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Article

# A methodological framework for AI-Assisted design and fabrication of patient-specific cranial plug prostheses

# Marco metodológico para el diseño y fabricación asistidos por IA de prótesis craneales personalizadas tipo tapón

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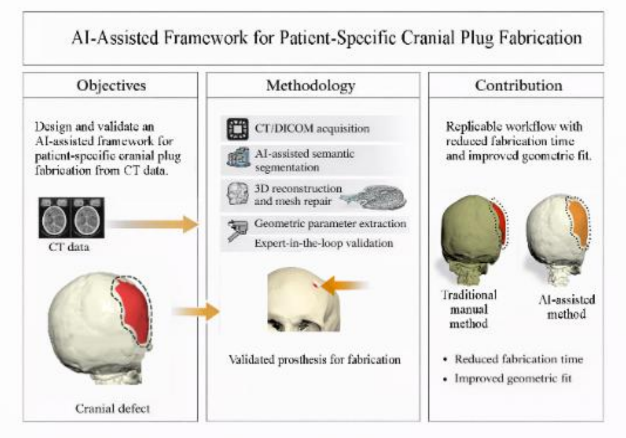
## Abstract

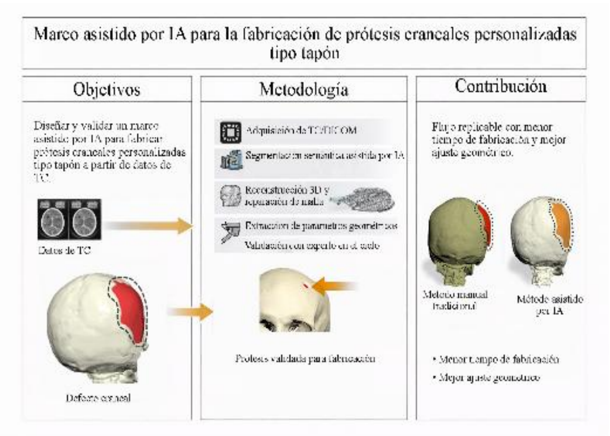
This paper presents an artificial intelligence-assisted methodological framework for the design and fabrication of patient-specific cranial plug prostheses from computed tomography data. The proposed workflow integrates AI-assisted semantic segmentation, three-dimensional reconstruction, topological repair of the anatomical model, geometric parameter extraction for prosthesis generation, and an expert-in-the-loop validation stage to ensure clinical viability prior to fabrication. The methodology was validated through a comparative analysis against a traditional manual fabrication procedure, using a small-scale cranial perforation as a test case with high geometric fit requirements. Results showed a substantial reduction in fabrication time and an improvement in the anatomical fit of the AI-generated device. Overall, the findings support the proposed framework as a replicable, precise, and efficient alternative for patient-specific prosthesis fabrication in clinically demanding settings.



**AI-assisted design; Patient-specific cranial prostheses; Semantic segmentation**

## Resumen

Este artículo presenta un marco metodológico asistido por inteligencia artificial para el diseño y fabricación de prótesis craneales personalizadas tipo tapón a partir de datos tomográficos. El flujo propuesto integra segmentación semántica asistida por IA, reconstrucción tridimensional, reparación topológica del modelo anatómico, extracción geométrica de parámetros protésicos y una etapa de validación con el experto en el ciclo para asegurar viabilidad clínica antes de la fabricación. La metodología se validó mediante un análisis comparativo frente a un procedimiento tradicional de fabricación manual, utilizando como caso de prueba una perforación craneal de pequeña escala con alta exigencia de ajuste geométrico. Los resultados mostraron una reducción sustancial del tiempo de fabricación y una mejora en el ajuste anatómico del dispositivo generado por IA. En conjunto, los hallazgos sostienen que el marco propuesto constituye una alternativa replicable, precisa y eficiente para la fabricación de prótesis personalizadas en contextos clínicamente exigentes.



