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Comparison of AI-generated and conventional CAD/CAM crown designs: An *in vitro* evaluation

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Abstract:

Artificial intelligence (AI) can automate crown design, but its accuracy and function require comparison with conventional CAD/CAM. Therefore, it is of interest to compare the both workflows on 30 standardized mandibular first-molar preparations. AI shortened design time (1.73 ± 0.43 vs 5.63 ± 1.14 min; $p < 0.001$) and reduced whole-crown RMS deviation. AI reduced marginal gap (60.3 ± 14.2 versus 68.8 ± 13.0 μm ; $p < 0.001$), while conventional CAD was better proximally. Thus, functional contacts were comparable, supporting AI as an efficient design aid with final technician or clinician verification.

Keywords: Artificial intelligence (AI), Computer-aided design and computer-aided manufacturing (CAD/CAM), crown design, digital dentistry, deep learning (DL), marginal fit, occlusion, prosthodontics

Background:

Computer-aided design and computer-aided manufacturing (CAD/CAM) have become central to fixed prosthodontics because they allow digital acquisition, virtual restoration design and machine-based fabrication within a reproducible workflow. Conventional CAD crown design, however, still depends heavily on technician experience for selecting tooth libraries, establishing emergence profile, controlling proximal contacts, refining occlusion and adapting restoration contours to patient-specific anatomy. These manual steps can increase active design time and create inter-operator variability, particularly in high-volume laboratory settings. Artificial intelligence (AI), including deep-learning and generative architectures, has therefore been introduced to automate the construction of patient-specific crown morphology from the prepared tooth, neighboring teeth and the opposing dentition [1-4]. Three-dimensional generative models have demonstrated that crown surfaces can be reconstructed from contextual dental anatomy while preserving clinically relevant morphology. Ding *et al.* showed that a three-dimensional deep convolutional generative adversarial network could produce crown forms with promising morphological and mechanical characteristics [1]. Cho *et al.* subsequently reported that deep-learning-based software generated crowns with broadly comparable external morphology to technician-designed crowns, although internal fit and contact patterns varied between systems [2]. Liu *et al.* also observed substantial gains in workflow efficiency and acceptable restoration trueness with AI-supported design [3]. A recent narrative review emphasized that generative dental restoration design has advanced rapidly but remains dependent on the quality and quantity of input data, the architecture of the algorithm and the definition of the finish line [4]. Recent comparative studies have increasingly focused on

whether automated design can match expert CAD workflows rather than merely generate plausible tooth shapes. Cakmak *et al.* found clinically promising anterior crown morphology but identified functional deviations that could benefit from technician refinement [5]. Wu *et al.* showed that AI-powered crown-design platforms were considerably faster than conventional CAD while not uniformly surpassing experienced operators for every surface [6]. Nagata *et al.* similarly reported a clear reduction in design time and more uniform output with AI-equipped CAD systems [7]. Other work has shown that the amount of contextual input, such as adjacent and opposing teeth, influences crown morphology [8, 9], while clinical evaluation indicates that generative AI crowns can achieve acceptable marginal and internal fit when finish lines are well defined [10]. Therefore, it is of interest to compare AI-generated and conventional CAD/CAM posterior crowns using standardized scan data. A 2026 systematic review of 12 studies likewise found AI-assisted crown designs to provide clinically acceptable marginal and internal fit with generally comparable occlusal accuracy, while emphasizing variability among AI models and the need for continued professional oversight [15].

Materials and Methods:**Study design and specimen standardization:**

This paired *in vitro* comparative study used 30 standardized mandibular first-molar typodont teeth mounted with intact second premolars, second molars and opposing maxillary teeth. A paired design was selected so that each preparation served as its own control. Before preparation, the complete dental arch and antagonists were digitized to record the original crown morphology. All teeth were prepared by one experienced prosthodontist using a 1.0-mm circumferential chamfer finish

line, approximately 1.2 mm axial reduction, 1.5-2.0 mm occlusal reduction and a total occlusal convergence of approximately 10-12 degrees. Preparations with visible undercuts, incomplete finish lines or scan defects were remade before inclusion. Because commercial typodont teeth were used and no human biological material or patient data were involved, institutional ethics approval was not required for this laboratory model.

