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Concise review

# Generative Artificial Intelligence: Applications and Future Prospects in Dentistry

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A B S T R A C T

Generative artificial intelligence (GenAI) is rapidly advancing in healthcare and is poised to transform dentistry. Given its increasing adoption in clinical and educational contexts, a comprehensive review is needed to evaluate current progress and future directions. This narrative review investigates its applications, challenges, and prospects. 74 studies from 2020 to 2025 were analyzed, covering various branches of dental medicine. GenAI has shown promise in crown design, tooth alignment, radiographic diagnosis, and educational content generation, using generative adversarial networks, diffusion models, and large language models. However, limitations remain, including insufficient clinical validation, non-standardized datasets, fragmented workflows, and ethical concerns such as data privacy and transparency. Overall, GenAI represents a transformative technology with potential to enhance diagnosis, treatment planning, and education, but continued research and standardized protocols are essential for safe integration.



## Introduction

Oral health is a fundamental determinant of human well-being, shaping nutrition, speech, psychosocial interaction, and overall quality of life.[1] Global epidemiological surveys[2] reveal that untreated dental disease contributes to systemic disorders such as cardiovascular pathology, diabetes, and adverse pregnancy outcomes, imposing a considerable clinical and socio-economic burden. These realities place dentistry at the center of public health strategy and create an urgent mandate for precise, accessible, and equitable care.

Artificial intelligence has begun to advance that mandate. In dentistry, conventional AI systems—typically based on discriminative deep learning architectures—learn to recognize and classify existing data rather than create new information.[3,4] Such models identify and categorize existing information rather than generate new content. Image-based diagnostic models trained on radiographs,[5] cone beam computed tomography (CBCT),[6] and intra-oral scans[7] have already matched or exceeded experts' performance in detecting caries,[8,9] periodontal bone loss,[10,11] and periapical lesions,[12] maxillary structure,[13] and temporomandibular joint osteoarthritis.[14,15] Meanwhile, natural language processing techniques are accelerating the triage and analysis of electronic dental records.[16] By improving diagnostic accuracy, reducing observer variance, and enabling risk stratification, conventional AI systems demonstrate how data driven approaches can augment clinical decision making across the dental continuum.[17]

Building upon these advances, Generative AI (GenAI) models learn the underlying probability distributions of multimodal data to generate realistic and novel outputs—such as images, text, audio, or 3D biological structures—from noise or conditional inputs, rather than merely analyzing existing samples.[18,19] Technically, GenAI encompasses several major

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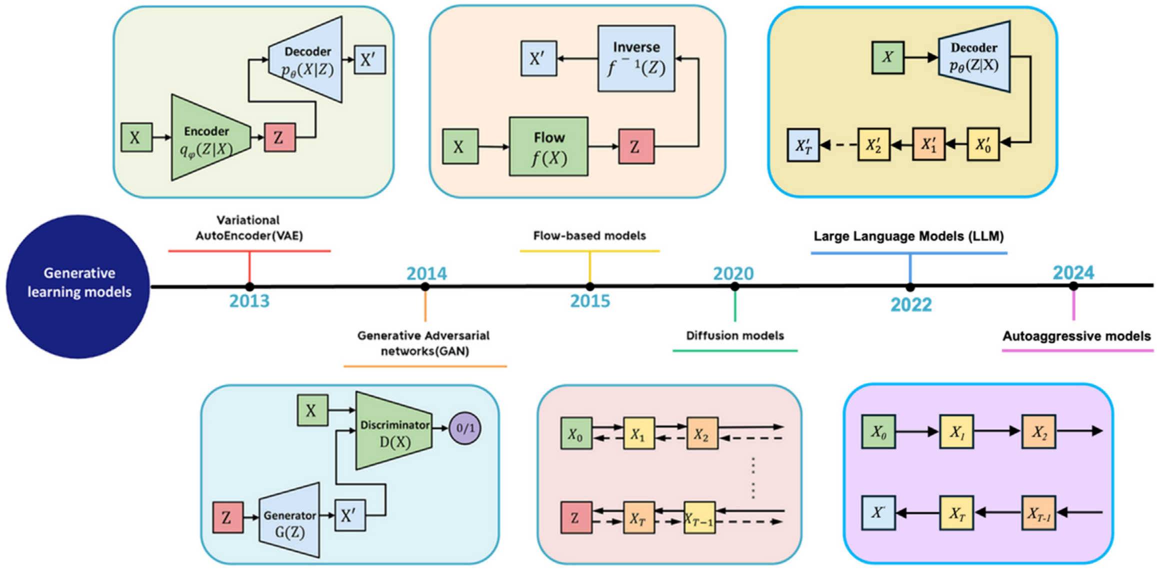


**Fig. 1 – Timeline of generative learning models, illustrating the evolution from Variational Autoencoders (VAEs)[21] and Generative Adversarial Networks (GANs)[22] to Flow-based,[23] Diffusion,[24] Large Language models,[25] and Autoregressive models,[26] with schematic diagrams depicting their core architectures and data flow mechanisms.**

paradigms as shown in Figure 1[20]: variational autoencoders (VAEs),[21] which learn latent probabilistic representations for controllable and stable reconstructions; generative adversarial networks (GANs),[22] which generate high-fidelity data through an adversarial interplay between a generator and a discriminator; flow-based models,[23] which explicitly model data likelihoods through invertible or energy-based transformations, offering both stability and interpretability; diffusion models,[24] the current state of the art, which iteratively denoise random noise to achieve exceptional realism and diversity; large language models (LLMs),[25] which specialize in text-based reasoning and generation; and autoregressive models[26], which predict each element sequentially based on prior outputs and excel in text and structured sequence generation.

This new capability has begun to reshape biomedical research: diffusion-based RFdiffusion[27] can generate functional proteins directly from textual prompts, dramatically broadening the pool of therapeutic candidates. The SE(3)-equivariant DiffSBDD model[28] produces high-affinity ligands within three-dimensional binding pockets, streamlining structure-based drug discovery. Additionally, medical LLMs like Med-PaLM 2[29] now reach specialist-level performance on clinical QA tasks and can draft discharge summaries comparable to those written by physicians,[30] while Sentence-BERT-based model[31] generates imaging reports directly from Chest X-rays, greatly reducing documentation burden.

Unlike traditional AI, which is limited to tasks such as segmentation and classification, GenAI can generate high-precision new samples on demand. This capability highlights its great potential to surpass traditional AI amid the growing demand for efficient, accurate, and patient-centered healthcare[32,33] (Figure 2). However, its current applications in dentistry remain fragmented—marked by heterogeneous tasks, inconsistent validation standards, and varied regulatory concerns. To address this, we present a narrative review of peer-reviewed studies from the past five years across key dental specialties, including prosthodontics, orthodontics, periodontics, pediatric dentistry, endodontics, oral and maxillofacial surgery, radiology, and education. We analyze model architectures, training workflows, and evaluation strategies, highlighting how generative methods support data augmentation, diagnosis, treatment planning, and patient communication. Furthermore, we discuss the existing challenges and future directions for integrating GenAI into precision oral healthcare.

