et al. (2016) found it had comparable diagnostic performance to traditional in-person exams, reporting high concordance between a dentist's diagnosis from photos and an actual clinical exam, often with sensitivity and specificity in similar range. Steinnmeier et al.'s (2020) study on the accuracy of remote diagnoses using intraoral scans also found high concordance between teledentistry and clinical in-person dental diagnosis, validating the concept of teledentistry hubs where mid-level providers or patients send images to specialists for evaluation.The COVID-19 pandemic accelerated AI integration into teledentistry particularly for emergency triage, as AI-assisted teleconsultations successfully distinguished urgent cases from those manageable via remote guidance with case reports indicated that over 50% of patients using tele-triage avoided unnecessary in-person visits, optimizing resource allocation while ensuring timely intervention for true emergencies (Ghai, 2020). Acccording to Flores et al. (2020), synergy between AI-driven image analysis, mobile-based reporting and teleconsultation has reshaped dental care delivery, making oral healthcare more accessible as it integrates into national telehealth systems and community-based programs to enhance preventive care, particularly in regions with limited access to dental professionals.

Ghai, S. (2020). Teledentistry during COVID-19 pandemic. Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14(5), 933-935.

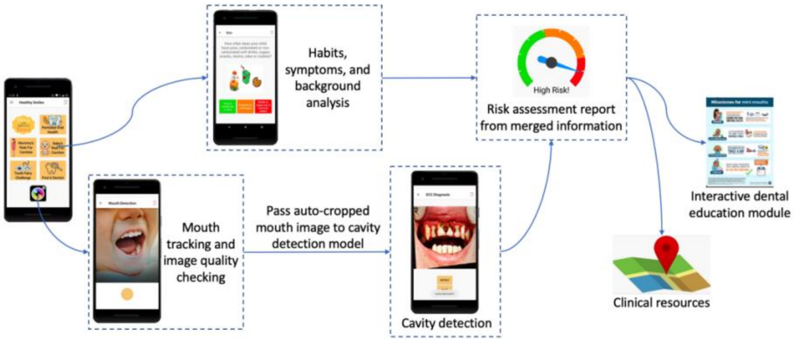

Figure 11: Smartphone caries diagnosis system (Zhang et al., 2020, p3)

Stage 5: Next generation dental AI(2021 – present)

Natural language processing (NLP) for automated dental charting and predictions

Rapid advancement of AI technologies in recent years has created an era dubbed as "robodentistry"and "next-gen dentistry" by Sikri & Sikri (2021). A study by Zhang et al. (2021)developed an NLP algorithm to transcribe clinical oral exam recordings into a dental chart, reaching 98.4% precision and recall in identifying conditions in oral examinations.NLP models have also been applied to electronic dental records text parsing, Chen et al. (2021) created a workflow combining deep learning and keyword methods to extract key details (attributes like diagnosis and tooth number) from free-text Chinese dental notes (Figure 12). The proposed hybrid model achieved high precision (~94%) with reasonable recall (74–82%) for automatically structuring chart data to convert dentists' unstructured notes into coded information (e.g. existing restorations, caries) suitable for decision support.Advancement in NLP technologies have facilitated the extraction and longitudinal tracking of disease, Patel et al. (2023) developed two automated algorithms to analyze clinical notes and classify periodontal disease (PD) progression over time in a large retrospective study of 28,908 patients, leveraging Python-based data processing frameworks (including Pandas, TensorFlow, and PyTorch), their model systematically categorized patients into three cohorts included disease progression, disease improvement and no significant change. Patel et al.'s (2023) study demonstrated that AI-driven analysis is efficient for monitoring PD trends across an extended timeframe, approximately 34% of patients had up to five years of recorded follow-up data with an average of 2.78 periodontal charting entries per patient. Among those with clinician-documented PD diagnoses, 72% exhibited no change in disease status, while 13% showed progression and 11% demonstrated improvement, confirming AI's ability to standardize periodontal disease tracking, mitigating inconsistencies in manual chart reviews while enabling large-scale epidemiological assessments.

