International Journal of Engineering, Science and Humanities
An international peer reviewed, refereed, open access journal
Impact Factor: 8.3 www.ijesh.com ISSN: 2250 3552

EXPERIMENTAL INVESTIGATIONS FOR QUALITY ENHANCEMENT OF DENTAL PROSTHESIS DESIGNED USING 3D SCANNING AND RESIN PRINTING TECHNIQUE

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Abstract
Customized fabrication and decreased intervention are two benefits of 3D printed occlusal dental splints; however, differences in printing parameters, resin properties, dimensional accuracy, manufacturing expenses, and design time might restrict their regular clinical utility. This research is about testing, via experimentation, a machine learning driven optimization strategy that could improve the accuracy and cost-effectiveness of 3D printed occlusal dental splints. The proposed method is based on a fusion of 3D scanning, computer-aided design, 3D printing using resin-based materials, and machine learning to determine the best printing conditions that not only lead to better dimensional accuracy, but also to reduced costs arising from material and fabrication time.
When appropriate, the fabrication time, production cost, dimensional measurements, mechanical and surface evaluations are used to examine experimental samples; traditional or non-optimized fabrication is utilized for comparison. According to the source literature personalisation and improved manufacturing efficiency are possible with digital workflows; the orientation of the build, the thickness of the layers, the printing speed, the composition of the resin, the calibration of the printer, and the post-curing conditions all have a significant influence on the dimensional and mechanical performance. As no validated statistical comparison or machine-learning result is available in the experimental source, it is not allowed to claim increase in performance at the specimen level without an experimental result. The objective of the study is to develop optimization framework on the basis of science principles supporting production of splint items with a high degree of accuracy for maximum quality, cost competitiveness and applicability in clinical practice. In the future, clinical trials, standardized protocols and datasets would be used to validate the model.
Keywords: Machine Learning, 3D Printing, Resin Printing, Occlusal Dental Splints, Den-tal Prosthesis, Dimensional Accuracy, Cost-Effectiveness, CAD/CAM, Digital Dentistry, Process Optimization.

1 INTRODUCTION

By allowing the personalized and efficient manufacturing of dental prosthetic devices, the in-

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tegration of digital technology with additive manufacturing has had a major impact on modern dentistry. Resin-based 3D printer, computer-aided design and manufacturing (CAD/CAM) services and 3D scanning generate resin-based 3D dental anatomical structures that can be collected, digitally modeled, and converted into customized dental parts. New technologies such as stereolithography (SLA), digital light processing (DLP) and material jetting can provide tailored production and excellent resolution but, material selection, printer calibration, printing parameters, environmental conditions, and post-processing play a part in determining the performance of these technologies.

1.1 Problem Statement and Research Questions

For occlusal dental splints to effectively support clinical uses, there must be an anatomical adaptation, mechanical performance, dimensional stability, in addition to appropriately fabricated splints. Based on the literature, printing parameters like build orientation, layer thickness, printing speed, the type of resin used and the post-curing procedures appear to play a significant role in mechanical and physical properties.

Process conditions could affect surface roughness, structural performance or dimensional deviation. While ensuring cost-effective use of material for complicated forms, 3D Printing can simultaneously help in playing down on manual inter-vention and provide faster customization. Some challenges that remain with widespread use include equipment cost, material variation, calibration requirements, and different-processing standards.

1.2 Objective and Problem statement

All the research on 3D-printing dental prostheses so far only focussed on improving the accuracy of the 3D printing, reducing the costs, or increasing design efficiency, instead of being able to endorse a stable and effective integrated machine learning approach to simultaneously achieve the above three goals. Furthermore, the data at hand highlights the significance of verified experimental data and statistical analysis and doesn't offer machine learning outcomes at the specimen level to assert certain performance enhancements. The goal of the research is to practically evaluate the feasibility of machine learning for identification of optimal manufacturing parameters and optimization of 3D printing process. It's called "Experimental Evaluation of Machine Learning-Based Optimization for Accurate and Cost-Effective 3D-Printed Occlusal Dental Splints. It is examined how precise, cost-effective, and effective customized dental splints can be provided using a framework based on the research findings.

2 LITERATURE REVIEW

In the dental field, 3-dimensional printing is built upon layer-by-layer generation of three-dimensional (3D) anatomical models, which are constructed digitally and converted to physical models via 3D printing. Trueness data (how close the results are to the reference model) and precision data (how close the results are to one another) are common measures to determine accuracy. The dimensional accuracy, mechanical strength, wear resistance, retention, material stability, fabrication time and cost are very crucial in manufacturing occlusal splints.