## Materials and methods

This article is a narrative review that aims to summarize and critically evaluate the current state of research on the applications of GenAI in the field of dental medicine. This review follows the standards set by the Scale for the Assessment of Narrative Review Articles (SANRA),[34] and is guided by the following focused question: What are the main applications of GenAI in the field of dental medicine in recent years, what are the similarities and differences in the specific technical approaches, and what limitations exist?

The scope of this review includes studies published from 2020 to 2025. The literature search was conducted using Google Scholar, PubMed, and IEEE Xplore databases. The search strategy combined the term "Generative Artificial Intelligence" with discipline-specific keywords using Boolean operators. The search string was formulated as: ("Generative Artificial Intelligence" OR "GenAI") AND ("Dentistry" OR "Prosthodontics" OR "Orthodontics" OR "Oral and Maxillofacial Surgery" OR "Periodontics" OR "Endodontics" OR "Pediatric Dentistry" OR "Oral Mucosal Diseases" OR "Dental Implantology" OR "Tooth Reconstruction" OR "Dental Radiology" OR "Dental Education"). This combination ensured the

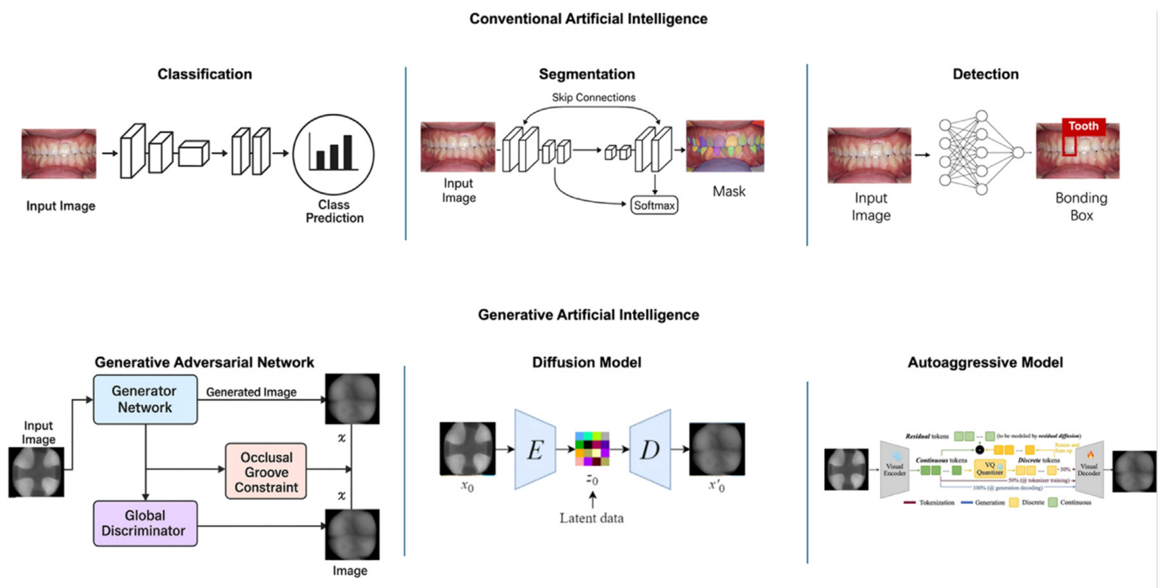


**Fig. 2 – Comparison between conventional artificial intelligence and generative artificial intelligence in dentistry, highlighting the transition from discriminative models—focused on classification, segmentation, and detection—to generative paradigms such as GANs, diffusion models, and autoregressive models that enable realistic image synthesis, reconstruction, and data-driven creation.**

inclusion of all studies addressing applications of generative AI within various dental disciplines. A two-step screening—title/abstract review and full-text assessment—was independently conducted by two reviewers, with discrepancies resolved by discussion or a third reviewer. Standardized criteria were applied to minimize bias, and the search was expanded to include relevant references and studies by the same first or corresponding authors. The inclusion criteria encompassed studies investigating the use of GenAI across different branches of dental medicine. Studies were excluded if they focused solely on traditional AI or did not explicitly describe the employed method as GenAI, were not published in English, lacked full-text availability, or were duplicate publications.

## Results

A total of 620 records were identified through database searches and other sources. After removing 112 duplicates and excluding 415 articles based on titles and abstracts, 93 full texts were screened. Ultimately, 74 studies met the inclusion criteria for qualitative synthesis, as shown in Figure 3. Studies were excluded at the eligibility stage for being unrelated to GenAI, lacking accessible full text, or having unclear methodologies. Substantial inter-reviewer agreement was achieved during study selection (Cohen's Kappa = 0.82). The included studies were further categorized by dental discipline and application type, as illustrated in Figure 4.

### Prosthodontics

Prosthodontic rehabilitation demands accurate, patient-specific solutions to restore function, aesthetics, and biomechanical integrity. Common design methods (e.g., lost-wax casting, CAD-CAM) depend on manual expertise, leading to variability and extended occlusal adjustment time. GenAI offers a transformative alternative by automating design, enhancing structural precision, and enabling personalized restorations. Trained on large datasets of dental morphologies, GenAI can generate biomechanically sound crowns, accommodate occlusal dynamics, and streamline workflows. The generative models employed to tooth reconstruction are GANs and Diffusion-based models—GANs generate synthetic dental structures by training a generator and discriminator in tandem, while diffusion models iteratively denoise random input to produce anatomically accurate, high-fidelity teeth.

*Inlay design*

Inlays, which restore localized tooth defects, require meticulous adaptation to cavity margins and occlusal dynamics. GANs and their evolved architectures are initially useful for generating both synthetic and realistic images. While in dentistry, with the help of depth map, GANs can generate virtual inlays which resemble natural teeth with high fidelity. Tian et al[35] introduced the DAIS framework, a deep adversarial network that automates inlay margin fitting and occlusal adaptation. However, its reliance on 2D surface representations limits its ability to capture complex undercuts and full cavity morphology. Brol et al[36] extended GANs to generate morphology-specific inlays and evaluated their visual quality via a blinded dentist survey, though without biomechanical validation.

*Crown Design*

Full-coverage crowns pose complex challenges, requiring accurate internal fit (adaptation to prepared teeth) and external morphology (occlusal morphology, proximal contacts).