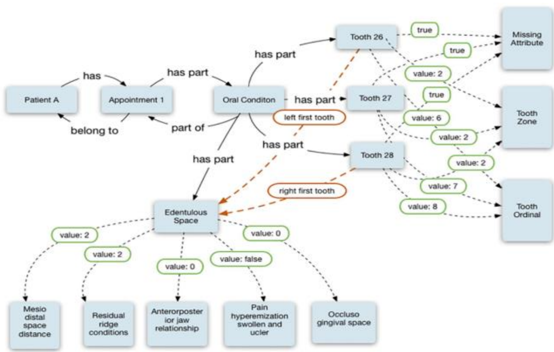

Figure 12: NLP deep learning workflow network (Chen et al., 2021)

Generative AI for synthetic data

GANs are increasingly adopted for creating synthetic dental images that augment training datasets, especially for rare pathologies where real images are scarce, emerging as a key research focus according to Yang et al.'s (2024) systematic review. Mehandru et al. (2021) tackled the detection of radicular cysts on panoramic radiographs by training a convolutional neural network (CNN) to recognize cysts and used GANs to create additional synthetic pano X-rays with and without cyst lesions. The result was a significant boost in accuracy with the CNN trained with GAN-synthesized images achieved 95.1% accuracy, compared to 89.3% when trained on real images alone, as GAN provided extra examples of rare pathology through generating realistic cyst images for the model to learn and extend to other uncommon findings (e.g. tumors, developmental anomalies) to balance datasets.Kong et al. (2022) demonstrated a similar benefit for diagnosing chronic maxillary sinusitis on dental X-rays, utilizing an auxiliary classifier GAN (AC-GAN) to produce synthetic panoramic radiographs exhibiting sinus pathologies. When a deep learning model was trained on the combination of real plus GAN-generated sinusitis images, its diagnostic performance improved beyond training on real data alone, the synthetic data helped the model detect sinus disease on pans more reliably, overcoming the limited availability of expert-labeled caseswhich shows that GANs can alleviate long-standing data scarcity issues in dentistry (Kong et al., 2022). Generative AI is also being explored for simulation and enhancement tasks. For example, CycleGANs have been used to predict post-orthognathic surgery facial changesforpatient with class II and III malocclusion to undergo bimaxillary surgery(Andlauer et al., 2021), and to normalize or super-resolve dental imagesusing a Pix2Pix-GAN model(Kim et al., 2023). The researchconsensus on synthetic imaging via GANs confirms that it is a viable strategy to expand training datasets, improve model robustness on rare dental pathologies, creating realistic scenarios for educational or planning purposes (Umer & Adnan, 2024). This can ultimately lead to AI models that perform better in detecting and diagnosing infrequent conditions which human practitionersmight otherwise encounter too seldom to confidently recognize (Villena et al., 2024).

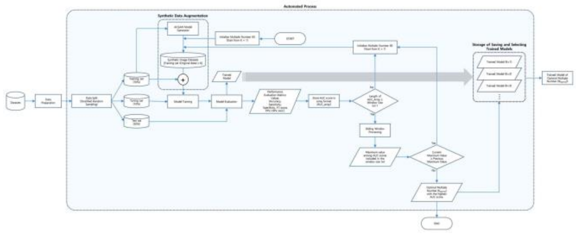

Figure 13: Flowchart on the automation pipeline of GAN-based synthetic data augmentation (Kong et al., 2022)

Robotics in dentistry

Coined under the term “dentronics” by Grischke et al. (2020), AI assisted robotic systems are revolutionizing dental practices by enhancing precision in implant placement and other clinical applications, as illustrated in Figure 14. Xia et al.’s (2024) systematic review on robotics application in dentistry found that robot-guided implant surgery achieved significantly lower angular deviations than dynamic computer-assisted methods, translating to higher placement accuracy. In Wang et al.’s (2024) pilot clinical trial of a novel autonomous robot, the mean entry and apex errors were only ~0.65 mm with ~1.5° angulation deviation, comparable to the best static/dynamic guidance and with no adverse events. Additionally, Neugarten’s (2024) evaluated the FDA-cleared Yomi® robotic platform in a large series of 273 implants, showing average deviation under 0.2 mm and ~1.4° which is substantially more precise than traditional freehand and static guide techniques. The unparalleled accuracy and consistency confirm that haptic robot guidance can outperform other implant modalities in placing implants exactly as planned, offering practical efficiency benefits such as maintaining full surgical field visibility and allowing intraoperative plan adjustments that were traditionally impractical with static guides (Yang et al., 2024). Overall, empirical findings suggest that AI-driven robots can improve implant outcomes and workflow, potentially becoming a new standard for safe, exact implantology.