**Diseño asistido por IA; Prótesis craneales personalizadas; Segmentación semántica**

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## Introduction

Artificial intelligence [AI] has become increasingly relevant in medical image analysis and in the optimization of digitally assisted manufacturing workflows. In craniofacial prosthetic rehabilitation, these advances are especially important because prosthetic quality depends not only on material selection, but also on the precision with which patient-specific anatomy can be segmented, reconstructed, and translated into a manufacturable design. Recent studies indicate that digital workflows continue to improve prosthetic fabrication; however, reproducibility and standardization remain limited when multiple manual steps are still required and when image processing, model preparation, and fabrication are not integrated into a single controlled sequence [II, III].

As previously demonstrated by Hernández-Maldonado and Rios-Solis [I], precise digital modeling and three-dimensional printing of biocompatible craniofacial prostheses are both feasible and clinically relevant. However, that earlier work focused on demonstrating the practical viability of digital fabrication rather than formalizing an AI-assisted methodological framework specifically oriented to patient-specific cranial plug prostheses derived from computed tomography data. The present study extends that line of research by proposing a structured workflow in which AI-assisted processing, three-dimensional reconstruction, topological repair, geometric parameter extraction, and expert validation are explicitly integrated into a single methodological sequence [I].

The added value of the proposed framework, in comparison with conventional manual techniques, lies in its methodological integration. Instead of relying primarily on iterative manual modeling, the workflow combines CT/DICOM acquisition, AI-assisted semantic segmentation, mesh repair, computational extraction of prosthetic parameters, and expert-in-the-loop validation prior to fabrication. This integration is particularly relevant for small-scale cranial defects, where minor dimensional deviations can directly affect fit, stability, and clinical usability. In this sense, the contribution of this study is not merely the fabrication of a single prosthetic device, but the formalization of a replicable process capable of reducing manual variability while preserving clinical oversight [II, IV, V].

Accordingly, the problem addressed in this article is the absence of a sufficiently standardized and integrated AI-assisted workflow for the design and fabrication of patient-specific cranial plug prostheses with high geometric precision. The central hypothesis is that an AI-assisted methodological framework, complemented by expert-in-the-loop validation, can improve fabrication efficiency and geometric fit when compared with a traditional manual fabrication procedure, without eliminating the need for human clinical judgment [I, III, V].

Based on this hypothesis, the first objective of the study is to evaluate the capacity of an AI-assisted workflow to support the design of a patient-specific cranial plug prosthesis from CT-derived anatomical data. The second objective is to assess the practical efficiency of the framework through comparison with a traditional manual fabrication procedure, focusing on fabrication time and geometric fit as the two central performance criteria. In this way, the article seeks to demonstrate that an AI-assisted and expert-validated workflow can provide a more precise, reproducible, and efficient alternative for the fabrication of patient-specific cranial plug prostheses in clinically demanding settings [III, IV, V].

The remainder of this article is organized as follows. Section 2 presents the methodological framework, including data preparation, AI-assisted segmentation, three-dimensional reconstruction, topological repair, geometric parameter extraction, and expert validation. Section 3 describes the comparative procedure used to evaluate the proposed workflow against a traditional manual fabrication method. Section 4 presents the results of the comparison, with emphasis on fabrication time and geometric fit. Finally, Section 5 discusses the implications, limitations, and future validation needs of the proposed framework, and Section 6 summarizes the main conclusions.

## 2. Methodology

### 2.1 Data Collection and Preparation

Computed tomography [CT] scans in DICOM format were acquired in collaboration with specialized clinical professionals, ensuring that the volumetric data were suitable for patient-specific anatomical reconstruction.

These data were preprocessed using the open-source platform 3D Slicer, which has been widely used in medical image analysis workflows and supports semi-automatic segmentation for anatomical modeling [II]. In particular, the Segment Editor modules, including AI-assisted tools such as Grow from Seeds, were used to delineate the relevant cranial structures. This preprocessing stage also included the removal of noise and imaging artifacts in order to preserve data fidelity throughout the modeling workflow [VII].