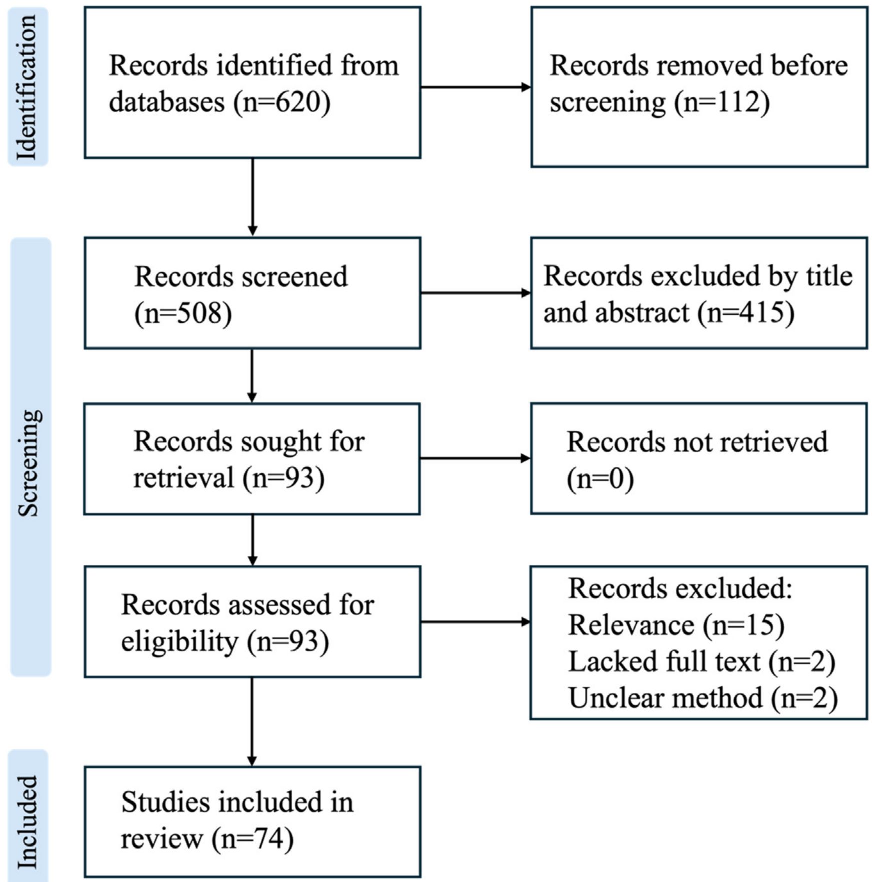


**Fig. 3 – Flow chart of the search process and selection of studies.**

Due to high individual variation in tooth shape, model training is difficult. Yuan et al[37] proposed a Pix2pix-based network for occlusal surface generation but failed to capture key anatomical features like occlusal fingerprints. Tian et al.'s DCPR-GAN[38] introduced a two-stage process, which captures the global structure in the first stage and incorporates occlusal fingerprint constraints and groove parsing in the second stage, though remained limited to 2D surface reconstruction.

Depth images could only recover the occlusal surface, not the whole surface of a single tooth. Therefore, 3D representation becomes crucial. Lessard et al[39] used GAN to generate point clouds of teeth starting from normalized incomplete point clouds. Zhu et al[40] and Feng et al[41] took the incomplete point cloud of a missing tooth as input and use a transformer encoder with a multi-scale decoder to reconstruct its 3D model, after which the crown point cloud is converted into a mesh model. The above methods do not take the shape of the tooth preparation into account, making it impossible to generate the inner surface needed for a complete dental crown. In order to solve the problem and simplify steps, Hosseinimanesh et al[42] and Su et al[43] respectively propose a point-to-mesh generation transformer to directly generate dental crown meshes from point inputs of antagonist and preparation teeth. Recently, diffusion models have shown promise in generating high-fidelity 3D crown surfaces via iterative noise refinement, but their slow inference and high computational cost limit clinical application.[44]

*Clinical evaluation*

Currently, most studies have focused solely on performance evaluations among various generative models, while only a few have compared AI-generated crown designs with those created by CAD and with the original natural tooth.[45-47] However, to transition GenAI from research to clinical application, comprehensive clinical feasibility evaluations are essential, primarily encompassing three aspects: (1) morphological characteristics, including occlusal morphology and internal fit; (2) functional performance, such as occlusal contacts and fatigue resistance; and (3) generation efficiency Table 1.

### Orthodontics

Orthodontic treatment is a long-term and collaborative process, typically lasting around two and a half years. Success depends not only on the orthodontist's expertise to guide treatment in a precise, stepwise manner but also on effectively helping patients visualize expected outcomes before beginning therapy and answering patients' questions during the whole treatment. This visualization and Q&A tools help to build patients' trust, enhance communication, and strengthen their confidence in undergoing treatment.

Given these disciplinary demands, GenAI in orthodontics has primarily been applied in three areas. First, automated tooth arrangement[48] mitigates suboptimal clinical outcomes caused by practitioners' inexperience while providing

