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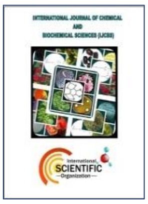

Accuracy of Restorations Designed by Artificial Intelligence and Conventional Software: A Narrative Review

Rana Hatem Hanafy Mahmoud[1]*, Maged Mohammed Zohdy[2], Hoda Mohamed Abdel Sadek[3], Fatma Adel Mohamed Ahmed[4], Tarek Mohamed ElSaaedi[5]

[1,2,3,4]Fixed Prosthodontics Department, Faculty of Dentistry, Ain Shams University, Cairo, Egypt.*

[5]Oral and Maxillofacial Prosthodontics Department, Faculty of Dentistry, Ain Shams University, Cairo, Egypt.

Abstract

Advancements in computer aided designing/computer aided manufacturing (CAD/CAM) technology have enhanced the precision and efficiency of indirect restorations; however, conventional workflows remain operator-dependent and require technical expertise for accurate customization. Recently, artificial intelligence (AI)–based design platforms have emerged to automate crown generation, aiming to reduce technique sensitivity and improve workflow consistency. Nevertheless, evidence regarding the accuracy and reliability of these systems remains limited. The success of CAD/CAM restorations is influenced by multiple variables, including preparation design, scanning accuracy, CAD algorithms, manufacturing processes, and material properties, with errors at any stage potentially compromising restorative accuracy. The aim of this narrative review was to synthesize current evidence comparing conventional and AI-driven CAD software, with emphasis on internal fit, marginal adaptation, restoration morphology, and the reliability of finish line detection. Available data suggests that AI-based systems can achieve accuracy comparable to conventional workflows, supporting their potential clinical feasibility, although further validation studies are warranted.

Keywords: CAD/CAM, Artificial intelligence, Accuracy, CAD software, Digital dentistry

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1. Introduction

Prosthodontics is shifting from conventional workflows, which rely on physical impressions and lost-wax techniques, to fully digital approaches using intraoral scanning and subtractive, additive, or hybrid manufacturing, improving precision, reproducibility, and efficiency. Hybrid analog–digital workflows further combine the strengths of both methods to optimize clinical outcomes [1]. Computer aided designing/computer aided manufacturing (CAD/CAM) systems are now widely used in dental clinics and laboratories, enabling standardized, high-precision restorations with prefabricated materials and improved efficiency. Ongoing hardware and software advancements continue to expand their clinical applications and cost-effectiveness [2]. Recently Artificial intelligence (AI) particularly deep learning (DL)–based dental design systems, has been integrated to automate workflows, reduce operator dependence, and enhance accessibility for less experienced clinicians, offering intuitive, user-friendly alternatives to traditional technician-driven methods [3-4]. Despite these advances, restoration accuracy remains affected by scanning quality, CAD algorithms, manufacturing methods, and preparation design. Variations between software platforms may affect restoration precision even when identical design parameters are applied [5-8]. The reliability of automated finish line detection remains insufficiently investigated, and standardized protocols for evaluating dental design software are still lacking [9]. This review provides current evidence on CAD and AI-driven systems, focusing on marginal adaptation, internal fit, finish line detection, and morphological outcomes to highlight their strengths and limitations.

2. CAD software

CAD systems can be broadly categorized into dental-specific and open-source platforms [10]. Dental software is designed for clinical applications but offers limited flexibility, whereas open-source programs provide more versatile and cost-effective design options but are less user-friendly. These systems are also divided into clinical and laboratory platforms, with clinical software providing streamlined tools for practitioners in private practice and laboratory systems providing more advanced design capabilities for technicians engaged in comprehensive digital workflows [8-10-11].

2.1. Conventional CAD software

Conventional CAD software forms the foundation of digital restorative dentistry and primarily relies on rule-based algorithms [12] that require continuous operator input, making restoration accuracy partly dependent on user expertise [13]. Common examples include 3Shape Dental System and exocad DentalCAD [12]. The workflow typically involves case setup (restoration type, material, and tooth selection), followed by manual finish line identification on the digital model [9-14]. The insertion path and cement space parameters are then defined to ensure proper seating and internal adaptation [8]. Finally, restorations are generated from anatomical libraries and refined through manual adjustments of occlusion, contacts, and contours, making the final morphology largely dependent on technician experience [14-15]. These steps are illustrated in Fig.1.

