Comparative Evaluation of Biomechanical Parameters of Tissues After Aesthetic Rehabilitation Using Generative Neural Networks and Standard Planning Protocols

[1] Volodymyr Kachmar

[1] Dr., Boston, USA

Received: 07th Nov 2025 | Received Revised Version: 14th Dec 2025 | Accepted: 19th Jan 2026 | Published: 04th Feb 2026

Volume 08 Issue 02 2026 | Crossref DOI: 10.37547/tajmspr/Volume08Issue02-02

Abstract

Objective: *The current advancements in digital workflows and artificial intelligence in estimating tissue overload, restoration failures, and longevity predictions have increased the biomechanical precision in the field of esthetic dental rehabilitation and aim to analyze and compare the biomechanical parameters of aesthetic dental rehabilitation using generative neural networks versus traditional clinician-driven methods.*

Methodology: *A narrative review from 2015 to 2025 examined the PubMed, Scopus, Web of Science, IEEE Xplore, and Cochrane library for studies in English concerning finite element, laboratory, clinical, and AI studies that include the outcomes of biomechanics.*

Results: *GNN assisted planning showed significant biomechanical gains in intricate rehabilitations, especially in multi-unit and implant-supported restorations. Declined peak stresses and more uniform distribution in peri-implant and periodontal structures, improved control of deformations, and thorough reconstruction in more optimized geometries, especially in the stresses or deformations, were noted. The evidence is mostly simulation-based, methodologically heterogeneous, and lacks thorough and sustained clinical validation.*

Conclusions: *GNN-based planning indicates possible biomechanical advantages, notably less peak stress for complicated dental rehabilitations; however, most evidence is simulation-based. The GNN workflow's clinical implementation requires biomechanical principles and relies on predictive analysis, explainable AI, and cross-disciplinary substantiation.*

Keywords: aesthetic dental rehabilitation; biomechanical parameters; artificial intelligence; generative neural networks; finite element analysis.

Cite This Article: Kachmar, V. (2026). Comparative Evaluation of Biomechanical Parameters of Tissues After Aesthetic Rehabilitation Using Generative Neural Networks and Standard Planning Protocols. The American Journal of Medical Sciences and Pharmaceutical Research, 8(2), 08–29. https://doi.org/10.37547/tajmspr/Volume08Issue02-02

1. Introduction

Today's dental practices provides aesthetic rehabilitation including complete smile redesigns, and the use of veneers, crowns, and implant-supported prostheses. These restorations help to improve function and appearance. Beyond improvements in dental health, such interventions positively impact mastication, speech, self-esteem, social confidence, and overall patient wellbeing, which speaks to the holistic benefits of rehabilitative dentistry (Alwabel et al., 2025). Integrating new technologies into clinical practices has improved consistency and reliability in aesthetic dentistry. These include intraoral scanning, cone beam computed tomography (CBCT), photographic analysis, and computer-aided design and manufacturing (CAD/CAM) (Kabbin et al., 2025). These improvements have enhanced communication and treatment predictability across the clinician, technician, and patient triad. Restorative and prosthetic interventions alter the biomechanical aspects of the dentofacial system. Modified occlusal contacts, load directions and magnitudes change the stress distributions in the dental structures, periodontal ligaments, alveolar bone, and the tissues surrounding the dental implants. Such biomechanical changes affect the remodeling of the periodontium, adaptation of the soft tissues, and the longevity of the restoration. Numerous studies in Modified Element Analysis (MEA) and in-vitro and in-clinic studies have shown that the amount, direction and contact area of the load greatly affect the stress distribution in the dental tissues and the restoration (Saini et al., 2020). The clinical importance of biomechanics and aesthetics rehabilitation breaks down the importance of a biological breakdown of systems. Biomechanical assessments shine a light on the uneven and excessive stress/strain systems experience. The foundation of every successful rehabilitative dental treatment is appropriate treatment planning. Decisions made during treatment planning will determine the shape of the restorations, material used, the schemes of dental occlusion, and how the prosthetist components will connect with the biological tissues. Conventional planning methodologies are built mostly on years of experience in the clinical field and rooted in biomechanics and dental occlusion. Numerous techniques like articulator mounting, diagnostic wax-ups, and trial restorations are still popular, and employed to assist in the planning of treatments and the visualizations of the anticipated restorations (Gomes et al., 2021). However, these methodologies are still dependent on the clinician's experience, and mostly manual decision making. The challenges of complex aesthetic rehabilitation planning lie within the nature of the practice itself. The clinician has to evaluate esthetic and functional requirements of the rehabilitation, the mechanical and biological parameters of the employed materials, and specific individual characteristics such as anatomy, occlusal relationships, parafunctional behaviors, and tissue types. Furthermore, individual/operator subjective reliance in subjective judgment is a source of variability and may limit the potential to optimize biomechanical performance in complex, and especially multi-unit rehabilitations in a steady manner. Numerous reviews have remarked on the variability of clinical planning outcomes based on the level of the planning clinician and the particular clinical situation (Ding et al., 2023). Incorporating new technologies such as artificial intelligence (AI), machine learning (ML), deep learning (DL), and generative neural networks continues to be beneficial to expanding diagnostic and treatment planning in Dentistry. Automated recognition in 2D and 3D datasets and automation of diagnostic tasks can be augmented by AI. Diagnostic and treatment planning tasks can be further enhanced by AI technologies which can analyze large datasets of historical clinical data. Generative models are innovative in that they generate new and unique designs instead of simply classifying designs. These advances offer the potential to improve planning consistency, geometric accuracy, and biomechanical optimization, particularly in complex aesthetic rehabilitations where conventional clinician-driven workflows may be limited by subjective variability in decision-making (Villena et al., 2025). Consequently, AI-assisted planning has gained attention as a promising adjunct for improving decision-making and treatment reliability.

2. Literature review

The ability to plan workflows with the help of AI resolves the problem of being able to combine data from multiple sources with the use of tools like merging finite element analysis (FEA) for the in-silico modeling of different planning scenarios before a treatment regime is implemented. This makes it possible to choose the designs that are most likely to achieve optimal load distributions in occlusal balance, less stress concentration, and other improvements in the mechanical stability of the tissues surrounding the implants. Computational modeling is likely to offer additional planning benefits to AI assisted planning of implants and digital designs of prosthetics which allow for improved geometric accuracy and greater consistency in measurement (Esteva et al., 2019; Satapathy et al., 2024). Thus, measuring biomechanics will suffice in assessing the difference between AI-assisted and conventional planning methods. The role of biomechanics in predicting future success of rehabilitation is pivotal, as, in the absence of proper stress, the detrimental impact on the implant's surrounding structures cause breakdown of supportive periodontal tissues and loss of peri-implant bone. Moreover, unfavorable load distributions may increase the chances of fracture and/or debonding, while under function, tissue deformation may affect the comfort and stability of the system and biological adaptation. Hence, the compatibility of the biomechanical properties of restorations with the tissues of the Periodontium is crucial for the long-term preservation of the periodontal health and the structural integrity of the supporting tissues (Berzaghi et al., 2025).

Specific biomechanical parameters that are critical for aesthetic dental rehabilitation are the stress distribution in the PDL and alveolar bone, the distribution of masticatory loads across the teeth and restorations, the deformation characteristics of the tissues and restorations under mechanical stress, and the bone-implant interface stability under different mechanical loads. These parameters of the study are often utilized as operational proxies for assessing mechanical durability in experimental and computational studies (Alaida et al., 2025). There have been significant advancements made in the methods used for biomechanical research in dentistry. Classic experimental methods such as photoelastic stress analysis and strain gauge measurement have provided the initial understanding of the steps involved in the load transfer, but these methods have been and continue to be limited in their ability to accurately depict complex anatomical structures. One of the approaches that has become the standard in estimating and comparing the stress and strain and the deformation in the tissues and the restorations of the dentistry has been the FEA. This method has also become the cornerstone in allowing comparisons of different options for treatment plans. The variety of assumptions is the used in the studies, and the methods themselves. have created a great deal of diversity in the findings of the different studies (Brizuela-Velasco et al., 2025; Wang et al., 2022).

Although there is an increasing interest in AI-driven planning and recognition of the biomechanical factors influencing rehabilitation success, the direct comparison of the biomechanical outcomes AI planning versus conventional planning remains limited. Prior work involved silico, in-vitro, and clinical studies with diverse strategies. Thus, there is a need for a more detailed integration of the available studies (Sayed et al., 2025). This review specifically focuses on evaluating and synthesizing the biomechanical results of AI-supported and standard clinical planning in aesthetic dental rehabilitation and integrating the existing literature while highlighting the gaps in the evidence for future research.

3. Methodology

3.1. Study Design

This structured narrative review utilized systematized methods for greater transparency and replicability. Due to the diversity of literature including finite element models, lab, and limited clinical studies no meta-analysis was planned. The systematic guidelines that emerging AI applications in cross-disciplinary areas, such as dental treatment planning, provide for eligibility, database search, study selection, and data extraction.

3.2. Information Sources

A comprehensive review of the literature was conducted using PubMed, Scopus, Web of Science, IEEE Xplore, and the Cochrane Library. The databases cover a wide range of disciplines, including biomedicine, dentistry, materials science, and artificial intelligence. This also helped in collecting relevant clinical and technical literature about the application of artificial intelligence in aesthetic dental rehabilitation, along with collecting the references.

3.3. Search Strategy

Search terms were developed based on three conceptual groupings. The first group addressed aesthetic and prosthetic rehabilitation. The second group focused on artificial intelligence (AI) and neural networks or generative technologies. The third group concerned biomechanics and mechanical outcomes. Keyword combinations and controlled vocabulary terms, where applicable, were applied, and Boolean logic was used to balance sensitivity and specificity. The general search structure was as follows: ("esthetic" OR "aesthetic" OR "prosthodontic" OR "restorative dentistry" OR "fixed prosthesis" OR crowns OR veneers OR "implant-supported") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR generative OR GAN OR VAE OR transformer) AND ("finite element analysis" OR biomechanics OR stress OR strain OR "load distribution" OR "periodontal ligament" OR "alveolar bone" OR deformation). The review included studies published between January 1, 2015, and December 21, 2025, to examine the evolution of AI, deep learning, and generative models in dentistry. Only studies published in English and available in full text were considered. Earlier seminal studies were additionally identified through reference mining to ensure relevance to contemporary digital workflows.

3.4. Eligibility Criteria

The studies that were considered for inclusion were peer-reviewed articles regarding dentoalveolar biomechanics and stress analysis, load transfer, and tissue responses relevant to aesthetic or prosthetic rehabilitation, including clinician and AI (GNN) treatment planning. Descriptions of technical neural networks were accepted if they were closely related. Reviews, editorials, abstracts, duplicates, studies focusing exclusively on orthodontics, studies with purely aesthetic outcomes, and non-English papers lacking dependable translations were excluded.