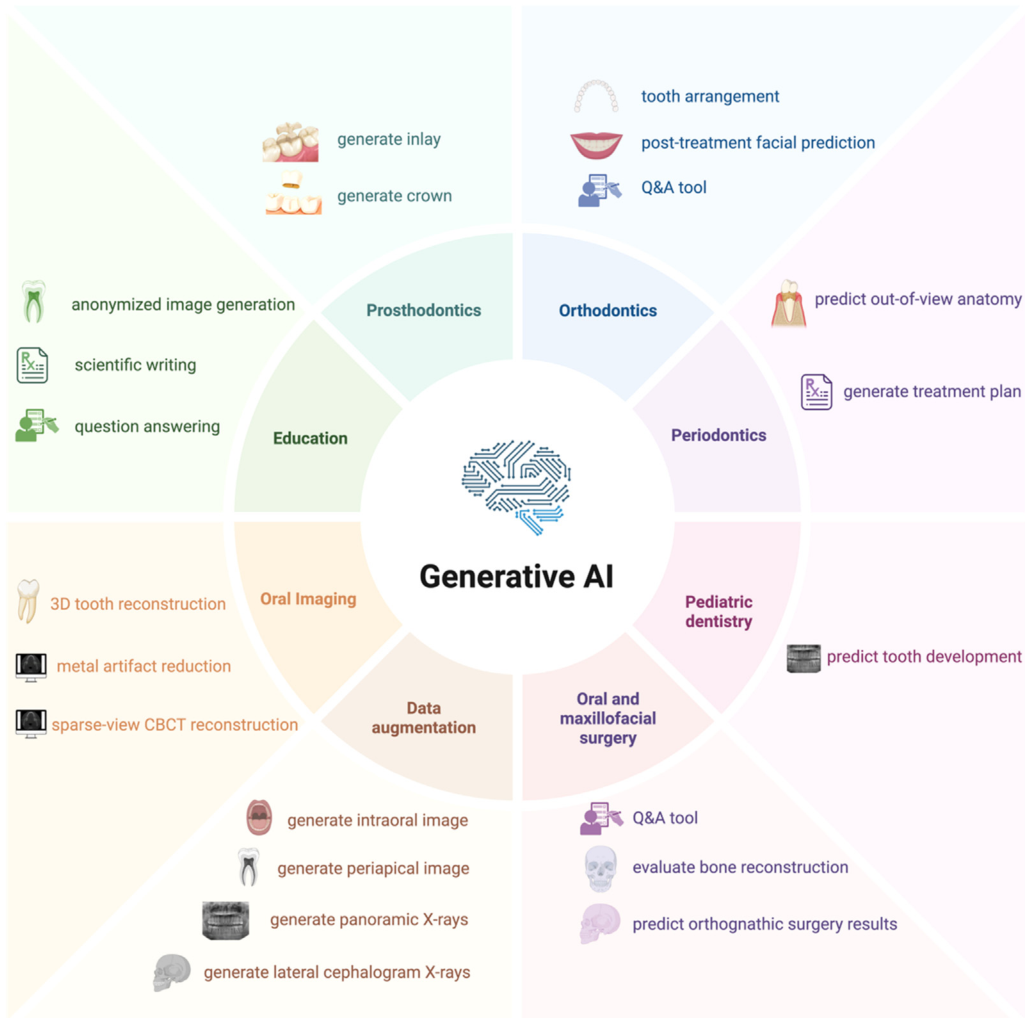


**Fig. 4 – Generative AI application examples in dentistry.**

patients with visualizations of treatment progression. Second, post-treatment facial prediction—including portraits[49-54] and profile assessments[55]—enhance patient understanding of predicted therapeutic outcomes and guide clinicians in refining treatment goals. Finally, AI-driven consultation platforms[56-60] streamline patient communication by resolving common orthodontic queries through intuitive interfaces.

*Tooth arrangement*

To automate tooth arrangement, most methods predict 6-DoF transformation parameters for individual tooth movements. Early works like TANet[61] used PointNet with graph-based propagation, followed by hierarchical[62] and spatially-aware[63] models to enhance feature learning. Ma et al[64] further introduced a framework with spatiotemporal attention for orthodontic staging. Despite advances, regression-based methods are limited by malocclusion variability and scarce annotated 3D data.

Lei et al[48] addressed this with MeshMAE, a self-supervised framework combining masked autoencoding and a conditional diffusion model[19] to generate 6-DoF tooth arrangement. Wang et al[65] further supported the field by releasing the first public 3D orthodontic dataset. Building on the success of diffusion models, Fan et al[49] represented teeth using their frame and latent shape code, and employed a diffusion model to generate multiple intermediate steps based on the initial and target alignments, enhancing the model's clinical applicability.

*Post-treatment facial prediction*

GenAI plays a vital role in predicting post-treatment facial changes to support patient communication. Early models like iOrthoPredictor[50] combined 2D images and 3D data but required complex inputs. OrthoAligner[51] improved usability with a single frontal photo, introducing a StyleGAN-based editing method for simulating orthodontic alignment and BlendingNet to maintain visual consistency. However, it often overestimates treatment outcomes. To improve accuracy and realism, Chen et al[52] proposed a method that reconstructs 3D dentition from a single frontal image, integrating precise tooth segmentation, template-based modeling, physics-informed simulation, and multi-level style encoding. While interpretable, its reliance on templates limits flexibility. Dou et al[53]proposed a 3D structure-guided tooth alignment

**Table 1 – Characteristics of the included studies related to prosthodontics.**

| Studies | Task | Network | Dimension | Input | Output | $n_{train}$ | $n_{val}$ | $n_{test}$ | target teeth | Metrics |
|---|---|---|---|---|---|---|---|---|---|---|
| Tian et al[35] | Inlay design | GAN | 2D | depth map | depth map | 750 | n/a | 80 | 36,46 | PSNR; RMSE; MS-SSIM; FSIM |
| Brol et al[36] | Inlay design | StyleGAN | 2D | depth map | depth map | 89 | n/a | 3 | n/a | RMSE; Clinical Comparison |
| Yuan et al[37] | Crown design | CGAN | 2D | depth map | depth map | 500 | n/a | 100 | 36 | PSNR; RMSE; MS-SSIM; FSIM |
| Tian et al[38] | Crown design | CGAN | 2D | depth map | depth map | 700 | n/a | 80 | 36, 46 | PSNR; RMSE; SSIM; FSIM |
| L et al[39] | Crown design | GAN | 3D | point cloud of missing tooth | point cloud | 93 | 24 | 43 | molars, canines and incisors. | CD |
| Zhu et al[40] | Crown design | Transformer-based point cloud completion network | 3D | point cloud of missing tooth | mesh | 5469 | n/a | 640 | arbitrary | CD; EMD |
| Feng et al[41] | Crown design | Transformer-based point cloud autoencoder for shape generation | 3D | point cloud of missing tooth | mesh | 480 | n/a | 120 | 11-13, 21-23 | average deviation |
| H. et al[42] | Crown design | Transformer-based Point-to-Mesh generation network | 3D | point cloud of prepared tooth | mesh | 388 | 97 | 71 | molars, canines and incisors | CD; F-score; MSE |
| Sale et al[44] | Crown design | multi-scale perception enhanced point cloud autoencode | 3D | point cloud of missing tooth | mesh | 129 | n/a | n/a | 21, 27, 34, 36; 12 –22 and 34–36 | RMS; MAE |
| Su et al[43] | Crown design | Transformer-based point cloud completion network | 3D | point cloud of prepared tooth | mesh | 1393 | 464 | 460 | molars | CD; F-score; NC; MAE; $R^2$; SDE |
| Cho et al[45] | Performance evaluation | StyleGAN | 3D | point cloud of prepared tooth | n/a | 30 | n/a | n/a | posterior teeth | RMS of occlusal morphology; RMS of internal fit; elapsed time; distance of finish line |
| Ding et al[46] | Performance evaluation | 3D-DCGAN | 3D | point cloud of missing tooth | n/a | 600 | n/a | 12 | 45 | cusp angle; 3D discrepancy (heat map, RMS, MPD, MND); occlusal contact; Dynamic Finite Element Analysis |
| Chau et al[47] | Performance evaluation | 3D GAN | 3D | point cloud of missing tooth | n/a | 159 | 10 | n/a | 16 | HD; IoU |

RMSE, Root Mean Square Error; RMS, Root Mean Square; MAE, Mean Absolute Error; HD, Hausdorff Distance; IoU, Intersection over Union; CD, Chamfer distance; NC, Normal Consistency; $R^2$, coefficient of determination; SDE, Surface distance error; MPD, mean positive deviation; MND, mean negative deviation; PSNR, Peak Signal Noise Ratio; SSIM, Structural Similarity Index Measure; FSIM, Feature Similarity Index Measure; EMD, Earth Mover's Distance; MSE, Mean Square Error.

network, pre-trained on paired pre- and post-orthodontic 3D scans to learn orthodontic knowledge. The model then takes 2D photos as input and uses diffusion model to align teeth within the 2D space.