2.2. Artificial intelligence

2.2.1. Classification of Artificial intelligence

AI can be classified as weak or strong. Weak AI, which encompasses most current applications, is designed for specific tasks, whereas strong AI remains theoretical due to ethical and practical limitations. Within weak AI, machine learning (ML) and knowledge-based systems represent different approaches: knowledge-based systems rely on predefined databases, require manual tuning, and offer limited adaptability and personalization, while DL, a subset of ML, uses artificial neural networks (ANNs) to automatically extract features from large datasets. This data-driven approach enables automated and highly individualized crown design [16].

2.2.2. Neural Network Architectures in AI

Artificial Neural Networks (ANNs) consist of interconnected neurons organized into input, hidden, and output layers, allowing data features to be processed into increasingly complex patterns and summarized in the output layer. ANNs form the foundation of deep learning models [17]. Convolutional Neural Networks (CNNs) are specialized DL models for image recognition and generation [18], using convolutional layers to extract feature maps, pooling layers to reduce dimensionality, and fully connected layers for classification, achieving higher accuracy and efficiency than traditional ANNs [18-19]. Generative Adversarial Networks (GANs) are unsupervised models that discover patterns in input data and generate realistic new samples [20], with extensions such as 3D-GANs enabling direct creation of three-dimensional (3D) objects from 2D or 3D data [21].

3. Fundamentals of Restoration Accuracy

A successful prosthesis requires precise adaptation to the prepared tooth, accurately reproducing the parameters established during digital design while maintaining proper occlusal and proximal relationships [22]. Inadequate marginal or internal fit may lead to microleakage, cement dissolution, secondary caries, impaired seating, and reduced fracture resistance, while inaccurate morphology or occlusion can cause functional disturbances and periodontal complications [6-22-27].