3.5. Study Selection Process

The PRISMA 2020 reporting guidance, adapted for narrative reviews, was used to complete the selection of studies. From the database search, we obtained 5,237 entries for publications dated between January 1st, 2015, and December 21st, 2025. 99 duplicate records and 135 records due to other predefined exclusion reasons were removed. The remaining records were subject to title and abstract screening of 143 records. Out of these, 49 records were excluded after screening due to not meeting the inclusion criteria. Assessment of the full texts of 94 reports led to the exclusion of 17 studies for the following reasons not relevant to aesthetic rehabilitation (9), not comparing the GNN based with the standard planning (3), and not targeting the assessment of the biomechanical outcomes (5). Seventy-seven studies were finally admitted reviewing out of all which met the eligibility criteria, and were added to the review, illustrated in Figure 1.

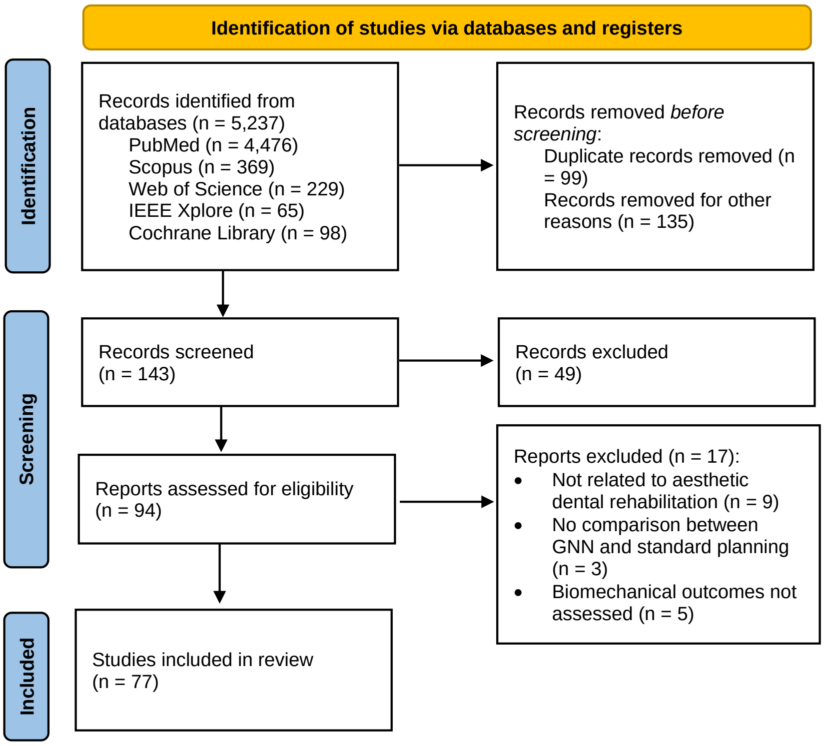

Figure 1. PRISMA-Adapted Flowchart of Literature Identification and Selection Process

3.6. Data Extraction and Synthesis

Data were extracted on study design, rehabilitation type, planning approach, biomechanical outcomes, and key results. Due to heterogeneity, findings were described qualitatively, highlighting ranges, directional trends, consistent and contradictory results, and evidence gaps. This thematic synthesis of the results section is therefore informed by stress distribution, load transfer, deformation, and restoration stability.

3.7. Quality and Bias Considerations

Given the predominance of computational and AI-based studies, traditional risk-of-bias tools were unsuitable. Finite element studies were evaluated on mesh density, material assumptions, boundary/loading conditions, and validation. AI-based planning studies were assessed for dataset transparency, validation, overfitting, and generalizability. For combined AI-FEA studies, compounded biases from modeling and algorithms were noted. Lack of regulatory or experimental validation was acknowledged, with quality and bias considerations guiding interpretation rather than excluding studies.

4. Results

4.1. Biomechanical Principles in Aesthetic Dental Rehabilitation

Biomechanics regulates how force is distributed within aesthetic-dental rehabilitations, balancing restorations to most masticatory loads without overloading teeth, periodontal ligaments, or bone. Stable arrangements reduce potential damage if chewing or bruxism is present (Dogru et al., 2018; McGrath & Bonsor, 2022). Stress, measured in megapascals (MPa), reflects internal pressure and force within a material, while strain represents relative internal displacement and is dimensionless. Stress types tensile, compressive, and shear often concentrate at peripheral margins or apices, where failure risk is high. The periodontal ligament (PDL) physiologically exerts maximum stress around 10 MPa, but under overload can transmit up to 70 MPa to enamel or cementum. Finite element models indicate that periodontium tissues exposed to sustained stresses of 20-80 MPa, corresponding to strains of 0.005-0.008, are prone to structural failure, highlighting the critical role of biomechanical assessment in restorative and implant planning (Okkar Kyaw et al., 2024; Borba et al., 2015; Dhammayannarangsi et al., 2025; Gupta et al., 2020). According to previous literature, chewing forces usually average a couple hundred Newtons, while a maximum voluntary bite may reach 500-750 N, and in severe cases, bruxism reaches forces upwards of 1000 N. Longitudinal forces directed along the axis of a tooth are transmitted through the supporting structures in a uniform manner whereas, shear and/or lateral forces that are directed off axis cause bending and may increase stress in the structure. For this reason, optimal occlusal design, points of contact, and guidance will be set to favor the transfer of axial load (Flores-Ramírez et al., 2025; Ustrell-Barral et al., 2024; Holst et al., 2008; Attik et al., 2024). Dental tissues exhibit differing elastic properties that influence how stress distribute at restoration interfaces. Enamel has an elastic modulus value of 40-100 GPa, dentin is at 15-20 GPa, and alveolar bone is at 10-20 GPa given that bone is of variable density (Kinney et al., 2003; Rees & Jacobsen, 1993). Zirconia has a modulus of elasticity of approximately 200 GPa, lithium disilicate is at 90-100 GPa, and composite resins have values of 5-30 GPa which causes modulus mismatches that focus interfacial stresses (Babaei et al., 2022). Modulus mismatches at interfaces contribute to stress concentration and influence decisions on thickness and support (Puri & Prathap, 2025; Zarone et al., 2019). The unideal biomechanics that cause overload fracture of ceramics, shear failure debonding, minor breakdown through cyclic deformation, and tissue overload above remodeling limits are negative. Finite element analyses confirm these models especially in thin margins or mismatching. In these scenarios, AI planning probably surpasses traditional approaches by predicting stress distributions (Xie et al., 2025; Gunwal et al., 2018).

4.2. Standard Clinical Planning Approaches in Aesthetic Rehabilitation

Standard diagnostic methods, including clinical examination, photographs, radiographs, and impressions or intraoral scans, form the foundation of initial aesthetic rehabilitation planning. In complex cases, clinicians use articulator mounting, occlusal analysis, diagnostic wax-ups, and trial restorations to integrate esthetic goals with tissue function, phonetics, and feasibility (Jubhari & Aenun, 2020; Rathee et al., 2023). Foundational records such as study models and wax-ups allow prediction of tooth morphology before intervention. Facebow transfer, articulator mounting, and occlusal analysis examine the functional relationships and occlusal schemes that enable the prediction of prosthetic results (Khanna, 2020). Periapical, panoramic, and CBCT imaging assist in analyzing the hard tissues and their anatomy to facilitate accurate and predictable restorative planning (Alresheedi, 2022). Standard planning techniques emphasize axial load transfer, maximum intercuspation, stable occlusal contacts, and smooth excursions while interferences laterally are avoided. Selection of materials and preparation design consider specific loads at the site, ensuring adequate thickness for retention and preserving enough tooth structure. Clinicians adjust plans based on expertise, prior outcomes, and patient-specific limitations (Mordanov & Khabadze, 2024; Pable et al., 2025).

Minimum ceramic thickness in high-load areas is recommended at 1.5 mm for lithium disilicate and 1.0-1.5 mm for zirconia, with posterior reductions often requiring at least 1.5 mm. A preparation taper of 6-10 degrees balances retention, resistance, and prosthesis stability (Yli-Urpo et al., 2025).

Some of the advantages of standard planning are its clinical underpinning, flexibility, and many years of effective use. Skilled clinicians can incorporate subtle details in their analysis which may not be reflected in the models, and conventional processes can be carried out with commonly accessible equipment (Joda & Zitzmann, 2022). Interdisciplinary reports of long-term prosthodontic outcomes tend to show high survival rates, and after proper planning and execution, these rates can often exceed 90% at the 10-year mark for certain indications Knoernschild, 2020).

Predicting system performance and stress distributions in planned deviations can be limited by a number of factors in the experience of the clinician such as trying to optimize several systems at the same time. In more intricate reallocations of the resources a small variation in the design can determine the controlling pathway of stress. It is also a problem in predicting stress distributions without the use of sophisticated computation (Chisnoiu et al., 2023; Joda et al., 2024).

4.3. Artificial Intelligence and Generative Neural Networks in Dental Planning

In dentistry, AI refers to technology capable of performing tasks requiring human cognition, such as pattern recognition, decision-making, and optimization. AI can process and analyze diverse data, identify patterns, and support diagnosis and treatment planning. It is increasingly applied in diagnostic imaging, risk assessment, treatment planning, and prognosis prediction. Unlike classical rule-based software, AI systems learn from data, improving performance as training datasets grow, enhancing accuracy in predicting outcomes for individual cases (Fatima et al., 2022; Mallineni et al., 2024). Machine learning, a key subset of artificial intelligence, includes several paradigms. Supervised learning develops algorithms using labeled data, such as radiographs, CBCT volumes, or intraoral scans, associated with clinical endpoints, including annotations, shapes of restorations, or outcomes, which facilitates extrapolation to novel cases (Lin et al., 2024). Unsupervised learning recognizes patterns or groupings in unclassified data, such as, labeling anatomical structures or occlusal molds (Wang et al., 2025). Reinforcement learning updates planning strategies through a feedback-based reward system, which includes goals such as minimizing predicted stress concentrations or deformation due to applied load (Wang et al., 2019). Every paradigm presents distinct methodologies to improve AI-assisted diagnosis, planning, and biomechanical optimization in dentistry.