For full-face predictions, Park et al[54] developed a model using patient characteristics and incisor movement to forecast 3D facial changes. Despite clinically acceptable accuracy at key landmarks, its generalizability is limited. To enhance profile prediction, Gong et al[55] introduced Soft-P-CGAN, generating lateral cephalograms conditioned on orthodontic parameters. While helpful for less experienced clinicians, it faced challenges such as high nasolabial angle error, reliance on 2D data, and lack of expert oversight.

*Q&A tool*

GenAI is also used as a Q&A tool to help patients understand relevant orthodontic knowledge more conveniently. Studies have evaluated models like ChatGPT, Google Bard, and Bing, finding generally accurate and helpful responses, though with limitations in citation support and consistency. While some works reported high accuracy and positive reception,[56,58] others noted moderate reliability[59,60] or suboptimal performance in specific topics like clear aligners.[57]

### Oral and maxillofacial surgery

The applications of GenAI in the field of oral and maxillofacial surgery (OMS) are primarily manifested in evaluating the accuracy of bone reconstruction,[66] predicting orthognathic surgery results by generating postoperative lateral cephalograms[67] and the use of ChatGPT in: research and scientific writing,[68,69] patient information and communication[70-72] and medical education.[73] Xiong et al[66] used GAN to repair the bony midfacial defect, and the dataset includes 518 normal CT data, with 415 in training set and 103 in testing set. The research used cosine similarity, mean error and surgeons to assess the accuracy and achieves good results. Kim et al[67] generated post-operative lateral cephalograms using a diffusion model that took pre-operative cephalograms and the intended surgical movement as input. They used visual Turing test to demonstrate the high realism of the synthesized images.

However, classic OMS topics—such as fractures, abscess management, alveolar surgery, dental implant procedures, and oncologic surgeries—have not been adequately explored in current literature.

### Others

Periodontics: Kearney et al[74] presented an inpainting algorithm using GANs coupled with partial convolutions to predict out-of-view anatomy to enhance clinical attachment levels prediction accuracy. ChatCAD+[75] is a universal interactive CAD system that processes multi-domain medical images. Its hierarchical in-context learning enabled training-free radiology report generation, while the LLM-powered knowledge retrieval autonomously accessed medical databases for evidence-based treatments. The system incorporated a periodontal diagnosis model to interpret panoramic X-rays of periodontitis patients and generated precise therapeutic solutions. In a study on periodontal question answering,[76] ChatGPT-4 provided more comprehensive responses than ChatGPT-3.5, yet occasional inaccuracies in professional questions highlight both the strengths and limitations of LLMs in addressing oral health consultations.

Pediatric dentistry: Kokomoto et al[77] employed StyleGAN-XL to extract latent vectors from primary/mixed dentition images and linearly interpolated them with permanent dentition vectors using panoramic radiography, thereby providing dynamic representations of tooth development.

Endodontics: Ana et al[78] compared ChatGPT's and endodontic experts' responses to endodontic questions, finding that ChatGPT achieved 85.44% consistency and 57.33% accuracy, indicating it is not yet capable of replacing dentists in clinical Q&A. Ozbay et al[79] compared ChatGPT-4, ChatGPT-3.5, and Google Bard on endodontic question answering, finding that ChatGPT-4 delivered the highest accuracy, though continued optimization is required before clinical adoption.

Dental implantology: Wu et al[80] compared ChatGPT-o3, DeepSeek-R1, Grok-3, Gemini-2.0-flash-Thinking, and Qwen2.5-max on implant dentistry tasks, concluding that various LLMs exhibit distinct capabilities in dental implantology. They recommended context-specific model selection, with Gemini-2.0-flash-Thinking showing the best comprehensive ability.

Oral mucosal diseases: M et al[81] compared ChatGPT's responses with expert consensus on oral potentially malignant disorders, finding that while ChatGPT can accelerate clinical workflows, it still generates misleading information; thus, a collaborative approach integrating clinicians and AI tools is recommended.

Researches on GenAI in the aforementioned domains have primarily focused on comparing ChatGPT's performance rather than developing dedicated models or frameworks. Therefore, there is a pressing need to move beyond comparative evaluations and explore domain-specific model development and adaptation.

### Oral imaging

With the growing demand for precise and low-radiation imaging in dentistry, generative models have emerged as powerful tools for 3D reconstruction and radiographic image enhancement.

*Tooth reconstruction*

CBCT images contain both crown and root information but suffer from limited resolution (about 0.3–1.0 mm spacing), while intra-oral scans offer high-resolution crown surfaces (about 0.03mm spacing) but lack root data. To combine the advantages of both, Fang et al[82] first segmented individual teeth from CBCT and then employed an implicit function network with a curvature enhancement module to generate high-quality tooth models with detailed crowns and complete root structures.

To facilitate remote monitoring of dental conditions and minimize patient exposure to radiation, several studies have explored the use of intra-oral photos[83] and panoramic X-rays (PX)[84-87] to reconstruct 3D tooth models as an alternative to CBCT.

To enable remote orthodontic monitoring, Xu et al[83] employed a pretrained diffusion model conditioned on segmented intra-oral images to generate multi-view color images and normal maps, followed by neural surface reconstruction guided by geometry-aware supervision. The output is just teeth model without root information. Song et al[84] employed GAN to reconstruct 3D oral structures from a single PX image and an oral photo by back-projecting into 3D space and deforming it to match the dental arch. This method can reconstruct the mandibular bone density and curved surface though tooth detail quality declines compared to the original PX. Liang et al[85] used GAN to reconstruct 3D oral structures from a single PX image by segmenting teeth, sampling patches for individual tooth reconstruction, and assembling them along a $\beta$ function-fitted dental arch, though jawbone morphology is not recovered. Building on this, and to further improve accuracy, Mei et al[86] introduced an implicit function network to capture the complex shapes of teeth in geometric space. Meanwhile, Ma et al[87] introduced an end-to-end method PX2Tooth which generated 3D point cloud teeth from single 2D PX images, ensuring higher precision.

*Radiology*

Representative generative tasks for oral medical imaging including sparse-view CBCT reconstruction[88] and CT metal artifact reduction.[89]

With respect to the former task, Liu et al[88] encoded multi-view 2D X-ray projections with 2D CNN, back-projected them into 3D space based on CBCT geometry, and used a 3D CNN decoder—leveraging learned priors and geometric consistency—to enable high-quality reconstruction even from as few as 5 or 10 input views without individual training. Unlike most single-domain generative models, Zhang et al[89] introduced a dual-domain framework that leverages patterns in both acquisition and image domains with multi-level similarity constraints, achieving superior performance in dental CBCT metal artifact reduction and other image generation tasks.

### *Data augmentation*

AI holds great promise for dental diagnosis, but challenges like expert labeling, privacy concerns, and data variability hinder dataset availability—making data augmentation essential for advancing dental research.