Sample-size calculation:

Sample size was estimated for a two-sided paired comparison using an anticipated standardized within-pair effect size of 0.55, $\alpha=0.05$ and 80% power. The calculation indicated a minimum of 28 paired specimens; 30 preparations were therefore included to allow for possible scan or fabrication failure.

Digital acquisition and reference dataset:

Each prepared typodont was scanned with its adjacent teeth and opposing arch using a calibrated laboratory optical scanner at a nominal accuracy below 20 micrometres. The same post-preparation STL dataset was imported into both design workflows. The intact pre-preparation scan was registered to the prepared-arch scan using stable adjacent-tooth surfaces and was retained as the anatomical reference for three-dimensional morphology. Margin lines were verified by the same operator before duplication of the dataset to avoid differences caused by margin selection.

AI-generated crown design:

For the AI workflow, each scan was processed using a commercial deep-learning-based automatic crown-design platform. The prepared tooth, neighboring teeth and antagonist were provided as input. The software generated a full-contour molar crown automatically; only final verification of margin integrity was performed before export. Cement space was standardized at 60 micrometres beginning 1 mm above the finish line, minimum wall thickness at 0.8 mm and occlusal contact target at light virtual contact. Automated generation time and any manual refinement time were recorded separately with a digital timer.

Conventional CAD/CAM crown design:

The paired conventional crown was created from the identical scan by an experienced dental technician using non-AI CAD software. The same margin line, cement space, minimum thickness and virtual contact parameters were applied. A standard mandibular first-molar library tooth was selected and manually adapted to the adjacent and opposing dentition. Active design time was measured from opening of the verified margin dataset to final STL export. The operator was blinded to the quantitative performance of the paired AI design.

Three-dimensional morphological analysis:

AI and conventional STL crowns were aligned separately to the pre-preparation anatomical reference using unchanged adjacent-tooth geometry and a standardized best-fit protocol. After

trimming the internal surface, the external crown was divided into occlusal, axial, proximal and marginal zones. Root-mean-square (RMS) surface deviation was calculated for the complete external surface and for each region. Lower RMS values represented closer reproduction of the reference morphology. Positive and negative surface deviations were visually inspected to confirm that local outliers did not arise from registration error.

Fabrication and fit assessment:

All 60 crowns were fabricated using the same CAM unit and the same batch of tooth-colored resin blocks to minimize material- and machine-related variability. Crowns were seated on their respective preparations under a standardized 20-N axial load without cement. Marginal gap was measured at 24 equidistant points with a calibrated digital microscope. Internal adaptation was assessed using a light-body silicone replica technique sectioned buccolingually and mesiodistally. Axial, occlusal and overall internal gaps were measured at predefined sites by a blinded examiner.

Occlusal and proximal contact assessment:

After complete seating, static occlusal contacts were recorded in the mounted typodont using a digital occlusal-analysis system. Total contact area and number of discrete contact points on the restored tooth were recorded. Proximal contacts were assessed with standardized 50-micrometre contact strips and categorized as acceptable when the strip passed with firm resistance without tearing or remaining completely loose. The need for minor proximal or occlusal adjustment before achieving the predefined acceptance criterion was also recorded.

Measurement reliability and statistical analysis:

Ten randomly selected crown pairs were remeasured after 2 weeks. Intra-examiner reliability was excellent for RMS deviation (ICC=0.96) and marginal-gap measurement (ICC=0.94), while agreement for categorical contact scoring was substantial to almost perfect ($\kappa=0.88$). Distributional assumptions were checked with the Shapiro-Wilk test and visual inspection of Q-Q plots. Paired continuous outcomes were compared with paired t tests. Paired categorical outcomes were analyzed with exact McNemar tests. Mean paired differences and 95% confidence intervals were calculated for the primary outcomes. Statistical significance was set at $p<0.05$.

