

DESIGNING A DIGITAL RESTORATION STRATEGY FOR MUSEUM ARTIFACTS USING AI AND AUGMENTED REALITY: FROM CONCEPTUAL SCENARIOS TO FUNCTIONAL APPLICATION

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Abstract

This study proposes a design-driven framework for restoring damaged museum artifacts using artificial intelligence (AI) and augmented reality (AR). Based on an evaluation of current virtual restoration methods, seven conceptual scenarios were formulated, with Scenario 6 implemented as a functional AR prototype.

Three primary research questions guided this study:

RQ1: How can AI and AR be combined to restore incomplete artifacts while maintaining historical authenticity and enhancing public engagement?

RQ2: Which restoration scenario provides the most efficient, scalable, and accurate outcome for museum workflows?

RQ3: How can AR presentation balance interpretive depth with curatorial integrity?

Two hypotheses were evaluated:

H1: Integrating AI inpainting with AI-driven 3D modeling significantly reduces restoration time compared to manual or hybrid workflows.

H2: Presenting AI-restored artifacts via AR improves visitor engagement and contextual comprehension compared to static displays.

The results supported H1 and provided preliminary validation for H2, demonstrating the practicality of combining AI and AR for digital artifact reconstruction and museum display.

Keywords : Digital Restoration, Generative AI, Augmented Reality, Cultural Heritage, 3D Reconstruction, Interactive Museology

1. Lay Summary

Cultural heritage artifacts are frequently damaged or incomplete, yet physical restoration carries risks of altering the original object. Digital tools offer a non-invasive alternative. This study introduces a framework combining artificial intelligence (AI) to reconstruct missing portions of artifacts with augmented reality (AR) for interactive visualization. Among seven conceptual workflows evaluated, Scenario 6 was implemented as a functional application. The resulting system overlays AI-generated 3D restorations onto physical artifacts in real time, enabling interactive historical interpretation without compromising physical authenticity.

2. Introduction

Cultural heritage institutions frequently encounter artifacts that are damaged, fragmented, or missing key components. While traditional physical restoration risks permanently altering the original object, digital methods provide non-invasive, reversible alternatives. Incorporating artificial intelligence (AI) and augmented reality (AR) enables virtual reconstruction without compromising physical artifact integrity.

This study addresses three central research questions:

RQ1: How can AI and AR be combined to restore incomplete artifacts while maintaining historical authenticity and enhancing public engagement?

RQ2: Which restoration scenario provides the most efficient, scalable, and accurate outcome for museum workflows?

RQ3: How can AR presentation balance interpretive depth with curatorial integrity?

Based on these research questions, two testable hypotheses were formulated:

H1: Integrating AI inpainting with AI-driven 3D modeling significantly reduces restoration time compared to manual or hybrid workflows.

H2: Presenting AI-restored artifacts via AR improves visitor engagement and contextual comprehension compared to static displays.

To address these questions and test the hypotheses, seven conceptual restoration scenarios were developed. Among these, Scenario 6 was selected for implementation, combining AI image inpainting and 3D modeling with real-time AR visualization for museum environments.

3. Related Work

Digital Restoration in Museums

Museums and heritage institutions increasingly use digital restoration to preserve, interpret, and display damaged artifacts without physical intervention. These workflows rely primarily on 3D scanning, photogrammetry, and virtual reconstruction to restore missing elements while preserving the original object. In digital heritage literature, key considerations focus on authenticity, reversibility, and transparency during the reconstruction process (Bruno et al., 2019; Reilly, 2015).

Loizides et al. (2012) established a workflow for digitizing, reconstructing, and visualizing fragmented terracotta figurines from Nea Paphos, Cyprus. Using a ZScanner 700CX alongside MeshLab and MATLAB, their study generated complete digital models from physically incomplete originals. The manual restoration methodology in their work provided the baseline for Scenario 1 in this study, which adapts their approach by integrating AI inference directly into the scanning process.

Recent applications of Neural Radiance Fields (NeRF) and AI inpainting have expanded image-based artifact restoration. Jaramillo and Sipiran (2024) introduced a hybrid pipeline generating 3D surrogates from incomplete artifact images, demonstrating the integration of generative diffusion models with geometric reconstruction.

Augmented Reality as a Communicative Medium for Heritage

Augmented Reality (AR) facilitates museum communication by overlaying digital reconstructions and contextual narrative onto physical artifacts. Research demonstrates that AR improves visitor engagement and information retention in cultural heritage displays (Bekele et al., 2018; Wojciechowski & Cellary, 2013). However, applying AR specifically to display AI-driven artifact restorations remains limited.

Artificial Intelligence in Supporting Restoration and Archaeological Analysis

Generative AI and deep learning models are increasingly applied in artifact classification, pattern recognition, and geometric reconstruction. These algorithms reconstruct damaged surface textures, predict shapes from existing fragments, and generate missing geometry (Fiorucci et al., 2020). However, integrating generative AI workflows with real-time AR visualization remains sparsely addressed in current research.

Demonstrating the efficiency of generative models in cultural heritage, Kachkine et al. (2025) developed a real-time digital repair system that significantly reduces processing time for artwork restoration. Their findings emphasize the scalability of AI-driven reconstruction pipelines compared to manual 3D modelling.

This study integrates digital restoration theory, AI inference, and AR visualization into a single functional framework designed around curatorial requirements.

4. Conceptual Scenarios for Digital Restoration:

This section outlines seven technical scenarios for the virtual reconstruction of incomplete cultural artifacts. Figure

1 illustrates the seven conceptual scenarios developed during the initial design phase. These workflows vary by input data, degree of AI integration, level of automation, and user interaction. The diagram structures the evaluation process that led to selecting Scenario 6 for implementation, using directional arrows for data flow and color coding to differentiate manual, hybrid, and AI-driven processes. The seven technical scenarios are presented sequentially in Figures 2 through 8, followed by an in-depth analysis of each pathway across four structured dimensions: Input Data, AI/Manual Processing, Feature Extraction, and Final Output.