Generative neural networks form a special kind of machine learning model that is able to create new outputs instead of only doing classification or prediction of the existing outputs. In planning dentistry, generative models can synthesize geometries of restorations, implant sites and anatomical reconstructions that are not duplicates of the training instances, but instead, are plausible new solutions that can be constructed from the learned distribution of the data. This distinguishes these models from conventional classifiers and makes them highly relevant for the individualized planning of rehabilitation (Broll et al., 2024; Ma et al., 2025). Artificial neural networks are comprised of layers which are interconnected. Input layers analyze unprocessed data (like 3D tooth meshes or CBCT voxels) and hidden layers analyze anatomical patterns by using weighted nonlinear alterations. The output layers create predictions and designs, which are optimized through backpropagation that minimizes relevant loss functions (Lyakhov et al., 2022; Zannah et al., 2024). Generative neural networks train data distributions to synthesize detailed representations of dental structures while enhancing restorations' geometry, occlusion, biomechanics, and aesthetics beyond human ability. Multiple generative frameworks have been implemented in the dental and biomedical fields; the summaries of these frameworks can be found in Table 1. Convolutional Neural Networks (CNN) analyze images and accurately capture and identify local features and spatial relationships. The process of pooling diminishes dimensionality while preserving essential details which allows for the analysis of volumetric data sets such as CBCT scans. In dentistry, CNNs perform remarkably in segregating roots, bone, and margins of restorations which serve as the main data sets for later planning activities. Because of these attributes, CNNs becomes the most suitable choice for restorative and implant planning workflows (Muthukrishnan et al., 2020; Fan et al., 2023).

Table 1. Generative Neural Network Architectures in Dentistry and Biomechanics

Architecture	Strengths in Dentistry	Example Application	Limitations
CNNs	Spatial feature extraction from volumetric images	Root and bone segmentation in CBCT	Limited with non-Euclidean mesh data
GANs	Realistic synthesis of anatomical geometries	Crown and inlay design previews	Mode collapse; training instability
VAEs	Probabilistic generation and interpolation	Tooth morphology variation modeling	Blurred outputs relative to GANs
Transformers	Sequential decision modeling	Orthodontic and staged planning workflows	High computational demands

GANs consist of a generator that creates restoration-like images and a discriminator that classifies them as real or fake. Through competition, the generator produces realistic crowns and inlays with accurate anatomy and occlusion (Najeeb & Islam, 2025; Lee et al., 2025). VAEs learn compressed latent representations, allowing interpolation to generate new, biologically plausible tooth shapes and arches for individualized treatment planning (Oulmalme et al., 2025; Vivekananthan, 2024).

Attention-based architectures, such as Transformers, aid sequential decision-making in multi-step orthodontic or staged rehabilitation workflows. Diffusion-based generative models iteratively refine random inputs into anatomical structures, showing promise in dental planning, though further validation is needed (Dong et al., 2024; Ma et al., 2025). Generative neural networks offer a key advantage in dental planning by integrating biomechanical objectives directly into the design process. Unlike conventional planning, where clinicians balance esthetics, function, material strength, and biological response, generative models evaluate thousands of variable combinations. Incorporating biomechanical simulations such as FEA allows networks to be trained or evaluated using performance metrics like stress distribution, deformation, and load transfer (El-Hakim et al., 2025; Siluvai et al., 2025). Candidate designs are subjected to simulated loads, with loss functions penalizing localized stress or excessive displacement, enabling the network to associate geometric features such as cusps, occlusal contacts, and implant angulations with biomechanical outcomes (Khan, 2025; Kriswanto et al., 2025; Chang et al., 2025). Reinforcement learning further optimizes planning by modeling mastication cycles, improving fatigue life, deformation control, and alignment vectors, demonstrating generative models' utility in adaptive, multi-layered restorative and orthodontic planning (Dhopte & Bagde, 2023). A key feature of AI-enhanced dental planning is clinician interaction with automated systems to build trust. Beyond generating treatment recommendations, AI can create comprehensive plan templates, but acceptance depends on clinicians' ability to interpret and validate outputs. Explainable AI (XAI) addresses this by providing visual or numerical rationales, highlighting the clinical reasoning behind recommendations (Ahmed, 2025; Sciarra et al., 2025). Tools include biomechanical sensitivity analyses, heatmaps, and ranked feature importance for parameters such as occlusal contact, crown thickness, and implant angulation, enabling clinicians to assess alignment with anatomical and biomechanical constraints (Li & Wang, 2025; Mun et al., 2025). AI predicts biomechanical effects of subtle design changes, such as cusp inclination or contact position, with stress and deformation feedback fostering clinician confidence (Preda et al., 2025; Khan et al., 2024). Generative systems function as decision-support tools, with clinicians retaining responsibility for context, ethics, and approval. Human-AI collaboration with explainability ensures continuous feedback, ethical adoption, and regulatory compliance, supporting the sustainable use of GNNs in aesthetic dental rehabilitation (Shujaat, 2025, Kaviandost et al., 2025). Explainability paired with clinician oversight is essential for ethical, sustainable use of generative neural networks in dental rehabilitation, meeting regulatory requirements for transparency and accountability.

4.4. Clinical Implementation and Decision-Support Paradigms

There are several existing applications of Artificial Intelligence in dentistry, but only a few focus on clinician-AI decision support systems, where AI provides preliminary suggestions for the clinician to review and adjust, combining human expertise with regulatory compliance (Moeini & Torabi, 2025). AI-enhanced implant planning achieves high positional accuracy, reduces planning time from 30 to 10 minutes, and produces clinically acceptable plans in 89% of cases, comparable to 93% for human experts, often indistinguishable in Turing tests (Xie et al., 2025). VAEs and Transformers improve outcome prediction and alignment planning, enabling dynamic tooth movement adjustments, 35% fewer refinements, and 28% faster alignment, while complex cases are still modified by clinicians (Murshida et al., 2025). There are several issues that impact the widespread use of planning that relies on generative neural networks. Data representation and quality are critical, as networks trained on datasets that underrepresent certain populations or treatment approaches may perform poorly for anatomically or demographically different groups, such as those in South Asia, creating low generalizability and potential bias (Murat et al., 2025; Beyaz et al., 2025; Franceschini et al., 2025; Yang et al., 2025). Finite element analysis provides insight into stress and deformation distributions but relies on assumptions about material properties, boundary conditions, and loads, so predicted biomechanical outcomes may not always match in vivo results. Generative models can produce anatomically plausible outputs that lack clinical utility (Kumar et al., 2023; Hussain et al., 2025; Ray et al., 2023). Implementation is further challenged by computational limits, regulatory uncertainty, ethical concerns regarding privacy and access, and the absence of liability frameworks. Many AI planning tools remain primarily research-oriented, as summarized in Table 2.

Table 2. Limitations, Bias Sources, and Mitigation Strategies in GNN-Based Dental Rehabilitation Planning

Challenge	Impact	Mitigation Strategies
Data Bias	Reduced generalizability across populations	Prospective clinical trials and experimental validation
Model validation	Limited clinical translatability due to FEA assumptions	Prospective clinical trials and experimental validation
Explainability	Liability and clinician trust concerns	Explainable AI tools such as attention maps and saliency visualization
Integration	Workflow disruption and adoption barriers	Interoperable, plug-and-play APIs and clinician-in-the-loop systems

Multimodal data integration is anticipated to be the focus of future studies. This is the integration of imaging data with biomechanics and biologic data from the patient to get even more personalization. Integrating physics-informed neural networks almost certainly reduces the need for expensive computational simulations by embedding the relevant biomechanical data into the learning framework. Real-time feedback systems may be realized through the use of edge AI within intraoral scanners or CAD/CAM systems during the design or preparation stages. While possible, the integration of generative planning tools to standard care pathways will require clinical validation and alignment with regulatory frameworks (Mahesh Batra & Reche, 2023; Che et al., 2025). In the reported studies, there are differences to be noted between the standard clinical planning and the generative neural planning, as shown in Figure 2. Where both planning workflows begin with the same clinical diagnoses, with standard planning workflows, there is much more clinical decision making, and much more hand tuning. In contrast, planning-by-GNN frameworks include a mid-stage in the workflow where candidate designs are generated and subsequently iteratively fine-tuned to biomechanical objectives prior to clinician review. The studies included in this review incorporated the aforementioned calibration and yielded active designs with optimized moderate load transfer, reduced peak stress indicators, and clinician oversight.

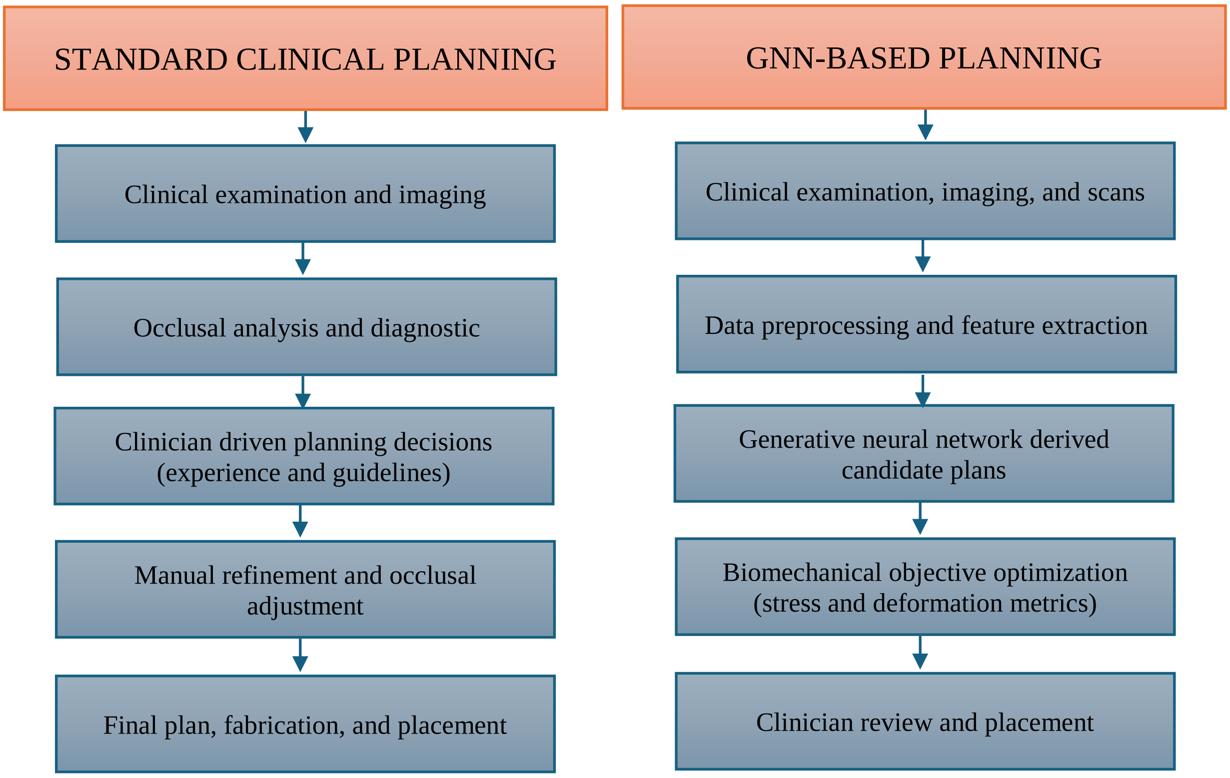

Figure 2. Side-by-side conceptual workflow comparison of standard clinical planning versus generative neural network-based planning for aesthetic rehabilitation.