The present study focuses on a restricted geometric problem: the design and fabrication of a patient-specific cranial plug prosthesis derived from CT data. In contrast with previous work that established the feasibility of precise digital modeling and 3D printing of craniofacial prostheses [I], the current framework emphasizes methodological integration and geometric precision in a localized cranial defect.

The proposed workflow was validated using a clinical case involving a small circular perforation located on the left side of the skull, originally created to accommodate a ventriculoperitoneal [VP] shunt valve, as shown in Figure 1. This case was selected because it represents a demanding geometric condition: although the defect is small, it requires a high degree of dimensional precision and close anatomical adaptation. In methodological terms, this makes it an appropriate test case for evaluating the performance of AI-assisted segmentation, three-dimensional reconstruction, and geometric parameter extraction in a controlled prosthetic design workflow.

**Box 1**

**Figure 1**

Left side of the skull, highlighting the perforation in the upper region where the drainage valve was placed.

*Source: STL model visualized in Autodesk 3ds Max 2025.*

The relevance of this case also lies in its anatomical context. The patient presented a broader history of cranial intervention, including a decompressive craniectomy, which increased the complexity of the dataset and required the workflow to isolate the specific region of interest without confusing it with larger cranial defects. In this sense, the case allowed the proposed framework to be tested not only as a design routine, but also as a selective processing strategy for localized reconstruction problems in a complex cranial anatomy [VIII].

Accordingly, the data collection and preparation stage was designed to ensure that the subsequent methodological phases were grounded on a clean, anatomically reliable, and clinically interpretable digital model. This step was therefore not limited to image acquisition, but served as the foundation for segmentation, reconstruction, geometric analysis, and later expert validation within the complete workflow.

Furthermore, to document the full complexity of the anatomical dataset processed by the AI-assisted workflow, the patient's contralateral [right] skull side is shown in Figure 2. This image reveals an extensive decompressive craniectomy that is unrelated to the target plug prosthesis.

Its inclusion is methodologically relevant because it shows that the workflow had to operate within a highly asymmetric cranial anatomy rather than in an isolated or simplified defect scenario. In this context, the proposed segmentation strategy was able to isolate and process the small-scale region of interest corresponding to the plug defect [Figure 1] without confusion from the larger cranial defect visible on the opposite side [Figure 2].

This supports the use of the proposed workflow as a selective processing strategy for localized prosthetic reconstruction in anatomically complex cases.

**Box 2**

**Figure 2**

Lateral view of the right side of the skull, showing the extent of the decompressive craniectomy and the large bone removal.

*Source: STL model visualized in Autodesk 3ds Max 2025.*

Finally, Figure 3 provides an anterior [frontal] view that is relevant to the methodological validation stage. This perspective was used to define the boundaries of the two regions of interest within the same dataset: the small plug defect selected for prosthetic reconstruction and the larger craniectomy defect present elsewhere in the skull.

**Box 3**

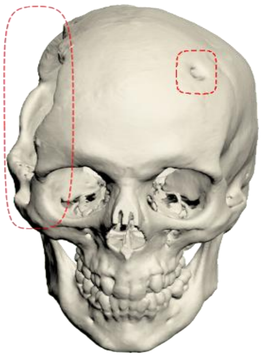

**Figure 3**

Fractured skull without the two prostheses in place, illustrating the extent of the cranial damage.

*Source: STL model visualized in Autodesk 3ds Max 2025.*

This figure also illustrates the anatomical complexity of the case. The proposed workflow had to operate on a highly asymmetric and damaged cranial structure while still isolating the correct target for plug prosthesis design. In addition, this unified view served as the anatomical baseline for the quantitative fit analysis presented in the Results section, where the final prosthesis was evaluated against the original defect margins.

