

Artificial Intelligence–Based Versus Conventional Computer-Aided Design Software for Full and Partial Coverage Restorations: A Narrative Review

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Abstract

Computer-aided design and computer-aided manufacturing (CAD/CAM) technology has fundamentally transformed fixed prosthodontics by improving precision, efficiency, and reproducibility of indirect restorations. Conventional computer-aided design (CAD) software has demonstrated predictable outcomes for full- and partial-coverage restorations; however, restoration quality remains influenced by operator experience and manual design decisions. Recently, artificial intelligence (AI) has emerged as a promising advancement in digital restorative dentistry by incorporating machine learning and deep learning algorithms into CAD workflows to automate restoration design and improve efficiency. The aim of this narrative review was to summarize and critically evaluate current evidence comparing AI-based and conventional CAD software for designing full- and partial-coverage restorations. The available literature on CAD/CAM workflows, conventional and AI-driven design platforms, restoration accuracy, marginal adaptation, internal fit, occlusal morphology, and restorative materials, was reviewed and analyzed. Current evidence indicates that both conventional and AI-assisted CAD systems can produce restorations with clinically acceptable marginal adaptation and internal fit. AI-based software consistently reduces design time and enhances workflow efficiency while demonstrating accuracy comparable to conventional CAD systems for single-unit restorations. Nevertheless, Conventional CAD software operated by experienced clinicians or dental technicians generally remains superior for reproducing complex occlusal morphology and individualized proximal contact relationships. Restoration accuracy is influenced by restoration type, preparation design, restorative material, scanning protocol, software algorithm, and manufacturing technique. Although AI substantially improves efficiency and standardization, clinician oversight and final design refinement remain essential for optimal prosthetic outcomes.

Keywords: Artificial intelligence; Computer-aided design; Fixed prosthodontics; Full-coverage restorations; Partial-coverage restorations

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1. Introduction

The integration of computer-aided design and computer-aided manufacturing (CAD/CAM) technology has transformed fixed prosthodontics by enabling highly standardized and predictable digital workflows for the fabrication of indirect restorations. Compared with conventional laboratory techniques, CAD/CAM systems improve manufacturing precision, reduce operator-dependent variability, shorten production time, and facilitate fabrication of restorations with clinically acceptable marginal adaptation, internal fit, and occlusal morphology. Consequently, digital workflows have become an integral component of contemporary restorative dentistry for the fabrication of full- and partial-coverage restorations, including crowns, inlays, and onlays [1]. A conventional digital workflow consists of three principal stages: digital data acquisition, virtual restoration design, and computer-aided manufacturing. Among these stages, restoration design is one of the most

critical determinants of the final prosthetic outcome, as it directly influences marginal integrity, internal adaptation, proximal contacts, occlusal morphology, and functional performance. Current CAD software platforms, including Exocad, 3Shape Dental System, CEREC InLab, and Ceramill Mind, provide sophisticated design tools capable of producing clinically successful restorations. Nevertheless, these systems continue to rely substantially on operator experience for margin identification, morphology generation, occlusal adjustment, and final restoration refinement, leading to variability in design quality and efficiency [2]. Recent advances in artificial intelligence (AI), particularly machine learning and deep learning, have introduced a new generation of CAD systems capable of assisting restoration design through automated analysis of dental anatomy.

Unlike conventional CAD software, these systems employ data-driven algorithms to generate restoration proposals that require less manual intervention. Early studies

have demonstrated encouraging results, supporting AI as a promising advancement in digital prosthodontics [3]. Despite these technological advances, the clinical performance of AI-assisted restoration design remains an area of active investigation. Although several laboratory studies have reported that AI-generated restorations achieve marginal and internal fit comparable to those produced using conventional CAD software, conflicting evidence exists regarding their ability to accurately reproduce complex occlusal morphology, proximal contacts, and functional anatomy. Differences in software algorithms, restorative materials, preparation designs, scanning protocols, and manufacturing techniques further contribute to the heterogeneity of the available evidence. Therefore, a comprehensive and critical synthesis of the available evidence is required to clarify the capabilities and limitations of AI-assisted restoration design and to compare its performance with established conventional CAD systems. The aim of this narrative review is to critically evaluate the current evidence regarding AI-based and conventional CAD software for the design of full- and partial-coverage restorations, with particular emphasis on restoration accuracy, marginal adaptation, internal fit, occlusal morphology, workflow efficiency, available commercial platforms, and current challenges.

2. Evolution of CAD/CAM Technology in Fixed Prosthodontics

2.1. Historical Development of CAD/CAM Technology

Computer-aided design and computer-aided manufacturing (CAD/CAM) technology has transformed restorative dentistry by enabling the digital design and fabrication of indirect restorations. Since its introduction in late twentieth century, CAD/CAM has evolved from a laboratory-based manufacturing concept into comprehensive digital workflow integrating intraoral scanning, virtual restoration design, and computer-controlled manufacturing. This transition has significantly improved the precision, reproducibility, and efficiency of prosthetic rehabilitation while reducing dependence on conventional laboratory procedures and operator-sensitive techniques [1-4]. The concept of CAD/CAM was originally developed for industrial engineering applications before being adapted for medical and dental use. One of the earliest milestones in digital dentistry was the work of François Duret, who introduced the concept of computer-assisted prosthetic fabrication during the 1970s and demonstrated the feasibility of digitally designing and manufacturing dental restorations. His pioneering investigations established the theoretical framework for integrating optical impression systems with computer-assisted design and automated manufacturing, laying the foundation for modern digital prosthodontics [1-4].