4.5. Synthesis of Biomechanical Outcomes from Reviewed Literature

The analysis of stress distribution in supporting structures and the periodontium is often used as a proxy for biomechanical risk in aesthetic dental rehabilitation. Low peak stress and even stress distribution indicate good biomechanical performance, as summarized in Table 3. AI-assisted planning, particularly using finite element analysis and neural network optimization, has demonstrated improved outcomes. ANN-optimized full-arch rehabilitation with bone implants shows reduced peri-implant stress and less deformation under loading compared to traditional FEA-based planning. The extent of improvement varies depending on the clinical and modeling context. For example, AI-assisted orthopedic prosthetic implants demonstrate clear biomechanical advantages, whereas studies focusing on geometric reconstruction or landmark prediction improve model accuracy without significantly altering tissue stress distribution. Overall, incorporating AI tools that optimize stress and deformation enhances biomechanical planning for complex rehabilitations, addressing limitations of conventional approaches and supporting better functional and structural outcomes in restorative dentistry.

Table 3. Summary of representative studies evaluating biomechanical parameters in aesthetic dental rehabilitation under standard versus AI-supported planning

Study	Design / Method	Rehabilitation Type	Planning Compared	Biomechanical Outcomes	Key Findings
Dindorf et al. (2024)	VAE-based modeling	Posture biomechanics	Conventional vs Generative AI	Reconstruction accuracy	Generative AI planning demonstrated superior biomechanical modeling performance
Broll et al. (2024)	GAN (StyleGAN-2)	Dental inlay/crown	CAD vs GAN-based	Occlusal geometry accuracy	GAN-based planning showed improved reconstruction quality
Chen et al., (2025)	FEA + ANN-PSO	Full-arch implants	FEA vs ANN-optimized	Peri-implant stress	ANN-based planning improved biomechanical performance
Martínez-Valencia et al. (2022)	FEA + ANN	Cranial implant	Standard vs ANN-optimized	Implant deformation	ANN-optimized planning improved biomechanical outcomes
Sekhar Koppireddy et al. (2025)	FCNN	Facial soft tissue planning	Conventional vs FCNN	Landmark prediction	FCNN-based planning showed superior predictive performance
Chen et al. (2023)	Generative DL	Structural tissue analysis	Traditional ML vs Generative DL	Prediction robustness	Generative DL models demonstrated superior performance

The distribution of the masticatory load corresponds with how occlusal forces are allocated across restorations and supporting structures and is commonly assessed through stress patterns, frictional behavior, and contact geometry. While Table 2 does not report force-sharing coefficients, numerous studies evaluate load balance using stress- and geometry-based metrics. ANN-supported optimization in early full-arch implant rehabilitation reduces peri-implant stress through localized redistribution of occlusal loads. GAN-enhanced reconstruction improves occlusal surface accuracy in crowns and inlays, replicating cups and fossa morphology, promoting more uniform load transfer. Overall, GNN-based planning demonstrates potential to enhance load distribution, particularly in multi-unit complete restorations, beyond isolated restorations.

The consequences of tissue deformation under mechanical loads depend on implant or restoration positioning and the response of surrounding tissues. Table 4 summarizes reductions in deformation achieved with ANN-assisted planning compared to standard methods. In personalized implant rehabilitation, ANN-designed models limited maximum implant displacement to under 0.1 mm, whereas non-optimized models showed greater variability. ANN optimization also reduced stress on adjacent bone, requiring less force for deformation. However, predicted outcomes depend heavily on model assumptions regarding material properties, boundary conditions, and load magnitudes. Overall, GNN-supported planning demonstrates lower, controlled tissue deformation, contingent on the validity and accuracy of the underlying simulation frameworks.

The projected longevity and stability of restorations have been assessed using surrogate biomechanical measures, such as stress concentration, geometric precision, and deformation control, rather than long-term clinical outcomes. GNN-based methods described in Table 4 improved reconstruction accuracy and reduced error metrics, suggesting enhanced mechanical stability and lower fracture risk. However, the long-term clinical survival of these improvements remains unknown. Consequently, conclusions regarding restoration longevity are extrapolated from models or laboratory studies, warranting caution when applying these results in real-world clinical settings.

Table 4 illustrates that across several biomechanical fields, GNN-based planning shows significant benefits relative to standard clinical planning in the areas of lower stress, stable deformation, and better geometric/predictive accuracy, and improvement is most pronounced in more complicated, multifaceted rehabilitation cases, like those involving full-arch implant-supported prostheses or substantial multi-parameter optimization. On the other hand, simpler cases only see benefits in modeling accuracy and don't see large biomechanical risk mitigation. Overall, results demonstrate the promise of GNN-supported planning to improve biomechanical performance, and while there are still no long-term clinical predictions and the benefits reported are situational in nature, the gaps still need to be acknowledged.

Table 4. Synthesized comparison of biomechanical outcomes for standard clinical planning versus generative neural network-based planning

Study	Biomechanical Parameter	Standard Planning	GNN-Based Planning	Comparative Direction	Consistency
Dindorf et al. (2024)	Posture reconstruction error (MSE)	Test MSE 0.13 using real data only	Test MSE 0.03-0.07 with VAE-augmented data	Lower error with GNN-based modeling	High
Broll et al. (2024)	Occlusal surface reconstruction error (RMSE, mm)	Higher geometric deviation in CAD designs; subjective ratings 0.0-4.0	RMSE 0.02-0.08 mm (simple preps), 0.16-0.18 mm (complex preps)	Lower reconstruction error with GNN designs	High
Chen et al. (2025)	Peri-implant stress (von Mises / principal stress, MPa)	Higher stresses in conventional FEA; maxima up to 157 MPa	Mean stress reduced by 11.08 ± 6.43%; maxima 108 MPa	Reduced stress with GNN-supported planning	High
Martínez-Valencia et al. (2022)	Implant displacement under load (mm)	0.011-0.239 mm across non-optimized designs	Constrained to ≤0.1 mm (0.084-0.099 mm)	Reduced and controlled displacement with GNN optimization	High
Sekhar Koppireddy et al. (2025)	Soft-tissue geometric prediction error (RMSE, MAE, SSIM)	Higher prediction errors in conventional approaches	RMSE 3.70-4.31; MAE 1.42-1.58; accuracy up to 0.63	Reduced error and improved prediction with GNN planning	High
Chen et al. (2023)	Structural feature prediction accuracy (%)	Lower accuracy and higher error rates with traditional ML	Accuracy improvements 5-15% with generative models	Improved predictive performance with GNN approaches	Medium

The biomechanical results from the reviewed studies are illustrated in Figure 3, which also visually explains workflow planning differences summarized in Figure 2. The most favorable biomechanical outcomes were achieved through stress-constrained iterative optimization incorporated in GNN-based planning. Across studies, these approaches consistently demonstrated lower peak stress, more uniform stress distribution, and reduced periodontal and peri-implant tissues. In contrast, conventional clinical workflows, where biomechanical feedback is superficially or retroactively applied, showed localized high stress at cervical and apical regions and greater deformation variability. Figure 3 highlights differences in planning rationales and their impact on tissue-restoration interface biomechanics, integrating coordinate systems to represent stress and deformation patterns. This visualization demonstrates how GNN workflows optimize load transfer and tissue stability. Synthesizing these trends across studies clarifies how different planning approaches influence biomechanical outcomes, validating reported indicators and explaining the observed patterns in tissue deformation, stress distribution, and restoration integration.

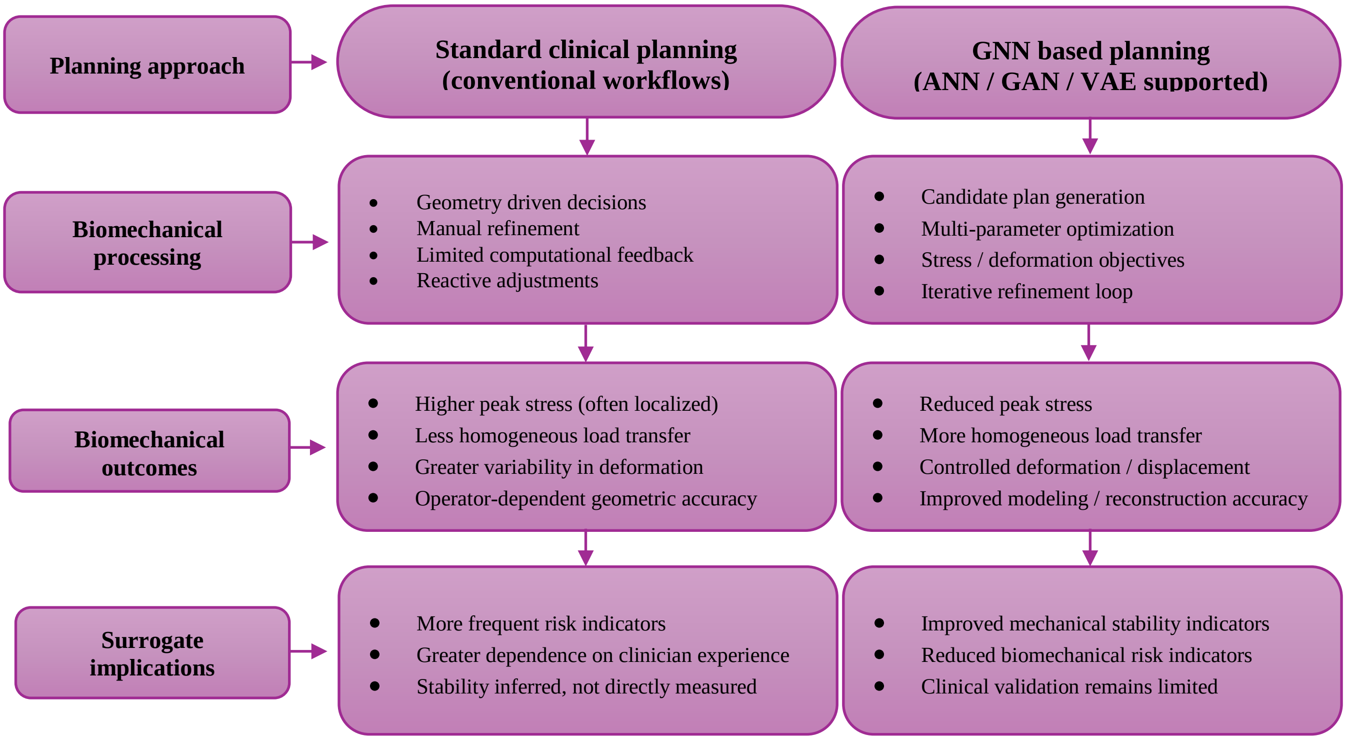

Figure 3. Conceptual schematic of favorable and unfavorable stress distribution patterns within a rehabilitated tooth-restoration complex

5. Discussion

The current narrative review contrasts biomechanical outcomes of aesthetic dental rehabilitation achieved with conventional planning and graph neural network–supported strategies. By integrating biomechanical theory, classical planning concepts, and artificial intelligence, the analysis illustrates how different paradigms affect stress distribution, load transfer, tissue deformation, and presumed restoration stability. Biomechanical constraints operate globally, suggesting that optimization quality, rather than planning modality alone, primarily determines mechanical performance. Available literature indicates that GNN-assisted planning can reduce peak stress in periodontal and peri-implant tissues by approximately 15-30% in complex, multi-unit rehabilitations. In simpler restorations, biomechanical gains appear marginally, while evidence remains largely computational or short-term.