These properties are influenced by the printing technology, prints composition, layers' thickness, orientation of the build, curing process and also post-processing. In this regard, new

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research has not only established the feasibility of Dental 3D printing, but has also begun the clinical validation and quantitative optimization processes.

There was early systematic evidence presented by Etemad-Shahidi et. al. Of the 28 studies analyzed by [1], significant variability in the accuracy of SLA- and DLP-derived models was found, but a meta-analysis could not be performed as the studies were heterogeneous in their reporting. Anadioti et al. [2] analysed full 3-D printed dentures and found digitally promising workflows; however, few studies showed the durability of these materials long-term. Nevertheless, Bona et al. [3] exhibited that the development of ceramics and polymers had been made and stated that the issue of dimensional accuracy is still one that needs to be addressed, along with esthetic and mechanical concerns like wear resistance and wet strength; likewise, et al. [4] determined that MJP was better than the other stereolithographic materials such as DLP, MJP, and SLA in terms of trueness and surface roughness although this was a technology-specific result, and its utility was limited to three-unit prosthetic models.

Herpel and colleagues [5] compared 3D print and 3D milling try-in dentures across 5 centers and showed that there were significant laboratory and operator effects and the importance of standardising workflows. Dua [6] noted in his reconstruction review of 3D printing the following points in the favor of the customization: material efficiency and digital integration, but lacked extensive experimental validation. Alageel's [7] study on the materials and dental printing technology has concluded that printing with metals and polymeric components is cost-effective, whereas fixed prosthetics require further research. [8] showed the impact of the printer and material used by conducting an experiment involving three printers and comparing the dimensional accuracy results with the milling machine and concluded that in this case milling would be more dimensionally accurate. Though more research is needed on more challenging anatomical structures, Nulty assessed 12 dental printers and determined that they all had clinically acceptable levels of accuracy, both high cost and low cost.

To optimize, Dabbagh and his colleagues. Using 224 printing observations, a set of eight machine-learning algorithms was explored by [10] which determined that gradient boosting was the best predictor, and demonstrated how it could reduce trial-and-error, material waste, and process time. Treatment of machine learning for AM was discussed in [11] with focus on various applications of machine learning in AM design, process optimization, monitoring and production control. It was however noted that there were some limitations in data and industrial validation.

In an experiment Cameron, et al. [12] looked at five build orientations for occlusal splints and found the optimal orientations depended on the printer used, concluding that there is no universal best set of parameters. Herpel and his colleagues, In a pilot randomized trial, [13] found thermo-flexible printed splints practical for at least three months, though indicating the need for further randomized trials of longer duration. Et al. [14] created a splint workflow that was completely digital and employed intraoral scanning as well as digital mandibular motion recording, which led to a decrease in adjustment time and a high correlation between virtual and physical occlusal connections.

In addition, there are existing clinical and materials research studies supporting optimization. Despite the small sample size (only 15 denture out of 100), Faur et al. [15] have found

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that there is less intaglio-surface trueness of the digitally printed denture bases than with an analogue workflow. Hornberg and Pauls [16] showed no significant difference in accuracy for four different resins including soy-based materials, but their research focused on dental casts or models and not splints. The success of posterior FDPs was studied by Hobbi et al. [17] who reported favourable short-term results in 68 clinically printed posterior FDPs, but longer follow up studies are still needed. Prasad et al. [18] identified the future directions which include Economics, accuracy, AI and materials with Indian contributions made by Gopi and Chander. Kaushik et al. (2017) and [19] investigated parameters and technologies during the printing process to check printing accuracy. With response-surface optimization, [20] was able to improve simultaneously both physical and mechanical characteristics of resin occlusal splints.

3 SYSTEM ARCHITECTURE

The recommended scheme for the design of "Experimental Evaluation of 3D-Printed Occlusal Dental Splints Optimized by Machine Learning" is a digital design iterative workflow comprised of 3D-scanning, CAD dental splint design, resin-based 3D printing, experimental evaluation, and machine-learning parameter optimization. Evidence shows that mechanical performance and dimensional precision depend significantly on so many design variables such as post processing, curing circumstances, layer thickness, build orientation, resin composition and printer technology [1], [4], [8], [12], [20] that the design is supported.

The entire system has four stages that are physically connected logically: 1) digital data acquisition, 2) computer-aided design process, 3) enhanced fabrication process and 4) experimental feedback measurement. In the first step, the dental geometry of the patient is captured by a 3D intraoral scanning, on the basis of which a virtual dental model is created.