Kim et al[90] and Kokomoto et al[91] used progressive growing GAN to generate lateral cephalogram X-ray image and intraoral image respectively. The quality of generated lateral cephalogram X-ray images was evaluated by three methods: signal-to-noise ratios, image Turing test conducted by non-orthodontists and orthodontists and cephalometric tracing by expert orthodontists. While the quality of intraoral image is assessed by Sliced Wasserstein Distance and d prime of 12 dentists. Yang et al[92] used StyleGAN to generate periapical images for classifying C-shaped root canals and evaluate the images by average Frechet inception distance and the visual Turing test conducted by two radiologists. Al-Haddad et al,[93] Pedersen et al[94] and Shirsat et al[95] used GANs to generate panoramic dental radiographs. All of above generated images exhibit satisfactory visual quality. The classification performance of the neural network, when augmented with GAN data, showed improvements compared with using real data alone, and could be advantageous in addressing data conditions with class imbalance. Besides, using these data has no privacy restrictions so it's more convenient to carry out scientific research.

What's more, the data augmentation is applied to not only the images, but also textual data. Chuang et al[96] leveraged ChatGPT-4 to generate synthetic notes to address the significant issue of structured data missingness in dental records Table 2.

### *Education*

GenAI is increasingly used in dental education for scientific writing,[97,98] question answering,[99-105] and anonymized image generation.[106] Tools like ChatGPT, Bing Chat and Google Bard, especially ChatGPT-4,[102,107,108] perform well in dental problem-solving.[100,103,104,109] Simulating clinical scenarios and offering timely feedback can help students' to consolidate professional knowledge while practice clinical reasoning and decision-making. However, concerns remain over reduced critical thinking,[110] data privacy risks,[106] and hallucinated or outdated responses due to GenAI's lack of true understanding and static knowledge base. To improve accuracy and relevance, domain-specific models like DentQA[99] trained on high-quality dental datasets are a promising direction Table 3.

## Discussion and future directions

Our review underscores both the promise and the precariousness of GenAI in contemporary dentistry. On one hand, neural networks capable of synthesizing anatomically faithful crowns, simulating orthodontic movements or drafting clinical reports herald a paradigm shift in digital dentistry. On the other, most of these demonstrations remain confined to controlled datasets, removed from the complexity of real clinical workflows. This tension between technological aspiration and practical applicability surfaces in several recurring themes: an evident scarcity of clinical validation, the lack of common standards and datasets, a tendency to oversimplify the biological intricacies of the dentofacial complex, the compounding of errors across fragmented pipelines and a general absence of clinician-friendly interactivity. Added to these are broader ethical considerations around data privacy, algorithmic bias and the reliability of language-based tools .

### *Lack of clinical validation*

Despite impressive advances in image synthesis and shape generation, few generative models have been evaluated beyond the computer screen. Crown design algorithms are typically benchmarked against digital ground truth rather than chairside adjustments or long-term performance.[35,37-44] Likewise, orthodontic prediction tools often rely on synthetic or retrospective cases, making it unclear how they would fare in the messiness of routine practice.[48-55] To bridge this translational gap, prospective clinical trials should be explicitly

**Table 2 – Characteristics of the included studies related to orthodontics.**

| Studies | Task | Network | Input | $n_{train}$ | $n_{val}$ | $n_{test}$ | Metrics | Comparison with human |
|---|---|---|---|---|---|---|---|---|
| Lei et al[48] | tooth arrangement | DDPM | mesh& point clouds | 2120 | n/a | n/a | ADD; PA-ADD; CSA; $ME_{rot}$; $FD_{cur}$ | YES |
| Fan et al[49] | tooth arrangement | DDIM | point clouds | 787 | 105 | 158 | $R_{error}$, $T_{error}$, $AUC_{point}$ | NO |
| Yang et al[50] | smiling portrait prediction after orthodontic treatment | Style GAN | frontal smiling image<br>3D teeth model | 1000<br>8000 | n/a<br>n/a | 100<br>995 | F1-score; FID; Angular Error; Translation Error | YES |
| Chen, B et al[51] | smiling portrait prediction after orthodontic treatment | Style GAN | frontal smiling image | 5600 | n/a | 1400 | FID | YES |
| Chen, Y et al[52] | smiling portrait prediction after orthodontic treatment | Style GAN | frontal smiling image | 1800 | n/a | 200 | FID | NO |
| Dou et al[53] | smiling portrait prediction after orthodontic treatment | Conditional Diffusion Model | frontal smiling image | 1267 | n/a | 100 | L1, L2 and LPIPS error | YES |
| Park et al[54] | 3D post-orthodontic face prediction | conditional GAN | CBCT | 268 | n/a | 44 | mean prediction error; accuracy | YES |
| Gong et al[55] | lateral appearance prediction after orthodontic treatment | conditional GAN | lateral cephalogram | 409 | 51 | 51 | SSIM; PSNR; MAE; MS-SSIM; MRE; SDR | NO |

DDPM, Denoising Diffusion Probabilistic Models; DDIM, Denoising Diffusion Implicit Model; GAN, Generative Adversarial Network; ADD, mean point-wise distance between the predicted and ground truth models; PA-ADD, the ADD calculated after the rigid alignment between predicted jaw and ground truth jaw using Procrustes Analysis; PCT@K , the percentage of tooth predicted by the network with the error smaller than a threshold K; PCT-AUC, the area under the PCT curve, which is the integral of PCT with respect to K; TRE, target registration error; CSA, cosine similarity accuracy; $ME_{rot}$, mean error of rotation; $FD_{cur}$, Fréchet Distance between dental arch curves of prediction and ground truth; L2P and L2Q, average L2 distance of global position and global quaternion rotation per step; MPE, Mean Position Error; MRE, Mean Rotation Error; $ME_{rotat}$, mean error of rotation; $ME_{trans}$, mean error of translation; FID, Frechet inception distance; MRE, mean radial error; SDR, successful detection rate; L1 and L2, quantifying discrepancies between generated results and the target; LPIPS, calculates the perceptual distance and visual similarity between images.

designed to assess real-world impact. For instance, randomized controlled studies could compare AI-generated crowns with those designed conventionally in terms of fit accuracy, adjustment time, material integrity, and one-year survival rate. Similarly, orthodontic trials might longitudinally evaluate whether AI-predicted tooth movements correspond with actual post-treatment outcomes and patient-reported satisfaction metrics. Embedding GenAI-assisted planning modules into digital workflows of dental hospitals could also enable pragmatic trials, in which clinician feedback loops iteratively refine model behavior under routine clinical conditions.