Results:

All 30 preparations produced complete AI and conventional design files and all 60 crowns were successfully fabricated and measured. No specimen was excluded because of scan failure, incomplete seating or manufacturing defect. The design-time and three-dimensional morphology findings are summarized in **Table 1**, marginal and internal adaptation in **Table 2** and functional contact outcomes in **Table 3**. AI-assisted design required 1.73 ± 0.43 minutes compared with 5.63 ± 1.14 minutes for the conventional CAD workflow, corresponding to a mean paired reduction of 3.90 minutes (95% CI 3.48-4.32; $p<0.001$).

Manual refinement time was also shorter in the AI workflow (0.58 ± 0.25 vs 2.50 ± 0.78 minutes; $p<0.001$). Whole-crown RMS deviation from the pre-preparation reference was significantly lower for the AI-generated crowns (160.6 ± 31.9 micrometres) than for conventional CAD crowns (181.0 ± 29.9 micrometres; $p<0.001$). The conventional workflow, however, showed a lower proximal-surface RMS deviation (152.6 ± 30.6 vs 164.0 ± 32.9 micrometres; $p=0.021$). Differences in occlusal, axial and marginal RMS values were not statistically significant. Mean marginal gap was 60.3 ± 14.2 micrometres for AI-generated crowns and 68.8 ± 13.0 micrometres for conventional crowns ($p<0.001$). Axial internal gap did not differ significantly between the two workflows (82.7 ± 14.1 vs 83.8 ± 16.5 micrometres;

$p=0.699$). AI crowns demonstrated a modestly smaller occlusal gap (110.1 ± 22.1 vs 118.5 ± 27.2 micrometres; $p=0.043$) and overall internal gap (89.8 ± 14.6 vs 94.9 ± 11.0 micrometres; $p=0.035$). Total occlusal contact area and the number of discrete contacts were comparable between workflows (both $p>0.05$). Acceptable mesial contacts were obtained in 27 of 30 AI crowns and 28 of 30 conventional crowns ($p=1.000$), while acceptable distal contacts were present in 26 and 28 crowns, respectively ($p=0.625$). Twenty-five AI crowns and 27 conventional crowns met the predefined occlusal-contact acceptance criterion without adjustment ($p=0.688$). The proportion requiring any minor occlusal or proximal refinement was also not significantly different.

Table 1: Design efficiency and three-dimensional morphological accuracy (n=30 paired specimens)

Outcome	AI-generated	Conventional CAD	p value
Total active design time (min)	1.73 ± 0.43	5.63 ± 1.14	<0.001
Manual refinement time (min)	0.58 ± 0.25	2.50 ± 0.78	<0.001
Whole-crown RMS deviation (micrometres)	160.6 ± 31.9	181.0 ± 29.9	<0.001
Occlusal RMS deviation (micrometres)	202.9 ± 45.6	213.4 ± 46.0	0.209
Axial RMS deviation (micrometres)	121.8 ± 23.7	129.6 ± 27.2	0.089
Proximal RMS deviation (micrometres)	164.0 ± 32.9	152.6 ± 30.6	0.021
Marginal RMS deviation (micrometres)	98.4 ± 18.1	103.7 ± 23.0	0.111

Values are mean +/- SD. RMS, root-mean-square surface deviation. Paired t test.

Table 2: Marginal and internal adaptation after CAM fabrication

Outcome	AI-generated	Conventional CAD	p value
Marginal gap (micrometres)	60.3 ± 14.2	68.8 ± 13.0	<0.001
Axial internal gap (micrometres)	82.7 ± 14.1	83.8 ± 16.5	0.699
Occlusal internal gap (micrometres)	110.1 ± 22.1	118.5 ± 27.2	0.043
Overall internal gap (micrometres)	89.8 ± 14.6	94.9 ± 11.0	0.035

Values are mean +/- SD. Paired t test.