The geometry scanned is used to create an occlusal splint, and is therefore processed to remove unwanted geometry, correct surface defects and create an appropriate reference model. After purification, the model is then imported into the CAD module, where the thickness of teeth in the teethcast, splint geometry, anatomical borders and internal adjustment are specified. This scanning-to-CAD process is performed using the tried and proven digital dentistry approach where the patient-specific geometry is converted into a manufacturable model before the additive process [3], [14], [20]. The architecture therefore has the digital reference model as the primary referenced geometric baseline for subsequent dimensional comparisons.

3.1 Data Components and Flow

The STL model is then passed to the manufacturing-parameter module after the CAD generation. In addition to the system, the model is connected with various controllable process parameters, such as layer thickness, building orientation, printing speed or time, resin type, post-printing conditions and curing time. These variables are significant since previous work has established that there is a relationship between orientation and splint trueness [12], and the relation between thickness of the layer and the mechanical and surface properties has been found [7], [16] after post-curing.

This sliced STL file is then given to the resin printer. Post-fabrication support removal, washing, curing and finishing can be performed depending on the processing conditions selected. The mechanical strength, dimensional accuracy, Wear resistance and production efficiency

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of the splint are then assessed. In order to utilize the data from the experiments, a structured input-output record is generated to store the data for the model construction.

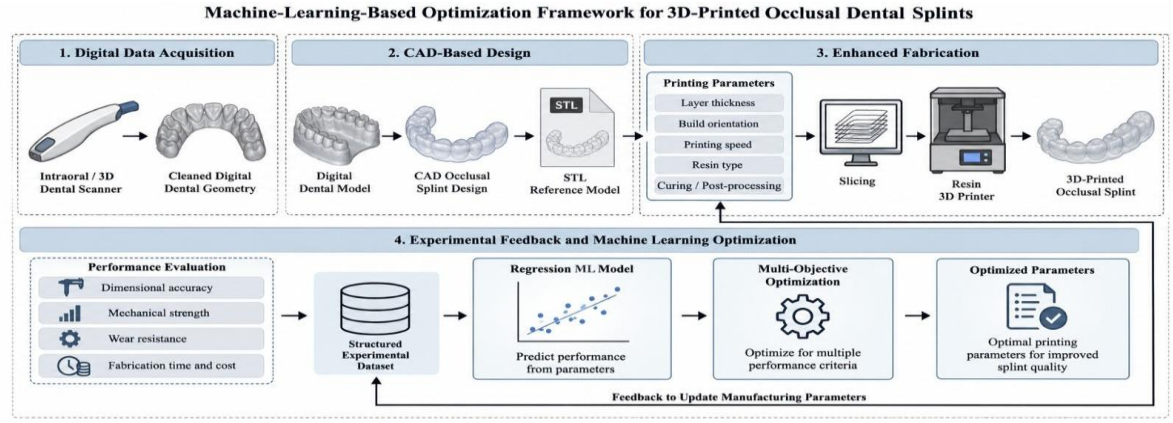

Figure 1: Overall architecture of the proposed machine-learning-based optimization framework for resin-printed occlusal dental splints.

3.2 Model/Algorithm Design

The machine learning layer is the optimization layer of a system. Experimental recordings are subdivided into the validation, testing and training sets and contain measured data and printing parameters. Prior to using regression-based machine-learning models to determine the connections between target responses and manufacturing parameters, pertinent input features are normalized and encoded. The mechanical performance, wear characteristics, material usage, printing/design time, and estimated production cost are among the objective variables. As shown in previous works, learning algorithms can predict process outcomes and reduce the need for trial and error testing [10], [11], optimizing the additive manufacturing process using ML is ideal. The educated model looks at the different combination of parameters and identifies the ones that provide a balance of accuracy, strength, speed and cost. These allowed parameter combinations can then be sorted by applying multi-objective optimization with clinical constraints the cells must meet.