## 2.2. 3D Model Generation

Following the segmentation process and the subsequent expert-in-the-loop validation of the anatomical model, the CT-derived data were converted from volumetric DICOM format into a three-dimensional surface mesh using standard tessellation formats such as STL and OBJ. This conversion step is essential because it transforms the validated anatomical information into a format compatible with Computer-Aided Design [CAD] software and additive manufacturing workflows.

The resulting STL model was then loaded into a Python environment hosted on Google Colab, which was used to perform the computational operations required for the subsequent stages of the workflow. Among these operations, the model was centered at the origin in order to establish a standardized coordinate system for geometric analysis and parameter extraction. The specific code used for this step is provided in Appendix A to preserve the readability of the main methodological section.

## 2.3. 3D Model Validation and Defect Inspection

Before prosthesis design, the skull STL model was subjected to a computational inspection in order to identify surface irregularities and topological inconsistencies that could affect geometric accuracy, structural integrity, or manufacturability. This inspection focused on the detection of discontinuities such as gaps, non-manifold regions, and inconsistent face normals.

To perform this analysis, the model was evaluated using mesh integrity checks available in the trimesh library, including watertightness, convexity, and winding consistency. This step was introduced as a preventive quality-control measure, since early identification of topological defects reduces the risk of geometric distortion during prosthesis design and later fabrication. The corresponding code is included in Appendix A.

## 2.4. Topological Repair and Model Finalization

The inspection stage confirmed that the skull STL model exported from the segmentation software presented common topological defects.

In particular, the mesh was not watertight, indicating the presence of gaps or holes in the surface, and it also showed inconsistent face normals.

To correct these issues, an automated topological repair was performed using functions from the trimesh library. Surface discontinuities were resolved through hole filling, and face normals were reoriented consistently outward. Mesh integrity is a critical prerequisite for downstream computational operations involving biomechanical analysis and digital fabrication [IV].

The result of this stage was a closed, topologically consistent, and geometrically reliable three-dimensional model, ready for the subsequent AI-assisted prosthesis design process.

### 2.5. AI-Assisted Geometric Parameter Extraction

This stage constitutes the central component of the proposed methodology. After isolating the perforation region of interest from the repaired skull model, the main challenge was to determine a prosthetic geometry capable of fitting the localized cranial defect with high precision.

Rather than relying on manual geometric modeling, an AI-assisted fitting procedure was applied. Given the circular morphology of the defect, a truncated cone was selected as the most appropriate geometric primitive for prosthesis generation. A computational fitting strategy, conceptually related to least-squares or primitive shape fitting approaches, was then used to analyze the topology of the defect boundary and estimate the dimensional parameters required for prosthesis construction. In line with AI-assisted three-dimensional reconstruction approaches [V], the objective of this step was to minimize the surface deviation between the generated primitive and the anatomical margins of the defect.

The output of this stage was not the final prosthesis itself, but the patient-specific dimensional parameters required to generate it: upper radius, lower radius, and height. These values were then used in the next stage to instantiate the prosthetic geometry.

### 2.6. Primitive Prosthesis Generation

Once the optimal geometric parameters had been obtained, the prosthesis was generated programmatically using the corresponding function in the trimesh environment. In this study, the truncated cone geometry was instantiated from the AI-derived dimensional values, producing a digital plug prosthesis consistent with the shape of the defect.

This stage represents the direct geometric materialization of the AI-assisted parameter extraction process. In other words, the prosthesis was not manually sculpted, but computationally generated from the dimensional solution estimated in the previous step. The code corresponding to this generation stage is provided in Appendix A.

### 2.7. Programmatic Assembly and Quantitative Analysis Preparation

Figure 4 shows the resulting STL mesh of the plug prosthesis generated from the AI-derived dimensional parameters. The final geometry corresponds to the dimensions obtained during the geometric extraction stage and represents the digital prosthetic model prior to its assembly with the skull.