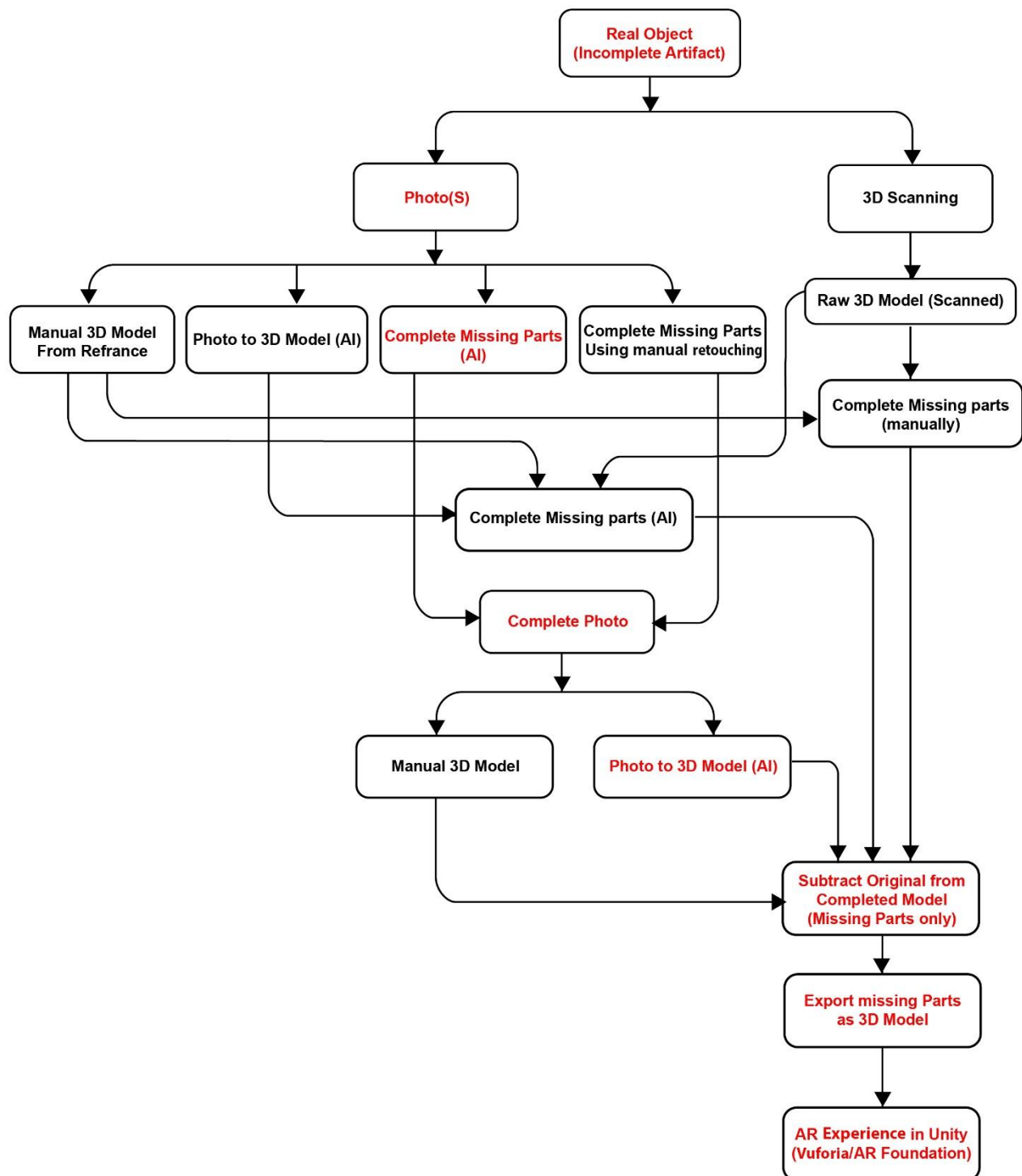


Figure 1. Schematic overview of the seven digital restoration workflows

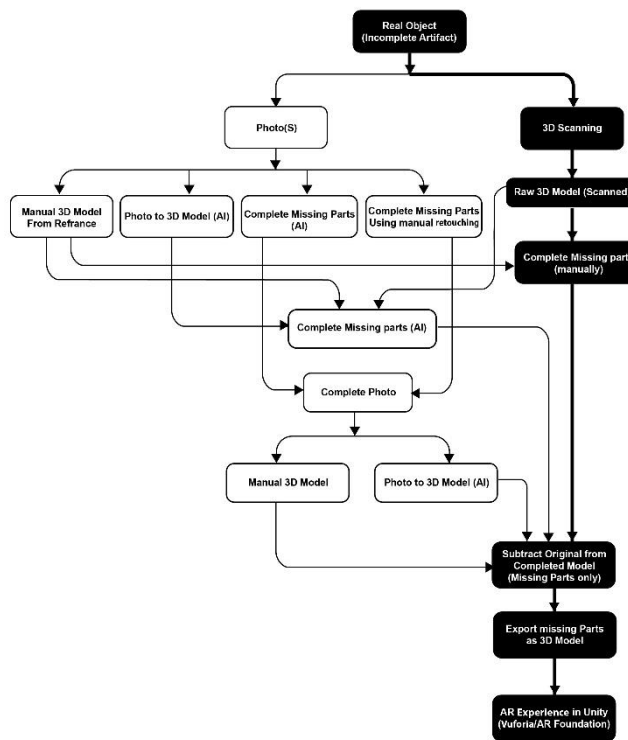


Figure 2. The workflow of Scenario 1

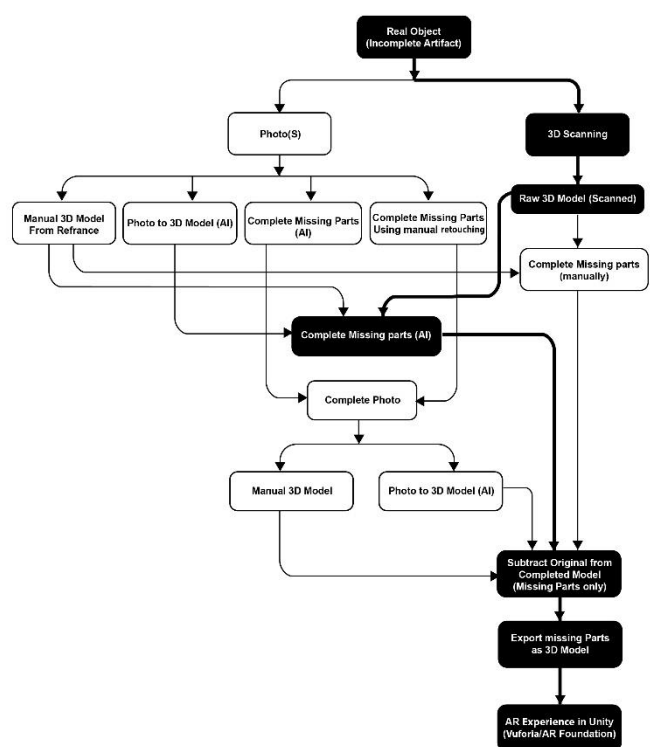


Figure 3. The workflow of Scenario 2

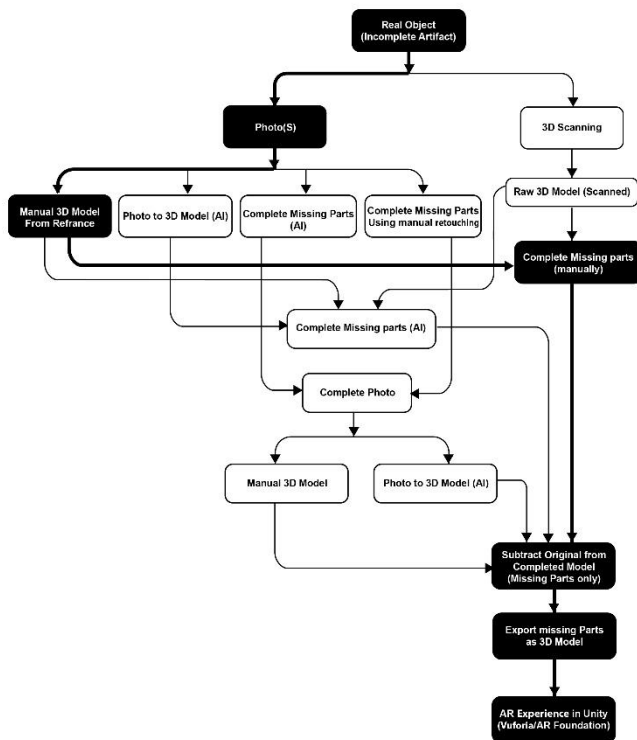


Figure4. The workflow of Scenario 3

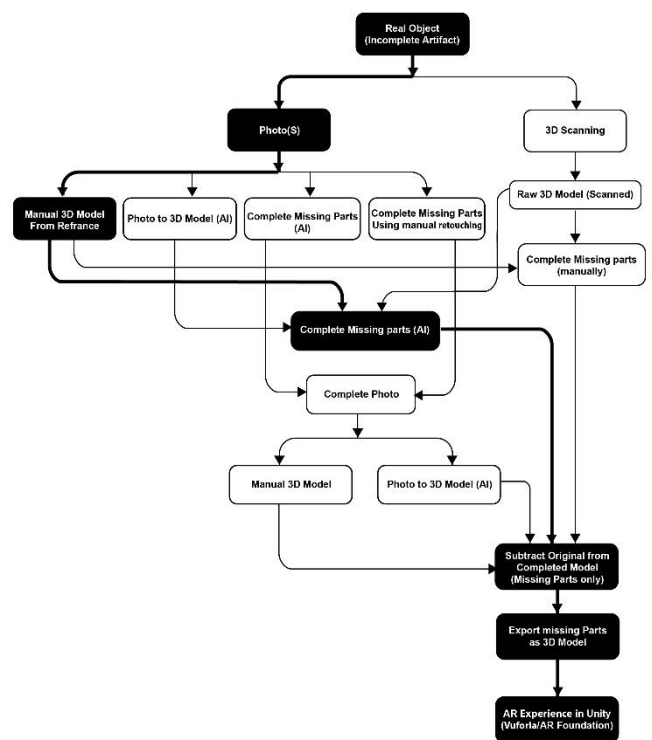


Figure5. The workflow of Scenario 4

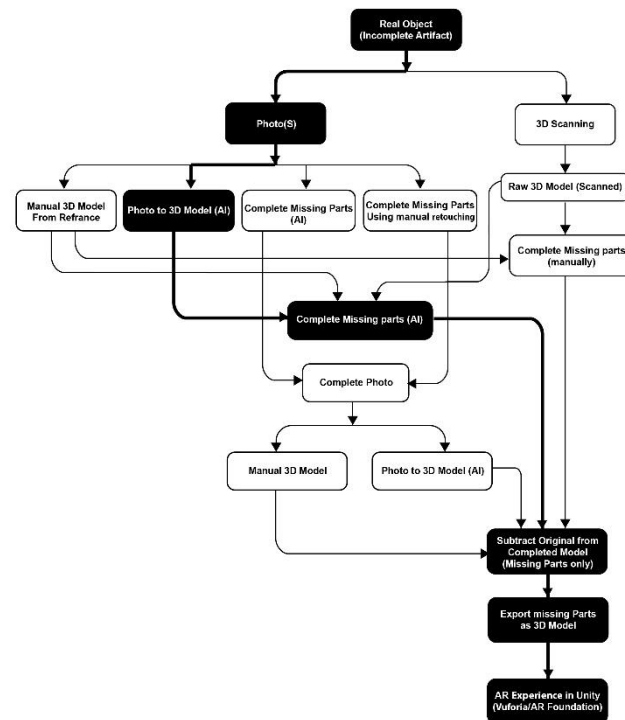


Figure6. The workflow of Scenario 5

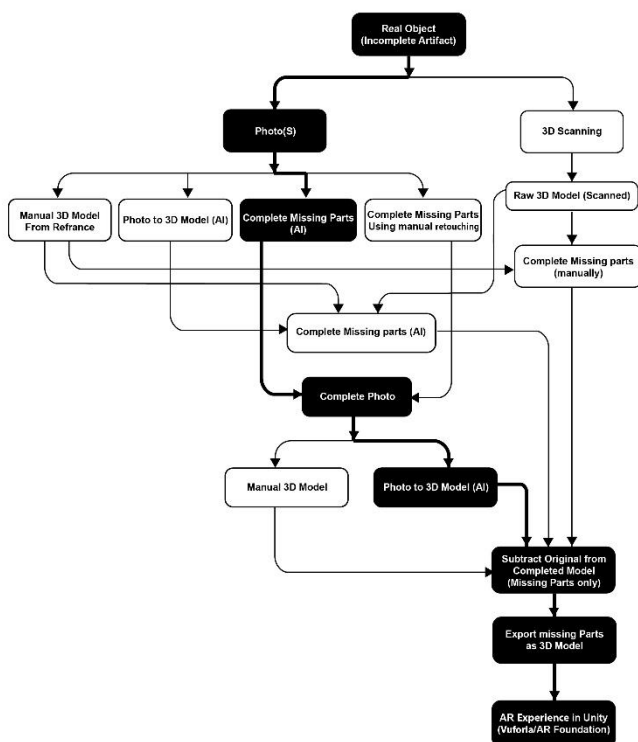


Figure 7. The workflow of Scenario 6

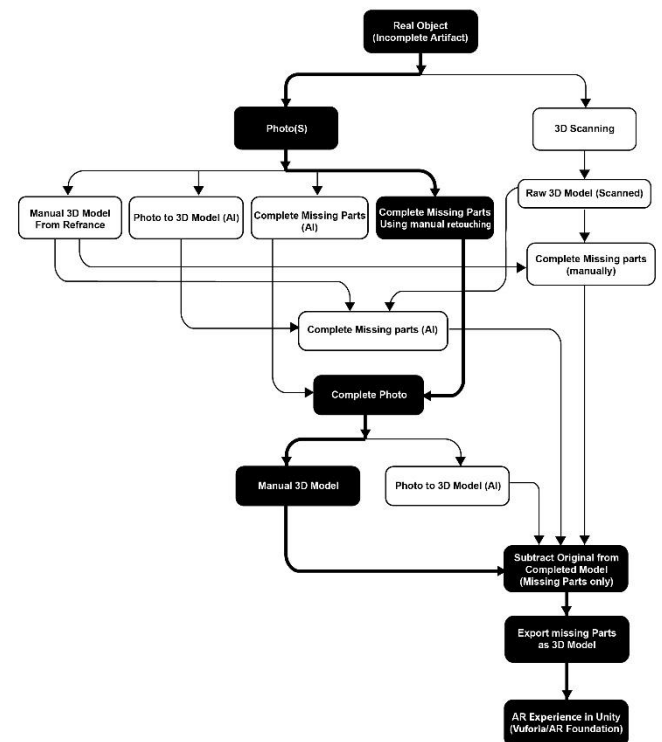


Figure8. The workflow of Scenario 7

Description of the seven scenarios:**Scenario 1: 3D Scanning → Manual Restoration → Extract Missing Parts → AR Deployment¹**

- Input: A real, incomplete artifact is scanned using photogrammetry.
- Process: A 3D mesh of the object is generated. A digital 3D artist manually reconstructs the complete shape using modelling tools such as Blender, 3ds Max, or ZBrush.
- Extraction: Boolean subtraction isolates the missing geometry by subtracting the scanned original mesh from the reconstructed volume.
- Output: The resulting mesh segment is exported in .fbx or .obj format and imported into Unity for AR deployment via Vuforia or AR Foundation.

Scenario 2: 3D Scanning → AI-Based Restoration → Extract Missing Parts → AR Deployment

- Input: A real, incomplete artifact is scanned using photogrammetry.
- Process: AI-based tools are used to complete the 3D mesh. Available options include:
 - AI features in Blender: Remesh Modifier, Auto Smooth, and add-ons like Mesh Recovery.
 - Online platforms like Meshy.ai, Kaedim, and Luma AI for automated mesh completion.
 - Deep learning models such as PCN, TopNet, VRCNet, and generative models for 3D shape completion.
- Extraction: Boolean subtraction isolates the missing geometry by subtracting the scanned original mesh from the completed volume.
- Output: The resulting mesh segment is exported in .fbx or .obj format and imported into Unity for AR deployment via Vuforia or AR Foundation.

Scenario 3: Single Photo → Manual 3D Modelling of Incomplete Object → Manual Restoration → Extract Missing Parts → AR

- Input: A single-angle photograph of an incomplete artifact
- Process: A 3D artist manually reconstructs the artifact using 3D modeling software (such as Blender) guided by reference imagery.
- Extraction: The reconstructed missing geometry is separated from the primary model and saved as an independent 3D asset.
- Output: The resulting mesh is exported in .fbx or .obj format and integrated into Unity for AR visualization via Vuforia or AR Foundation.

Scenario 4: Single Photo → Manual 3D Modelling → AI-Based Restoration → Extract Missing Parts → AR

- Input: A photo of an incomplete artifact.
- Process: The 3D Artist builds a base model manually, then uses AI-based tools to fill in the missing parts. Available methods include:
 - AI add-ons in Blender (Remesh, Mesh Recovery).