### *Insufficient standardization*

One reason for the variability in reported performance is the absence of shared benchmarks. At present, each research group tends to collect its own imaging data, apply bespoke preprocessing and report metrics that are not directly comparable.[35-44,48-55] Future progress hinges on multi-institutional consortia capable of assembling large, anonymized, and anatomically diverse datasets—covering crowns, inlays, implants, and orthodontic records—from academic centers and private clinics alike. Examples from other fields, such as the Medical Segmentation Decathlon or BraTS challenges,[113,114] illustrate how common testbeds can accelerate innovation while maintaining data governance. For dentistry, such consortia could establish federated data infrastructures that preserve patient privacy yet enable cross-center model training. Equally important is the convergence on standardized metrics. Beyond geometric fidelity (e.g., Chamfer distance, Dice score), evaluation protocols should incorporate functional and clinical parameters, such as occlusal force balance, contact tightness, and marginal integrity. Only through shared datasets and harmonized benchmarks can reproducibility and regulatory acceptance be achieved.

### *Neglect of anatomical completeness*

A persistent limitation of current generative systems is their focus on the “visible” aspects of dental anatomy. Inlay models are often confined to 2D occlusal surfaces, ignoring undercuts or material thickness,[35,36] while orthodontic algorithms typically simulate only crowns, neglecting roots, periodontal ligaments, and the craniofacial framework. Such oversimplification leads to unrealistic collision patterns and poor prediction of facial changes, especially in extraction cases.[48-54]

To achieve clinically meaningful modeling, future GenAI systems must integrate biologically complete structures—roots, alveolar bone, periodontal tissues, and facial

**Table 3 – Characteristics of the included studies related to oral imaging.**

| Studies | Task | Network | Input | $n_{train}$ | $n_{val}$ | $n_{test}$ | Metrics |
|---|---|---|---|---|---|---|---|
| Fang et al[82] | high-quality tooth models reconstruction from CBCT images | PointNet | CBCT | 20 | 10 | 20 | IoU; Chamfer-L2; Normals; OccAcc |
| Xu et al[83] | 3D tooth structure reconstruction from 5 intra-oral photos | Diffusion Model | 5 intra-oral photos | 3000 | 100 | 100 | HD; CD; IoU; PSNR; SSIM; LPIPS |
| Song et al[84] | 3D tooth and mandible structure reconstruction from PX | GAN | PX and intra-oral photo | 60 | 20 | 20 | PSNR; Dice; SSIM |
| Liang et al[85] | 3D tooth structure reconstruction from PX | GAN | PX | 15 | 1 | 7 | IoU; DA; FA |
| Mei et al[86] | 3D tooth structure reconstruction from PX | GAN | PX | 28 | 4 | 8 | SSIM; Dice; HD; ASD |
| Ma et al[87] | 3D tooth structure reconstruction from PX | PointNet | PX | 400 | 49 | 50 | IoU; MMD-CD; MMD-EMD |
| Liu et al[88] | sparse-view CBCT reconstruction | Neural Attenuation Fields | X-ray projections | 100 | 10 | 20 | PSNR; SSIM; efficiency (time and memory) |
| Zhang et al[89] | CBCT metal artifact reduction | CycleGAN | CBCT | 80 | n/a | 20 | PSNR; SSIM |

IoU, Intersection over Union; Chamfer-L2, measure a bidirectional distance between two surfaces; Normals, to measure the normal consistency between two surfaces; OccAcc, to evaluate the occupancy prediction; HD, Hausdorff Distance; CD, Chamfer Distance; PSNR, Peak Signal Noise Ratio; SSIM, Structural Similarity Index Measure; LPIPS, Learned Perceptual Image Patch Similarity; Dice, to reflect the deformation of the reconstruction; DA, detection accuracy; FA, identification accuracy; ASD, Average Surface Distance; MMD-CD, Maximum Mean Discrepancy – Chamfer Distance; MMD-EMD, Maximum Mean Discrepancy – Earth Mover's Distance; PX, panoramic X-rays Table 4.

musculature—enabling prediction of both functional occlusion and esthetic outcomes. Multimodal fusion of CBCT, IOS, and facial scans can provide volumetric priors for such models. For instance, conditional diffusion or implicit-field approaches could jointly learn crown–root–bone relationships, while biomechanics-informed priors simulate tooth mobility within the alveolar socket.

### *Loss of scale and spatial consistency*

Another limitation of current generative pipelines lies in their lack of metric grounding. Two-dimensional data, such as intraoral photographs or panoramic radiographs, are inherently non-metric, and models that reconstruct 3D dental structures[83,88] or CBCT volumes[82,84-87] from such inputs typically operate without explicit spatial calibration. As a result, although the reconstructed teeth and arches may appear visually realistic, they often exhibit geometric inconsistencies—such as distorted crown dimensions, irregular arch curvature, and unrealistic inter-occlusal spacing. These deviations, though subtle in appearance, undermine biomechanical validity and reduce the precision required for clinical applications. In contexts such as occlusal adjustment, prosthetic restoration, or orthodontic simulation, even sub-millimeter cumulative errors can lead to functionally significant discrepancies.

To overcome these issues, future work should incorporate spatial calibration and metric supervision into generative frameworks. Integrating depth cameras can improve geometric accuracy and ensure scale consistency. Furthermore, establishing calibrated paired datasets—such as panoramic–CBCT alignments—will provide standardized spatial references and enhance the clinical reliability of GenAI-based reconstructions.

### *Limited interactivity*

For generative AI to gain clinical traction, it must support interactive and explainable interfaces. At present, most systems deliver a single, fixed result without an opportunity for the user to adjust occlusal morphology, specify material thickness or explore alternative tooth arrangement treatments. Advances in vision–language models (VLMs) and multi-modal agents suggest feasible pathways. In radiology, systems like Med-PaLM Multimodal[115] and GPT-4V[116] already enable clinicians to query imaging results via natural language. Similar paradigms could be adapted for dentistry—e.g., "widen the contact on distal 46" or "reduce crown height by 0.5 mm." Such instruction-tuned dental VLMs could iteratively refine designs under human guidance while maintaining transparency and auditability.[117-120] Developing these systems will require domain-specific instruction datasets pairing dental images with textual commands and corresponding design adjustments. Prototyping within CAD/CAM or orthodontic simulation software could demonstrate early feasibility.

### *Domain-specific model deficiency*

Across dental subfields—including endodontics, periodontics, pediatric dentistry, oral mucosal diseases, and implantology—recent studies have largely focused on evaluating ChatGPT's performance rather than developing domain-specific generative frameworks.[76,78-81] This reflects an early exploratory stage of GenAI adoption and highlights the lack

