From Geometry to Clinic: A Physics-Aware Evaluation Framework and Benchmark for Automated Dental Crown Design

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Abstract. Recent advances in deep learning have demonstrated remarkable potential in automating dental crown design. However, existing evaluation protocols predominantly rely on geometric similarity metrics (e.g., Chamfer Distance), which are clinically agnostic and fail to capture functional failures such as occlusal interference or open contacts. To bridge this gap, we present CrownBench, a physics-aware evaluation framework and benchmark that shifts the paradigm from geometric approximation to clinical validity. We propose a set of clinically-interpretable digital metrics, mathematically formulating implicit clinical experiences into explicit constraints: Feasibility Metrics (e.g., Occlusal/Proximal Feasibility Rates) for survival validation, and Quality Metrics (e.g., Occlusal Contact Distribution) for personalized quality assessment. Benchmarking state-of-the-art methods on CrownBench reveals a severe "Geometric Trap," where geometrically accurate models still suffer from low clinical success rates. Furthermore, a rigorous blind user study confirms that our framework aligns significantly better with human expert judgments than traditional metrics. Our code and dataset are released at https://github.com/JiaminWoo/CrownBench.

Keywords: Digital Dentistry · Dental Restoration · Benchmark.

1 Introduction

Digital dentistry has witnessed a paradigm shift from manual wax-up procedures to Computer-Aided Design and Manufacturing (CAD/CAM) [4]. While traditional CAD software streamlines the workflow, it still heavily relies on the manual manipulation of complex parameters by experienced technicians, which is labor-intensive and subject to inter-operator variability. Recently, deep learning methods [6, 14, 15, 11, 2] have shown meaningful promise in digital dentistry. In automated crown design, the data-driven approaches [10, 12, 5, 16, 8] aim to generate patient-specific restorations that satisfy complicated clinical criteria.

Despite these algorithmic advances, a critical gap remains between geometric plausibility and clinical applicability. Current State-of-the-Art (SOTA) methods predominately rely on geometric similarity metrics, such as Chamfer Distance (CD) and Hausdorff Distance (HD), to evaluate generation quality. While effective for general 3D shape reconstruction, these metrics are clinically agnostic. A generated crown can achieve a low CD score by visually resembling a generic tooth, yet fail catastrophically in a clinical setting due to functional violations, such as occlusal interferences (penetration into opposing teeth), open proximal contacts (food impaction risks), or poor marginal adaptation (secondary caries risks) [7]. Consequently, the community faces a "geometric trap": models are optimized for shape similarity rather than functional survival, and evaluations often revert to non-scalable subjective visual inspections by clinicians.

To deploy AI agents in real-world clinical workflows, evaluation protocols must evolve from measuring "how much it looks like a tooth" to "how well it functions as a restoration." This requires translating implicit clinical experiences—such as the delicate balance of occlusal forces and the precision of proximal contacts—into explicit, computable, and physics-aware mathematical formulations. However, establishing such a unified benchmark is challenging due to the complex, multi-dimensional constraints involved in the stomatognathic system, where tolerance is measured in microns and constraints vary between "hard" survival limits and "soft" functional harmonies.

To bridge this chasm, we present CrownBench, a novel physics-aware evaluation framework and benchmark designed to standardize the assessment of automated dental crown design. Unlike previous works that treat crown generation as a pure shape completion task, CrownBench reformulates evaluation through the lens of clinical physics. We define a comprehensive set of digital clinical metrics, categorizing constraints into Feasibility Metrics for safety validation and Functional Metrics for personalized quality assessment. By grounding evaluation in the physical interactions between the restoration and its biological environment (opposing and adjacent dentition), our framework provides a rigorous "stress test" for generative models. Our main contributions are three-fold:

- A Paradigm-Shifting Evaluation Framework: We propose the first clinically-quantifiable evaluation framework that maps implicit clinical criteria (occlusion, proximal contact, margin) into explicit, physics-aware metrics, distinguishing between hard survival constraints and soft quality harmonies.
- The CrownBench Benchmark: We establish a comprehensive benchmark comparing SOTA crown generation methods. Our extensive experiments reveal a significant disconnect between geometric similarity metrics (CD/HD) and clinical success rates, highlighting the necessity of our proposed metrics.

– Human-AI Alignment Validation: We conduct a rigorous user study with experienced dentists, demonstrating that CrownBench rankings align significantly better with human expert judgments than traditional geometric metrics, validating its potential as a trusted standard for future research.