 - Online platforms (Meshy.ai, Luma AI).
 - Deep learning models like PCN, TopNet, VRCNet.
- Extraction: Boolean subtraction isolates the missing geometry by subtracting the scanned original mesh from the completed volume.
- Output: The resulting mesh segment is exported in .fbx or .obj format and integrated into Unity for AR deployment via Vuforia or AR Foundation.

Scenario 5: Single Photo → AI-Based 3D Model Generation → AI-Based Restoration → Extract Missing Parts → AR

- Input: A single-angle photograph of the damaged artifact
- Process: AI generates a 3D model from the image using:
 - Prompt-to-3D tools: DreamFusion, Magic3D, Point-E, Shap-E.
 - Image-to-3D tools: Kaedim, Meshy.ai, Sloyd.ai, Luma AI.
 - Blender add-ons like Dream Textures, Photo sculpt. Then, AI completes missing parts using the same methods as Scenario 2.

¹ This approach adapts the manual restoration framework of Loizides et al. (2012), who reconstructed terracotta statues from Paphos, Cyprus, using 3D scanning and processing software such as MeshLab and MATLAB. Scenario 1 extends this methodology by embedding pre-trained AI models into the scanning interface to automatically infer missing geometry and generate a complete 3D model in real time.

- Extraction: Boolean subtraction isolates the reconstructed missing geometry by subtracting the scanned base mesh from the generated volume
- Output: The resulting mesh segment is exported in .fbx or .obj format and integrated into Unity for AR visualization via Vuforia or AR Foundation

Scenario 6 (Implemented): Single Photo → AI-Based Inpainting → 3D Generation from Image → Extract Missing Parts → AR

- Input: A single-view image of an incomplete artifact.
- Process:
 - The image is completed via inpainting using AI tools like:
 - Photoshop with Firefly (Generative Fill)
 - Runway ML – Inpainting Workspace
 - Stable Diffusion (Stability AI)
 - DALL·E 3 (OpenAI)
 - Mask Optimization: A manual Solid Mask is created in Photoshop solely as an input pre-processing step to guide the generative diffusion model; no manual 3D sculpting or mesh editing is applied to the final geometry.
 - The completed image is converted into a 3D model using:
 - Prompt-to-3D (DreamFusion, Magic3D, Shap-E)
 - Image-based tools (Kaedim, Meshy.ai, Luma AI)
 - Blender AI add-ons (Dream Textures, Photosculpt)
- Extraction: Boolean subtraction isolates the missing geometry by subtracting the original base mesh from the completed volume.
- Output: The resulting mesh segment is exported in .fbx or .obj format and integrated into Unity for AR deployment via Vuforia or AR Foundation.

Scenario 7: Single Photo → Manual Retouching (Photoshop) → Manual 3D Modeling → Extract Missing Parts → AR

- Input: A single image of an incomplete artifact.
- Process:
 - Manual photo retouching using Photoshop's healing/clone tools.
 - Manual 3D modelling of the restored object using Blender.
- Extraction and Output: Isolate and export the missing parts for AR use.