Subsequent technological advancements culminated in the development of the Chairside Economical Restoration of Esthetic Ceramics (CEREC) system by Mörmann and Brandestini in the early 1980s [4-5]. The introduction of CEREC represented a landmark achievement because it enabled clinicians to fabricate ceramic restorations within a single clinical appointment using digital impressions, virtual design software, and chairside milling technology. Although early generations of system limited by scanner resolution, software capabilities, and material selection, continuous improvements in hardware, software algorithms, and ceramic materials substantially enhanced restoration accuracy and

clinical reliability [6]. During the following decades, digital dentistry expanded beyond chairside systems to include laboratory-based CAD/CAM platforms capable of designing increasingly complex prostheses. The introduction of high-resolution optical scanners, advanced design software, and multi-axis milling units enabled the fabrication of crowns, fixed dental prostheses, implant-supported restorations, veneers, inlays, onlays, and full-arch rehabilitations with greater consistency than conventional techniques.

More recently, additive manufacturing technologies have further broadened the applications of CAD/CAM by facilitating production of surgical guides, provisional restorations, definitive prostheses, and dental models with reduced material waste and enhanced manufacturing flexibility [1-4]. Today, CAD/CAM technology has shifted digital workflows from an alternative treatment option to preferred approach for many restorative procedures [7-8]. More recently, concept of the digital twin has emerged as a promising advancement in digital dentistry. A digital twin is dynamic virtual representation of a patient's oral structures that continuously integrates clinical, radiographic, intraoral scanning, and treatment data throughout patient's care. By enabling real-time simulation, treatment planning, outcome prediction, and long-term monitoring, digital twins have potential to further enhance precision, personalization, and efficiency of CAD/CAM-based prosthodontic workflows, particularly when integrated with artificial intelligence and cloud-based digital platforms [9-10]. Chronological progression of CAD/CAM technology and key innovations that have shaped modern digital prosthodontics are illustrated in Figure 1.

2.2. Contemporary Digital Workflow in Fixed Prosthodontics

Modern CAD/CAM workflows comprise three sequential stages: digital data acquisition, computer-aided design (CAD), and computer-aided manufacturing (CAM), each contributing to the accuracy and clinical performance of the definitive restoration [4]. The workflow begins with digital data acquisition using intraoral or laboratory optical scanners that capture the three-dimensional geometry of the prepared tooth, adjacent dentition, opposing arch, and occlusal relationship. Compared with conventional elastomeric impressions, digital impressions improve patient comfort, reduce dimensional distortion, facilitate immediate quality assessment, and enable rapid transfer of digital data between clinicians and dental laboratories [11]. Moreover, systematic reviews and clinical studies have consistently demonstrated that digital workflows provide equal or superior marginal and internal fit for single crowns compared with conventional impression techniques, reinforcing their clinical reliability [12-16]. Following image acquisition, the digital model is imported into CAD software, where the restoration is virtually designed. This stage includes identification of preparation margins, definition of the insertion path, adjustment of cement space parameters, establishment of proximal and occlusal contacts, generation of anatomical morphology, refinement of the emergence profile, and optimization of occlusal anatomy as illustrated in Figure 2. Because restoration design directly determines marginal adaptation, internal fit, occlusal function, and esthetic integration, the CAD stage is widely considered the most operator-dependent component of the digital workflow [1-4].

Once the virtual restoration has been finalized, the digital design is transferred to CAM software for manufacturing. Subtractive manufacturing remains the most widely adopted production method and involves milling restorations from prefabricated ceramic, zirconia, composite resin, or hybrid ceramic blocks using computer-controlled milling machines. Alternatively, additive manufacturing techniques fabricate restorations layer by layer through photopolymerization or material deposition. Although subtractive milling remains the gold standard for definitive ceramic restorations owing to its superior accuracy and material properties, additive manufacturing has expanded rapidly with improvements in printing resolution, printable materials, and production efficiency [17-19]. The integration of cloud computing, high-speed internet communication, and digital laboratory networks has further streamlined CAD/CAM workflows by enabling seamless transfer of digital files between clinicians, laboratories, and manufacturing centers. Consequently, digital workflows have become increasingly efficient, standardized, and scalable, supporting both chairside and laboratory production models [20]. These interconnected digital ecosystems also provide the infrastructure for emerging technologies such as cloud-based artificial intelligence and digital twins, which further enhance workflow automation and clinical decision-making.

2.3. Current Applications of CAD/CAM in Fixed Prosthodontics

The clinical applications of CAD/CAM technology have expanded considerably over past two decades. Initially developed for single-unit ceramic crowns, contemporary digital workflows are now routinely employed for fabrication of full- and partial-coverage restorations, laminate veneers, implant-supported prostheses, fixed dental prostheses, removable prosthodontic components, maxillofacial prostheses, surgical guides, and provisional restorations [21]. Among fixed prosthodontic applications, CAD/CAM has significantly improved fabrication of full-coverage crowns & conservative restorations by providing predictable marginal adaptation, optimized restoration thickness, accurate occlusal morphology, and enhanced manufacturing efficiency. Advances in restorative materials, including zirconia, lithium disilicate, resin-matrix ceramics, and hybrid ceramics, have further expanded clinical indications [7-8]. Beyond restorative applications, CAD/CAM technology has become an essential component of comprehensive digital dentistry by integrating seamlessly with cone-beam computed tomography, digital smile design, virtual articulators, facial scanners, and implant planning software. These technologies allow clinicians to perform prosthetically driven treatment planning while improving communication among clinicians, laboratories, and patients. Such integration supports more predictable restorative outcomes and contributes to the increasing adoption of fully digital workflows in contemporary prosthodontic practice [20-22]. Despite these advances, restoration design remains the least automated stage of digital workflow, requiring considerable operator experience to determine restoration morphology, proximal contacts, and occlusal anatomy. This dependence on user expertise has driven development of artificial intelligence-assisted CAD systems aimed at automating restoration design while maintaining clinically acceptable accuracy.