2 Method

We propose a comprehensive evaluation framework that transcends traditional geometric similarity metrics (e.g., Chamfer Distance). We formulate clinical experience into rigorous mathematical definitions, categorized into Feasibility Metrics (Hard Constraints) for safety validation and personalized functional quality (Soft Constraints) for personalized functional assessment.

2.1 Preliminary: Region-Aware Semantic Parsing

Given a generated dental crown mesh $\mathcal{M}_{gen}$ and the opposing dentition $\mathcal{M}_{opp}$, adjacent teeth $\mathcal{M}_{adj}$, and the preparation margin line $\mathcal{C}_{margin}$. We first compute the Signed Distance Fields (SDF) of the environmental scans: $\Phi_{opp}(\cdot)$ and $\Phi_{adj}(\cdot)$. To evaluate specific functional areas, we extract Regions of Interest (ROI) by querying the SDF values of the crown's surface points:

(1) Occlusal Surface (Ω_{occ}): Vertices on the crown top that are within a functional interaction range.

(2) Proximal Surface (Ω_{prox}): Vertices on the mesial/distal sides facing adjacent teeth.

(3) Finish Line ($\mathcal{C}_{GT}$): Critical curve that shall align with the boundary of crown.

2.2 Clinical Feasibility Assessment

These metrics determine whether a generated crown is clinically "safe" to fit without causing irreversible failure (e.g., open contacts or severe penetration). We simulate standard physical inspection tools used by dentists to define binary Pass/Fail indicators.

Occlusal Feasibility Rate (OFR). In clinical practice, dentists use articulating paper to check for high spots (interference). Inspired by this, we propose a Virtual Articulating Paper algorithm. We treat the Signed Distance Field (SDF) of the opposing teeth as the "ink thickness." We define a Valid Occlusal Interval $\mathcal{I}_{occ} = [-0.2mm, 0.5mm]$. The lower bound ($-0.2mm$) tolerates slight penetration (simulating periodontal elasticity), while the upper bound ($0.5mm$) allows for functional clearance but prevents open bite (simulating "no ink mark" on the paper). For a generated crown, we calculate the minimum distance (worst-case deviation) to the opposing teeth:

$$d_{occ}^{min} = \min_{p \in \Omega_{occ}} \Phi_{opp}(p) \tag{1}$$

The crown is classified as "Clinically Acceptable" if $d_{occ}^{min} \in \mathcal{I}_{occ}$. Otherwise, it is classified as Over-Penetration ($d < -0.2$) or Occlusal Loss ($d > 0.5$). The OFR is the percentage of successful cases in the test set.

Proximal Feasibility Rate (PFR). Proximal tightness is clinically verified using dental floss. The contact must be tight enough to snap the floss (preventing food impaction) but passable. For digital evluation, excessive contact is adjustable (grindable), but open contact is irreversible. Hence, we mimic this Digital Dental Floss by defining an asymmetric Valid Proximal Interval $\mathcal{I}_{prox} = [-0.3mm, 0mm]$. The lower bound ($-0.3mm$) tolerates slight penetration, while the upper bound ($0mm$) simulates the floss passes without resistance.

We evaluate the closest point on the proximal surface:

$$d_{prox}^{min} = \min_{p \in \Omega_{prox}} \Phi_{adj}(p) \tag{2}$$

A case passes if $d_{prox}^{min} \in \mathcal{I}_{prox}$. This asymmetric threshold explicitly reflects the clinical preference for "tight contact" over "open gaps."

Marginal Seal Integrity (MSI). The crown margin must perfectly align with the preparation finish line to prevent secondary caries. We compute the one-sided Hausdorff Distance from the crown boundary $\partial\mathcal{M}_{gen}$ to the ground truth margin curve $\mathcal{C}_{GT}$:

$$HD_{margin} = \max_{p \in \partial\mathcal{M}_{gen}} \min_{q \in \mathcal{C}_{GT}} \|p - q\|_2 \tag{3}$$

A strictly low HD_{margin} is required for clinical acceptance.

2.3 Personalized Functional Quality

Beyond binary survival, a high-quality crown must adapt to the personalized oral environment. We propose physics-aware metrics to quantify the digital design quality.