These scenarios establish a comparative framework spanning direct manual modeling to fully automated AI inference.

Table 1 outlines how technical complexity, human intervention, and data requirements vary across workflows to inform operational selection

Scenario	Input Type	Restoration Method	AI Involvement	3D Model Source	Missing Part Extraction	AR Output
1	3D scan	Manual reconstruction	✗ No	Manual 3D modelling	Boolean Subtraction	Unity + Vuforia
2	3D scan	AI-based restoration	✓ Yes	AI-enhanced 3D model	Boolean Subtraction	Unity + Vuforia
3	Photo (single view)	Manual modelling + manual restoration	✗ No	Manual 3D modelling	Boolean Subtraction	Unity + Vuforia
4	Photo (single view)	Manual modelling + AI restoration	✓ Partial	AI-enhanced 3D model	Boolean Subtraction	Unity + Vuforia
5	Photo (single view)	AI-based modelling + AI restoration	✓✓ Full	Fully AI-generated 3D model	Boolean Subtraction	Unity + Vuforia
6	Photo (single view)	AI inpainting (2D) + AI 3D modelling	✓✓ Full	AI-generated via optimized photo	Boolean Subtraction	Unity + Vuforia
7	Photo (single view)	Manual inpainting + manual 3D modelling	✗ No	Manual 3D model based on edited photo	Boolean Subtraction	Unity + Vuforia

Table 1. Comparative Summary of the Seven Proposed Restoration Scenarios Based on Input Type, AI Integration, 3D Reconstruction Method, and AR Output.

Table 1 provides a comparative analysis of the seven restoration pathways, detailing their technical inputs, AI dependencies, reconstruction mechanics, and deployment frameworks. This evaluation serves to determine the scalability and technical feasibility of each scenario for museum-grade digital preservation.

Why was Scenario Six chosen? (Academic Analysis):

Scenario 6 was selected for implementation due to its computational efficiency, reduced reliance on manual mesh editing, and high throughput. Unlike manual or hybrid workflows that require time-intensive 3D sculpting, this pathway employs generative diffusion and 2D-to-3D reconstruction algorithms to infer missing geometry directly from single-view photographs.

From a strategic workflow perspective, Scenario 6 offers a scalable and accessible framework that enables non-specialist museum staff—such as curators and educators—to initiate digital restorations. Integrated with AR deployment, the system delivers contextual artifact visualizations without compromising structural authenticity. Consequently, implementing this scenario directly evaluates RQ2 regarding technical efficiency and tests H1 by measuring automation-driven reductions in processing time.

5. System Design and Implementation

The prototype implementation adopts Scenario 6 due to its end-to-end AI architecture-integrating image inpainting directly with 3D reconstruction. This fully automated pipeline minimizes manual overhead, ensuring scalability, repeatability, and precise control for museum-grade applications. The execution comprised four sequential steps:

Step 1: Input Acquisition

A series of photographs were taken of various incomplete museum artifacts from different historical periods, located at the National Museum of Saudi Arabia. A specific object was selected and photographed from a single angle (Figure 9).



Figure 9. Incomplete museum artifact photographed at the National Museum of Saudi Arabia

Step 2: Image Inpainting Using AI

The incomplete image was digitally restored using **AI-based inpainting**, a process that relies on **diffusion models** or **GANs** to reconstruct the missing visual areas while preserving contextual accuracy.

Among the available tools, **Runway ML – Inpainting Workspace** was selected due to its user-friendly interface, support for high-resolution outputs, and its proven performance in art and heritage-related inpainting tasks compared to other AI tools was used. The user uploaded the image, masked the missing area, and prompted the system to fill it (Figure 10).

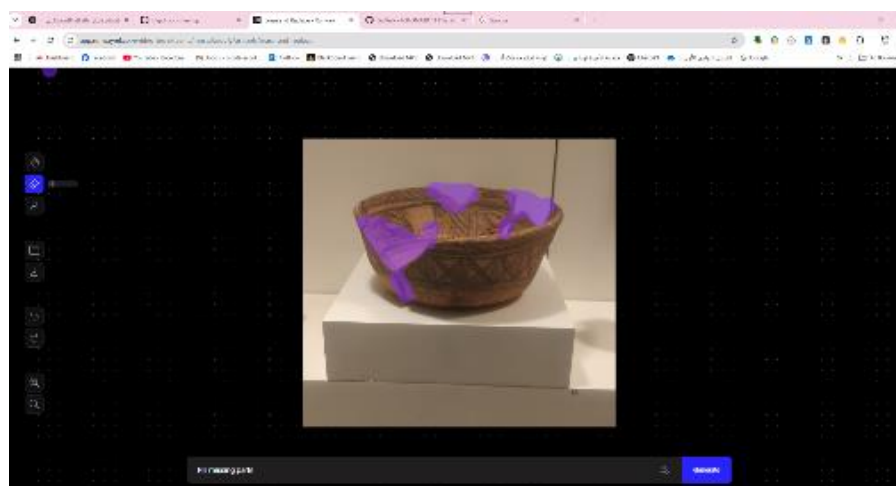


Figure 10. Masking the missing area in Runway ML – Inpainting Workspace

However, initial attempts yielded inaccurate results (Figure 11), especially in areas marked with red circles.

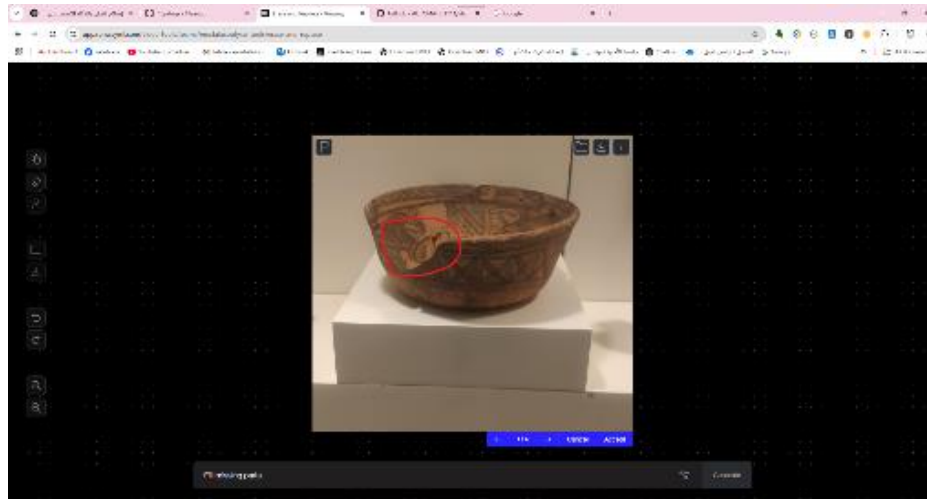


Figure 11. Initial low-quality inpainting result showing distortion in red-circled areas

To enhance accuracy, Photoshop was used to fill in the missing spaces with solid color masks, helping the AI model interpret the shape and structure more effectively (Figure 12).

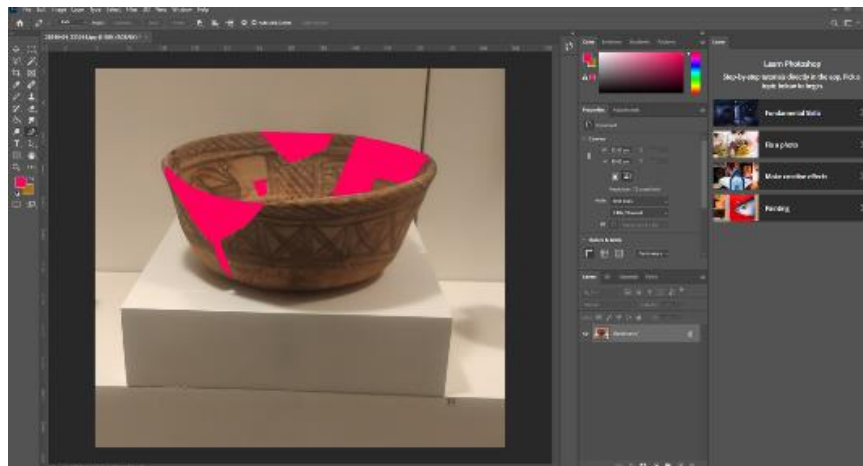


Figure 12. Using Photoshop to insert solid masks in the missing spaces before re-inpainting.

The modified image was reprocessed through Runway ML, resulting in significantly improved outputs (Figure 13).