Following generation, a programmatic assembly of the prosthesis with the skull model was performed. This was not a manual alignment process. Instead, the prosthesis was computationally translated and positioned according to the centroid and orientation of the target defect, as determined during the previous analytical stages. This ensured that both the skull and the prosthesis occupied a common coordinate system suitable for subsequent evaluation.

This assembly stage served as the basis for the later quantitative fit analysis, since it enabled direct comparison between the generated prosthesis and the original anatomical defect margins. In this way, the workflow moved from geometric generation to a verifiable configuration suitable for assessing adaptation accuracy in the Results section.

**Box 4**

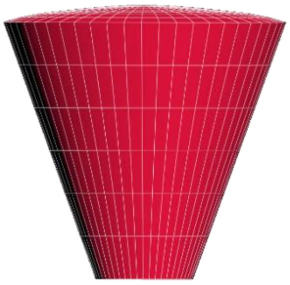

**Figure 4**

AI-generated truncated cone [plug prosthesis], showing the algorithm-derived dimensions prior to digital assembly.

*Source: STL model visualized in Autodesk 3ds Max 2025.*

Following prosthesis generation, the digital model was programmatically assembled with the skull in a shared coordinate system. Figure 5 illustrates this virtual placement of the AI-generated plug within the target defect. This alignment was not intended as a final result by itself, but as a necessary methodological step for the subsequent quantitative fit analysis.

By positioning both the skull and the prosthesis within the same reference system, the workflow enabled direct measurement of the spatial relationship between the generated prosthesis and the original anatomical margins of the defect. This made it possible to evaluate fit objectively through surface-distance analysis in the Results section.

**Box 5**

**Figure 5**

Virtual assembly of the AI-generated plug [red] programmatically placed into the target defect on the skull model. This assembly served as the basis for the quantitative fit analysis.

*Source: STL model visualized in Autodesk 3ds Max 2025.*

### 2.8. Expert-in-the-Loop [EitL] Validation.

This stage defines the interaction between the AI-assisted computational process and the human expert, constituting the Expert-in-the-Loop [EitL] validation step. In this workflow, the role of AI was not to generate the code itself, but to estimate the patient-specific dimensional parameters required for prosthesis generation by analyzing the topology of the defect boundary.

The resulting digital assembly was then presented to the professional prosthetist for evaluation. This validation logic is consistent with reported workflows in which AI-generated segmentations are subjected to structured expert review before downstream use [VI]. The expert's role was not to manually redesign the prosthesis, but to assess the computational solution in light of clinical and technical criteria. In practice, this involved reviewing the virtual fit and identifying any potential mismatch between the generated geometry and the anatomical defect, including cases in which the defect margins were ambiguous or where fabrication tolerances needed to be considered.

This stage allowed clinical judgment to remain active within the workflow. The expert could either validate the design for fabrication or request refinement of the segmentation boundaries before repeating the computational process. In this way, the proposed methodology preserved human oversight while maintaining the advantages of AI-assisted geometric estimation, ensuring that the final prosthesis was not only computationally derived but also clinically interpretable and fabrication-ready.

### 2.9. Benchmark definition and comparative methodology

To evaluate the efficacy of the proposed AI-assisted methodology, a comparative procedure was established using a traditional manual workflow as the benchmark. For the same cranial defect, a professional prosthetist manually fabricated a plug prosthesis following a conventional design process.

This manual procedure involved segmenting the defect in CAD software, taking digital measurements, and iteratively constructing the prosthetic geometry through manual modeling operations until an acceptable visual fit was achieved. In practical terms, this included the creation, scaling, and adjustment of a conical primitive to approximate the defect morphology.

Figure 6 shows the result of this traditional process: a physical three-dimensional printed skull model with the manually fabricated plug prosthesis shown in black. The total fabrication time for this benchmark method, including file preparation and modeling, was approximately three days.

