

Comparative Assessment of Efficiency and Productivity in Implant Crown Design Generated by Artificial Intelligence, Digital Designers, and Dental Students

Aleksandar Naydenov

a.naydenov@fdm.mu-sofia.bg

Medical University of Sofia

Todor Uzunov

Medical University of Sofia

Georgi Kostadinov

New Bulgarian University

Todor Bogdanov

Medical University of Sofia

Ilia Liondev

Medical University of Sofia

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Abstract

Objectives. This study aimed to compare the efficiency and productivity of a three-dimensional Generative Adversarial Network (3DGAN) with experienced digital operators and dental students in the design of screw-retained implant crowns.

Methods. Three groups were evaluated: Group A (experienced operators), Group B (second-year dental students), and Group C (3DGAN). Each group produced 10 crown designs. Design time (seconds) was recorded, and theoretical productivity (crowns/hour) was calculated. Statistical analysis included one-way ANOVA and Tukey's post hoc test. Ratio coefficients were used to quantify differences in speed and productivity between AI and human operators.

Results. Mean design time was 371 ± 24 s for Group A and 2873 ± 633 s for Group B, corresponding to productivities of 9.75 ± 0.63 and 1.32 ± 0.37 crowns/hour, respectively. The 3DGAN demonstrated a mean generation time of 0.0234 s and a productivity of $153,982 \pm 3,456$ crowns/hour. The AI system was approximately 1.6×10^4 times faster and more productive than experienced operators and over 1.2×10^5 times faster and 1.1×10^5 times more productive than students. A statistically significant effect of group on design time was observed ($F(2,27) = 182.5, p < 0.001$).

Significance. 3DGAN-based design enables near-instant generation of implant crowns and markedly higher productivity compared with conventional digital workflows. These findings support the role of artificial intelligence as an effective tool for automation in dental CAD design, while maintaining the need for clinical supervision and validation.

Introduction

The rapid development of digital technologies has transformed contemporary dental practice. Dental implantology and prosthetic dentistry are among the dental disciplines most affected by this transformation. Computer-aided design and computer-aided manufacturing (CAD/CAM) systems have become an integral part of clinical workflows, enabling improved precision, reproducibility, and efficiency in the fabrication of dental restorations, including implant-supported crowns [1, 2]. Despite these advancements, the design phase of implant restorations remains highly dependent on operator experience and technical expertise, which can introduce variability in both quality and production time [3].

In recent years, artificial intelligence (AI) and deep learning approaches have emerged as promising tools for automating complex tasks in dentistry. Neural networks, particularly generative models, have demonstrated the ability to learn from large datasets and generate anatomically realistic dental morphologies [4, 5]. Among these, Generative Adversarial Networks (GANs) have shown considerable potential in medical image synthesis, segmentation, and 3D model generation, offering new possibilities for fully automated prosthetic design workflows [6, 7].

The application of AI in dental CAD aims not only to reduce operator-dependent variability but also to significantly increase efficiency. Previous studies have demonstrated that AI-assisted systems can achieve comparable or even superior outcomes to conventional manual or semi-automated approaches in terms of morphology, occlusion, and contact accuracy [8, 9]. Furthermore, automation of design processes has the

potential to dramatically reduce the time required for prosthetic planning and fabrication, thereby improving productivity in both clinical and laboratory settings [10].

Despite these promising developments, there is still limited quantitative evidence comparing the performance of AI-based systems with human operators of varying experience levels, particularly in the context of implant-supported restorations. Evaluating parameters such as design time, productivity, and consistency is essential to assess the clinical applicability of such technologies.

Therefore, the aim of the present study is to compare the efficiency and productivity of a 3D Generative Adversarial Network (3DGAN) with experienced digital operators and dental students in the design of screw-retained implant crowns. The null hypothesis is that there is no significant difference in performance between the AI-based system and human operators.

Materials and methods

3.1. Study groups

Three study groups (A, B, and C) were evaluated. Each group consisted of 10 crown designs. In groups A and B, each design was produced by a different human operator, whereas in group C all 10 designs were generated sequentially by the 3DGAN model described in our previous study [11], using 10 different validation cases as input to the model. Groups A and B used Exocad TM software for digital crown design.