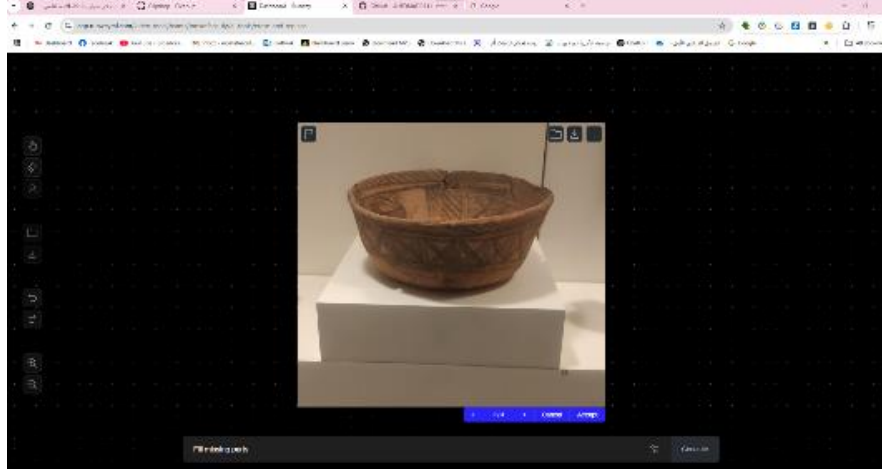


Figure 13. Final improved inpainting result after Photoshop pre-processing.

Step 3: 3D Model Generation Using AI

The restored image was then transformed into a 3D model using **Meshy.ai**², a web-based tool for converting 2D images into textured 3D models.

This method aligns with recent developments in AI-driven restoration workflows, such as the use of diffusion inpainting combined with NeRF-based 3D modeling described by Jaramillo and Sipiran (2024), which produced high-fidelity virtual surrogates of ceramic artifacts for museum display. The resulting object, shown in Figure 14

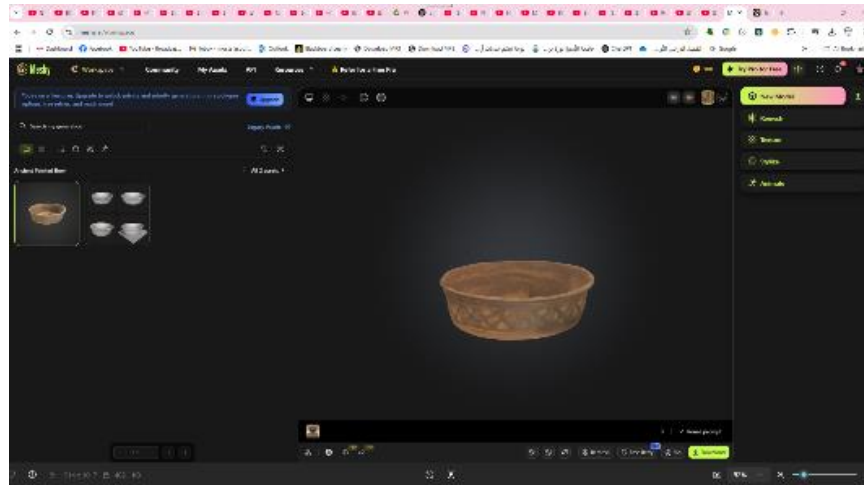


Figure 14. 3D model generated in Meshy.ai based on the inpainted image was downloaded in **.fbx** format, along with its material texture file (Figure15).

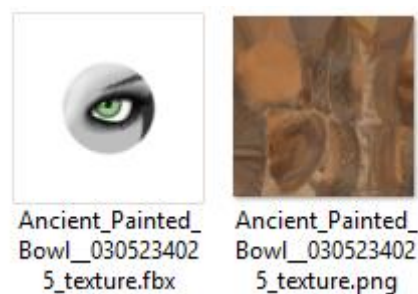


Figure 15. Exported FBX model and material texture files from Meshy.ai

Step 4: Blender Post-Processing and Mesh Extraction

The 3D model was imported into **Blender**, a 3D content creation suite used here to isolate the digitally reconstructed segments.

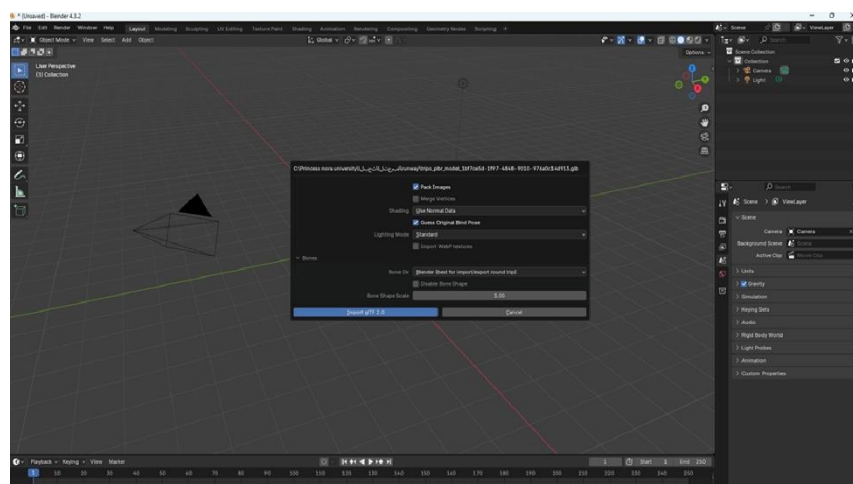


Figure 16. Imported FBX file into Blender for post-processing

² Meshy.ai. (2024).

Meshy - AI 3D Model Generator.

Retrieved from: <https://meshy.ai>



Figure 17. Blender scene showing 3D model before applying materials

The key operation applied was Boolean Subtraction, which enables the subtraction of the incomplete mesh from the complete version—precisely extracting only the newly generated parts.

This method ensures a clean, geometry-based separation suitable for downstream AR deployment. (Figures 16 and 17), where the associated materials were reapplied (Figure 18).



Figure 18. Model after applying original materials inside Blender

Boolean operations were used to subtract the original (incomplete) mesh from the complete one, isolating only the reconstructed (missing) segments (Figure 19).

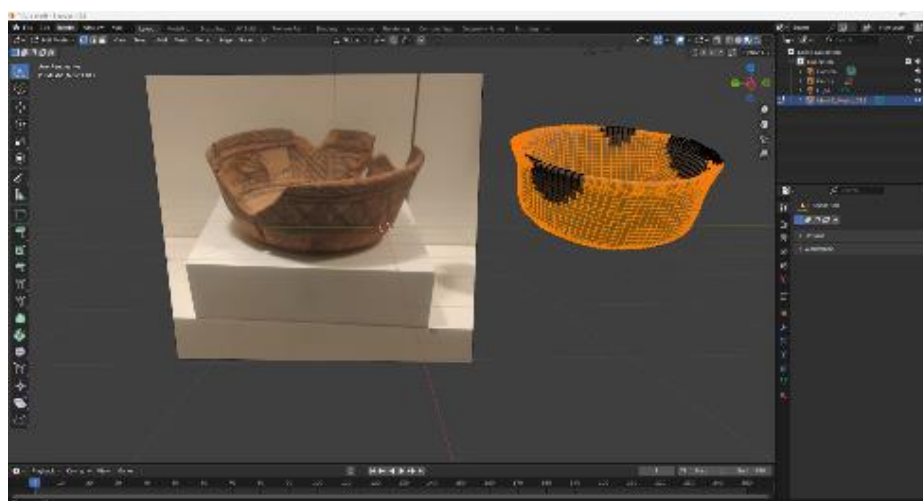


Figure 19. Boolean subtraction process to isolate digitally reconstructed mesh

The resulting output was a 3D file containing **only the restored portions** (Figure 20).

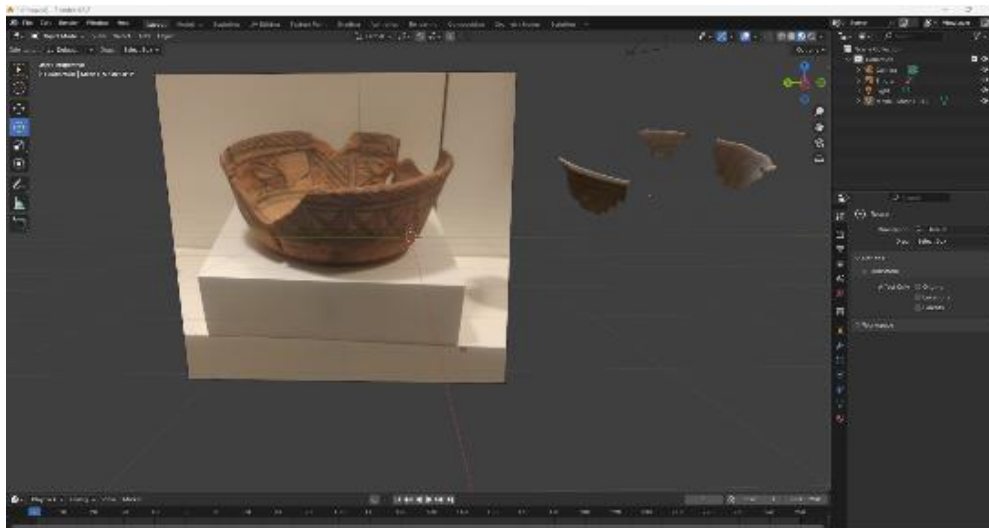


Figure 20. Final restored portions exported for AR deployment

Step 5: AR Integration with Unity and Vuforia

The isolated 3D model was exported in **.fbx/.obj** format and imported into a **Unity** project configured with **Universal 3D settings**. Necessary libraries, including Open JDK and Android SDK/NDK, were installed (Figures 21 and 22).