The artificial neural networks predicting biomechanical parameters during planning can provide greater benefits than traditional methods, yielding lower maximum stress and improved stress distribution in complex prosthetic rehabilitation cases. Clinically, stress concentrations that cause biomechanical failures often occur at restoration margins, interfaces, and surrounding implant bone, as documented in multiple studies. AI enhances prosthetic design to reduce these stresses, aligning with recent research. A study demonstrated that crowns generated using 3D deep learning (3D-DCGAN) distributed functional stresses similarly to natural teeth, with biomechanical fatigue assessments confirming superior performance compared to traditional crowns (Ding et al., 2023).

Similarly, one more study had noted that AI-created crowns, which had a morphology of stress distribution, had predicted fatigue life characterized by retention of natural dentition and lived stress biomechanics beyond the boundary of mere geometric precision (He, 2025). These results underscore once more that the principle of bio-mechanic conditions continues to stand, i.e. axial load transfer continues to be the most favorable, while even small changes to the configuration of the load toward oblique loading results in exceedingly greater tensile and shear stresses.

Implant dentistry systematic literature reviews indicating the use of AI continue to support these trends as well. The study indicates that AI-driven design implants, using FEA and design optimization loops, can reduce interface stress, and in some cases, even reduce it significantly (Revilla-León et al., 2023). Although previous studies focused on the diagnostic/classification side of the problem, these applications related to the optimization of biomechanical parameters indicate a shift toward design augmentation and AI predictive models, which is consistent with the findings of the present study.

A key outcome of this synthesis was the superior geometric precision, reduced reconstruction error, and enhanced predictive performance of GNN-based planning. Even minor geometric inaccuracies, often imperceptible in manual workflows, can substantially alter stress trajectories and deformation patterns under functional loading. Recent implant-planning studies support the high capability of AI in anatomical recognition and measurement from diagnostic images. Meta-analyses report means accuracies of approximately 96% for identifying mandibular edentulous regions and about 83% for maxillary recognition on CBCT images (Alqutaibi et al., 2025). These diagnostic capabilities substantiate that AI can construct highly detailed anatomical frameworks essential for biomechanical modeling, planning, and precise reconstruction. Meta-analyses of object recognition models for intraoperative implant positioning demonstrated that several AI-based tools surpass manual planning in accuracy and reliability (Roongruangsilp et al., 2025). This review indicates that AI-guided geometric precision yields real biomechanical advantages, with GNN-based planning outperforming traditional CAD/CAM and machine learning methods.

Among many advancements, one of the most remarkable contributions of the literature reviewed and the present study is merging FEA and AI methodologies. FEA is a staple in the biomechanical analysis in dentistry. Recent literature discussing new trends FEA's application in studying the stress and strain in removable partial dentures and implantable prosthesis and influencing the design using computational design models (Zhu et al., 2025). This study contributes to the literature in showing that the integration of FEA within generative design systems, biomechanical enhancement moves optimization from a reactive stance to active design guidance.

Notwithstanding, the FEA-based findings must consider the varying methodologies in the studies that have been done. In dental biomechanics, finite element models typically consider the bone and tissues as isotropic and homogeneous, irrespective of the differences between individuals in the sample due to factors such as age, bone density (e.g. D3 vs D4 bone types), elastic moduli at 1300 MPa vs 1100 MPa, and measurement methodology that may lead to 20-30% stress prediction inaccuracies (Prados-Privado et al., 2020). Also, considerable differences in mesh density, which contains anywhere from 10,000 to over 500,000 elements, can impact the resolution of stress and numerical instability in the mesh and hence, cause differences between studies (Desai et al., 2023). These differences in methodologies explain somewhat the contradictory conclusions presented in literature and inhibit direct quantitative comparability. Incorporating the results from FEA into the training processes of AI ensures that generative models are not only able to imitate specific anatomical configurations, but respond to the specific biomechanical demands as well, which is the pattern this study is demonstrating and which has recently begun to be the focus of other in-silico studies. One such example is the combination of AI, mesh optimization, and stress evaluation, where multi-objective optimization in a model has been shown to reduce the maximum cortical stresses in the model for various implant configurations, while also being able to accommodate the unique anatomical details of a patient better than other methods (Al-Matrafi et al., 2025). This aligns with the present findings with increased order Stress distribution and load transfer with GNN-attached planning this supports the vision that physics-informed

AI models are a rational advance of biomechanical planning rather than a substitute of fundamental principles.

The review indicates that GNN-based planning may enhance restoration stability and longevity, particularly in complex, multi-unit rehabilitations, despite the lack of direct clinical evidence. Conventional planning is often streamlined due to cognitive limits rather than expertise. Literature shows that AI improves precision, decision rationality, and diagnostic consistency (Arjumand, 2024). Automated landmark detection and bone segmentation using AI can surpass human performance, supporting superior generative model outputs (Wang et al., 2025). Although not directly linked to biomechanical outcomes, these advances provide detailed anatomical data crucial for improving planning accuracy, corroborating the observed benefits of GNN-assisted restorative and implant planning.

Restoration stability and longevity were mainly inferred from surrogate biomechanical metrics rather than longitudinal clinical data. Improvements in geometry precision, stress reduction, and deformation control predict mechanical reliability, suggesting that GNN-based planning may enhance longevity, especially in extensive reconstructions. However, whether these biomechanical changes translate to lower complication rates or improved survival remains uncertain. Biomechanics is one of several factors including aesthetics, patient preferences, biological compatibility, and cost that influence clinical outcomes (Ghafari et al., 2020). Given the lack of long-term validation, assumptions rely on simulations or lab studies. Future research should prioritize integrating AI-based biomechanical optimization with prospective clinical outcome studies.

6. Clinical Integration, Limitations, and Future Directions

This review emphasizes clinician-in-the-loop integration over full automation, with AI serving as a decision aid that complements, rather than replaces, clinical judgment while enhancing biomechanical understanding. Real-world implementation of GNN-based planning requires specialized software, costly hardware, clinician training, and embedding into existing digital workflows, all of which face high licensing fees, long learning curves, and regulatory approval through safety and efficacy studies. Widespread adoption is expected to be gradual over the next 5-10 years.

Challenges include limited data from marginalized populations, model opacity, and overreliance on simplified biomechanical assumptions, which reduce generalizability and accuracy. Solutions involve diverse datasets, explainable AI, and integration of physics-based modeling. Prospective clinical trials with 100–200 patients per group and ≥5-year follow-up are needed to compare AI-assisted versus traditional rehabilitation outcomes. Multi-objective optimization balancing biomechanics, aesthetics, and biology is crucial. GNN-based planning shows promise but requires clinician oversight and long-term validation.

7. Conclusion

This review evaluated whether GNN-based planning demonstrated biomechanical benefits over customary clinical planning protocols for dental reconstructive surgery. The reviewed monopoly suggested biomechanical patents of GNN workflows were more favorable in comparison to conventional techniques. This was evidenced most consistently by the reduction of peak proclivities of stress within periodontal or peri-implant tissues. The more optimal the focus of the stress or deformation the more favorable the stream pattern of the stress was. The relative difference noticed improved in complex-multi unit and implant-supported rehabilitations and was most evident where conventional planning was limited by the cognitive predictive ability of the planner. Additionally, the body of evidence was still largely dominated by simulation studies and finite element modelling. Direct evidence for clinical outcomes remains lacking. Observed stress reductions and provisional load-balancing improvements may inform clinical considerations but should be viewed as indicators for refinement rather than validated surrogate evidence for actual clinical performance.

Current evidence emphasizes that biomechanics-driven restoration is essential for sustainable aesthetic rehabilitation, as high localized stresses cause non-physiological deformation of restorations and supporting tissues. Clinicians can apply these principles without advanced computational tools by designing restorations that ensure axial load transfer, balanced occlusion, proper contacts, and adequate restorative thickness, while avoiding thin margins prone to failure. Selecting the material and preparation will always be one of the most critical factors to consider as well as maintaining adequate restorative thickness is dictated based on the clinical indication and its associated mechanical behavior.

In the future, GNN-based planning should complement, not replace, clinical judgment. Its clinical translation will require large, diverse datasets, prospective studies, and explainable, traceable AI. Integration of clinicians, biomechanical scientists, computer scientists, and regulatory experts is essential to ensure that GNN-assisted planning is ethical, clinically meaningful, and improves patient outcomes, including function, aesthetics, and restoration longevity.