Group A: 10 designs produced by 10 experienced operators, including dentists and dental technicians. Group B consisted of 10 designs produced by 10 second-year dental students who completed a 1-month extracurricular training course in digital modeling. The course was conducted under the supervision of teaching staff from the Department of Prosthodontics at the Faculty of Dental Medicine, Medical University of Sofia, in 2025. Group C: 10 designs generated by the 3DGAN neural network described in a previous publication [11].

3.2. Time measurement

Design time (t) was recorded using the stopwatch function in OBS Studio during screen recording of each design session.

For group C, timing began at the start of the automated design generation by the neural network. For groups A and B, timing began after the desktop video recording had started and the design procedure had started.

3.3. Statistical analysis

One-way analysis of variance (ANOVA) was used to compare crown design time (t) among the three investigated groups (A, B, and C). For each operator/design, theoretical productivity was also calculated as the number of crowns generated per 1 hour of work. To assess how many times artificial intelligence outperformed the human groups in terms of speed and productivity, ratio coefficients were calculated between the mean time and mean productivity of 3DGAN and those of the experienced operators and students, respectively. Pairwise multiple comparisons among the three groups were performed using Tukey's post hoc test. SPSS was used for the statistical analysis.

Results

Table 1 presents the design times, in seconds, for the three study groups: group A - the time required by an experienced operator to perform the virtual design of a screw-retained implant crown in the site of the missing mandibular left first molar (tooth 36); group B - the time required by a second-year dental student to perform the same virtual design; and group C - the time required for the automated modeling of a screw-retained implant crown by the three-dimensional generative network across 10 consecutive generated designs.

Table 1

The assessed time for the fabrication/generation of the design of a screw-retained implant crown in: Group A (experienced digital operators), Group B (second-year students), and Group C 3DGAN—the neural network.

Nº	Group A - experienced digital operators (t, s)	Group B - second year students (t, s)	Group C - 3DGAN generated design (t, s)
1	345	3240	0.0241
2	372	3475	0.0241
3	398	3380	0.0240
4	355	1750	0.0234
5	389	1928	0.0231
6	332	2883	0.0232
7	361	3181	0.0233
8	410	3422	0.0232
9	378	2371	0.0225
10	367	3098	0.0230

Table 2 presents the mean time, minimum and maximum time, theoretical productivity expressed as the number of crowns generated per hour, and standard deviation.

Table 2

Results in seconds and productivity per hour for the studied Groups A, B, and C.

Group	Mean time (s)	SD (s) time	Median time (s)	Min time (s)	Max time (s)	Mean time (min)	Mean productivity (crowns/hour)	SD productivity (crowns/hour)
A	371	24.0	370	332	410	6.18	9.75	0.633
B	2873	633	3140	1750	3475	47.88	1.32	0.366
C	0.0234	0.000526	0.0232	0.0225	0.0241	0.000390	153 982	3 456

The mean time required to design a single implant crown for the experienced operators (group A) was 371 ± 24 s (approximately 6.2 min). The shortest time recorded was 332 s and the longest was 410 s. The theoretical productivity was 9.75 ± 0.63 crowns/hour.

The mean time required to design a single implant crown for the second-year students (group B) was 2873 ± 633 s (approximately 47.9 min), with a shortest time of 1750 s and a longest time of 3475 s. The theoretical

productivity was 1.32 ± 0.37 crowns/hour.

The mean time required to design a single implant crown using the 3DGAN neural network (group C) was 0.0234 s. The shortest recorded time was 0.0225 s and the longest was 0.0241 s. The theoretical productivity was $153\,982 \pm 3\,456$ crowns/hour.

The theoretical productivity of the three groups is shown in (Fig. 1).