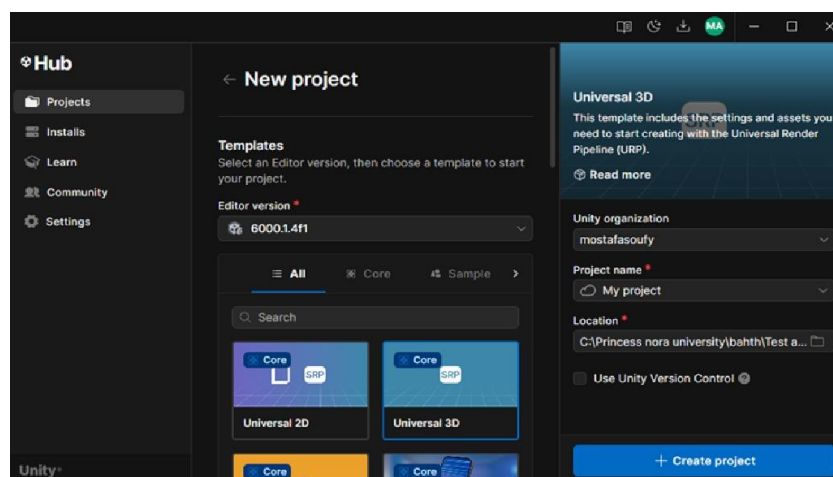


Figure 21. Creating a new Unity project for AR integration

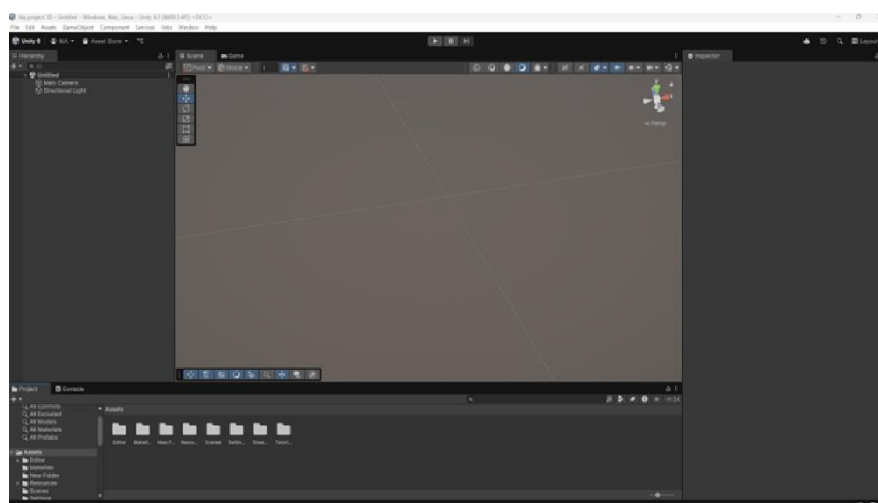


Figure 22. Unity editor interface for setting up AR functionality

To enable AR functionality, **Vuforia Engine SDK** was integrated (Figure 23).

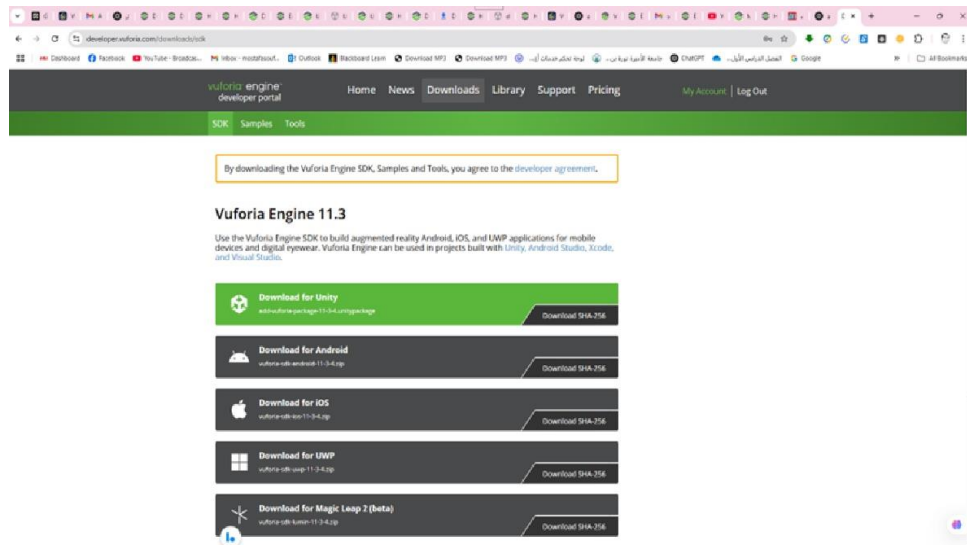


Figure 23. Integration of Vuforia Engine SDK into Unity

The **Model Target Generator** tool was used to generate a model target from the incomplete museum object (Figures 24 and 25).

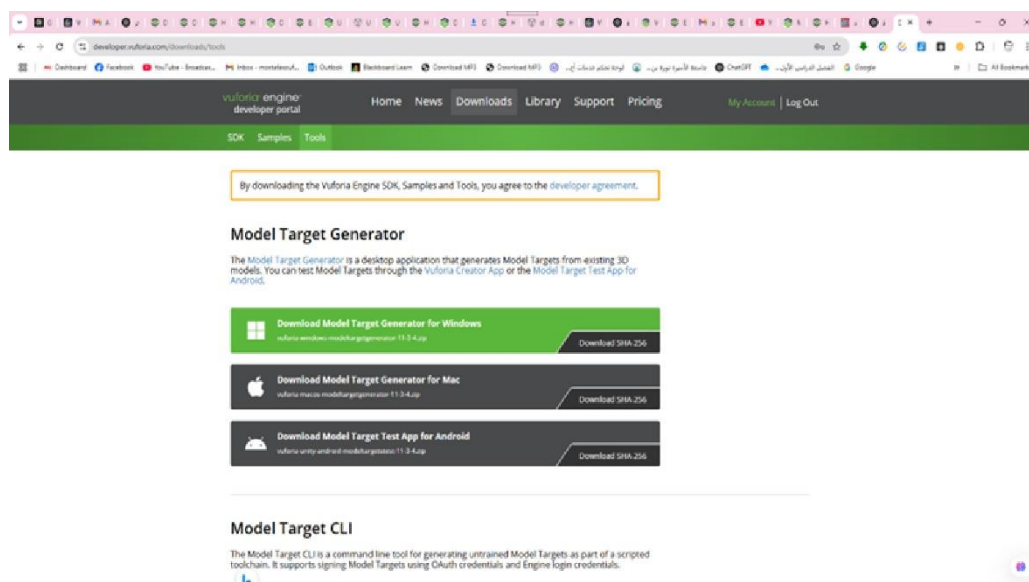


Figure 24. Downloading Model Target Generator for Vuforia

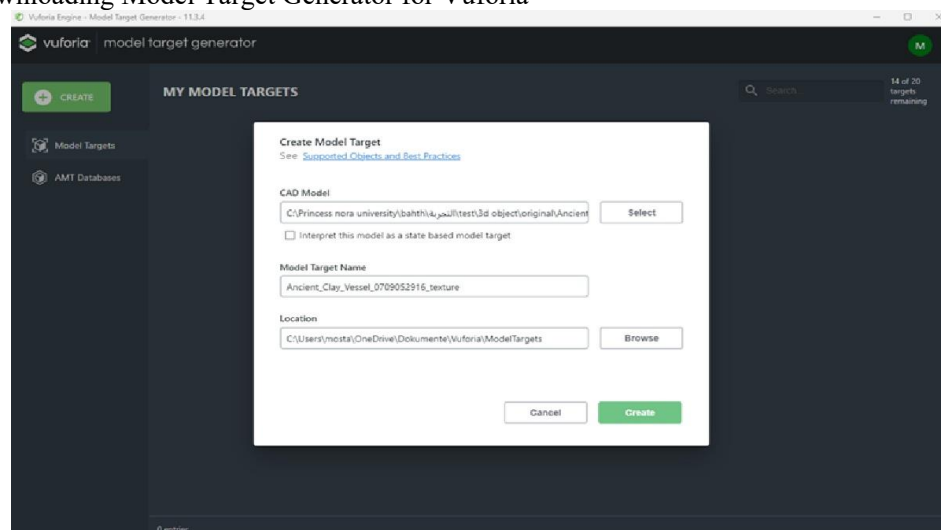


Figure 25. Creating Model Target from imported FBX file

Guide views were created, and a Vuforia package was generated and imported into Unity (Figure 26 and 27).