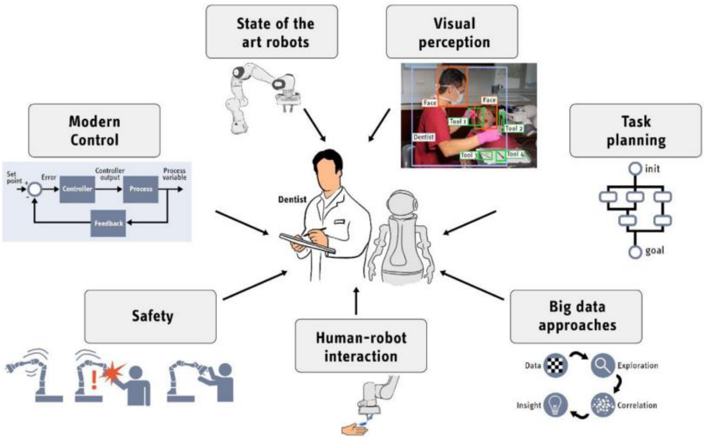

Figure 14: Dental practices utilizing robotics (Grischke et al., 2020, p3)

CONCLUSION

This study chronologicallytraced the evolutionary trajectory of AI developments and applications dentistry, delineating its transformation from rudimentary rule-based expert systems to sophisticated generative AI and robotic-assisted interventions under five stages. The findings reflect the paradigm shift AI has induced in dental diagnostics, treatment planning and clinical decision-making. Early implementations in forms of expert systems and CAD/CAM technology provided the foundational computational infrastructure that later facilitated advanced automation. With the integration of machine learning (ML) in the early 2000s, AI applications began exhibiting diagnostic superiority over human practitioners in radiographic analysis, particularly in caries detection and cephalometric landmark identification. This momentum accelerated in the 2010s as deep learning (DL) architectures, particularly convolutional neural networks (CNNs), redefined precision in lesion detection, occlusal analysis and orthodontic assessment, attaining human-comparable and in certain domains, superior diagnostic capabilities.The period from 2016 onward witnessed AI's expansion beyond diagnostic imaging into predictive analytics, electronic health record (EHR)-driven risk stratification and remote teleconsultation frameworks, enhancing accessibility and clinical efficiency. The proliferation of FDA-approved AI-driven diagnostic tools such as Diagnocat further catalyzed mainstream clinical adoption. More recently, NLP algorithms have emerged as a transformative force in dental informatics, automating charting procedures and mitigating administrative burdens. Concurrently, generative adversarial networks (GANs) have demonstrated their potential in synthetic data augmentation, effectively addressing the longstanding data scarcity challenge for training AI models on rare dental pathologies. The most recent phase (2021–present) has ushered in AI-assisted robotic systems with platforms such as Yomi® setting unprecedented benchmarks for precision in implantology and surgical workflows, marking a transition toward semi-autonomous and data-driven procedural execution.Despite these remarkable strides, formidable challenges persist. Algorithmic bias as exacerbated by dataset homogeneity raises concerns regarding diagnostic disparities and the equitable distribution of AI's benefits across diverse populations. The inherent opacity of deep learning models, commonly referred to as the "black-box" problem, complicates clinical accountability and necessitates the development of explainable AI (XAI) methodologies. Furthermore, regulatory inertia and ethical ambiguities surrounding AI-driven decision-making represent the urgent need for robust legal frameworks that delineate liability and ensure clinician oversight in AI-assisted treatment modalities.

Recommendations and implications for future studies

Future research must prioritize the development of ethical AI frameworks that emphasize fairness, transparency and bias mitigation in AI-driven dental applications. The establishment of geographically and demographically diverse datasets is imperative to enhance model generalizability and preempt diagnostic disparities. Moreover, interdisciplinary collaborations among AI engineers, clinical practitioners, scientific researchers, patientsand regulatory bodies should focus on standardizing validation protocols to ensure AI systems meet rigorous empirical benchmarks before widespread implementation.Explainable AI (XAI) should be further explored to enhance interpretability, fostering clinician trust in AI-driven diagnostics and ensuring transparency in algorithmic decision-making. Additionally, AI governance mechanisms should be formulated to delineate legal accountability in cases of misdiagnosis or procedural failure. Ethical AI decision-making models should be developed to guide automated treatment recommendations while maintaining human oversight as a safeguard against algorithmic fallibility.Moreover, the psychological and professional implications of AI adoption in dentistry warrant further investigation. Studies should explore how AI integration influences clinical autonomy, decision-making paradigms and the dentist-patient relationship. Research into the long-term impact of AI-driven automation on workforce dynamics including the potential deskilling of practitioners and shifts in clinical roles is also crucial. Addressing these multifaceted challenges will be instrumental in ensuring that AI's integration into dentistry remains not only technologically progressive but also ethically sound, clinically reliable and aligned with patient-centered care principles.

Author contributions

The sole author conducted the research, analyzed the literature, and wrote the manuscript in its entirety.

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