Table 3: Occlusal and proximal contact outcomes

Outcome	AI-generated	Conventional CAD	p value
Occlusal contact area (mm2)	3.59 ± 0.78	3.49 ± 0.88	0.467
Number of occlusal contacts	5.26 ± 1.16	5.55 ± 1.24	0.251
Acceptable mesial contact, n (%)	27 (90.0)	28 (93.3)	1.000
Acceptable distal contact, n (%)	26 (86.7)	28 (93.3)	0.625
Occlusion acceptable without adjustment, n (%)	25 (83.3)	27 (90.0)	0.688
Any minor adjustment required, n (%)	6 (20.0)	8 (26.7)	0.688

Continuous variables: paired t test. Categorical paired outcomes: exact McNemar test.

Discussion:

The present paired *in vitro* comparison found that AI-assisted crown design substantially reduced active design time while producing overall geometric and fit outcomes that were broadly comparable with and in several measures better than, conventional technician-driven CAD. The primary finding was a reduction of approximately 3.9 minutes per crown, with the AI workflow requiring less than one third of the time used for conventional design. Whole-crown RMS deviation and marginal gap were also lower in the AI group. Nevertheless, the conventional CAD workflow produced a smaller proximal-surface RMS deviation, showing that AI performance should not be interpreted as uniformly superior across every clinically relevant region. The marked reduction in design time agrees with recent experimental work. Wu *et al.* reported significantly greater time efficiency for AI-powered crown design systems than for computer-aided design performed by human operators [6]. Nagata *et al.* similarly found that AI-equipped CAD substantially shortened design time and reduced the effect of

technician experience on crown output [7]. Liu *et al.* also showed improved production efficiency with AI-designed restorations [3]. These observations are clinically relevant because crown design is repeated at scale in dental laboratories; even a modest reduction per unit can translate into considerable workflow savings. The time benefit observed here remained substantial even after inclusion of brief manual verification, suggesting that automation may be most useful when it replaces repetitive morphology generation while leaving final quality control to the technician. Whole-crown morphological accuracy favored AI in the present dataset, but regional analysis produced a more nuanced result. AI crowns showed a lower global RMS value, whereas the proximal surface was more accurately reproduced by conventional CAD. This is consistent with the literature showing that automated systems can generate anatomically convincing crown forms but may differ from expert designs in specific surfaces. Cho *et al.* found broadly similar external morphology among deep-learning and technician-designed posterior crowns, while differences emerged in internal fit,

occlusal contacts and proximal relationships [2]. Wu *et al.* likewise reported that AI systems did not consistently exceed experienced technicians in surface-specific morphological accuracy [6]. Cakmak *et al.* showed clinically acceptable deep-learning crown morphology in anterior restorations but found functional deviations that improved after technician modification [5]. Therefore, a global RMS value is useful for overall comparison but should be supplemented by regional analysis whenever crown function is being assessed. The proximal finding may reflect the complexity of recreating contact position, contact intensity and emergence contour simultaneously. A proximal surface can appear anatomically plausible in three dimensions yet still create a contact that is too tight, too light or vertically misplaced. Deep-learning algorithms infer this geometry from contextual input and their performance may depend on how much of the neighboring dentition is provided. Broll *et al.* showed that reducing input from quadrant-level information to only adjacent teeth increased reconstruction failures and morphological deviation [9]. Personalized point-to-mesh models likewise emphasize the importance of contextual anatomy for crown generation [8]. In clinical use, the quality of intraoral scan data and the inclusion of stable neighboring and opposing surfaces are therefore likely to be as important as the underlying AI architecture. Marginal and internal adaptation was within laboratory-acceptable ranges and the AI group showed a smaller mean marginal gap. The clinical literature is increasingly supportive of acceptable AI-generated crown fit when margins are well defined. Win *et al.* reported that generative AI crown designs could achieve marginal and internal fit comparable with conventional CAD, although some surface- and occlusion-related discrepancies remained [10]. Liu *et al.* also observed close marginal adaptation for AI and digital designs [3]. The present results suggest that automated morphology generation does not necessarily compromise seating or cement space when the same design parameters and CAM process are applied. However, marginal fit in a digital workflow is influenced by several steps beyond crown morphology, including scanning, margin identification, and milling tool diameter and fabrication behavior. For this reason, the observed marginal advantage should be interpreted as a workflow-level finding rather than as an isolated property of the AI algorithm. Occlusal contact area, number of contact points and proximal-contact acceptability were statistically similar between groups. This is encouraging because occlusal refinement is one of the most clinically important steps after crown seating. Nevertheless, the lack of a significant difference should not be equated with formal equivalence because no pre specified equivalence margin was used. Recent evidence suggests that AI-generated restorations can reproduce functional contacts reasonably well, but expert adjustment may remain beneficial in complex situations [2, 5 and 10]. Hlaing *et al.* further showed that automated design quality changes across different occlusal scenarios and that software performance can vary between anterior and posterior teeth [13]. These findings support a human-in-the-loop approach in which AI proposes the initial crown and a clinician or technician verifies contact distribution,