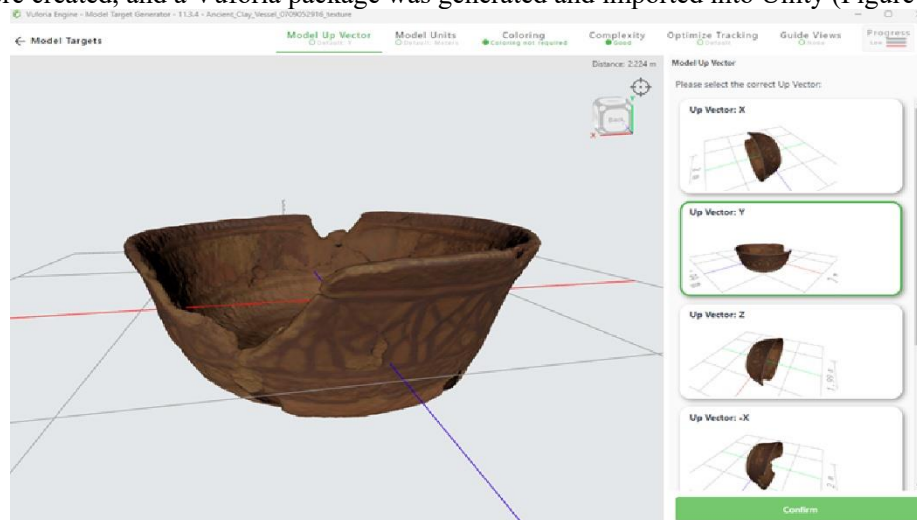


Figure 26. Guide view creation process inside Model Target Generator

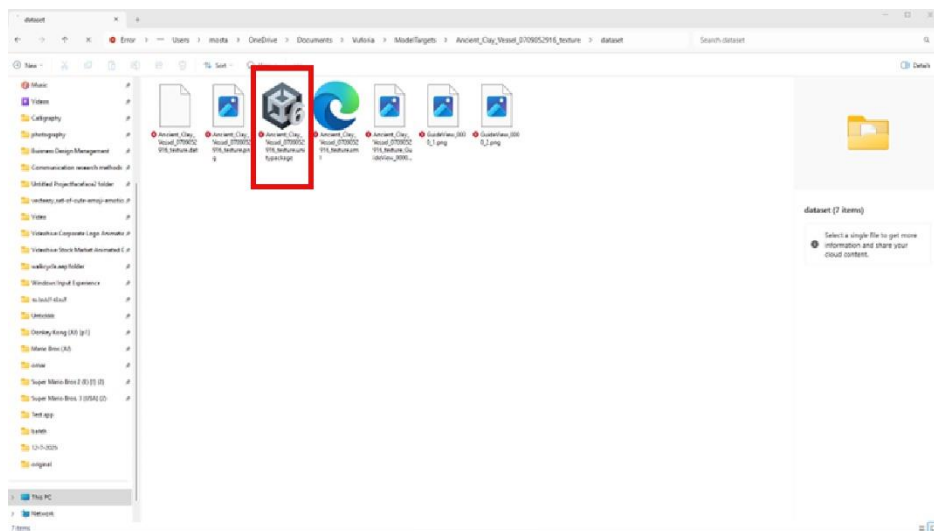


Figure 27. Generating guide view package for Unity

In Unity, After Import Vuforia packages, the **Main Camera** was replaced with an **AR Camera**, and the **Model Target** was created and assigned as a child to the AR Camera (Figures 28–30).

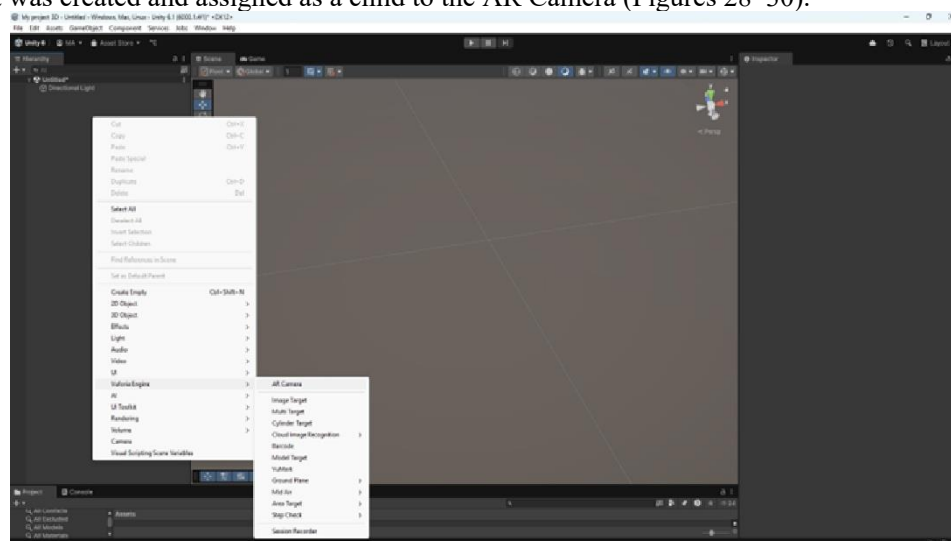


Figure 28. Creating AR Camera inside Unity

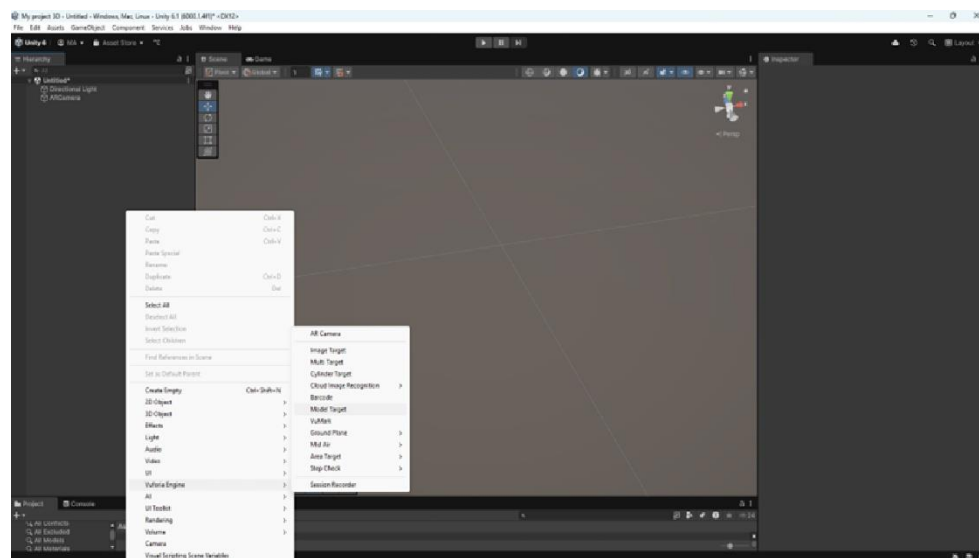


Figure 29. Creating Model Target object in Unity

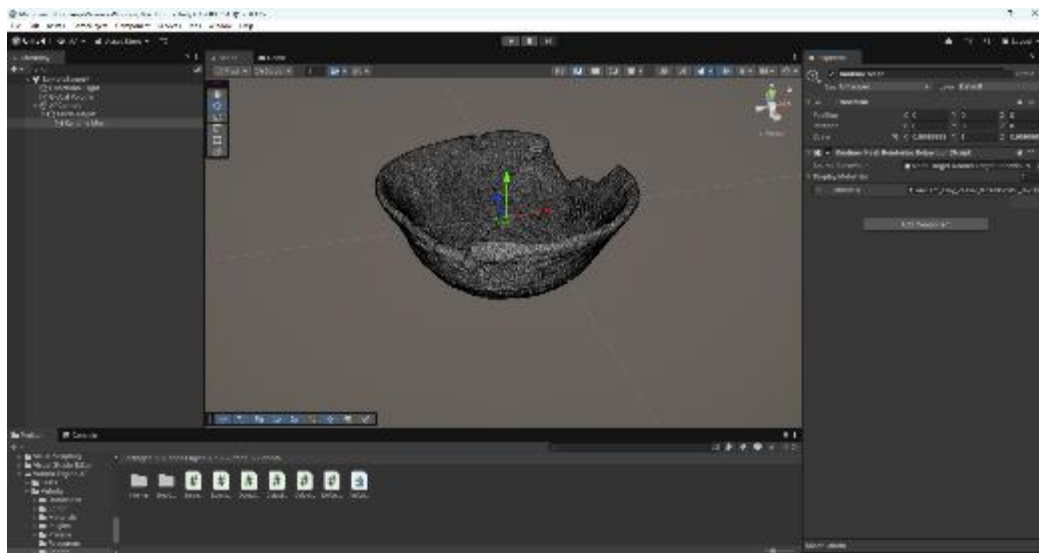


Figure 30. Assigning Model Target as child of AR Camera

The 3D model of the restored parts was added as a child of the Model Target, aligned precisely to the physical object (Figure 31).