Contextual Occlusal Consistency (COC). Occlusal contact area varies among patients (e.g., wear facets in elders vs. sharp cusps in youth). We propose a Reference-Based Evaluation using the adjacent tooth as a reference context. We define the Functional Contact Ratio (FCR) which represents the effective "ink mark area" left by our Virtual Articulating Paper:

$$FCR(\mathcal{M}) = \frac{\text{Count}(\{p \in \mathcal{M} \mid \Phi_{opp}(p) \leq \tau_{contact}\})}{\text{Count}(\{p \in \mathcal{M} \mid \Phi_{opp}(p) \leq \tau_{area}\})} \tag{4}$$

The COC measures the consistency between the generated crown's FCR and the neighbor's FCR using a negative exponential decay function:

$$COC_{\mathcal{M}} = \exp\left(-|FCR(\mathcal{M}_{gen}) - FCR(\mathcal{M}_{neighbor})|\right) \tag{5}$$

A higher $COC_{\mathcal{M}}$ indicates that the AI model has successfully learned the personalized occlusal pattern.

Occlusal Contact Distribution (OCD). Effective occlusion relies not only on the total contact area but also on the spatial distribution of forces. A stable restoration requires widely distributed contact points (e.g., tripodism) rather than a single concentrated stress point, which risks porcelain fracture or instability. We formulate this as a Density-Based Clustering problem on the manifold. Let $\mathcal{P}_{contact} = \{p \in \Omega_{occ} \mid \Phi_{opp}(p) \leq \tau_{cluster}\}$ be the set of effective contact vertices. We apply the DBSCAN algorithm (Density-Based Spatial Clustering of Applications with Noise) to partition $\mathcal{P}_{contact}$ into disjoint topological clusters $\{C_1, C_2, \dots, C_k\}$:

$$\mathcal{C} = \text{DBSCAN}(\mathcal{P}_{contact}, \epsilon, MinPts) \tag{6}$$

where ϵ is the spatial neighborhood radius and $MinPts$ is the density threshold. The metric is defined as the Number of Valid Clusters ($N_{clusters} = |\mathcal{C}|$). A higher $N_{clusters}$ (typically aiming for ≥ 3 for molars) indicates a mechanically stable, multi-point contact distribution.

Anatomical Detail Fidelity (ADF). To evaluate whether the generated surface preserves functional features (cusps and grooves) or is over-smoothed, we evaluate the Normal Consistency Score. Specifically, we first sample N points $\{p_i\}_{i=1}^N$ on the generated mesh surface $\mathcal{S}_{gen}$, and find their nearest corresponding points $\{q_i\}_{i=1}^N$ on the ground truth surface $\mathcal{S}_{GT}$. Then we compute the average cosine similarity of their normals:

$$S_{ADF} = \frac{1}{N} \sum_{i=1}^{N} \langle \mathbf{n}_{gen}(p_i), \mathbf{n}_{GT}(q_i) \rangle \tag{7}$$

where $\mathbf{n}(\cdot)$ denotes the normalized surface normal vector, and $\langle \cdot, \cdot \rangle$ is the dot product. A score closer to 1.0 indicates high fidelity in preserving anatomical morphology.

3 Experiments

3.1 Experimental Settings

Dataset Construction. To rigorously benchmark the clinical applicability of automated dental restoration, we constructed a real-world restoration dataset, comprising 500 paired molar crown cases collected from partner clinical institutions. Each case consists of dental model scans of the preparation jaw, the opposing jaw, and the corresponding Ground Truth (GT) crown designed by senior dental technicians using commercial CAD software. We randomly partitioned the dataset into training, validation, and test sets with a ratio of 8:1:1. Note that the test set is exclusively reserved as our proposed CrownBench, which was not seen during the training of any baseline models and test through our evaluation framework.

Data Preprocessing and Standardization. To ensure a fair and standardized comparison across different generative architectures, we implemented a unified data processing pipeline: We first employed a state-of-the-art dental segmentation network, 3DTeethSeg [3], to semantically parse the raw scans into individual components (preparation tooth, adjacent teeth, and antagonists). To eliminate algorithmic errors, the segmentation results underwent a rigorous Human-in-the-Loop verification process, where two dentists reviewed and refined the masks, particularly at the contact regions. The preparation margin lines were explicitly extracted from the GT designs to serve as boundary constraints.

Furthermore, to facilitate generative modeling, all mesh data were spatially normalized. We established a local canonical coordinate system for each case based on the GT crown's PCA axes [1], ensuring the insertion axis aligns with the Y-axis. All meshes were centered to the origin. This standardization ensures that performance differences arise solely from the generative models' capabilities rather than data inconsistencies.

Implementation Details. We benchmarked SOTA crown generation methods, including Dental-GAN, DCPR-GAN, 3D-Dental-GAN, PoinTr, DMC, VBCD, 3DShape2Vecset. All baseline models were retrained on the *CrownBench* training split until convergence, strictly following their official hyperparameter settings. The evaluation experiments were conducted on a RTX 4090 GPU using PyTorch framework. We set the SDF threshold of occlusal surface as 1.5mm to the opposing teeth. All hyperparameters can be adjusted to satisfy different manufacturing standards.