excursions and proximal relationships before manufacturing. The results also fit the broader direction of current evidence. Comparative work published in 2025 found differences between AI- and technician-generated full-crown morphology while confirming that data-driven systems can approximate natural tooth form [11]. Transformer-based models have also been extended to implant-supported crown design, indicating continued expansion of AI from tooth-borne restorations toward more complex prosthodontic applications [12]. A 2026 systematic review and meta-analysis concluded that AI-assisted crown design generally achieves clinically acceptable morphological accuracy, internal fit and occlusal integration while offering a consistent advantage in workflow efficiency; however, heterogeneity among software platforms and study protocols remains high [14]. The present study adds to this concept by emphasizing that speed and global accuracy should be considered together with regional and functional outcomes. A major strength of this study was the paired design: both crowns for each preparation were produced from exactly the same scan, margin and design parameters, and thereby reducing anatomical variation. The use of a pre-preparation scan as a morphological reference also allowed direct assessment of how closely each workflow reconstructed the original tooth form. Additional strengths included one CAM process for groups, examiner calibration and separate analysis of occlusal, axial, proximal and marginal surfaces. Several limitations should be acknowledged. First, the typodont model does not reproduce saliva, periodontal mobility, intraoral scanning challenges or patient-specific functional movement. Second, only mandibular first molars under a standardized occlusal arrangement were evaluated. Third, the results are software- and version-dependent and may change as cloud-based AI systems are updated. Fourth, static contact analysis does not fully represent excursive mandibular dynamics. Finally, laboratory fit measurements cannot predict long-term clinical survival, wear or biological response. Future studies should include multiple tooth types, different malocclusion patterns, clinician-rated adjustment time, dynamic occlusal analysis and prospective clinical follow-up. From a practical perspective, the findings support AI as an efficient first-pass design tool rather than a replacement for professional judgment. Automated crown generation can shorten repetitive digital procedures and standardize basic morphology, while human verification remains important for proximal surfaces, occlusal function and unusual anatomical situations. A collaborative workflow is therefore likely to provide the best balance between speed, consistency and individualized restorative quality. The systematic review by Alfaifi [15] supports the present findings by reporting clinically acceptable AI crown fit and generally comparable occlusal accuracy relative to CAD/CAM and technician-designed workflows. Our results extend that evidence by showing a clear time and marginal-fit advantage for AI while also identifying a proximal-surface limitation, reinforcing the need for human verification rather than fully unsupervised design.

Conclusion:

AI-assisted crown design significantly reduced active design time and achieved comparable or improved overall morphology and fit in this paired *in vitro* model. Conventional CAD retained an advantage for proximal-surface morphology, while occlusal and proximal contact acceptability was similar between workflows. AI-generated crowns should therefore undergo technician or clinician verification before manufacturing, particularly in anatomically or functionally demanding cases.

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