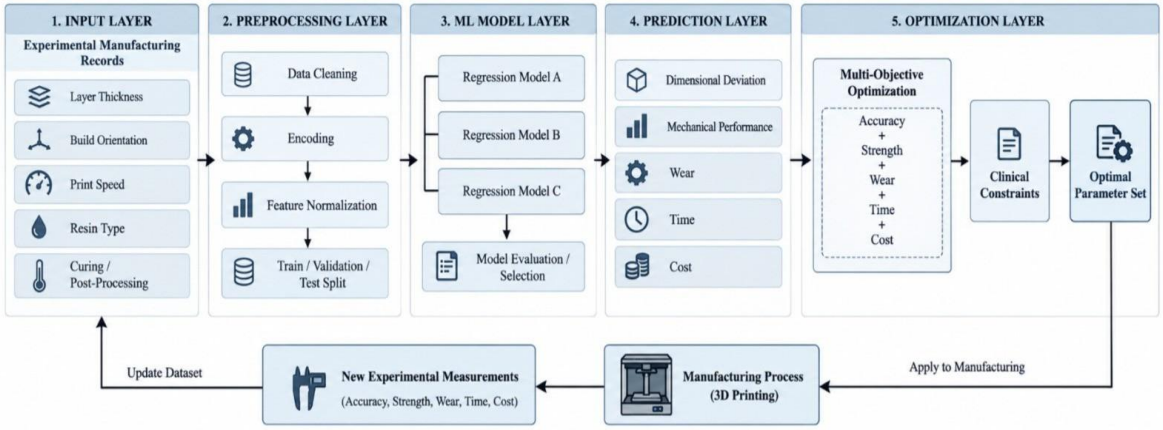

Figure 2: Machine-learning prediction and multi-objective optimization layer for manufacturing-parameter selection.

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4 Methodology

The proposed method is demonstrated in the creation of a controlled digital to physical approach for evaluation and optimization of resin printed occlusal dental splints. The following are the processes that followed in order: CAD splint design, post-processing, dimensional, mechanical and wear assessment, machine learning forecasting, parameter tweaking and the experimental verification. This architecture is adhering to the well-known digital dental workflow of scanning the geometry, converting it into CAD models and finally manufacturing them by 3D printing [3], [12], [14]. Since the furnished study does not specify numbers of samples, equipment model, complete set of printing parameters, comparison group results or validated metrics, it should not be presented as an experiment yielding fabricated numerical results, but rather as an approach and outline of an experimental study.

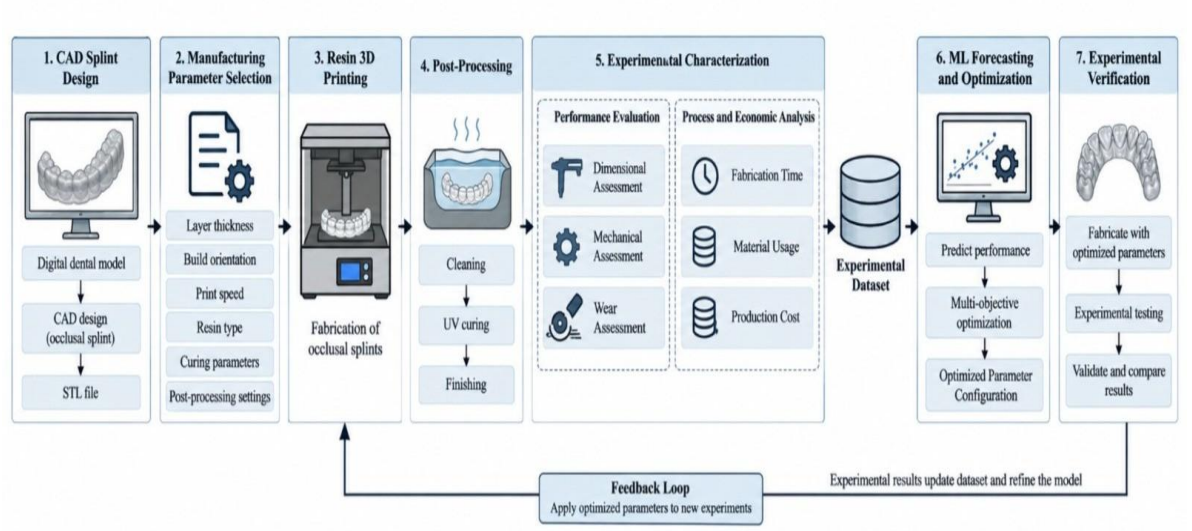

Figure 3: Experimental methodology integrating fabrication, characterization, machine learning, and verification.

4.1 Collecting Data

The data set is not existing from public data sets but rather experimentally generated using occlusal splints. The digital process starts with the use of a three dimensional dental scan, which is subsequently cleaned of surfaces, the artifacts are removed and a universal CAD/STL model is created. The production conditions and measured responses for each printed sample are connected by the experimental data. The resin kind, printing layer thickness, printing direction, curing conditions/property or post-curing conditions, and suitable printing conditions are the main independent variables. These variables are selected due to the fact that previous works have demonstrated that they affect the dimensional accuracy and the mechanical performance [7], [12], [20]. These include the printing/design time, cost of production, wear performance, mechanical strength and change in dimensions. The following table defines the structure in which the data will be collected and not refers to collection of data from the original document that outlines a number of dimensional, mechanical and wear tests.

Collection Method shows the method used for gathering measurements, which are variables categorised into data categories. Data categories are variables collected through Collection

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Method.