3.1. Marginal Adaptation

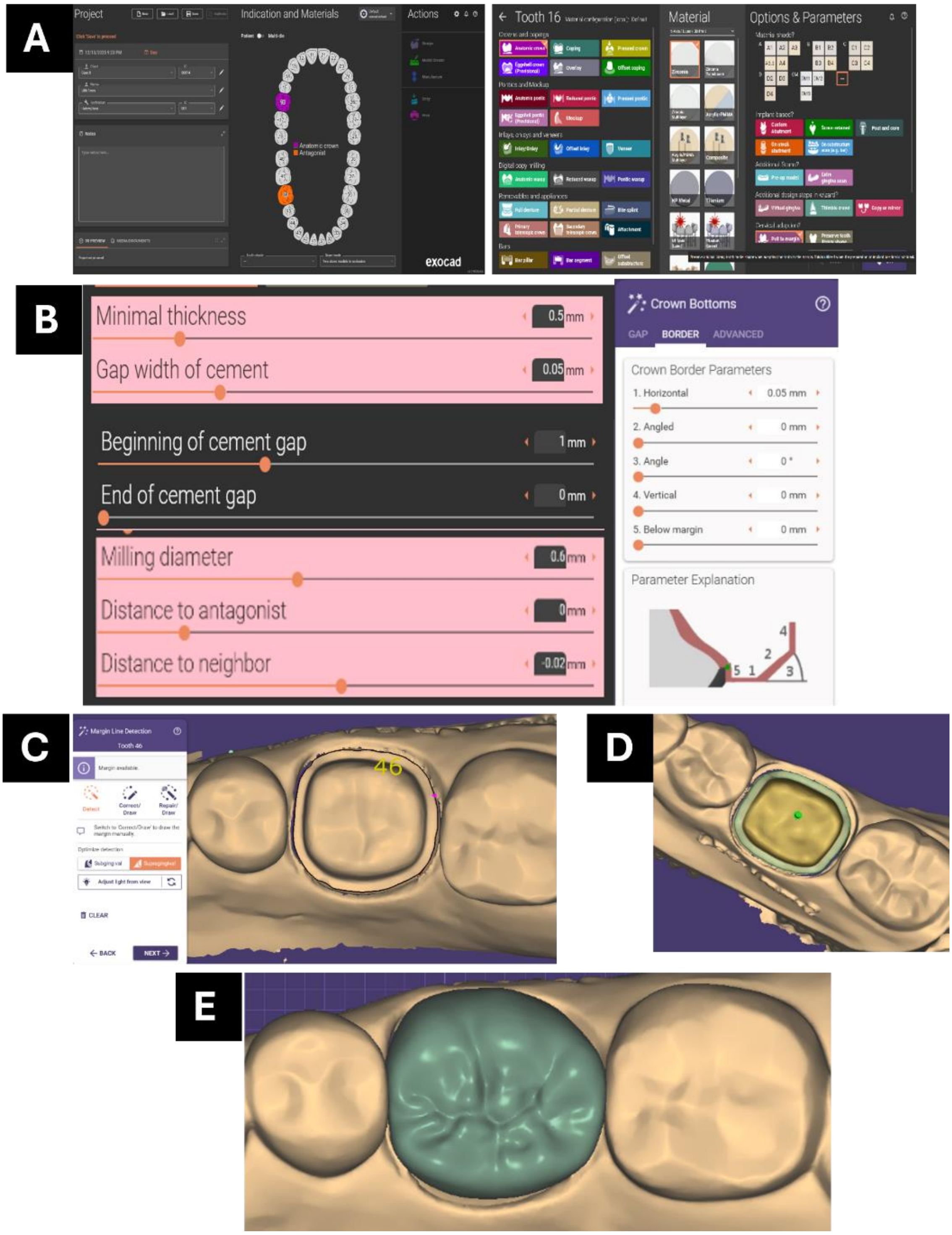
Holmes et al. (1989) introduced a classification for evaluating marginal and internal adaptation, defining the marginal gap as the perpendicular distance between the restoration's internal surface and the preparation margin. They also introduced the absolute marginal discrepancy (AMD), which combines marginal gap and extension errors to represent overall marginal misfit. Marginal gap values often increase after cementation, and several factors influence marginal adaptation, including finish-line configuration, cement space settings, veneering, and cementation, although only the finish-line design is directly controlled by the clinician [6-7-22-28]. Historically, a marginal gap of up to 120 μm was considered clinically acceptable based on McLean et al's long-term evaluation of fixed restorations [29]. However advances in digital dentistry have enabled restorations with marginal discrepancies often below 100 μm for CAD/CAM restorations [6-30-31].

3.2. Internal Fit

The internal gap is defined as the perpendicular distance between the crown's intaglio surface and the axial walls of the prepared tooth, representing the space available for luting cement. This parameter plays an important role in crown seating, retention, and overall clinical performance [28-32-35]. Although a universally accepted standard has not been established [36], studies generally report clinically acceptable internal gaps for all-ceramic crowns in the range of approximately 49-136 μm [30], with some investigations suggesting that discrepancies of 100–250 μm may still be clinically acceptable [22-23-37].

3.3. Morphological outcome

Conventional CAD systems rely on built-in tooth libraries as a starting point for prosthesis design, but these often require manual refinement by technicians to achieve optimal fit, occlusion, and function.[38]. However, DL-based software using architectures such as GANs and CNNs have demonstrated the capability of these systems to produce anatomically realistic restorations while reducing dependence on technician expertise [16]. For example, Hwang et al. [39] and Tian et al. [40] developed 2D-GAN methods that generate crowns from technicians' designs using 2D depth maps of 3D tooth models, while Ding [41] demonstrated a 3D-Deep Convolutional Generative Adversarial Network (3D-DCGAN) capable of directly producing 3D crowns with natural tooth–like morphology.