3. Conventional CAD Software for Digital Restoration Design

3.1. Principles of Digital Restoration Design

3.1.1. Preparation Design

The success of digitally designed restorations begins with an appropriately prepared tooth. Digital CAD software cannot compensate for inadequate preparation geometry; therefore, adherence to biomechanical and material-specific preparation principles is essential. Ideal preparations should provide adequate occlusal and axial reduction, smooth and continuous finish lines, rounded internal line angles, and a clearly defined path of insertion. Total occlusal convergence of approximately 6°–12° is generally recommended to optimize retention and resistance while facilitating restoration seating [23]. Material-specific preparation guidelines should also be considered, with monolithic zirconia requiring less reduction than lithium disilicate because of its superior mechanical properties. Preparation geometry directly influences scanner accuracy, margin identification, restoration thickness, internal adaptation, and long-term clinical performance [24].

3.1.2. Minimum Material Thickness

The recommended minimum thickness varies according to the restorative material and restoration type. For monolithic zirconia crowns, an occlusal thickness of 0.8–1.0 mm and an axial thickness of 0.5–0.8 mm generally considered sufficient because of the material's high flexural strength [25]. In contrast, lithium disilicate crowns require greater material thickness, with approximately 1.5–2.0 mm occlusally and 1.0–1.5 mm axially to achieve adequate fracture resistance [26-27]. Conservative restorations such as veneers are typically designed with a facial thickness ranging from 0.3–0.7 mm, depending on the preparation design and restorative indication, [28-29] whereas inlays and onlays generally require an occlusal thickness of at least 1.5–2.0 mm to withstand functional loading. For fixed dental prostheses, CAD software also verifies minimum connector dimensions, which are critical for ensuring adequate structural strength and reducing the likelihood of connector fracture [26]. Most contemporary CAD systems incorporate automated thickness analysis using color-coded maps that identify areas below minimum material requirements. These tools allow real-time modification of restoration morphology before manufacturing, ensuring compliance with material-specific recommendations while preserving anatomical form and functional occlusion. Consequently, digital thickness verification has become an indispensable component of contemporary CAD workflows, improving, restoration predictability and minimizing manufacturing errors [30].

3.1.3. Path of Insertion and Margin Identification

Following digital impression acquisition, restoration path of insertion is established to ensure complete seating without interference from undercuts. Contemporary CAD software automatically analyzes preparation geometry to determine the optimal insertion axis while allowing manual refinement when necessary. Accurate margin identification represents one of most critical stages of restoration design because errors during margin delineation directly affect marginal adaptation, cement thickness, and restoration longevity. Although modern software incorporates automatic margin detection

algorithms, clinician verification remains indispensable, particularly in subgingival or poorly defined finish lines [31].

3.1.4. Cement Space Design

The virtual cement space is a critical CAD parameter that determines the internal adaptation and seating behavior of the definitive restoration. Most CAD systems allow independent adjustment of marginal and internal spacer values according to the restorative material and cementation protocol. Current evidence generally recommends maintaining a minimal cement space near restoration margin (approximately 20–40 μm) to preserve marginal integrity, while larger internal spacer values (approximately 40–80 μm) facilitate complete seating and compensate for manufacturing inaccuracies [32]. A study by Zheng [33] found that a cement space of 30 μm resulted in the largest marginal discrepancy, while 60 μm and 120 μm settings showed better adaptation, indicating that smaller spaces can lead to significant fit issues. Shin [34] evaluated the influence of cement space settings (35, 50, 70, and 100 μm) on the marginal and internal fit of definitive 3D-printed resin crowns and reported clinically acceptable marginal discrepancies for all groups. However, the 70- μm cement space demonstrated most favorable marginal, axio-occlusal, and occlusal adaptation, leading study to recommend this setting for optimizing the fit of 3D-printed definitive resin crowns. Another investigation reported that cement spaces of 40 μm , 80 μm , and 120 μm yielded progressively smaller marginal gaps, with 40 μm showing least favorable results. Excessive cement space may reduce restoration support and increase cement thickness, whereas insufficient spacer settings may prevent complete seating and increase internal stresses. Consequently, optimization of cement space remains essential for achieving a balance between retention, adaptation, and clinical fit [35].

3.1.5. Marginal Adaptation and Internal Fit

Marginal adaptation and internal fit are among the most frequently investigated indicators of restoration accuracy because they directly influence the biological and mechanical performance of indirect restorations. Marginal discrepancies have been associated with plaque accumulation, cement dissolution, secondary caries, periodontal inflammation, and restoration failure, whereas inadequate internal fit may compromise restoration seating, increase cement thickness, and produce unfavorable stress distribution within the restorative material [36–38]. Although the clinically acceptable marginal discrepancy remains debated, values below approximately 120 μm are generally considered acceptable for fixed prosthodontic restorations. Numerous factors influence marginal and internal adaptation, including preparation geometry, scanner accuracy, software algorithms, cement space settings, restorative material, and manufacturing technique [39].

3.1.6. Occlusal Morphology and Proximal Contacts

CAD software generates occlusal morphology using anatomical tooth libraries, biogeneric reconstruction algorithms, or mirrored contralateral teeth, followed by manual refinement by the operator. Proper cusp morphology, fissure anatomy, and occlusal contact distribution are essential for maintaining functional efficiency while minimizing premature contacts and excessive chairside occlusal adjustment [40–42]. Most contemporary CAD

systems employ color-coded contact maps to visualize the intensity of occlusal and proximal contacts, enabling the operator to identify areas of clearance, light contact, and excessive interference. Although the factory default contact strength is commonly set at 25 μm , designing contacts near the green–yellow interface (approximately 49–50 μm) has been recommended to compensate for manufacturing inaccuracies and achieve predictable occlusal and proximal contacts after restoration fabrication [43].

3.1.7. Digital Design Verification

Before manufacturing, the virtual restoration undergoes comprehensive digital verification to ensure compliance with biological, mechanical, and manufacturing requirements. CAD software enables evaluation of minimum material thickness, cement space distribution, marginal integrity, proximal and occlusal contact strength, undercuts, and manufacturing feasibility. These verification tools reduce the likelihood of fabrication errors and improve the predictability of the definitive restoration. Nevertheless, despite sophisticated digital assistance, the final restoration quality continues to depend on the operator's ability to interpret and refine the virtual design [30].