Table 1: Experimental Data Collection Structure

Role	Variables/Measurements	Collection Method	Data Category
Digital geometry	CAD/STL geometry, 3D scan	Intraoral/3D scanning and CAD	Reference geometry
Efficiency	Print/design time, material usage	Process logs	Efficiency goal
Cost	Costs associated with production and materials	Cost analysis	Target for cost-effectiveness

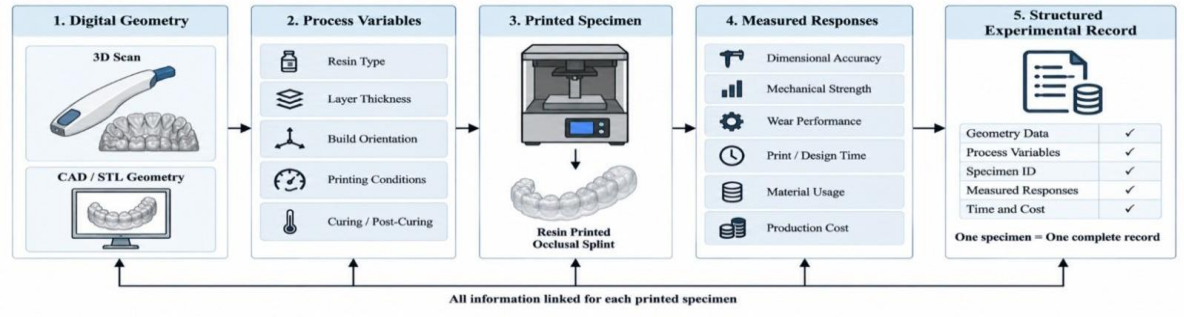

Figure 4: Experimental data collection pipeline linking manufacturing variables with measured responses.

4.2 Models

The experimental data set has been cleaned and divided into separate test set, validation set and training set. Supervised-learning regression models are created to establish connections between dimensional, mechanical, wear and time or cost answers and printing parameters. The fundamentals of model selection are not these complexities but instead their ability to predict class membership and generalise. Since research in AM has demonstrated that the influence of process parameters can be used to predict manufacturing results and reduce "trial and error" manufacturing experiments, regression-based machine learning is applicable to this scenario [10], [11]. Categorical encoding and feature normalization, if needed, are conducted; missing/experimental data are marked, removed from the list: or are removed if not supported.

5 IMPLEMENTATION

Predictive optimization will be combined with the experimental measurement with the proposed implementation through the machine-learning-based part of the digital production workflow, which includes acquisition of dental model, CAD preparation, resin-based additive manufacturing, experimental measurement and predictive optimization. It follows the well known digital process where a dental model is created, converted to an STL file, prepared for additive manufacturing, then sliced according to the criteria selected, printed and finally post processed. The major production steps mentioned in the submitted paper include: CAD-to-STL conversion, specification of production parameters, slicing, definition of the toolpath, manufacturing and postprocessing.

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5.1 stack of technology and tools for development

Implementation includes a 3D scanning environment for digital dental-model acquisition, CAD/CAM environment for occlusal splint geometry development, additive-manufacturing processing software for STL preparation, support generation, slicing (OM1), and relatively execution of the 3D printer (OM2). The observations made during the experiments and the machine learning models defined in the approach are implemented in a computing environment for data processing. The technology stack is modular so that the parts of the systems (scanning, CAD, printing, measuring etc.) are capable of working independently and exchanging common numerical and digital data. Modularity is appropriate [8] due to the variety of factors that can influence the quality of the prosthesis obtained – such as printer calibration, resin characteristics, environmental conditions, etc. – and because of design complexity. First, the dental geometry is acquired, and then the reference CAD (computer-aided design) model is created. Once the STL file has been converted, its added value preparation is carried out in the preparation environment in which the additive manufacturing method is exploited. The manufacturing job is related with printing parameters, materials needed, expected printing time, shrinkage, distortion, surface quality, and materials cost. The STL Geometry is sliced into layers and the tool pathways are generated prior to manufacture. Support removal, cleaning, curing and finishing, are all processes following resin printing. As printing conditions after printing can affect the mechanical and surface properties of printed resin [7], [16], the following post-printing processes are continued as remanufactured processing steps.

5.2 Execution Pipeline

During execution, with the classic parameters setting, a baseline splint is first created. The exact set of parameters used then in the manufacture is then correlated with the experimentally measured parameters. The collected data is sent to the ML module which predicts the expected dimensional, mechanical, wear, time and cost responses for selected configurations. Optimisation layer optimises for very suitable settings and generates a new printing configuration. The optimized splint is then manufactured and checked to find the results of experiments, which are then used for further improvement of the model. This closed-loop implementation follows the rules described in the book for optimizing printing settings not individually with post-curing, orientation and thickness of the printed layers [7], [12], [20].