The ratios presented in Table 3 indicate how much faster and more productive the 3DGAN system was than the human groups. In terms of design time, 3DGAN was 15 848.65 times faster than group A and 122 821.7 times faster than group B. In terms of productivity (crowns/hour), 3DGAN was 15 795.93 times more productive than group A and 116 218.4 times more productive than group B. In relative terms, 3DGAN was approximately 1.6×10^4 times faster and approximately 1.6×10^4 times more productive than the experienced operators, and more than 1.2×10^5 times faster and more than 1.1×10^5 times more productive than the students (Fig. 2).

Table 3

Comparisons results (faster/time and productive/generated crowns per hour) between our 3DGAN network and Groups A and B.

Parameter	Compared with Group A	Compared with Group B	Approximate interpretation
How many times faster 3DGAN is (time)	15 848.65	122 821.7	$\approx 1.6 \times 10^4$ and $\approx 1.23 \times 10^5$ times faster
How many times more productive 3DGAN is (crowns/hour)	15 795.93	116 218.4	$\approx 1.6 \times 10^4$ and $\approx 1.16 \times 10^5$ times more productive

One-way ANOVA showed that the factor “group/source” had a statistically significant effect on execution time ($F(2,27) = 182.5$, $p < 0.001$). The large F value indicates that variation between groups was substantially greater than variation within groups (Table 4).

Table 4

Df: degrees of freedom for the respective “source” (for group and residuals); Sum Sq: sum of squares for each source; Mean Sq: Sum Sq / Df; F value = Mean Sq(group) / Mean Sq(residuals); p-value: probability for F; significance coding: ***: $p \leq 0.001$ (very strong significance); **: $0.001 < p \leq 0.01$; *: $0.01 < p \leq 0.05$; .: $0.05 < p \leq 0.1$ (borderline / trend); $p > 0.1$ (no statistical significance).

Source	Df	Sum Sq	Mean Sq	F value	p-value
Group/Source	2	48 835 837	24 417 918	182.5	$< 2e-16$ (***)
Residuals/Residual variation	27	3 612 482	133 796	NA	NA

The Tukey post hoc test for pairwise group comparisons showed that group B was significantly slower than group A (diff = 2502.1 s, p approximately 0.000000). The comparison between groups C and B was also highly significant (diff = -2872.78 s, p approximately 0.000000). In the comparison between groups B and A, the difference did not reach statistical significance at the 0.05 level ($p = 0.078$). The sign of “diff” indicates the direction of the difference: a negative value for C-B and a positive value for C-A indicate a shorter time for group C relative to the corresponding group (Table 5).

Table 5

Comparative data between the individual pairs of groups. diff = difference between the mean values of the two groups: positive diff → slower group; negative diff → faster group; p adj (adjusted p-value) = corrected p-value for multiple comparisons.

Compared group pairs	Difference between mean values (diff)	Lower limit of the 95% confidence interval	Upper limit of the 95% confidence interval	Adjusted p-value
B – A	2502.1000	2096.5115	2907.6885	0.000000
C – A	-370.6766	-776.2651	34.9119	0.078175
C – B	-2872.7766	-3278.3651	-2467.1881	0.000000

Discussion

The time required for scanning, design, and fabrication in clinical and laboratory workflows is typically measured in tens of minutes [12, 13]. AI-based CAD systems reduce working time and minimize the need for manual adjustments, while increasing productivity and efficiency in the design of three-dimensional restorations [14, 15, 16]. The present work demonstrates a similar effect for screw-retained implant crowns, for which comparable published data on AI-based modeling and design time remain limited.

The recorded times showed that, for the 3DGAN group, the time required to generate the raw voxel-based design for the 10 generated crowns was extremely low and stable, with a mean of 0.0234 s (range: 0.0225–0.0241 s). The mean time recorded for the experienced digital operators, 371 s across the 10 investigated cases (range: 332–410 s), falls within the expected range for manual digital design in Exocad and is consistent with the design time reported by Park et al. (6 min 50 s) [13]. A discrepancy of approximately twofold was observed compared with the design times reported by a major online CAD provider, Dentbird, which reports average digital design times of 10 to 15 minutes when performed by qualified dentists and dental technicians [17]. However, it should be noted that Dentbird is an online CAD platform in which multiple additional factors, such as internet connection speed, may also influence the reported timing.