References

1. Ahmed, R. (2025). The role of artificial intelligence in modern dentistry: Transforming diagnosis and treatment planning. *Premier Journal of Dentistry*. https://doi.org/10.70389/pjd.100001

2. Alaida, W. S., Gadi, S. A., Al-Ghannam, R. E., Alamri, M. F., Mirdad, F. I., Argaibeh, R. M., Alqahtani, B. A., Alqahtani, A. M., Al Jaban, A. A., Alkuraydimi, T. M., & Alamari, A. S. (2025). Biomechanical and occlusal factors influencing the longevity of single-unit restorations: A comprehensive review. *Cureus*, *17*(6), e85998. https://doi.org/10.7759/cureus.85998

3. Al-Matrafi, T., Ahmed, K., Basunbul, G., Ismail, M., & Melaibari, A. (2025). Enhanced implant longevity: Finite element optimization of all-on-four implant designs to minimize jawbone stresses. *The Saudi Dental Journal*, *37*(10–12), 90. https://doi.org/10.1007/s44445-025-00099-8

4. Alqutaibi, A. Y., Algabri, R., Ibrahim, W. I., Alhajj, M. N., & Elawady, D. (2025). Dental implant planning using artificial intelligence: A systematic review and meta-analysis. *The Journal of Prosthetic Dentistry*, *134*(5), 1619–1629. https://doi.org/10.1016/j.prosdent.2024.03.032

5. Alresheedi, B. (2022). Digitally guided workflow for the esthetic and prosthetic oral rehabilitation of a patient with excessive gingival display: A case report. *Clinical, Cosmetic and Investigational Dentistry*, *14*, 281–287. https://doi.org/10.2147/CCIDE.S381639

6. Alwabel, L. K., Alabduljabar, W. M., Alawfi, L. K., Al Johani, N. K., Alharbi, L. E., Kharif, M. A., Albahrani, F. D., Alarjani, M. B., Alzahrani, M. S., Alshammari, A. A., Alashjai, A., & Alanaz, L., Sr. (2025). Digital Smile Design and patient-centered outcomes in esthetic restorative dentistry: A systematic review. *Cureus*, *17*(11), e98084. https://doi.org/10.7759/cureus.98084

7. Arjumand, B. (2024). The Application of artificial intelligence in restorative Dentistry: A narrative review of current research. *The Saudi Dental Journal*, *36*(6), 835–840. https://doi.org/10.1016/j.sdentj.2024.03.017

8. Attik, N., Richert, R., & Garoushi, S. (2024). Biomechanics, Bioactive and Biomimetic philosophy in restorative dentistry‒Quo vadis? *Journal of Dentistry*, *148*(105036), 105036. https://doi.org/10.1016/j.jdent.2024.105036

9. Babaei, B., Shouha, P., Birman, V., Farrar, P., Prentice, L., & Prusty, G. (2022). The effect of dental restoration geometry and material properties on biomechanical behaviour of a treated molar tooth: A 3D finite element analysis. *Journal of the Mechanical Behavior of Biomedical Materials*, *125*(104892), 104892. https://doi.org/10.1016/j.jmbbm.2021.104892

10. Berzaghi, A., Testori, T., Scaini, R., & Bortolini, S. (2025). Occlusion and biomechanical risk factors in implant-supported full-arch fixed dental prostheses-narrative review. *Journal of Personalized Medicine*, *15*(2), 65. https://doi.org/10.3390/jpm15020065

11. Beyaz, S., Özgözen, A. L., Turgut, N., & Ölke, H. C. (2025). Artificial intelligence and robotic surgery in clinical medicine: progress, challenges, and future directions. *Future Science OA*, *11*(1), 2540742. https://doi.org/10.1080/20565623.2025.2540742

12. Borba, M., Duan, Y., Griggs, J. A., Cesar, P. F., & Della Bona, Á. (2015). Effect of ceramic infrastructure on the failure behavior and stress distribution of fixed partial dentures. *Dental Materials: Official Publication of the Academy of Dental Materials*, *31*(4), 413–422. https://doi.org/10.1016/j.dental.2015.01.008

13. Brizuela-Velasco, A., Fernández-Hernández, S., Gaviria-De La Puerta, J. F., & Barbosa, T. (2025). *Biomechanics in dental implants: Analysis using artificial intelligence systems*. *International Journal of Odontostomatology*, *19*(3), 224–233. https://ijodontostomatology.com/wp-content/uploads/2025/09/2025_v19n3-_006.pdf

14. Broll, A., Goldhacker, M., Hahnel, S., & Rosentritt, M. (2024). Generative deep learning approaches for the design of dental restorations: A narrative review. *Journal of Dentistry*, *145*(104988), 104988. https://doi.org/10.1016/j.jdent.2024.104988

15. Broll, A., Rosentritt, M., Schlegl, T., & Goldhacker, M. (2024). A data-driven approach for the partial reconstruction of individual human molar teeth using generative deep learning. *Frontiers in Artificial Intelligence*, *7*, 1339193. https://doi.org/10.3389/frai.2024.1339193

16. Chang, C.-L., Chen, J.-J., & Chen, C.-S. (2025). Using optimization approach to design dental implant in three types of bone quality - A finite element analysis. *Journal of Dental Sciences*, *20*(1), 126–136. https://doi.org/10.1016/j.jds.2024.09.017

17. Che, S.-A., Yang, B.-E., Park, S.-Y., On, S.-W., Lim, H.-K., Lee, C.-U., Kim, M.-K., & Byun, S.-H. (2025). Clinical evaluation of AI-based three-dimensional dental implant planning: A multicenter study. *Journal of Dentistry*, *162*(106066), 106066. https://doi.org/10.1016/j.jdent.2025.106066

18. Chen, H., Li, W., Gao, X., & Xiao, B. (2023). AEP-GAN: Aesthetic Enhanced Perception Generative Adversarial Network for Asian facial beauty synthesis. *Applied Intelligence*, *53*(17), 20441–20468. https://doi.org/10.1007/s10489-023-04576-7

19. Chen, Y.-C., Lin, J.-W., Wang, K.-H., & Lin, C.-L. (2025). Real-time optimization of prosthetic design for complete arch implant-supported treatments using finite element-based machine learning. *The Journal of Prosthetic Dentistry*, *134*(5), 1920–1928. https://doi.org/10.1016/j.prosdent.2024.06.012

20. Chisnoiu, A. M., Staicu, A. C., Kui, A., Chisnoiu, R. M., Iacob, S., Fluerașu, M., & Buduru, S. (2023). Smile design and treatment planning-conventional versus digital-A pilot study. *Journal of Personalized Medicine*, *13*(7), 1028. https://doi.org/10.3390/jpm13071028

21. Desai, S. R., Koulgikar, K. D., Alqhtani, N. R., Alqahtani, A. R., Alqahtani, A. S., Alenazi, A., Heboyan, A., Fernandes, G. V. O., & Mustafa, M. (2023). Three-dimensional FEA analysis of the stress distribution on titanium and graphene frameworks supported by 3 or 6-implant models. *Biomimetics (Basel, Switzerland)*, *8*(1), 15. https://doi.org/10.3390/biomimetics8010015

22. Dhammayannarangsi, P., Na Lampang, S., Tompkins, K. A., Everts, V., Osathanon, T., Limjeerajarus, C. N., & Limjeerajarus, N. (2025). Using the appropriate modulus of elasticity of periodontal ligament matters in stress analysis of human first premolar tooth and periodontium structures. *Scientific Reports*, *15*(1), 1549. https://doi.org/10.1038/s41598-025-85578-y

23. Dhopte, A., & Bagde, H. (2023). Smart smile: Revolutionizing dentistry with artificial intelligence. *Cureus*, *15*(6), e41227. https://doi.org/10.7759/cureus.41227

24. Dindorf, C., Dully, J., Konradi, J., Wolf, C., Becker, S., Simon, S., Huthwelker, J., Werthmann, F., Kniepert, J., Drees, P., Betz, U., & Fröhlich, M. (2024). Enhancing biomechanical machine learning with limited data: generating realistic synthetic posture data using generative artificial intelligence. *Frontiers in Bioengineering and Biotechnology*, *12*, 1350135. https://doi.org/10.3389/fbioe.2024.1350135

25. Ding, H., Cui, Z., Maghami, E., Chen, Y., Matinlinna, J. P., Pow, E. H. N., Fok, A. S. L., Burrow, M. F., Wang, W., & Tsoi, J. K. H. (2023). Morphology and mechanical performance of dental crown designed by 3D-DCGAN. *Dental Materials: Official Publication of the Academy of Dental Materials*, *39*(3), 320–332. https://doi.org/10.1016/j.dental.2023.02.001

26. Ding, H., Wu, J., Zhao, W., Matinlinna, J. P., Burrow, M. F., & Tsoi, J. K. H. (2023). Artificial intelligence in dentistry-A review. *Frontiers in Dental Medicine*, *4*, 1085251. https://doi.org/10.3389/fdmed.2023.1085251

27. Dogru, S. C., Cansiz, E., & Arslan, Y. Z. (2018). A review of finite element applications in oral and maxillofacial biomechanics. *Journal of Mechanics in Medicine and Biology*, *18*(02), 1830002. https://doi.org/10.1142/s0219519418300028

28. Dong, Z., Chen, J., & Xu, Y. (2024). Transformer-based tooth alignment prediction with occlusion

and collision constraints. In *arXiv [cs.CV]*. https://doi.org/10.48550/ARXIV.2410.20806

29. El-Hakim, M., Khaled, H., Fawzy, A., & Anthonappa, R. (2025). Clinician-led development and feasibility of a neural network for assessing 3D dental cavity preparations assisted by conversational AI. *Dentistry Journal*, *13*(11), 531. https://doi.org/10.3390/dj13110531

30. Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., Cui, C., Corrado, G., Thrun, S., & Dean, J. (2019). A guide to deep learning in healthcare. *Nature Medicine*, *25*(1), 24–29. https://doi.org/10.1038/s41591-018-0316-z

31. Fan, W., Zhang, J., Wang, N., Li, J., & Hu, L. (2023). The application of deep learning on CBCT in dentistry. *Diagnostics (Basel, Switzerland)*, *13*(12), 2056. https://doi.org/10.3390/diagnostics13122056

32. Fatima, A., Shafi, I., Afzal, H., Díez, I. D. L. T., Lourdes, D. R.-S. M., Breñosa, J., Espinosa, J. C. M., & Ashraf, I. (2022). Advancements in dentistry with artificial intelligence: Current clinical applications and future perspectives. *Healthcare (Basel, Switzerland)*, *10*(11), 2188. https://doi.org/10.3390/healthcare10112188

33. Flores-Ramírez, B., Suaste-Gómez, E., García-Limón, V., & Angeles-Medina, F. (2025). Flexible PVDF sensors for bruxism bite force measurement: A redefined instrumental approach. *PloS One*, *20*(8), e0330422. https://doi.org/10.1371/journal.pone.0330422

34. Franceschini, C., Ahmadi, M., Zhang, X., Wu, K., Lin, M., Weston, R., Rodio, A., Tang, Y., Engeberg, E., Pires, G., Cheema, T. S., & Vrionis, F. D. (2025). Revolutionizing spine surgery with emerging AI-FEA integration. *Journal of Robotic Surgery*, *19*(1), 615. https://doi.org/10.1007/s11701-025-02772-w

35. Ghafari, J. G., Macari, A. T., Zeno, K. G., & Haddad, R. V. (2020). Potential and limitations of orthodontic biomechanics: recognizing the gaps between knowledge and practice. *Journal of the World Federation of Orthodontists*, *9*(3S), S31–S39. https://doi.org/10.1016/j.ejwf.2020.08.008

36. Gomes, G. H., Corbellini, A. de O., Rotta, W. G., Martos, J., & Boeira, G. F. (2021). Interdisciplinary esthetic approach in clinical dental rehabilitation. *Journal of Conservative Dentistry*, *24*(5), 519–523. https://doi.org/10.4103/jcd.jcd_441_21