This benchmark provided both a quantitative reference, represented by fabrication time, and a qualitative reference, represented by the fit achieved by the professional prosthetist. These two elements served as the control against which the AI-assisted workflow was evaluated in the Results section.

**Box 6**

**Figure 6**

Traditional fabrication benchmark: the three-dimensional printed skull with the plug prosthesis [black] manually fabricated by a professional prosthetist. The total fabrication time for this control method was approximately three days.

*Source: Actual photograph of the 3D printed prosthesis and skull.*

## 3. Results and Comparative Analysis

As established in the benchmark definition, the traditional manual fabrication method served as the control for evaluating the proposed AI-assisted workflow. As shown in Figure 6, the manually fabricated plug prosthesis was produced in approximately three days.

When placed in the printed skull model, tactile and visual inspection indicated that the control prosthesis protruded slightly above the surrounding cranial surface.

### 3.1. AI Methodology Results.

**Box 7**

**Figure 7**

AI-generated plug prosthesis [black] placed in the printed skull model. The prosthesis was produced in only a few hours, representing a substantial reduction in fabrication time compared with the traditional manual procedure.

*Source: Actual photograph of the 3D printed prosthesis and skull.*

In terms of fit, the AI-generated prosthesis exhibited a different geometric behavior from the control model. As shown in Figure 7, the prosthesis sat slightly recessed within the perforation rather than protruding above the skull surface. This difference indicates a distinct mode of anatomical adaptation and suggests that the AI-assisted workflow generated a closer integration with the defect margins, although the clinical implications of a recessed versus protruding fit require further evaluation.

### 3.2. Direct Visual Comparison

To facilitate direct visual comparison, Figure 8 presents a side-by-side enlarged view of both physical outcomes. The composite image highlights the principal difference in anatomical adaptation between the two methods.

On the left side of the red dividing line, the AI-assisted prosthesis is shown. This prosthesis exhibits a recessed fit that remains below the surrounding skull surface. On the right side, the manually designed prosthesis is shown. In contrast, this control prosthesis protrudes visibly from the skull surface. Taken together, these observations indicate that the AI-assisted workflow not only reduced fabrication time, but also produced a different and more controlled geometric adaptation to the localized cranial defect.

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Figure 8 summarizes this visual comparison, showing the recessed fit of the AI-generated prosthesis and the protruding adaptation of the manually fabricated control.

**Box 8**

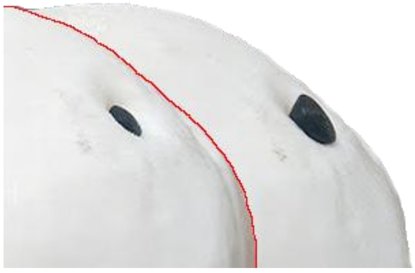

**Figure 8**

Enlarged comparison of the 3D-printed skull. The left side of the red dividing line shows the AI-generated plug prosthesis [black], exhibiting a recessed fit. The right side shows the manually designed prosthesis [black], exhibiting a protruding adaptation.

*Source: Actual photograph of both 3D printed prostheses and skull.*

## 4. Discussion

The proposed AI-assisted methodology was evaluated through direct comparison with the traditional manual fabrication procedure used as the benchmark. This comparison focused on the two central criteria defined in the study: fabrication time and geometric fit.

The results support the methodological hypothesis. First, the AI-assisted workflow reduced fabrication time from approximately three days in the traditional method to only a few hours. Second, the two workflows produced different modes of anatomical adaptation. As shown in Figure 8, the manually fabricated prosthesis protruded slightly above the skull surface, whereas the AI-generated prosthesis remained slightly recessed within the defect. Although the clinical implications of a recessed versus protruding fit require further validation, the AI-assisted workflow eliminated the protrusion observed in the control method.

These findings suggest that the value of the proposed framework lies not only in reducing production time, but also in providing a more controlled and reproducible geometric adaptation for localized cranial defects. In this sense, the contribution of the methodology is both technical and practical: it reduces dependence on iterative manual modeling while preserving expert oversight during validation.