In the student group, the mean time was 2873 s (range: 1750–3475 s) despite prior training. Greater variability was also observed in this group, suggesting that more extensive training may be required (more than 2 hours weekly over the course of 1 month) both for mastering the software and for acquiring the clinical principles of morphology and occlusion.

The reported results indicate that AI-based CAD solutions substantially reduce design time compared with conventional CAD and are in line with data reported in the literature [15, 18].

The findings also indicate that the 3DGAN model markedly outperformed the human operators in terms of speed and productivity for implant crown design. The differences spanned several orders of magnitude - artificial intelligence generated tens of thousands of designs per hour, whereas experienced clinicians and students could produce only single-digit to low double-digit numbers of crowns during the same period. This demonstrates that, if implemented in clinical or laboratory practice, such AI solutions have the potential to drastically reduce production time and free up substantial human resources that could be redirected toward more complex diagnostic and therapeutic activities. In this context, the role of digital operators may shift from fully manual digital modeling toward final quality control, post-processing, and file export. Shorter design times may also reduce the computational and energy resources required for design generation, with a potential reduction in

electricity consumption and, consequently, a potentially beneficial ecological impact. This is in agreement with the findings reported by Wolf et al. [19], who described the ecological effect of AI in medicine.

It is important to emphasize that the reported time of 0.0234 s refers to the “raw” voxelized design before final post-processing in Blender. This means that, even with additional time for routine post-processing and verification, the final latency of the automated approach remains practically negligible compared with manual CAD, especially in serial workflows or chairside scenarios. The post-processing steps in Blender are repeatable and can be automated relatively easily. The low variability of design time in the 3DGAN group is also a critical advantage for production-capacity planning, allowing more precise productivity forecasting and integration into automated manufacturing workflows.

Despite the substantial quantitative advantage, these results should be interpreted in the context of the quality and clinical acceptability of the resulting restorations. The speed of 3DGAN does not eliminate the need for professional oversight by dentists and dental technicians, nor the need for individual corrections in complex clinical cases. In addition, the comparison was performed in a controlled experimental environment and with a specific dataset; therefore, generalization to all implant scenarios should be made with caution.

This study has several limitations. The measured time excluded file import and covered only the modeling phase. Real end-to-end latency in a clinical environment would also include mandatory finishing and quality-control steps. The evaluation was performed for a single clinical case (tooth 36) and did not capture variation across different prosthetic scenarios, which was shown separately to be manageable but may alter the extent of post-generation correction required.

Despite these limitations, the results clearly outline the role of artificial intelligence as a highly efficient tool for automation and support in digital workflow planning and restorative design, rather than as a direct replacement for human expertise.

Conclusion

The 3DGAN-based crown design substantially improved workflow efficiency and reduced operator dependence during digital crown construction. The AI workflow showed high repeatability and time stability across consecutive designs, suggesting that such systems support automation and standardization in restorative digital dentistry.

Declarations

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This study received no funding.

10. Competing interests

All authors declare no financial or non-financial competing interests.

11. Corresponding author

Dr. Aleksandar Naydenov

Faculty of Dental Medicine, Medical University of Sofia, Sofia, Bulgaria

Email: a.naydenov@fdm.mu-sofia.bg

Telephone: 00359896363783

12. Author contributions

Aleksandar Naydenov: Contributed substantially to the study design, execution of the study tasks, interpretation of the findings, and drafting of the manuscript; Todor Uzunov: Supervised the overall study process.; Georgi Kostadinov: Developed the 3DGAN modeling workflow and evaluated the results obtained from the model.; Todor Bogdanov: Supervised and validated the data.; Ilia Liondev: Contributed to data collection and to the training of the students involved in the study tasks.

13. Data availability

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

14. Human Ethics and Consent to Participate Declaration

We confirm that all methods were carried out in accordance with relevant guidelines and regulations.

We confirm that all experimental protocols were approved by the Medical University of Sofia.