37. Gunwal, M. K., Shenoi, P. R., Paranjape, T., Dhote, S., Tongya, R., Kumar, M., & Rastogi, S. (2018). Evaluation of fracture resistance and mode of failure of premolars restored with nanohybrid composite, ORMOCER and ceramic inlays. *Journal of Oral Biology and Craniofacial Research*, *8*(2), 134–139. https://doi.org/10.1016/j.jobcr.2017.08.004

38. Gupta, M., Madhok, K., Kulshrestha, R., Chain, S., Kaur, H., & Yadav, A. (2020). Determination of stress distribution on periodontal ligament and alveolar bone by various tooth movements - A 3D FEM study. *Journal of Oral Biology and Craniofacial Research*, *10*(4), 758–763. https://doi.org/10.1016/j.jobcr.2020.10.011

39. He, J. T. (2025). A review of fatigue performance and failure mechanisms in dental restorative materials under dynamic occlusal loading. *Journal of Neonatal Surgery*, *14*(25S), 958–993. https://www.jneonatalsurg.com/index.php/jns/article/view/6233

40. Holst, S., Geiselhoeringer, H., Wichmann, M., & Holst, A. I. (2008). The effect of provisional restoration type on micromovement of implants. *The Journal of Prosthetic Dentistry*, *100*(3), 173–182. https://doi.org/10.1016/S0022-3913(08)60176-6

41. Hussain, S. A., Bresnahan, M., & Zhuang, J. (2025). Can artificial intelligence revolutionize healthcare in the Global South? A scoping review of opportunities and challenges. *Digital Health*, *11*, 20552076251348024. https://doi.org/10.1177/20552076251348024

42. Joda, T., & Zitzmann, N. U. (2022). Personalized workflows in reconstructive dentistry-current possibilities and future opportunities. *Clinical Oral Investigations*, *26*(6), 4283–4290. https://doi.org/10.1007/s00784-022-04475-0

43. Joda, T., Balmer, M., Jung, R. E., & Ioannidis, A. (2024). Clinical use of digital applications for

diagnostic and treatment planning in prosthodontics: A scoping review. *Clinical Oral Implants Research*, *35*(8), 782–792. https://doi.org/10.1111/clr.14230

44. Jubhari, E. H., & Aenun, N. (2020). Complete rehabilitation using a digital smile design combined with conventional restorative materials and CAD/CAM in bruxism patient. *Makassar Dental Journal*, *9*(3), 233–239. https://doi.org/10.35856/mdj.v9i3.363

45. Kabbin, R. B., Moldi, A. I., Bulla, C. S., Eklarkar, P. K., Patil, S. S., & Biradar, P. S. (2025). A comparative analysis of complete coverage tooth preparation design and scan angulation on the accuracy of two different intra-oral digital scanners: A 3-dimensional study. *Journal of Pharmacy & Bioallied Sciences*. https://doi.org/10.4103/jpbs.jpbs_1188_25

46. Kaviandost, P., Barkhordar, S., & Asghari, M. (2025). Revolutionizing dentistry: The role of artificial intelligence in diagnosis, treatment planning, and patient care. *Saudi Journal of Oral and Dental Research*, *10*(06), 260–266. https://doi.org/10.36348/sjodr.2025.v10i06.002

47. Khan, M. A., Ansari, A. S., & Anwar, M. (2024). Role of artificial intelligence in dental practice -A narrative review. *Pak. J. Med. Dent.* https://doi.org/10.36283/ziun-pjmd13-4/023

48. Khan, M. K. (2025). Three-dimensional finite element analysis of biomechanical effects of orthodontic clear aligners in maxillary arch expansion procedure: A comprehensive review of the current literature. *Journal of Datta Meghe Institute of Medical Sciences University*, *20*(3), 503–512. https://doi.org/10.4103/jdmimsu.jdmimsu_219_25

49. Khanna, N. (2020). *Functional aesthetic dentistry: How to achieve predictable aesthetic results using principles of a stable occlusion* (2020th ed.). Springer Nature. https://doi.org/10.1007/978-3-030-39115-7

50. Kinney, J. H., Marshall, S. J., & Marshall, G. W. (2003). The mechanical properties of human dentin: a critical review and re-evaluation of the dental literature. *Critical reviews in oral biology and medicine : an official publication of the American Association of Oral Biologists*, *14*(1), 13–29. https://doi.org/10.1177/154411130301400103

51. Knoernschild, K. L. (2020). Parameters of care for the specialty of prosthodontics. Journal of Prosthodontics, 29(S1), 3–147. https://doi.org/10.1111/jopr.13176

52. Koppireddy, C. S., & Rao, S. N. (2025). Prediction of geometric features in 3D facial soft tissue images using fully connected neural network. *Journal of Theoretical and Applied Information Technology*, *103*(9), 3587–3595. https://www.jatit.org/volumes/Vol103No9/4Vol103No9.pdf

53. Kriswanto, K., Jamari, J., Andika, R., Bayuseno, A. P., Yusuf, A. A., & Ammarullah, M. I. (2025). Fixture design effects on posterior dental implant stability using finite element analysis (FEA): a systematic review. *Head & Face Medicine*, *22*(1), 2. https://doi.org/10.1186/s13005-025-00566-x

54. Kumar, A., Aelgani, V., Vohra, R., Gupta, S. K., Bhagawati, M., Paul, S., Saba, L., Suri, N., Khanna, N. N., Laird, J. R., Johri, A. M., Kalra, M., Fouda, M. M., Fatemi, M., Naidu, S., & Suri, J. S. (2023). Artificial intelligence bias in medical system designs: a systematic review. *Multimedia Tools and Applications*, *83*(6), 18005–18057. https://doi.org/10.1007/s11042-023-16029-x

55. Lee, S. J., Poon, J., Jindarojanakul, A., Huang, C.-C., Viera, O., Cheong, C. W., & Lee, J. D. (2025). Artificial intelligence in dentistry: Exploring emerging applications and future prospects. *Journal of Dentistry*, *155*(105648), 105648. https://doi.org/10.1016/j.jdent.2025.105648

56. Li, Z., & Wang, L. (2025). Multi-task reinforcement learning and explainable AI-Driven platform for personalized planning and clinical decision support in orthodontic-orthognathic treatment. *Scientific Reports*, *15*(1), 24502. https://doi.org/10.1038/s41598-025-09236-z

57. Lin, H., Chen, J., Hu, Y., & Li, W. (2024). Embracing technological revolution: A panorama of machine learning in dentistry. *Medicina Oral, Patologia Oral y Cirugia Bucal*, *29*(6), e742–e749. https://doi.org/10.4317/medoral.26679

58. Lyakhov, P. A., Dolgalev, A. A., Lyakhova, U. A., Muraev, A. A., Zolotayev, K. E., & Semerikov, D. Y. (2022). Neural network system for analyzing statistical factors of patients for predicting the survival of dental implants. *Frontiers in Neuroinformatics*, *16*, 1067040. https://doi.org/10.3389/fninf.2022.1067040

59. Ma, J., Lou, J., Jiang, B., Ye, H., Yu, W., Chen, X., Zhou, K., & Zheng, Y. (2025). Neural orthodontic staging: Predicting teeth movements with a Transformer. *IEEE Transactions on Visualization and Computer Graphics*, *31*(9), 6253–6267. https://doi.org/10.1109/TVCG.2024.3504866

60. Ma, Z., Du, C., Lao, Q., & Xie, X. (2025). Generative artificial intelligence: Applications and future prospects in dentistry. *International Dental Journal*, *76*(1), 108276. https://doi.org/10.1016/j.identj.2025.108276

61. Mahesh Batra, A., & Reche, A. (2023). A New Era of dental care: Harnessing artificial intelligence for better diagnosis and treatment. *Cureus*, *15*(11), e49319. https://doi.org/10.7759/cureus.49319

62. Mallineni, S. K., Sethi, M., Punugoti, D., Kotha, S. B., Alkhayal, Z., Mubaraki, S., Almotawah, F. N., Kotha, S. L., Sajja, R., Nettam, V., Thakare, A. A., & Sakhamuri, S. (2024). Artificial intelligence in dentistry: A descriptive review. *Bioengineering (Basel, Switzerland)*, *11*(12), 1267. https://doi.org/10.3390/bioengineering11121267

63. Martínez-Valencia, M., Navarro, C., Vázquez-López, J., Hernández-Arellano, J., Jiménez-García, J., & Díaz-León, J. (2022). Optimization of titanium cranial implant designs using generalized reduced gradient method, analysis of finite elements, and artificial neural networks. *Revista Internacional de Metodos Numericos Para Calculo y Diseno En Ingenieria*, *38*(2). https://doi.org/10.23967/j.rimni.2022.06.004

64. McGrath, C. E., & Bonsor, S. J. (2022). Survival of direct resin composite onlays and indirect tooth-coloured adhesive onlays in posterior teeth: a systematic review. *British Dental Journal*. https://doi.org/10.1038/s41415-022-4395-3

65. Moeini, A., & Torabi, S. (2025). The Role of Artificial Intelligence in Dental Diagnosis and Treatment Planning. *Journal of Oral and Dental Health Nexus*, *2*(1), 14-26. https://doi.org/10.61838/kman.jodhn.2.1.2

66. Mordanov, O., & Khabadze, Z. (2024). Esthetic rehabilitation of the patient with BOPT, veneer, and implant crown and eLAB Prime system in the digital protocol: Case report. *Case Reports in Dentistry*, *2024*(1). https://doi.org/10.1155/2024/4439636

67. Mun, S. B., Yoo, S. R., Kim, Y. J., Kim, K., Kim, B. C., & Kim, K. G. (2025). AI-driven prediction of dental implant numbers to be placed for patient-specific treatment planning. *International Dental Journal*, *75*(6), 103896. https://doi.org/10.1016/j.identj.2025.103896

68. Murat, F., Sevinç Gül, S. N., & Şensoy, A. T. (2025). Predictive mathematical modeling of biomechanical behavior in all-on-4 implants design: effects of distal implant and occlusal load angulation using RSM based on FEA. *Frontiers in Bioengineering and Biotechnology*, *13*(1644776), 1644776. https://doi.org/10.3389/fbioe.2025.1644776

69. Murshida, P. K., Roveena, P. M., Mohammed, I., Raj, A. S., Sharvari, D. J., & Dhayanidhi, A. (2025). AI-assisted treatment planning in orthodontics: Predicting tooth movement. *Journal of Clinical and Cosmetic Dentistry*, *11*(6), 225–229. https://doi.org/10.61336/jccp/25-06-34