3.1.8. Biogeneric Design Algorithms

Biogeneric design algorithms represent an important advancement in conventional CAD software by generating anatomically realistic restorations based on the patient's existing dentition rather than relying solely on predefined tooth libraries. Introduced in the CEREC system, these knowledge-based algorithms use mathematical and morphometric analyses of natural tooth anatomy to reconstruct restorations with harmonious occlusal morphology and proximal contacts. Although highly automated, biogeneric algorithms are not artificial intelligence, as they follow predefined rules rather than learning from large datasets [44–45]. Three reconstruction modes are available. Biogeneric copy reproduces the original tooth morphology when a preoperative scan is available. Biogeneric individual generates a restoration by analyzing adjacent and opposing teeth, making it the most commonly used option for routine clinical cases. Biogeneric reference reconstructs the restoration by mirroring contralateral tooth, providing a symmetrical anatomical design when appropriate [44–45]. Compared with conventional library-based designs, biogeneric algorithms have demonstrated improved anatomical accuracy & reduced need for manual adjustments. However, unlike modern AI-based CAD systems, they do not employ machine learning or deep learning techniques. Instead, they represent an intermediate step between traditional rule-based CAD software and contemporary AI-assisted restoration design platforms [44–45].

3.2. Commercial CAD Software Platforms

Several commercial CAD software platforms are currently available for digital restoration design, each differing in workflow architecture, interoperability, automation, and available design tools. Despite these differences, comparative studies consistently demonstrate that contemporary CAD systems produce restorations with clinically acceptable marginal adaptation, internal fit, and dimensional accuracy. Consequently, software selection is often determined more by workflow requirements, laboratory preferences, and digital

ecosystem compatibility than by clinically significant differences in the restoration quality [46-47].

3.2.1. Open and Closed CAD Systems

Commercial CAD platforms can generally be classified as either closed or open systems. Closed systems operate within a proprietary digital ecosystem in which intraoral scanner, CAD software, milling unit, and restorative materials are supplied by the same manufacturer. This integrated approach simplifies digital workflow, minimizes compatibility issues, & optimizes communication between hardware and software components. However, it also limits interoperability and restricts users to manufacturer-specific equipment and materials. The CEREC system represents the best-known example of a closed CAD/CAM workflow [46-47]. In contrast, open CAD systems support Standard Tessellation Language (STL) and other universal file formats, allowing integration of scanners, CAD software, milling machines, and additive manufacturing devices from different manufacturers. This flexibility enables laboratories to customize digital workflows according to clinical requirements and technological preferences. Consequently, open systems such as Exocad, 3Shape Dental System, Ceramill Mind, and Blender for Dental have become increasingly popular in contemporary dental laboratories owing to their interoperability, scalability, and compatibility with a wide range of the digital manufacturing technologies [46-47].

3.2.2. Comparative Performance of Commercial CAD Platforms

Comparative investigations indicate that the major commercial CAD platforms—including Exocad, 3Shape Dental System, CEREC InLab, Dental System Premium, Ceramill Mind, and Elefsina—produce restorations with clinically acceptable marginal adaptation, internal fit, and dimensional accuracy [48]. Although individual studies have reported minor differences in parameters such as cement space distribution, coping thickness, connector dimensions, and anatomical reconstruction, these variations generally remain within clinically acceptable limits and are unlikely to affect clinical performance [49-50]. Lee [51] demonstrated excellent dimensional accuracy among multiple CAD systems used for fixed partial denture design, whereas El-Danasory [52] reported similarly acceptable framework dimensions and cement space distribution across different commercial platforms. Likewise, Wang [53] observed differences in crown morphology generated by various CAD software programs but concluded that all systems produced restorations suitable for clinical application. Sarhan [54] further demonstrated that differences in virtual cement gap parameters among CAD platforms had only a limited influence on restoration adaptation. Collectively, these findings suggest that restoration accuracy depends more on preparation geometry, scanning accuracy, manufacturing technique, and operator experience than on the specific commercial CAD software used.

3.2.3. Distinctive Features of Contemporary CAD Platforms

Although the overall restorative accuracy of commercial CAD systems is comparable, individual platforms offer distinct workflow characteristics that may influence software selection. Exocad is recognized for its

modular architecture, extensive customization options, and compatibility with numerous scanners and manufacturing systems, making it one of most widely adopted platforms in commercial dental laboratories [55]. In contrast, 3Shape Dental System emphasizes an intuitive user interface, comprehensive virtual articulation, and seamless laboratory integration, facilitating efficient restorative workflows [56]. CEREC InLab distinguishes itself through its proprietary biogeneric reconstruction algorithms and integration within a complete chairside digital ecosystem, allowing rapid restoration fabrication while preserving anatomical morphology [52]. Ceramill Mind similarly provides laboratory-oriented design tools with reliable framework construction and restoration planning capabilities [52]. Blender for Dental represents a unique open-source alternative, offers advanced mesh-editing and customization features, making it particularly valuable for research applications, implant prosthodontics, and complex patient-specific workflows, although it lacks many of the automated dental-specific design functions available in commercial software [49-50]. Overall, contemporary commercial CAD platforms provide comparable restorative accuracy for routine fixed prosthodontic applications. Therefore, software selection should be based primarily on workflow integration, interoperability, laboratory requirements, available design features, and user experience rather than expectations of superior restoration fit or accuracy.