Minimal thickness 0.5 mm
Gap width of cement 0.05 mm
Beginning of cement gap 1 mm
End of cement gap 0 mm
Milling diameter 0.6 mm
Distance to antagonist 0 mm
Distance to neighbor -0.02 mm

Crown Bottoms
GAP BORDER ADVANCED
Crown Border Parameters
1. Horizontal 0.05 mm
2. Angled 0 mm
3. Angle 0 °
4. Vertical 0 mm
5. Below margin 0 mm

Figure 1. A schematic overview of the crown design workflow on a Conventional CAD software. (A) Selection of the tooth. (B) Design Parameters. (C) Margin line detection. (D) Insertion axis detection. (E) The final design of the crown on the scanned model.

3.4. Reliability of finish line detection

Accurate finish line placement is critical for defining the interface between prepared and unprepared tooth structure and the margin of restoration. Traditional CAD methods, including 3Shape, exocad, and MEDIT, use rule-based algorithms like morphological skeleton segmentation, harmonic field extraction, and region-growing methods but are limited in robustness and lack fully automated boundary extraction.

DL-based approaches, employing networks such as TSegNet and MeshSegNet, improve boundary and landmark detection but can struggle with atypical arch shapes and often need carefully tuned post-processing parameters. Hybrid CAD–DL systems, exemplified by Dentbird [9-12], combine both approaches to enhance automation and accuracy, though performance still depends on factors like finish line design, data acquisition methods, and the anatomical location of the prepared tooth [26].

4. Literature review

Ding et al. [41] evaluated a DL–based approach using 3D-DCGAN for automatic crown design and compared it with CEREC Biogeneric and technician-designed crowns. The 3D-DCGAN crowns showed the closest similarity to natural tooth morphology, including cusp angles and overall 3D structure, while occlusal contacts were comparable across groups. Finite element analysis further demonstrated that these crowns most closely replicated natural stress distribution and fatigue behavior.

Similarly, a feasibility study [38] using a 3D GAN-based AI system showed that AI could generate single-molar prostheses that closely mimicked natural tooth morphology by learning from adjacent dentition, although further algorithm refinement and broader clinical validation were recommended to improve accuracy and applicability of AI-designed dental prostheses. Cho et al. (2023, 2024) [15-42] evaluated GAN–based AI systems for dental crown design in comparison with conventional CAD. AI-generated crowns consistently reduced design time, improved internal fit, and showed less deviation in occlusal morphology, minimizing the need for manual adjustments. When comparing two DL-based systems (3Shape Automate and Dentbird) with crowns designed by experienced technicians, all designs exhibited similar external, occlusal morphologies and cusp angles, although Dentbird achieved superior internal fit and 3Shape Automate produced more occlusal contact points, occasionally with heavier contacts. These findings indicate that DL-based AI can deliver clinically comparable outcomes to skilled technicians while enhancing efficiency, highlighting its potential as a reliable alternative for posterior crown restoration workflows.

Rençber Kızılkaya et al. 2024 [10] compared the marginal fit and internal clearance of provisional single crowns designed using Dentbird, Exocad, and Inlab with identical cement space parameters and fabricated by 3D printing. Significant differences were observed among the software systems, with Dentbird demonstrating the most favorable overall fit, particularly in buccal internal and marginal regions, while Exocad and Inlab showed surface-dependent variability, highlighting the influence of CAD software selection on restoration fit. In another study, Aktaş et al. 2024 [24] evaluated resin-based crowns for primary teeth designed by conventional CAD and AI-based software and fabricated using 3D printing and milling methods. AI-3D printed crowns exhibited superior marginal and axial adaptation, whereas CAD-milled crowns performed better in occlusal adaptation; however, all groups demonstrated clinically acceptable gap values, indicating that both design software and manufacturing technique affect crown adaptation.

Lemos et al. n.d. [16], in a systematic review, evaluated accuracy and time efficiency of DL–based CAD software for single-tooth crown design compared with conventional CAD systems. The review found that DL-generated crowns achieved accuracy comparable to or greater than technician-designed restorations, particularly in occlusal morphology and finish line [43] reproduction. In addition, DL-based designs demonstrated lower internal fit discrepancies within clinically acceptable limits (≤120 µm) and improved time efficiency, supporting their clinical feasibility. Consistent with these findings, Nagata et al. 2025 [43] compared crowns designed using conventional CAD (3Shape Dental System) and AI-equipped CAD (Dentbird). The AI-based system improved occlusal accuracy, reduced palatal misfits, ensured consistent marginal adaptation, and significantly shortened design time, while its web-based interface enhanced accessibility, lowered need for software installation and reduced costs and technical requirements.