At the same time, the results should be interpreted with caution. The present study does not claim definitive clinical superiority of one surface condition over the other. Rather, it demonstrates that the proposed workflow can generate a patient-specific prosthesis with a distinct and reproducible fit profile under a substantially shorter fabrication time. Therefore, the discussion should be centered on methodological performance rather than on definitive surgical conclusions.

### 4.1. Limitations and Future Validation Protocol.

Although the proposed AI-assisted methodology showed promising results, several limitations must be acknowledged. First, the workflow remains semi-automatic. The accuracy of the segmentation stage still depends on the quality of the CT data, the presence or absence of imaging artifacts, and the expert-in-the-loop validation process. Errors introduced during image preprocessing or segmentation could affect the geometric reliability of the final prosthesis.

Second, this study was conducted on a single clinical case. While the comparison successfully demonstrated differences in fabrication time and geometric adaptation, broader validation requires a larger sample and a more formal evaluation protocol.

To strengthen the clinical and methodological validity of the proposed framework, a three-stage validation strategy is proposed.

#### Stage 1: In vitro validation of geometric robustness

The AI-assisted parameter extraction process should be tested using controlled datasets. This may include anonymized public imaging repositories or experimental phantom models with defects of known dimensions. The purpose of this stage is to compare the dimensions predicted by the workflow against predefined geometric references.

#### Stage 2: Ex vivo validation of prosthetic fit.

The prostheses generated by the AI-assisted and manual workflows should be evaluated on physical anatomical models by experienced prosthetists or surgeons.

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This stage would focus on tactile fit, geometric adaptation, and practical manufacturability under controlled conditions.

### Stage 3: Prospective clinical validation

After ethical approval, the methodology should be assessed in a prospective clinical setting. At this stage, relevant variables may include fabrication time, intraoperative usability, postoperative fit, aesthetic outcome, and overall feasibility in clinical practice.

Only through this broader validation process can the proposed methodology be assessed for reliability, safety, and potential routine use in patient-specific cranial reconstruction.

## 5. Conclusions

This study presented and validated an AI-assisted methodological framework for the design and fabrication of patient-specific cranial plug prostheses. Rather than proposing an isolated prosthetic solution, the study formalized a replicable workflow aimed at improving geometric precision and fabrication efficiency in localized cranial reconstruction.

The main contribution of the framework lies in the integration of two complementary elements. First, it uses an AI-assisted geometric fitting procedure to extract the patient-specific dimensional parameters required for prosthesis generation directly from CT-derived anatomical data. Second, it incorporates an Expert-in-the-Loop validation stage that preserves clinical oversight before fabrication. Together, these elements allow the workflow to combine computational consistency with professional judgment.

The comparative analysis showed that the proposed methodology reduced fabrication time from approximately three days to only a few hours. It also produced a different mode of anatomical adaptation, characterized by a recessed fit that contrasted with the protruding fit observed in the manually fabricated control prosthesis. Although the clinical implications of this difference require further validation, the results support the methodological value of the proposed workflow in terms of efficiency, reproducibility, and geometric control.

Accordingly, the study concludes that an AI-assisted and expert-validated workflow can provide a viable alternative to traditional manual fabrication for patient-specific cranial plug prostheses. Future work should focus on broader validation through controlled experimental studies, physical fit assessment, and prospective clinical evaluation.