4. Artificial Intelligence in Digital Dentistry

Artificial intelligence (AI) encompasses several computational approaches that differ in their complexity and learning capabilities. Machine learning (ML) is a subset of AI in which algorithms learn patterns from data to make predictions or decisions without being explicitly programmed. Deep learning (DL), a more advanced subset of machine learning, employs artificial neural networks with multiple hidden layers to automatically extract complex features from large datasets, making it particularly suitable for dental image analysis and restoration design. Among deep learning architectures, convolutional neural networks (CNNs) are primarily designed for image analysis and have been widely applied in dentistry for radiographic interpretation, tooth segmentation, and automated landmark detection. Generative adversarial networks (GANs) consist of two competing neural networks that generate realistic synthetic images & three-dimensional anatomical structures, making them valuable for reconstructing dental morphology and restoration proposals. More recently, transformer models, which use self-attention mechanisms to analyze relationships within complex datasets, have demonstrated promising applications in medical image analysis and multimodal data integration. Although their use in restorative CAD systems is still emerging, transformer-based architectures expected to further improve automated restoration design and personalized digital workflows [3-57]. Artificial intelligence has rapidly expanded across multiple disciplines of digital dentistry, including diagnosis, treatment planning, image analysis, and computer-aided design/manufacturing (CAD/CAM). Among these applications, AI-assisted restoration design has attracted particular interest because of its potential to automate crown generation, reduce operator dependency, and improve workflow efficiency [7-8]. Early investigations, such as work

of Raith [58], demonstrated that artificial neural networks could accurately classify tooth morphology from three-dimensional scan data, providing foundation for subsequent AI-based restoration design systems.

4.1. Current Applications of Artificial Intelligence in Digital Dentistry

Artificial intelligence has become integrated throughout the digital dental workflow, extending well beyond restoration design. In diagnostic dentistry, AI systems assist clinicians in detecting dental caries, periapical lesions, periodontal bone loss, root fractures, and oral pathologies through automated analysis of radiographic images [3-57]. In orthodontics, AI facilitates cephalometric landmark identification, malocclusion classification, treatment simulation, and clear aligner planning [59]. Similarly, implant dentistry benefits from AI-assisted implant positioning, anatomical risk assessment, and prosthetically driven treatment planning [60-61]. Within prosthodontics, AI applications continue to expand rapidly. Machine learning algorithms are increasingly employed for tooth segmentation, automatic margin detection, occlusal analysis, smile design, facial analysis, restoration proposal generation, and virtual patient simulation. These technologies reduce manual intervention while improving standardization and communication between clinicians and dental laboratories. Furthermore, AI integration with intraoral scanners, cone-beam computed tomography, facial scanners, and virtual articulators has enabled the development of comprehensive digital workflows that support personalized prosthetic treatment planning [62-63]. Despite these advances, current AI systems function primarily as decision-support tools rather than autonomous decision-makers, requiring clinician verification before clinical application [62-63].

4.1.1. Comparison of AI Algorithms Used in Digital Restoration Design

Various artificial intelligence algorithms have been incorporated into dental CAD systems to automate tasks including image analysis, restoration design, and workflow optimization. Although these algorithms differ in their computational principles and clinical applications, each offers distinct advantages and limitations [3-57]. A comparison of the principal AI algorithms used in digital restoration design is presented in Table 1.

4.2. Commercial AI-Assisted CAD Platforms

The growing integration of artificial intelligence (AI) into digital prosthodontics has led to the development of several commercial software platforms that automate restoration design through machine learning, deep learning, and data-driven algorithms. Unlike conventional rule-based CAD systems, AI-assisted platforms analyze large datasets of natural dentition and previously designed restorations to generate anatomically accurate restoration proposals while reducing operator intervention and design time. Although degree of automation varies among platforms, contemporary AI-based CAD software primarily aims to improve workflow efficiency, design consistency, & restoration reproducibility.

4.2.1. Exocad AI Design

Exocad has incorporated artificial intelligence into its DentalCAD software through AI-assisted design tools that

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automate restoration proposal generation based on extensive anatomical datasets and advanced reconstruction algorithms. AI Design enables rapid generation of crowns and other indirect restorations while allowing the operator to modify occlusal morphology, proximal contacts, emergence profile, and restoration contours before manufacturing. The software maintains flexibility of an open CAD system while improving workflow efficiency and reducing manual design time [20].

4.2.2. 3Shape Automate

3Shape Automate is a cloud-based AI platform that automatically designs dental restorations with minimal operator input. Using machine learning algorithms trained on extensive restorative datasets, the software generates crowns, inlays, onlays, and implant restorations within minutes while maintaining compatibility with the 3Shape digital workflow. Operators retain the ability to review and refine the proposed restoration before manufacturing, ensuring clinical control over the final design [20].

4.2.3. Dentbird Crown

Dentbird Crown is an AI-powered cloud-based CAD platform that automatically generates crown designs from digital impressions. The software employs deep learning algorithms to reconstruct anatomical morphology, establish proximal contacts, and optimize occlusal anatomy while substantially reducing design time. Its web-based architecture enables seamless communication between clinicians and dental laboratories without requiring complex local software installation [20].

4.2.4. Atomica AI

Atomica AI is a next-generation AI-driven CAD platform that combines machine learning with cloud computing to automate restoration design. The software analyzes preparation geometry, adjacent dentition, and occlusal relationships to generate patient-specific restorations with minimal manual intervention. AI-assisted reconstruction of occlusal morphology and proximal contacts aims to reduce operator variability while improving consistency across restorative cases [64]. Despite differences in software architecture and automation strategies, commercially available AI-based CAD platforms share common objective of reducing operator dependency while maintaining clinically acceptable restoration accuracy. Current evidence indicates that these systems substantially decrease design time and improve workflow standardization without compromising marginal adaptation or internal fit for single-unit restorations. Despite their high level of automation, AI-generated restoration proposals require clinical review and refinement before manufacturing.