3.2 Experimental Results

Comprehensive Benchmarking on CrownBench. Table 1 presents the quantitative comparison across 50 test cases. While recent methods like 3Dshape2Vecset [18] and VBCD [13] achieve remarkable geometric accuracy ($CD \approx 0.25 - 0.40mm$), a significant gap remains in clinical feasibility. Specifically, although VBCD reduces the CD to $0.251mm$, its Occlusal Feasibility Rate (OFR) is only 82.0%, implying that nearly 1 in 5 "geometrically precise" crowns still suffer from functional failures (penetration or open bite). Furthermore, regarding Functional Quality, most methods struggle to reproduce the complex occlusal topography found in human designs (GT), as evidenced by lower OCD scores (< 2.0) compared to GT (3.12). This quantitative benchmark exposes the limitation of current SOTA methods: they master the overall shape distribution but often miss the fine-grained physical constraints essential for clinical survival.

Threshold Robustness. We performed a sensitivity analysis around the feasibility intervals by perturbing the OFR lower/upper bounds and the PFR lower bound by ± 0.05 mm. Absolute pass rates changed with tolerance strictness, but method rankings remained unchanged, indicating that the main trend in Table 1 is not an artifact of one empirical threshold.

The "Geometric Trap" in High-Fidelity Generation. To validate the necessity of physics-aware evaluation, we investigated whether geometric metrics remain reliable when the generation quality is already high. We curated a

Table 1. Quantitative benchmarking on CrownBench. Note the discrepancy between geometric metrics (CD/HD) and clinical metrics (Feasibility/Quality).

Method	**Geometric**		**Clinical Feasibility**			**Functional Quality**		
	CD(↓)	HD(↓)	OFR(↑)	PFR(↑)	MSI(↓)	COC(↑)	ADF(↑)	OCD
Dental-GAN[10]	1.641	4.951	0.58	0.08	5.05	0.71	0.83	1.91
DCPR-GAN[12]	0.976	1.459	0.62	0.20	0.36	0.73	0.27	1.84
3D-Dental-GAN[5]	0.839	2.233	0.32	0.14	1.80	0.79	0.48	1.54
PoinTr[17]	0.958	2.366	0.46	0.20	1.36	0.79	0.49	1.81
DMC[9]	0.489	1.130	0.52	0.16	0.83	0.80	0.87	1.96
3Dshape2Vecset[18]	0.397	1.149	0.78	0.62	0.62	0.81	0.95	2.59
VBCD[13]	0.251	1.122	0.82	0.76	0.63	0.82	0.95	3.96
Human Design (Ref)	0.000	0.000	0.92	0.90	0.00	0.83	1.00	3.12

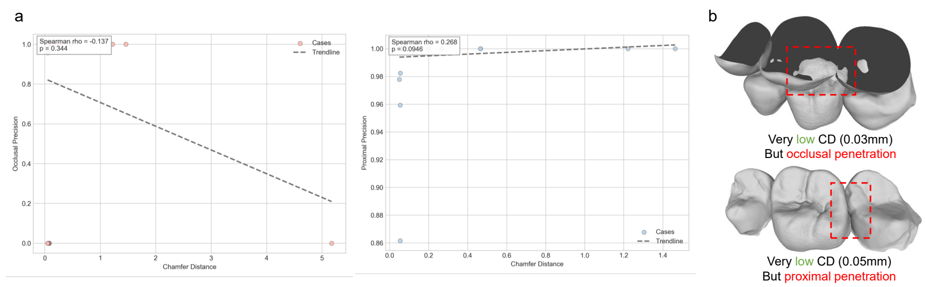

Fig. 1. Analysis of the "Geometric Trap". (a) Scatter plots showing no significant correlation between Chamfer Distance (CD) and clinical precision (Occlusal/Proximal) on 50 high-fidelity samples. (b) Visualization of two "Trap Cases": crowns with extremely low CD scores that nevertheless fail due to occlusal penetration (left) or proximal interference (right). Red regions indicate clinically unacceptable penetration.

subset of 50 high-fidelity cases from the top-performing models (VBCD and 3Dshape2Vecset), where all samples exhibit low Chamfer Distances ($CD < 0.5mm$). Fig. 1(a) visualizes the correlation analysis. Despite the low geometric error, we observe a distinct **"Geometric Trap"**: the CD shows negligible or even counter-intuitive correlation with clinical precision (Occlusal Precision $\rho = -0.137, P = 0.344$; Proximal Precision $\rho = 0.268, P = 0.09$). This confirms that in the high-precision regime, geometric similarity decouples from clinical utility.