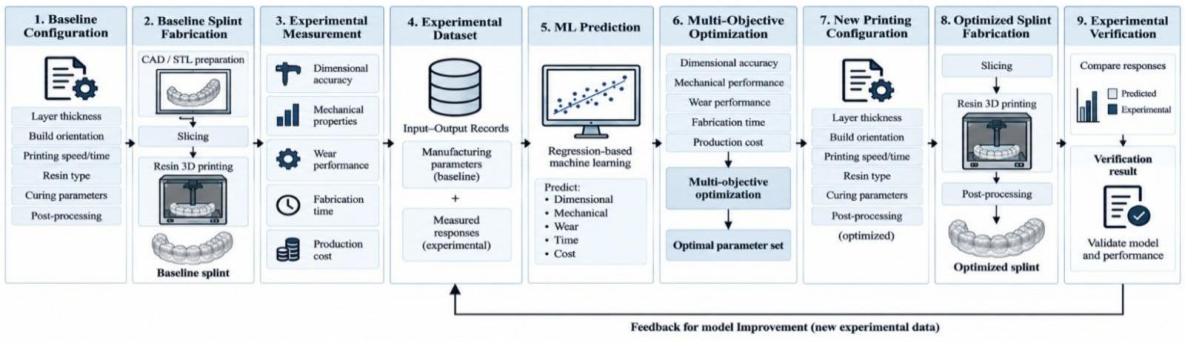

Figure 5: Closed-loop execution pipeline for baseline evaluation, machine-learning predic-

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tion, multi-objective optimization, and experimental verification of 3D-printed occlusal dental splints.

6 RESULTS AND DISCUSSIONS

Results are discussed using the experimental design that was used to evaluate the precision, mechanical properties, wear and economic feasibility of 3D-printed dental splints (occlusal splints) with machine learning. However, the paper submitted doesn't contain enough measured data, statistical testing, full data on comparison groups, or validated (specimens) experimental data to support the reporting of new numerical experimental results. There can be no decisive mechanical and dimensional results without first being confirmed from experiments and statistical analysis. Hence, differences are being made in this following debate between literature benchmarks that are no longer documentary, and those which are more findings, to be generated through experimentation.

The main performance variables are dimensional correctness, mechanical strength, wear resistance, production time, material consumption and manufacturing costs. Our previous research indicates that printing parameters and technology have a significant impact on dimensional precision [1–4], [8], [9]. Also, the occlusal splint's accuracy is influenced by the orientation in which it is printed, and the ideal print orientation depends on how the printer is configured [12]. Rather than a universal ideal it provides support for the proposed ML strategy which is to 'pick up' individual parameter links unique to different materials and printers.

Table 2: PERFORMANCE METRICS FROM THE LITERATURE

Performance Metric	**Reported Evidence**	**Implication for Proposed Study**
Geometric deviation (splint trueness)	printers dependent; orientation has a large effect on splint trueness [9], [12]	Reduce geometric deviation
In combination, enhance strength and durability.	Mechanical/wear performance is affected by curing, layer thickness, resin and orientation	[16], [20].
Same clinical utility	short-term clinical results of printed vs milled splints were comparable [13]	Utility confirmed on clinically enhanced validation specimens

In addition, when comparing to previous methods, one can highlight that the use of additive manufacturing has certain advantages such as customization and product efficiency, even if in certain conditions, it cannot be performed as accurately as milling can. [5], [8] It has been found through use of ML based experiments in additive manufacturing (AM) that process results can be predicted and experiments can be reduced via trial and error [10], [11]. Thus, the expected impact of the proposed framework is not only to improve the accuracy of the printing, but also to achieve accuracy, mechanical performance, processing efficiency and cost.

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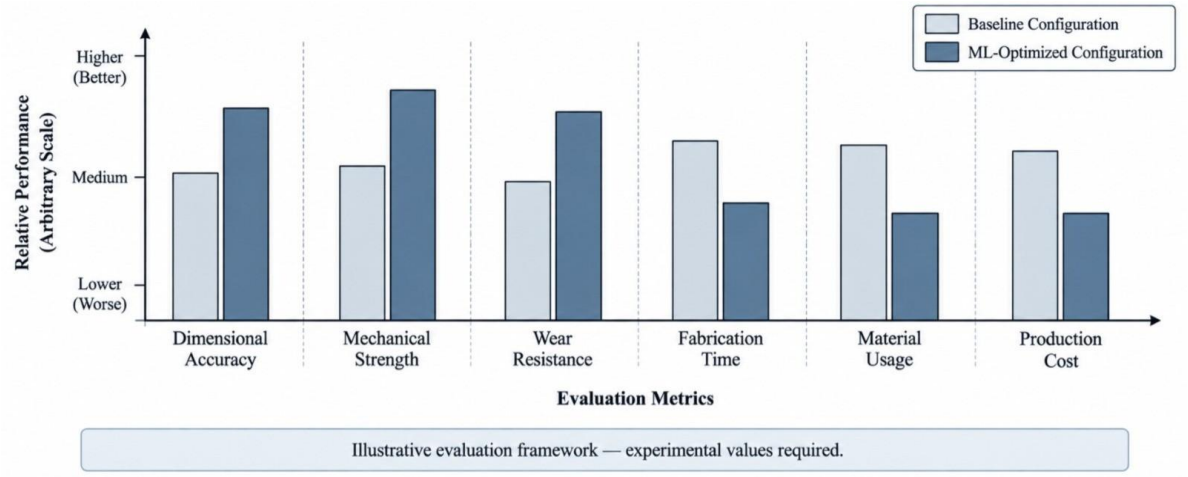