5. Artificial Intelligence–Based versus Conventional CAD Software for Restoration Design

The comparison between artificial intelligence (AI)-assisted and conventional computer-aided design (CAD) software has become a major focus of contemporary digital prosthodontics. Conventional CAD systems rely predominantly on operator expertise to define restoration margins, generate anatomical morphology, establish proximal and occlusal contacts, and refine the final restoration. In contrast, AI-assisted systems employ machine learning and deep learning algorithms trained on extensive

datasets of dental anatomy to automate many of these design processes while aiming to improve efficiency, standardization, and reproducibility. Although both approaches have demonstrated clinically acceptable outcomes, important differences remain regarding restoration accuracy, morphology generation, workflow efficiency, and operator dependence.

5.1. Restoration Accuracy: Marginal Adaptation and Internal Fit

Marginal adaptation and internal fit are the primary indicators of restoration accuracy because they directly influence restoration longevity, cement integrity, and periodontal health. Current evidence consistently demonstrates that AI-assisted and conventional CAD systems produce comparable marginal adaptation and internal fit. Liu [65] compared AI-assisted restoration design, conventional digital CAD, and conventional wax-up techniques and reported that AI-generated restorations achieved marginal adaptation and reproducibility comparable with conventional digital CAD while significantly reducing design time. In contrast, conventional wax-up techniques demonstrated the largest marginal discrepancies and lowest overall accuracy. Similarly, Cho [66] evaluated crowns designed using two deep learning-based CAD systems and reported clinically acceptable internal fit comparable to technician-designed restorations despite minor differences in internal adaptation and contact relationships. These findings suggest that current AI algorithms are capable of generating restorations that satisfy clinical requirements for marginal and internal adaptation. Overall, current evidence indicates that restoration accuracy is influenced more by scanner accuracy, preparation geometry, cement space parameters, restorative material, and manufacturing technique than by whether the restoration designed using the AI-assisted or conventional CAD software.

5.2. Occlusal Morphology and Anatomical Reproduction

Reproduction of natural occlusal anatomy remains one of the principal challenges of current AI-assisted CAD systems. Chen [8] compared lithium disilicate crowns generated using the CEREC biogeneric AI algorithm with restorations designed manually by experienced technicians and dental students. While fracture resistance did not differ significantly among groups, technician-designed restorations more closely reproduced natural occlusal morphology, whereas AI-generated crowns exhibited greater occlusal discrepancies. Likewise, Wu [3] reported that AI-powered crown design substantially reduced design time but failed to achieve same level of morphological accuracy as conventional CAD performed by experienced operators. Conversely, Ding [68] introduced a deep learning-based three-dimensional deep convolutional generative adversarial network (3D-DCGAN) capable of generating crowns with anatomical morphology more closely resembling natural teeth than those produced using conventional technician-based CAD software. Furthermore, finite element analysis demonstrated favorable stress distribution & fatigue behavior comparable to natural dentition. These findings suggest that although recent deep learning algorithms have significantly improved anatomical reconstruction, experienced operators remain superior in reproducing secondary occlusal anatomy,

functional cusp morphology, fissure configuration, and individualized occlusal characteristics.

5.3. Workflow Efficiency and Design Time

One of the most consistently reported advantages of AI-assisted CAD systems is the substantial reduction in restoration design time. Multiple studies have demonstrated that automated restoration proposals significantly decrease manual design steps while maintaining clinically acceptable restoration quality. Liu [65], Wu [3], and AbdelHafez [68] all reported significantly shorter design times for AI-assisted workflows while maintaining clinically acceptable restoration quality. The reduction in manual intervention not only increases laboratory productivity but also decreases inter-operator variability and improves workflow standardization. These advantages may become increasingly important as digital laboratories continue to expand production capacity.

5.4. Operator Dependency and Reproducibility

AI-assisted CAD systems improve workflow reproducibility by reducing inter-operator variability through standardized restoration proposals based on large anatomical datasets. Accurate margin delineation, anatomical reconstruction, proximal contact adjustment, and occlusal refinement require considerable technical expertise, and restoration quality may vary substantially among operators. In contrast, AI-assisted systems generate restoration proposals based on large datasets of previously designed restorations, thereby reducing operator-dependent variability and improving reproducibility [67]. Nevertheless, current AI algorithms remain unable to fully replace clinical judgment. Human verification continues to be essential for evaluating margin accuracy, occlusal function, esthetic integration, emergence profile, and contact relationships before manufacturing. Accordingly, AI should currently be regarded as decision-support technology that complements rather than replaces experienced clinicians and dental technicians [6].

5.5. Advantages and Limitations of AI and Conventional CAD Systems

Overall, the current literature indicates that AI-assisted CAD offers greater efficiency and reproducibility, whereas conventional CAD provides superior flexibility for individualized restoration design and complex occlusal refinement [62]. The principal differences between conventional CAD and AI-assisted CAD systems reported in the current literature are summarized in Table 2.

6. Challenges and Limitations of AI-Based CAD

Despite the promising performance of AI-assisted CAD systems, several challenges continue to limit their widespread clinical adoption. The accuracy of AI-generated restorations depends heavily on quality, size, and diversity of the datasets used for model training, which are often biased toward ideal tooth morphology and standard preparation designs, thereby reducing performance in complex clinical situations involving atypical anatomy or extensive tooth loss. Furthermore, many deep learning models function as "black-box" systems, providing limited transparency regarding how restoration designs are generated, which may reduce clinician trust and complicate validation.