We confirm that informed consent was obtained from all subjects and their legal guardians.

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Figures

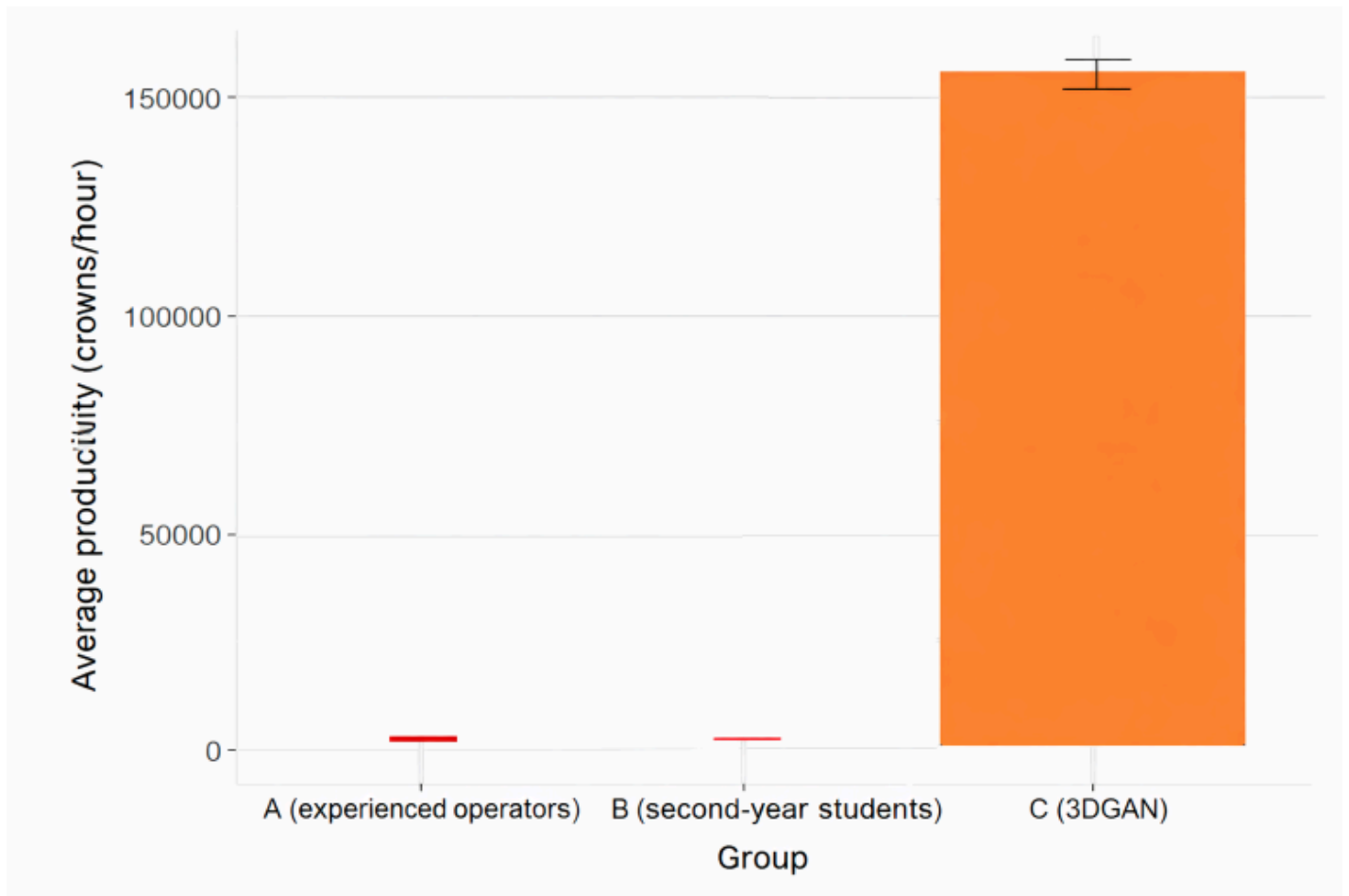


Figure 1