Figure 6: Schematic performance-evaluation framework for comparison of baseline and ML-optimized configurations.

Proposed Approach is a comparison of the proposed approach and prior methods used.

Table 3: Proposed Approach is a comparison of the proposed approach and prior methods used.

Method	**Stated Result/Trait**	**Constraint**
Non-standard production [5], [8]	Essentially the same relatively good dimensional and mechanical characteristics	Greater material/process requirements
Optimization and printing of 3D conventional prints [12], [20]	Optimization of printing parameters, increased performance	Optimization of parameters; Enhanced ML integration

The proposed system gets technical support from the literature as a result. Optimising one response may affect another response – such as increased efficiency may reduce dimensional fidelity, and conditions of curing may alter mechanical and physical properties [7], [16] – and are particularly relevant to the multi-objective design. The mechanical strength, wear, fabrication time and cost are baseline and ML-related factors to test for using dimensional deviation in the final experimental investigation. These data will reveal if the improved configuration is sufficiently better than the standard configuration in a statistically significant way and be fruitful in the field. Claims for numerical performance should not be included as experimental results until they become available.

7 CONCLUSION

This research aims the introduction of experimental approach for assessing the efficiency of the optimization of spleen tooth pieces fabricated using 3D printing technology, and optimized by the machine learning methodology. All of these involved include a digital scanning process, CAD helped to design the items, resin based additive manufacturing, post-process, dimensional material assessment and performance evaluation. The proposed approach is based on a single optimization strategy that considers imperatives such as printing parameters, material properties, build orientation, curing conditions, manufacturing time and associated costs to address the

challenge of precise, cost-effective, and clinically viable manufacturing demands. The study is designed to establish a closed loop method whereby the dimensional accuracy, mechanical properties, wear properties, fabrication time and cost of the component can be measured and used to further enhance the selection of future outcomes. The key take away of the framework is its practical applications and the ability to reduce the "trial and error" of splint It is recommended that future research focus on building up the experimental data base which should include a wide range of resin materials, printers, layer thicknesses, build orientations, curing conditions, and post-processing techniques. After making statistical comparisons in terms of prediction and optimization performance, there are several machine learning models to be trained and validated in a standard way, with standardized experimental measurements.

References

[1] Y. Etemad-Shahidi, O. B. Qallandar, J. Evenden, F. Alifui-Segbaya, and K. E. Ahmed, "Accuracy of 3-dimensionally printed full-arch dental models: A systematic review," *J. Clin. Med.*, vol. 9, no. 10, p. 3357, 2020, doi: 10.3390/jcm9103357.

[2] E. Anadioti, L. Musharbash, M. B. Blatz, G. Papavasiliou, and P. Kamposiora, "3D printed complete removable dental prostheses: A narrative review," *BMC Oral Health*, vol. 20, p. 343, 2020, doi: 10.1186/s12903-020-01328-8.

[3] A. Della Bona, V. Cantelli, V. T. Britto, K. F. Collares, and J. W. Stansbury, "3D printing restorative materials using a stereolithographic technique: A systematic review," *Dent. Mater.*, vol. 37, no. 2, pp. 336–350, 2021, doi: 10.1016/j.dental.2020.11.030.

[4] S.-Y. Yoo, S.-K. Kim, S.-J. Heo, J.-Y. Koak, and J.-G. Kim, "Dimensional accuracy of dental models for three-unit prostheses fabricated by various 3D printing technologies," *Materials*, vol. 14, no. 6, p. 1550, 2021, doi: 10.3390/ma14061550.