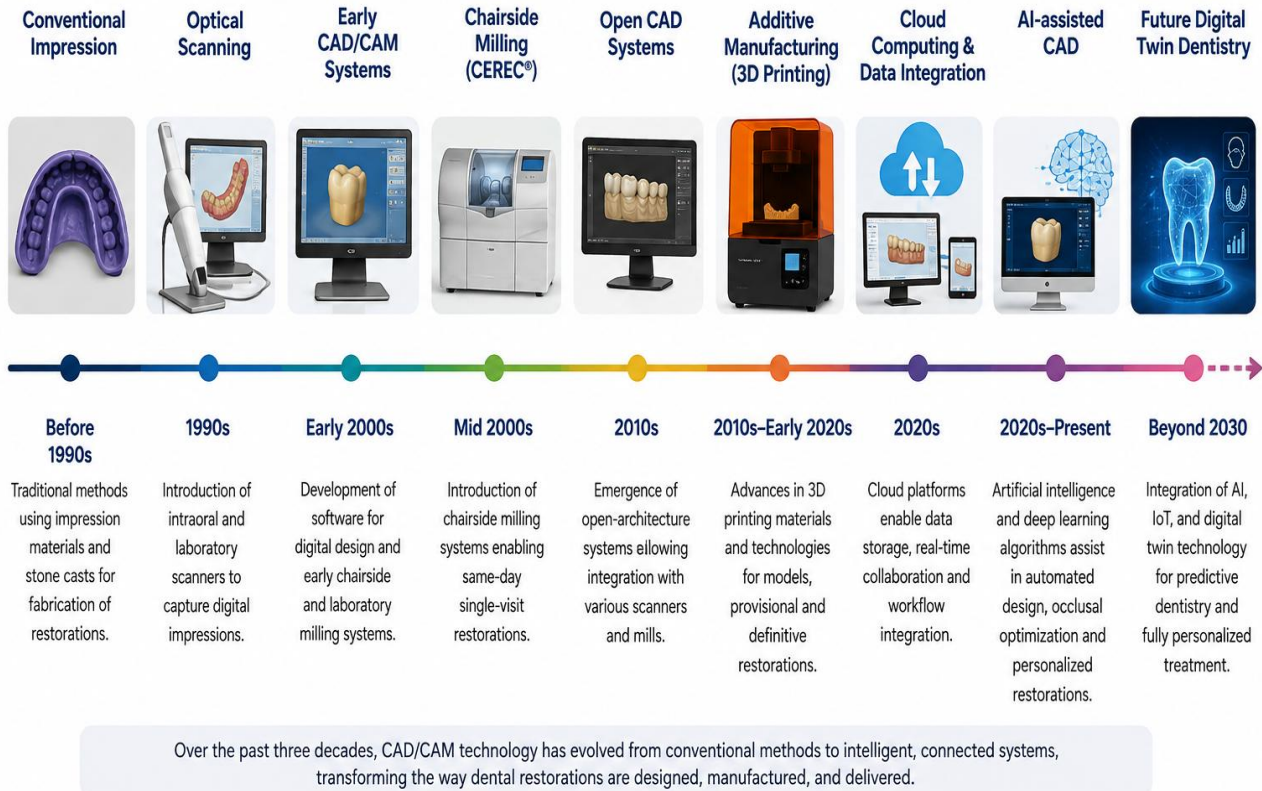


Figure 1: Evolution of CAD/CAM Technology in Restorative Dentistry

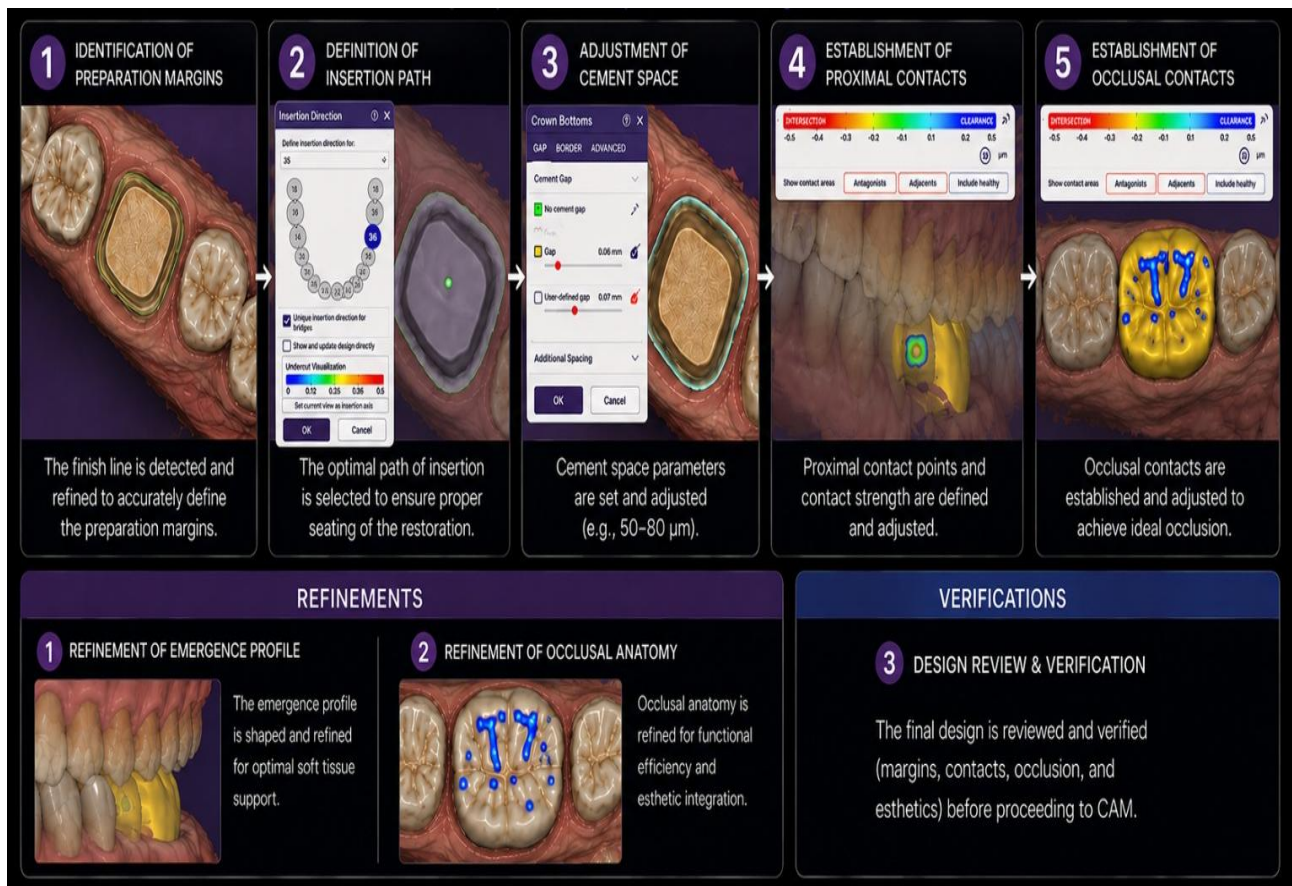


Figure 2: Workflow of the CAD stage in digital crown design

Table 1: Comparison of the principal artificial intelligence (AI) algorithms used in digital restoration design, highlighting their underlying principles, main applications in dental CAD, key advantages, and current limitations.

AI Algorithm	Principle	Main Dental CAD Application	Advantages	Limitations
CNN	Image feature extraction	Margin detection, tooth segmentation	High image accuracy	Requires large annotated datasets
GAN	Generator–discriminator network	Crown morphology generation, missing tooth reconstruction	Produces realistic anatomy	Difficult to train, possible instability
Transformer	Self-attention architecture	Personalized restoration design, multimodal integration	Captures long-range relationships	High computational cost
Machine Learning	Pattern recognition from structured data	Design optimization, workflow prediction	Faster implementation	Less effective for complex 3D morphology

Table 2: Comparison of conventional computer-aided design (CAD) and artificial intelligence (AI)-assisted CAD systems for the design of full- and partial-coverage restorations based on the current literature.

Parameter	Conventional CAD	AI-Assisted CAD
Design time	Longer; requires extensive manual modification	Significantly shorter through automated design generation
Operator dependency	High	Lower
Marginal adaptation	Clinically excellent	Clinically excellent; comparable to conventional CAD
Internal fit	Excellent	Excellent; comparable to conventional CAD
Occlusal morphology	Superior for complex anatomy and individualized morphology	Generally good but may be slightly inferior for complex occlusal anatomy
Reproducibility	Moderate; depends on operator experience	High owing to standardized AI algorithms
Learning curve	Steeper; requires extensive CAD experience	Lower for routine restoration design, although software familiarity remains necessary
Clinical judgment	Essential	Essential; AI proposals require clinician verification and refinement

Additional concerns include need for rigorous software validation and external clinical testing, uncertainty regarding legal responsibility for AI-generated treatment decisions, protection of patient data and compliance with privacy regulations during cloud-based processing, and evolving regulatory approval requirements for AI-based medical software. Practical barriers such as software costs, subscription models, dependence on reliable cloud computing and internet connectivity, and the continued need for clinician oversight further emphasize that AI should currently be regarded as a decision-support tool rather than a replacement for professional judgment [59-60]. Another important limitation is limited external validation of many commercially available AI systems. Most published studies are laboratory investigations involving single software platforms and standardized preparations, whereas evidence from multicenter randomized clinical trials remains scarce. Consequently, the generalizability of current findings to diverse clinical settings, different restorative materials, and complex prosthodontic cases remains uncertain.

7. Clinical Implications and Future Directions