Average productivity – crowns per hour for the three groups A, B and C

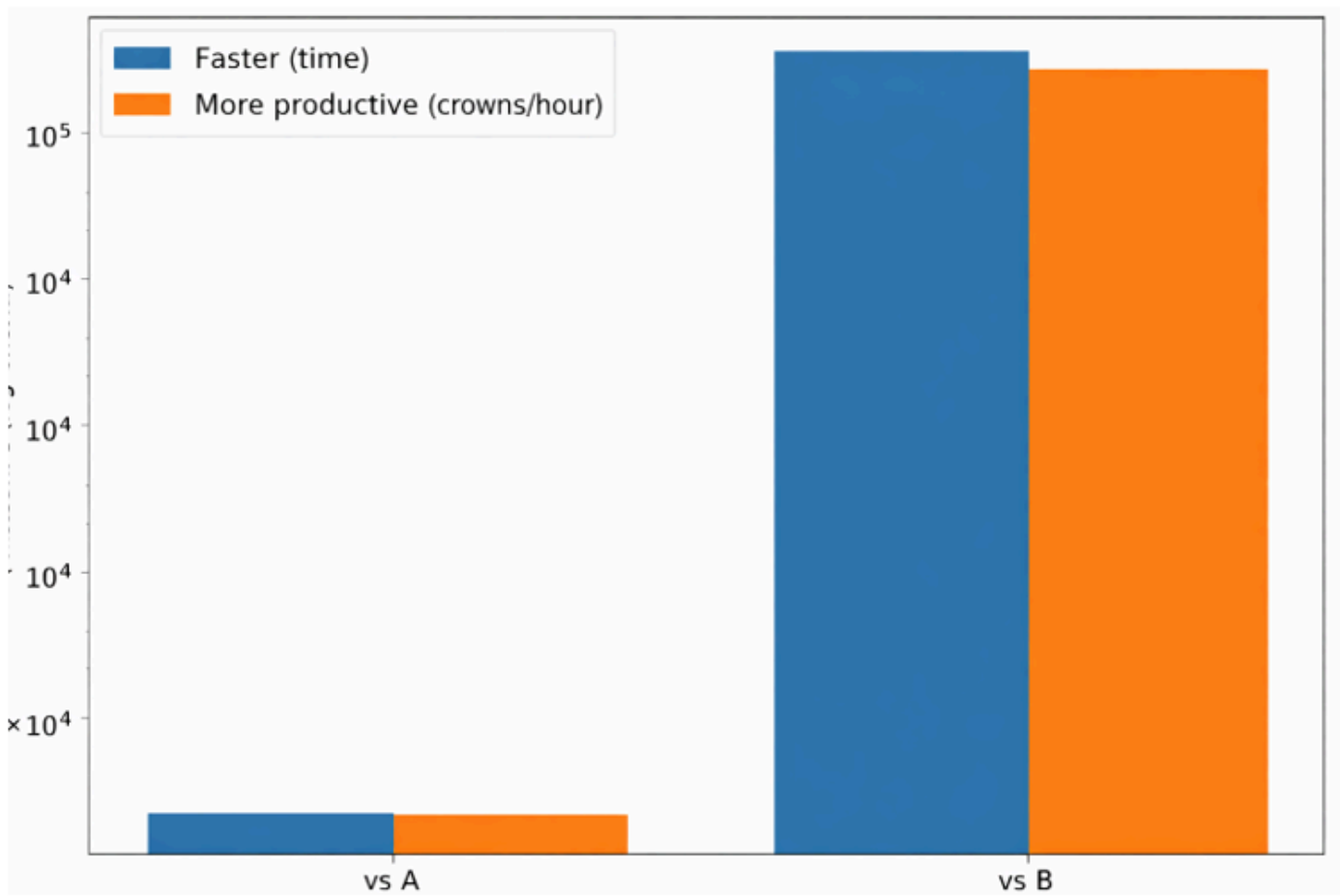


Figure 2

Compares Group C with Groups A and B in terms of relative speed and productivity.