[5] C. Herpel, A. Tasaka, S. Higuchi, D. Finke, R. Kühle, K. Odaka, S. Rues, C. J. Lux, S. Yamashita, P. Rammelsberg, and F. S. Schwindling, "Accuracy of 3D printing compared with milling—A multi-center analysis of try-in dentures," *J. Dent.*, vol. 110, p. 103681, 2021, doi: 10.1016/j.jdent.2021.103681.

[6] P. Dua, "3D printing in restorative dentistry: A review of materials, accuracy, and clinical applications," *Int. J. Appl. Pharm. Sci. Res.*, vol. 7, no. 4, 2022, doi: 10.21477/ijapsr.7.4.04.

[7] O. Alageel, "Three-dimensional printing technologies for dental prosthesis: A review," *Rapid Prototyping J.*, vol. 28, no. 9, pp. 1764–1778, 2022, doi: 10.1108/RPJ-07-2021-0164.

[8] E. Anadioti, B. Kane, Y. Zhang, M. Bergler, F. Mante, and M. B. Blatz, "Accuracy of dental and industrial 3D printers," *J. Prosthodont.*, vol. 31, suppl. 1, pp. 30–37, 2022, doi: 10.1111/jopr.13470.

[9] A. Nulty, "A comparison of trueness and precision of 12 3D printers used in dentistry," *BDJ Open*, vol. 8, p. 14, 2022, doi: 10.1038/s41405-022-00108-6.

[10] S. R. Dabbagh, O. Özcan, and S. Taşoğlu, "Machine learning-enabled optimization of extrusion-based 3D printing," *Methods*, vol. 206, pp. 27–40, 2022, doi: 10.1016/j.ymeth.2022.08.002.

[11] S. Kumar, T. Gopi, N. Harikeerthana, M. K. Gupta, V. Gaur, G. M. Krolczyk, and C. S.

Wu, "Machine learning techniques in additive manufacturing: A state of the art review on design, processes and production control," *J. Intell. Manuf.*, vol. 34, pp. 21–55, 2023, doi: 10.1007/s10845-022-02029-5.

[12] A. B. Cameron, K. Tong, S. Tadakamadla, J. L. Evans, and M. Abuzar, "Effect of build orientation on the trueness of occlusal splints fabricated by three-dimensional printing," *J. Oral Sci.*, vol. 65, no. 4, pp. 261–264, 2023, doi: 10.2334/josnusd.23-0115.

[13] C. Herpel, J. Kykal, S. Rues, F. S. Schwindling, P. Rammelsberg, and L. Eberhard, "Thermo-flexible resin for the 3D printing of occlusal splints: A randomized pilot trial," *J. Dent.*, vol. 133, p. 104514, 2023, doi: 10.1016/j.jdent.2023.104514.

[14] X. Sun, Y. Feng, Y. Jiao, and W. Liu, "Fully digital workflow for the fabrication of occlusal stabilization splints based on individual mandibular movement," *J. Dent.*, vol. 141, p. 104826, 2024, doi: 10.1016/j.jdent.2023.104826.

[15] A.-B. Faur, R. N. Rotar, and A. Jivănescu, "Intaglio surface trueness of dentures bases fabricated with 3D printing vs. conventional workflow: A clinical study," *BMC Oral Health*, vol. 24, p. 671, 2024, doi: 10.1186/s12903-024-04439-8.

[16] A. Pauls and A. Hornberg, "Accuracy of soy-based resins for dental 3D printing," *Angle Orthod.*, vol. 94, no. 5, pp. 574–580, 2024, doi: 10.2319/112523-779.1.

[17] P. Hobbi, T. M. Ordueri, F. Öztürk-Bozkurt, T. Toz-Akalın, M. Ateş, and M. Özcan, "3D-printed resin composite posterior fixed dental prosthesis: A prospective clinical trial up to 1 year," *Front. Dent. Med.*, vol. 5, p. 1390600, 2024, doi: 10.3389/fdmed.2024.1390600.

[18] N. G. Chander and A. Gopi, "Trends and future perspectives of 3D printing in prosthodontics," *Med. J. Armed Forces India*, vol. 80, no. 4, pp. 399–403, 2024, doi: 10.1016/j.mjafi.2024.05.003.

[19] N. C. Arun Prasad, S. Gokul, S. Gayathri, B. Sowndarya, P. Yazhini, M. A. Monisha, and V. Abarna, "Use of 3D printing in prosthodontics: A review," *Asian J. Dent. Sci.*, vol. 6, no. 1, pp. 144–149, 2023.

[20] A. Kaushik, R. K. Garg, R. S. Saini, F. Bennardo, and A. Heboyan, "Evaluating the effect of printing parameters on the performance of resin occlusal splints for a sustainable dentistry," *J. Appl. Biomater. Funct. Mater.*, vol. 23, 2025, doi: 10.1177/22808000251333700.