Artificial intelligence has the potential to enhance digital prosthodontic workflows by reducing restoration design time, improving standardization, and minimizing operator-dependent variability while maintaining clinically acceptable restoration accuracy. Nevertheless, clinician and dental technician oversight remains essential to verify

preparation margins, occlusal morphology, proximal contacts, and esthetic outcomes before manufacturing. Future research should emphasize standardized multicenter clinical trials with long-term follow-up to validate clinical performance of AI-generated restorations. Further advances in deep learning algorithms and their integration with virtual articulators, facial scanners, and digital patient technologies are expected to improve restoration accuracy and support more personalized digital prosthodontic workflows.

8. Clinical Recommendations

AI-assisted CAD software is most appropriate for routine single-unit restorations, including posterior crowns, inlays, and onlays, where it consistently reduces design time while maintaining clinically acceptable marginal adaptation and internal fit. These systems are particularly beneficial in high-volume practices and dental laboratories that seek greater workflow efficiency and reproducibility. Conventional CAD remains preferable for restorations requiring extensive anatomical customization, such as anterior esthetic cases, full-mouth rehabilitation, severe tooth wear, altered occlusal schemes, and unusual tooth morphology. In these situations, clinician and technician expertise remain essential to optimize occlusal morphology, proximal contacts, emergence profile, and esthetic integration. Based on current evidence, the most appropriate clinical approach is a hybrid workflow in which AI generates the initial restoration proposal and the clinician or dental

technician performs the final verification and refinement before manufacturing. As AI algorithms continue to evolve, their role is expected to expand; however, professional judgment remains indispensable for treatment planning and restoration approval.

9. Conclusion

Artificial intelligence has emerged as a significant advancement in digital prosthodontics by enhancing the efficiency, reproducibility, and standardization of computer-aided restoration design. Current evidence indicates that AI-assisted CAD systems achieve marginal adaptation and internal fit comparable to conventional CAD software while substantially reducing restoration design time. Nevertheless, conventional CAD remains advantageous for cases requiring individualized occlusal morphology, complex anatomical reconstruction, and extensive operator refinement. At present, AI should be regarded as a decision-support technology rather than a replacement for clinician or dental technician expertise. The most effective digital workflow combines automated AI-generated restoration proposals with expert clinical verification and refinement to ensure optimal biological, functional, and esthetic outcomes. As deep learning algorithms, digital twins, and virtual patient technologies continue to evolve, AI-assisted CAD is expected to play an increasingly central role in personalized prosthodontic rehabilitation.

10. Conflict of Interest

The authors declare no conflict of interest related to this work.

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