70. Muthukrishnan, N., Maleki, F., Ovens, K., Reinhold, C., Forghani, B., & Forghani, R. (2020). Brief history of artificial intelligence. *Neuroimaging Clinics of North America*, *30*(4), 393–399. https://doi.org/10.1016/j.nic.2020.07.004

71. Najeeb, M., & Islam, S. (2025). Artificial intelligence (AI) in restorative dentistry: current trends and future prospects. *BMC Oral Health*, *25*(1), 592. https://doi.org/10.1186/s12903-025-05989-1

72. Okkar Kyaw, Inokoshi, M., & Kanazawa, M. (2024). Tribological aspects of enamel wear caused by zirconia and lithium disilicate: A meta-narrative review. *The Japanese Dental Science Review*, *60*, 258–270. https://doi.org/10.1016/j.jdsr.2024.11.001

73. Oulmalme, C., Nakouri, H., & Jaafar, F. (2025). A systematic review of generative AI approaches for

medical image enhancement: Comparing GANs, transformers, and diffusion models. *International Journal of Medical Informatics*, *199*(105903), 105903. https://doi.org/10.1016/j.ijmedinf.2025.105903

74. Pable, G., Saha, S. G., Saha, M. K., Agarwal, R. S., Meena, S. S., & Poddar, G. (2025). Comparative evaluation of stress distribution in maxillary premolar restored with onlay fabricated with different restorative materials - A three-dimensional finite element analysis study. *Journal of Conservative Dentistry and Endodontics*, *28*(8), 783–789. https://doi.org/10.4103/JCDE.JCDE_788_24

75. Prados-Privado, M., Martínez-Martínez, C., Gehrke, S. A., & Prados-Frutos, J. C. (2020). Influence of bone definition and finite element parameters in bone and dental implants stress: A literature review. *Biology*, *9*(8), 224. https://doi.org/10.3390/biology9080224

76. Preda, F., Elshazly, N., & Jacobs, R. (2025). AI-enhanced orthodontic treatment planning - a scoping review on evidence-based clinical application with commercial software overview. *Journal of Dentistry*, *163*(106112), 106112. https://doi.org/10.1016/j.jdent.2025.106112

77. Puri, A., & Prathap, M. S. (2025). Biomimetic strategies for the rehabilitation of compromised anterior teeth. *Contemporary Clinical Dentistry*, *16*(3), 218–223. https://doi.org/10.4103/ccd.ccd_231_25

78. Rathee, M., Divakar, S., Jain, P., Chahal, S., & Singh, S. (2023). Anterior esthetic rehabilitation with full and partial veneers using conventional and digital techniques: A case series. *Journal of Conservative Dentistry and Endodontics*, *26*(5), 601–607. https://doi.org/10.4103/jcd.jcd_157_23

79. Ray, T. R., Kellogg, R. T., Fargen, K. M., Hui, F., & Vargas, J. (2023). The perils and promises of generative artificial intelligence in neurointerventional surgery. *Journal of Neurointerventional Surgery*, *16*(1), 4–7. https://doi.org/10.1136/jnis-2023-020353

80. Rees, J. S., & Jacobsen, P. H. (1993). The elastic moduli of enamel and dentine. *Clinical Materials*, *14*(1), 35–39. https://doi.org/10.1016/0267-6605(93)90045-9

81. Revilla-León, M., Gómez-Polo, M., Vyas, S., Barmak, B. A., Galluci, G. O., Att, W., & Krishnamurthy, V. R. (2023). Artificial intelligence applications in implant dentistry: A systematic review. *The Journal of Prosthetic Dentistry*, *129*(2), 293–300. https://doi.org/10.1016/j.prosdent.2021.05.008

82. Roongruangsilp, P., Narkbuakaew, W., & Khongkhunthian, P. (2025). Performance of two different artificial intelligence models in dental implant planning among four different implant planning software: a comparative study. *BMC Oral Health*, *25*(1), 984. https://doi.org/10.1186/s12903-025-06336-0

83. Saini, H., Ackland, D. C., Gong, L., Cheng, & Röhrle, O. (2020). Occlusal load modelling significantly impacts the predicted tooth stress response during biting: a simulation study. *Computer Methods in Biomechanics and Biomedical Engineering*, *23*(7), 261–270. https://doi.org/10.1080/10255842.2020.1711886

84. Satapathy, S. K., Kunam, A., Rashme, R., Sudarsanam, P. P., Gupta, A., & Kumar, H. S. K. (2024). AI-assisted treatment planning for dental implant placement: Clinical vs AI-generated plans. *Journal of Pharmacy & Bioallied Sciences*, *16*(Suppl 1), S939–S941. https://doi.org/10.4103/jpbs.jpbs_1121_23

85. Sayed, A. J., Mohsin, S. F., Garg, K. K., Agwan, M. A. S., Tareen, S. U. K., Alruthea, M. S., & Mohan, S. (2025). Finite Element Analysis (FEA) for influence of variation in Dental Implant dimensions (length and diameter) on Peri-implant Bone Stress/strain distribution: A systematic review. *Pakistan Journal of Medical Sciences Quarterly*, *41*(1), 318–330. https://doi.org/10.12669/pjms.41.1.8991

86. Sciarra, F. M., Caivano, G., Cacioppo, A., Messina, P., Cumbo, E. M., Di Vita, E., & Scardina, G. A. (2025). Dentistry in the era of artificial intelligence: Medical behavior and clinical responsibility. *Prosthesis*, *7*(4), 95. https://doi.org/10.3390/prosthesis7040095

87. Shujaat, S. (2025). Automated machine learning in dentistry: A narrative review of applications, challenges, and future directions. *Diagnostics (Basel, Switzerland)*, *15*(3), 273. https://doi.org/10.3390/diagnostics15030273

88. Siluvai, S., Narayanan, V., Ramachandran, V. S., & Lazar, V. R. (2025). Generative pre-trained transformer: Trends, applications, strengths and challenges in dentistry: A systematic review. *Healthcare Informatics Research*, *31*(2), 189–199. https://doi.org/10.4258/hir.2025.31.2.189

89. Ustrell-Barral, M., Zamora-Olave, C., Khoury-Ribas, L., Rovira-Lastra, B., & Martinez-Gomis, J. (2024). Reliability, reference values and factors related to maximum bite force measured by the Innobyte system in healthy adults with natural dentitions. *Clinical Oral Investigations*, *28*(11), 620. https://doi.org/10.1007/s00784-024-06014-5

90. Villena, F., Véliz, C., García-Huidobro, R., & Aguayo, S. (2025). Generative artificial intelligence in dentistry: A narrative review of current approaches and future challenges. *Dentistry Review*, *5*(4), 100160. https://doi.org/10.1016/j.dentre.2025.100160

91. Vivekananthan, S. (2024). Comparative analysis of generative models: Enhancing image synthesis with VAEs, GANs, and Stable Diffusion. In *arXiv [cs.CV]*. https://doi.org/10.48550/ARXIV.2408.08751

92. Wang, C., Zhu, X., Hong, J. C., & Zheng, D. (2019). Artificial intelligence in radiotherapy treatment planning: Present and future. *Technology in Cancer Research & Treatment*, *18*, 1533033819873922. https://doi.org/10.1177/1533033819873922

93. Wang, J.-Q., Zhang, Y., Pang, M., Wang, Y.-Q., Yuan, J., Peng, H., Zhang, W., Dai, L., & Li, H.-W. (2022). Biomechanical comparison of six different root-analog implants and the conventional Morse taper implant by finite element analysis. *Frontiers in Genetics*, *13*, 915679. https://doi.org/10.3389/fgene.2022.915679

94. Wang, L., Xu, Y., Wang, W., & Lu, Y. (2025). Application of machine learning in dentistry: insights, prospects and challenges. *Acta Odontologica Scandinavica*, *84*, 145–154. https://doi.org/10.2340/aos.v84.43345

95. Wang, Y.-C. C., Chen, T.-L., Vinayahalingam, S., Wu, T.-H., Chang, C. W., Chang, H. H., Wei, H.-J., Chen, M.-H., Ko, C.-C., Moin, D. A., van Ginneken, B., Xi, T., Tsai, H.-C., Chen, M.-H., Hsu, T.-M. H., & Chou, H. (2025). Artificial intelligence to assess dental findings from panoramic radiographs -- A multinational study. In *arXiv [cs.CV]*. https://doi.org/10.48550/ARXIV.2502.10277

96. Xie, B., Zhang, L., Wang, Y., Chu, Y., & Lu, Y. (2025). Finite element analysis in the Dental Sciences: A Bibliometric and a Visual Study. *International Dental Journal*, *75*(2), 855–867. https://doi.org/10.1016/j.identj.2024.08.005

97. Xie, B.-Y., He, X., Hu, L., Guo, S.-L., Chen, J.-L., Zhang, J., Shen, X.-Q., Geng, Y.-M., & Li, W. (2025). Morphological comparison between artificial intelligence-driven and manual CAD design in single tooth restoration: a preliminary study. *BMC Oral Health*, *25*(1), 1633. https://doi.org/10.1186/s12903-025-07004-z

98. Yang, G., Shen, H., Jang, Y., & Cheng, X. (2025). Finite element analysis-assisted surgical planning and evaluation of flap design in hand surgery. *Frontiers in Bioengineering and Biotechnology*, *13*, 1611993. https://doi.org/10.3389/fbioe.2025.1611993

99. Yli-Urpo, T., Lassila, L., Närhi, T., & Vallittu, P. (2025). Cement layer thickness and load-bearing capacity of tooth restored with lithium-disilicate glass ceramic and hybrid ceramic occlusal veneers. *Dental Materials: Official Publication of the Academy of Dental Materials*, *41*(2), 212–219. https://doi.org/10.1016/j.dental.2024.11.004

100. Zannah, R., Bashar, M., Mushfiq, R. B., Chakrabarty, A., Hossain, S., & Jung, Y. J. (2024). Semantic segmentation on panoramic dental X-ray images using U-net architectures. *IEEE Access: Practical Innovations, Open Solutions*, *12*, 44598–44612. https://doi.org/10.1109/access.2024.3380027

101. Zarone, F., Di Mauro, M. I., Ausiello, P., Ruggiero, G., & Sorrentino, R. (2019). Current status on lithium disilicate and zirconia: a narrative

review. *BMC Oral Health*, *19*(1), 134. https://doi.org/10.1186/s12903-019-0838-x

102. Zhu, Y., Hu, J., Luo, B., Yuan, Y., & Jiang, Q. (2025). Biomechanical considerations in RPD design: application and perspective of finite element method in distal extension removable partial denture rehabilitation. *Frontiers in Dental Medicine*, *6*(1667504), 1667504. https://doi.org/10.3389/fdmed.2025.1667504