As shown in Fig. 1(b), we visualize two representative "Trap Cases" with minimal geometric errors. Although visually plausible, the heatmaps reveal critical failures: one exhibits deep occlusal penetration ($-0.4mm$), and the other shows severe proximal interference. These defects render the crowns clinically unusable despite their "perfect" CD scores.

Human-AI Alignment Validation. To verify that *CrownBench* serves as a reliable surrogate for expert judgment, we conducted a blind user study on the same subset of 50 high-fidelity cases. Three senior dentists (experience > 5 years)

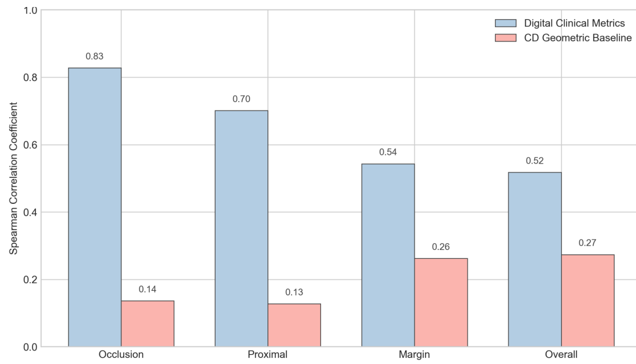

Fig. 2. Human-AI Alignment Study. Spearman correlation coefficients between automated metrics (Blue: Our DCMs; Red: Chamfer Distance) and human expert ratings across four clinical dimensions. Our framework demonstrates significantly higher alignment with dentists' judgments, particularly in functional dimensions (Occlusion/Proximal), validating its reliability as a clinical benchmark.

rated each case on a Likert scale (1-5) across four dimensions: *Occlusion*, *Proximal Contact*, *Marginal Adaptation*, and *Overall Acceptability*. Dentists reviewed anonymized 3D visualizations with method identity hidden and sample order randomized; mean ratings served as human references for Spearman analysis, with high inter-rater agreement (ICC=0.868, 0.874, 0.884, and 0.844 for occlusion, proximal, margin and overall acceptability).

Fig. 2 reports the Spearman correlation coefficients (ρ) between automated metrics and human scores. Our proposed Digital Clinical Metrics (DCMs) demonstrate superior alignment with human perception compared to CD. For *Occlusion* and *Proximal* dimensions, our physics-aware metrics (OFR/PFR) correlate strongly with dentist ratings ($\rho > 0.8$), whereas CD shows weak correlation ($\rho < 0.3$). This indicates that dentists prioritize functional safety over global shape similarity. For *Overall Acceptability*, dimension-specific metrics were normalized to $[0, 1]$ and averaged with equal weights. Our comprehensive framework aligns much better with expert decisions. In clinical deployment, CrownBench can be used as an interpretable report card where OFR/PFR/MSI serve as safety gates before COC/OCD/ADF evaluate personalized quality.

4 Discussion and Conclusion

Limitations. Despite the promising results, CrownBench has several limitations. First, it focuses on relatively structured posterior molar cases with available opposing dentition, mesial/distal adjacent teeth, and a clear preparation margin. Corner cases such as missing adjacent teeth, pathological wear, or unusual occlusal schemes may require upstream screening and condition-specific thresholds. Second, extending the framework to anterior teeth would require incorporating aesthetic metrics such as symmetry and smile line alignment. Finally, although we formulate differentiable metrics, this study focuses on evaluation. Integrating these physics-aware constraints directly into the training loop (e.g., via Reinforcement Learning) to explicitly optimize for clinical feasibility is a promising avenue for future work.

Conclusion. In this paper, we identified and quantified the "Geometric Trap" in automated dental restoration: the disconnect between geometric similarity and clinical utility. To address this, we introduced CrownBench, the first clinically-quantifiable evaluation framework that digitizes implicit expert knowledge into clinically-interpretable, physics-aware metrics. Our extensive benchmarking reveals that current SOTA methods, while geometrically precise, often fail to meet basic clinical safety standards. Moreover, our user study demonstrates that these metrics, spanning hard feasibility constraints and soft functional quality, serve as reliable surrogates for human expert evaluation. CrownBench thus provides a standardized benchmark for developing AI agents that restore function rather than only reconstruct shape.

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