Kong et al. 2024, in a scoping review [44], reported the growing role of AI in dental crown design, traditionally performed using wax-up techniques or conventional CAD/CAM workflows. Among seven included studies, [15-38-40-41-42-45-46] four evaluated commercially available AI software [15-42-45-46] three employed 3D generative adversarial network (3D-GAN) models [38-40-41] for crown morphology generation. Most studies demonstrated higher design accuracy with AI-based workflows compared with conventional CAD or manual approaches, although one study reported greater occlusal morphology discrepancies with AI software [45]. Two studies also reported improved time efficiency with AI-driven design systems [15-46]. Similarly, Che-Ming Liu [46] found that AI-generated crowns showed significantly better reproducibility than wax-up restorations and comparable performance to digital CAD designs, with significantly smaller marginal gaps and markedly reduced design time, supporting the clinical feasibility of AI-assisted crown fabrication.

A comparative study [12] evaluated finish line extraction accuracy of a hybrid AI–CAD method implemented in Dentbird against conventional CAD platforms (3Shape, exocad, and MEDIT) using 182 jaw scans from desktop and intraoral sources. The hybrid AI approach showed comparable or superior performance, especially for intraoral scans, suggesting that combining deep learning with traditional CAD algorithms may improve margin detection and overall restoration design accuracy. Sawangsri et al. 2025 [26] evaluated two fully automated AI-based CAD software (Atomica AI and Dentbird) for designing anterior and posterior 3-unit fixed dental prostheses (FDPs) compared with designs by dental technicians (DT). Dentbird generated all designs successfully, while Atomica AI achieved a 93% overall success rate, performing comparably to DT in posterior FDPs, whereas Dentbird showed lower esthetic and functional scores, especially in anterior FDPs. Both AI systems reduced design time, with Atomica faster than Dentbird for anterior FDPs, but both scored lower than DT in occlusal and proximal contacts and connector areas. Overall, AI improved efficiency and achieved clinically acceptable posterior FDPs, but human supervision remains essential for anterior FDPs and critical contact or connector regions.

Xie et al. 2025 [47] compared AI-generated crowns (3Shape Automate) with technician designs (3Shape Dental System). Morphological trueness was comparable between the two approaches, although AI designs exhibited higher maximum discrepancies. While the AI system enabled efficient batch processing, 6.7% of cases required manual intervention due to suboptimal tooth preparations, indicating the importance of careful case selection and further algorithm refinement. In another study, Wu et al. 2025 [48] evaluated posterior crown designs generated by two AI-powered programs (AI Automate and Dentbird Crown) against designs created by experienced and novice Exocad users. AI designs were markedly faster taking only a quarter of the time of novice users demonstrating superior efficiency. However, morphological accuracy varied by surface, with Dentbird showing lower accuracy on occlusal surfaces and experienced technicians outperforming AI Automate on distal surfaces, indicating that although AI improves efficiency, it does not yet fully match the morphological precision achieved by experienced technicians.

5. Conclusions

The use of AI in designing dental crowns and fixed prostheses offers improved efficiency and clinically acceptable morphological accuracy, particularly for posterior restorations. However, challenges remain in anterior teeth, occlusal and proximal contacts, and cases with suboptimal preparations, where human supervision is still essential. Continued refinement of AI algorithms, integration of dynamic occlusal modeling, and broader clinical validation are needed to enhance precision and reliability. Future research should explore different AI architectures, training datasets, and different clinical conditions to optimize restorative outcomes and ensure safe clinical adoption.

6. Clinical recommendations

1. AI design is efficient and accurate for posterior crowns and multi-unit FDPs, reducing design time while providing clinically acceptable morphology and internal fit.
2. Human supervision remains essential for anterior teeth, occlusal and proximal contacts, and cases with suboptimal preparations to ensure proper fit and function.

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Conflict of interest

The authors declare no conflict of interest.

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