## Appendix A. Code Snippets for Methodological Implementation.

### A.1. 3D Model Centering.

This code snippet, written in Python using the trimesh library, was used to load the skull STL model, compute its centroid, and translate the mesh to the origin [0,0,0] in order to standardize its position before geometric analysis.

```
import trimesh

# Load the model
path = "path/to/skull_model.stl"
mesh = trimesh.load(path)

# Compute centroid
current_centroid = mesh.centroid

# Translate to origin
mesh.apply_translation(current_centroid)

# Verify new centroid
print("New centroid:", mesh.centroid)

# Save centered model
output_path =
"path/to/output/skull_plug_centered.stl"
mesh.export(output_path)
print(f"Centered model saved at: {output_path}")
```

### A.2. 3D Model Integrity Inspection

This code was used to inspect the skull STL model for topological defects that could affect subsequent prosthesis design, including lack of watertightness, non-convexity, and inconsistent face normals.

```
import trimesh

# Load the model
path = "path/to/perforated_skull.stl"
mesh = trimesh.load(path)

# Detect possible defects
is_watertight = mesh.is_watertight
```

```
is_convex = mesh.is_convex
is_winding_consistent =
mesh.is_winding_consistent

print(f"Is the model watertight?:
{is_watertight}")
print(f"Is the model convex?: {is_convex}")
print(f"Are normals consistent?:
{is_winding_consistent}")

# Summarize issues
issues = []

if not is_watertight:
   issues.append("The model is not watertight
(has gaps).")

if not is_convex:
   issues.append("The model is not convex.")

if not is_winding_consistent:
   issues.append("There are faces with
inconsistent normals.")

if issues:
   print("Issues found in the model:")
   for issue in issues:
      print(f"- {issue}")
else:
   print("No issues detected in the model.")
```

### A.3. Prosthesis Generation from AI-Derived Parameters

This code snippet was used to generate the truncated cone prosthesis after the AI-assisted fitting procedure determined the patient-specific geometric parameters, including upper radius, lower radius, and height.

```
import trimesh
import shutil

# Define dimensions in centimeters (values
determined by AI analysis)
radius_large = 1.1
radius_small = 0.5
height = 1.0

# Create the truncated cone
truncated_cone = trimesh.creation.cone(
   radius=radius_large,
   radius_top=radius_small,
   height=height,
   sections=64
)

# Save prosthesis model in a temporary STL file
temp_file_cone = "truncated_cone_temp.stl"
truncated_cone.export(temp_file_cone)
print("Truncated cone prosthesis generated and
saved as 'truncated_cone_temp.stl'.")

# Define destination path
destination =
"path/to/output/truncated_cone_temp.stl"

# Move the new prosthesis file
shutil.move(temp_file_cone, destination)
print(f"Truncated cone prosthesis moved to:
{destination}")
```

## Declarations

### Conflict of Interest

The author declares that there is no conflict of interest. The author has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

### Author Contributions

*Hernández-Maldonado, Victor Miguel: W*as solely responsible for the conception, development, and execution of this study. His contribution included the identification of the research problem, the formulation of the methodological approach, the design of the AI-assisted workflow, the preparation and processing of the tomographic data, the implementation of the computational procedures, the generation and evaluation of the prosthetic models, the comparative analysis against the traditional method, the interpretation of the results, and the writing and revision of the manuscript.

He also carried out the integration of the clinical, computational, and fabrication stages of the study, as well as the preparation of figures, appendices, and supporting materials required for the article.

### Data Availability

The data used in this study are not publicly available due to privacy and ethical restrictions associated with the use of patient-specific medical imaging data. Access to the underlying materials is therefore restricted and cannot be openly shared.

However, the methodological workflow, descriptive procedures, and supporting technical information necessary to understand and evaluate the study are provided within the manuscript and its appendices.

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## Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| CAD | Computer-Aided Design |
| CT | Computed Tomography |
| DICOM | Digital Imaging and Communications in Medicine |
| EitL | Expert-in-the-Loop |
| ROI | Region of Interest |
| STL | Standard Tessellation Language |
| VP shunt | Ventriculoperitoneal shunt |

## References

### Background

[I] Hernández-Maldonado, V. M., & Rios-Solis, L. [2023]. Precise modeling and 3D printing of biocompatible craniofacial prostheses. ECORFAN Journal-Republic of Guatemala, 9[17], 31–43.

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