**Table 4 – Characteristics of the included studies related to dental education.**

| Studies | Task | Input | Human evaluator | Statistical Analysis | Evaluation criteria | Results |
|---|---|---|---|---|---|---|
| G et al. [107] | Evaluated the answers generated by Bard, ChatGPT-3.5, ChatGPT-4, and Bing Chat. | 20 open-type, clinical dentistry–related questions | YES | Friedman and Wilcoxon tests | comprehensiveness, scientific accuracy, clarity, and relevance | (1) ChatGPT-4 outperformed other models. (2) All models occasionally exhibited inaccuracies, over-generalization, and outdated content. |
| Aldukhail [108] | Evaluated the responses generated by ChatGPT-3.5 and Google Bard. | 7 dental education-related questions | YES | Wilcoxon tests | comprehensive, accurate, clear, relevant and specific | (1) ChatGPT-3.5 outperformed other models. (2) Bard was successful in retrieving relevant research evidence. |
| Uribe et al[97] | Assessed ChatGPT's use in dental research writing. | 299,695 PubMed-indexed dental research abstracts (2018–2024) | NO | normalized ratios | keyword analysis | Demonstrated the rapid growth of ChatGPT use in dental research publications. |
| S-R et al[111] | Evaluated the influence of ChatGPT on academic tasks. | 55 undergraduates' scientific writing assignments (ChatGPT-assisted vs. conventional methods). | YES | Mann–Whitney U-test | problem identification, use of evidence, evaluation of arguments, generation of alternatives, effective communication | (1) Dental students highly valued ChatGPT for academic tasks. (2) Conventional methods yielded higher scores overall. |
| Prakash et al[99] | Developed and evaluated the DentQA system. | 50 dental-related questions | YES | BLEU scores and Fisher's exact test | accuracy, relevance, absence of hallucination, response time | (1) DentQA performed better than ChatGPT-3.5 in accuracy and absence of hallucination. (2) No significant improvement was observed in relevance. |
| Molena et al[100] | Evaluated the responses generated by ChatGPT. | 30 binary and descriptive dental questions | YES | Wilcoxon test and Mann-Whitney test | accuracy and completeness | (1) ChatGPT showed good accuracy and completeness but sometimes provided incomplete references. (2) When questions were imprecise, replicated responses became progressively more accurate over time due to machine learning. |
| Tian et al[106] | Developed a GAN network to alter facial identities in dental patient images. | smiling and non-smiling frontal facial pictures | YES | NA | reality | Demonstrated the feasibility of privacy-preserving image generation for dental education. |
| Kunzle et al[102] | Evaluated the responses generated by ChatGPT-3.5, ChatGPT-4.0, and Google Gemini 1.0. | 151 questions | NO | chi square and p value analyses | accuracy | ChatGPT-4.0o was the most performant in subcategories direct and indirect restorations as well as caries, while ChatGPT-4.0 was the most performant in endodontics. |
| K et al[112] | Evaluated ChatGPT's performance in supporting dental students' learning processes. | 77 dental students' exam grades(ChatGPT group& literature-based group) | NO | Mann-Whitney U test | grades | ChatGPT-assisted students achieved higher academic performance. |
| Danesh et al[103] | Evaluated the responses generated by ChatGPT in periodontal education. | 311 multiple-choice questions | NO | two-tailed t test and two-tailed $\chi 2$ test | accuracy, response length, explanations | ChatGPT4 showed a higher proficiency |
| Chau et al[104] | Evaluated the responses generated by ChatGPT-3.5 and ChatGPT-4.0 in dental licensing examinations. | 1461 multiple-choice questions | NO | NO | accuracy | ChatGPT-4 outperformed ChatGPT-3.5, except in pediatric and orthodontic sections. |
| Ali et al[109] | Evaluated ChatGPT's responses in undergraduate dental education. | 50 questions including MCQs, SAQs, SEQs, true or fulse questions and fill in the blanks items | YES | NO | accuracy | ChatGPT performed above satisfactory level except critical appraisal of literature |
| A-P et al[98] | Evaluated ChatGPT's performance to generate dental research abstracts. | 20 scientific articles(10 with original abstracts&10 with AI generated abstracts) | YES | NO | formatting, accuracy, orthography, punctuation, terminology, text fluency, writing style. | GPT-generated abstracts were comparable to human-written versions but remain detectable by AI tools. |

of methodological innovation tailored to dental data and workflows. Advancing beyond this comparative phase requires specialty-oriented model development, fine-tuning, and multimodal adaptation aligned with each discipline's anatomical and diagnostic characteristics.

Currently, few generative models have been applied to dental imaging or design tasks, with most relying on GAN or diffusion architectures. However, broader advances in generative modeling offer promising directions. Autoregressive models capture fine structural continuity for crown margin refinement and tooth surface reconstruction, while flow-matching models[121] provide interpretable and biomechanically consistent mappings between real and generated anatomies, which is critical for biomechanical plausibility in occlusal and implant modeling. Integrating these paradigms could evolve the current GAN- and diffusion-dominated landscape into a more unified and controllable generative framework that better supports dental clinical translation.

### *Future directions*

Addressing these challenges will require coordinated efforts across research, clinical practice, and regulation. In the near future, priority should be given to the prospective clinical validation of GenAI systems through randomized and pragmatic trials that evaluate AI-generated restorations and orthodontic plans under real-world conditions, assessing not only geometric precision but also functional integrity, workflow efficiency, and patient satisfaction. Equally important is the establishment of multi-institutional data alliances and federated infrastructures that enable the creation of standardized, diverse, and privacy-preserving benchmarks for algorithmic training and evaluation. To improve biological realism, models must evolve toward biologically complete representations that integrate crowns, roots, alveolar bone, periodontal tissues, and facial soft structures, achieved through multimodal alignment of CBCT, intraoral, and facial scans. In parallel, end-to-end and physics-informed generative architectures should be developed to minimize cumulative errors and to ensure that generated designs satisfy both morphological and biomechanical requirements. The incorporation of interactive, vision–language-based interfaces will further empower clinicians to refine generative outputs via natural language, bridging the gap between algorithmic automation and human expertise. Moreover, future studies should enhance figure clarity and annotation in scientific communication—using simplified pipeline schematics and anatomical call-outs—to improve accessibility for readers without technical AI backgrounds. Finally, continuous ethical and regulatory oversight, emphasizing data privacy, fairness, interpretability, and transparency, will be essential to ensure that GenAI strengthens, rather than undermines, clinician and patient trust in digital dentistry.

## Conclusion

This review offers a comprehensive assessment of the current applications and limitations of GenAI in dentistry. It highlights promising uses of GenAI, such as crown and inlay generation in prosthodontics, automated tooth alignment and facial outcome prediction in orthodontics, tooth reconstruction in radiology, and simulation of pediatric tooth development. Existing studies primarily employ GANs, diffusion models, and LLMs, utilizing diverse input formats such as 2D depth maps and point clouds. The development of standardized datasets and evaluation protocols, alignment of multimodal data, creation of end-to-end neural networks, and integration of vision-language models are required for better clinical translation of GenAI in dentistry.

## Author contributions

Zeyao Ma conceptualized and designed the study, conducted literature screening and data analysis, and drafted the initial manuscript. Chenlin Du supervised the overall research framework, curated and interpreted data, and critically revised the manuscript for important intellectual content. Qicheng Lao provided technical support in artificial intelligence methodology, figure preparation, and assisted with the interpretation of model architectures. Xianju Xie secured project funding, supervised the research process, and provided clinical and methodological guidance throughout manuscript development. All authors reviewed and approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

## Conflict of interest

None disclosed.

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