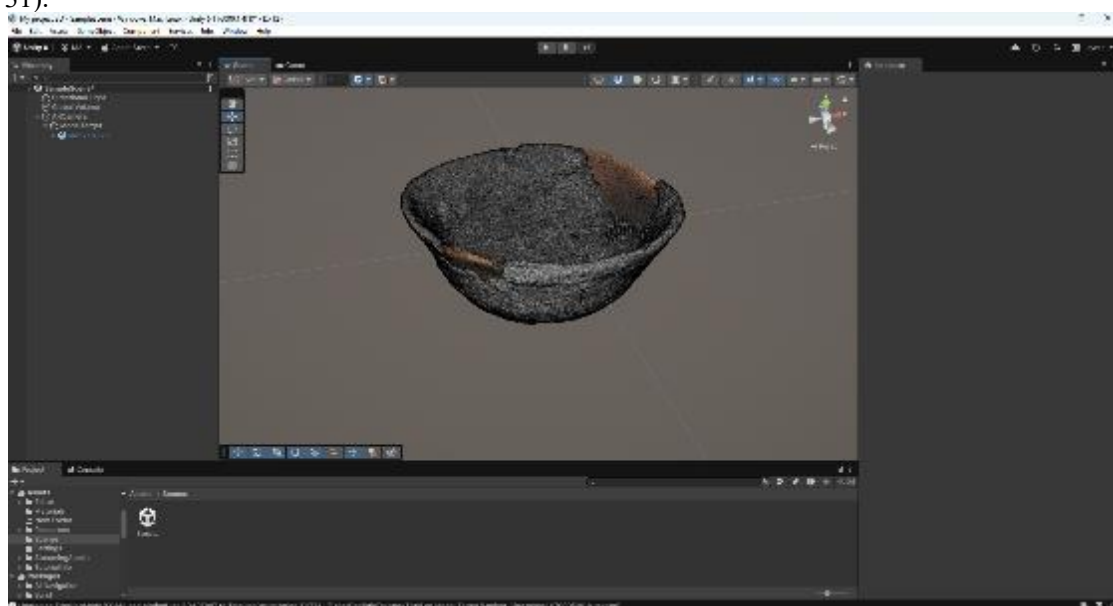


Figure 31. Assigning restored mesh as child of Model Target

Finally, the AR application was built and exported as an APK file for Android (Figure 32).

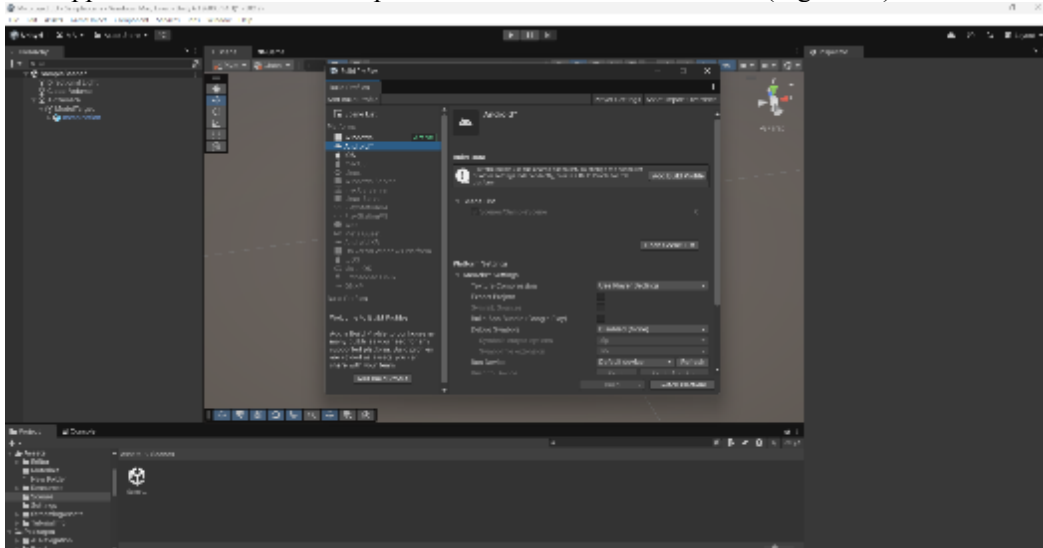


Figure 32. Building and exporting the AR application as APK file

During deployment testing on target mobile devices, the AR system consistently recognized the damaged artifact and accurately aligned the generated missing geometry in real time. (Figure 33).

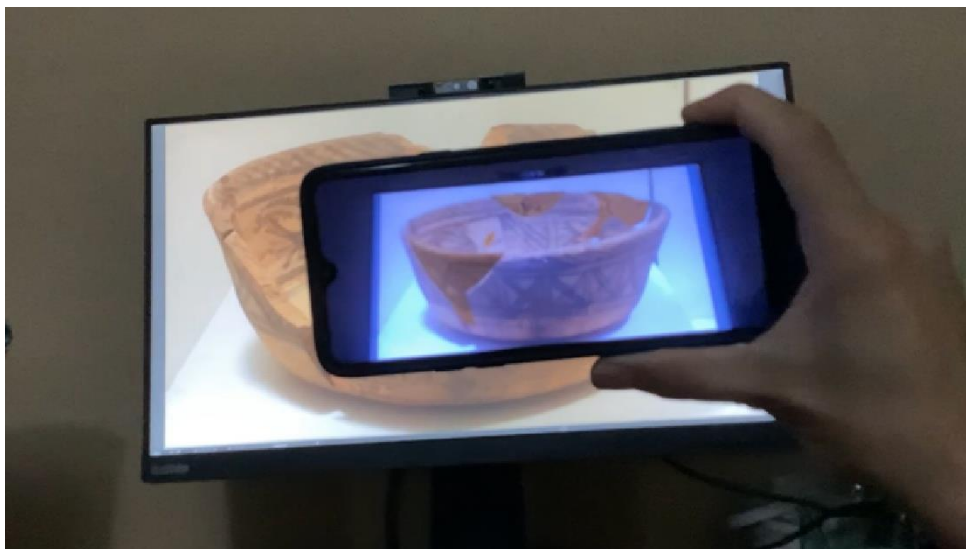


Figure 33. Testing the mobile AR application showing restored parts

Prototype execution validated Scenario 6, demonstrating that an end-to-end AI pipeline significantly reduces processing latency and manual intervention compared to traditional workflows. Empirical evaluation confirmed H1, as the automated alignment and geometry synthesis maintained spatial fidelity while accelerating total restoration throughput.

6. Future Restoration Pathway Proposal

This study proposes a future research direction aimed at developing an intelligent 3D scanning system that incorporates AI during the scanning process itself. This system would:

1. Automatically detect missing regions in damaged artifacts.
2. Predict the complete shape using trained models based on similar cultural datasets.
3. Isolate and generate the missing segments as independent 3D models.
4. Export them directly for AR use or digital archiving.

Such a pipeline would merge **technical efficiency** with **academic rigor**, offering cost-effective and precise virtual restorations adaptable to both scholarly research and public engagement.

The study proposes an intelligent 3D scanning system capable of detecting and reconstructing missing regions in real time, exporting AR-ready files directly. This aligns with RQ3 and supports H2, as real-time, interactive restoration may enhance audience engagement.

7. Theoretical Contribution and Discussion

Integrating artificial intelligence with augmented reality reframes digital heritage restoration from a purely technical execution into a communicative design practice—connecting machine inference, curatorial authority, and audience interaction. By evaluating the operational integration of these technologies within museum workflows, this study advances design research in media augmentation and human-computer interaction across three critical dimensions:

1. Algorithmic Imagination as a Restoration Tool

Generative AI transforms digital restoration from a purely automated task into speculative reconstruction, wherein neural models infer plausible geometric completions from fragmented visual inputs. This capacity validates the premise that AI can algorithmically reconstruct damaged artifacts. However, it necessitates critical scrutiny regarding curatorial authorship, authenticity, and algorithmic transparency. Rather than asserting definitive historical fidelity, the proposed framework positions AI-generated restorations as plausible visual hypotheses, facilitating both critical curatorial evaluation and public engagement with heritage items

2. Spatial Anchoring and Situated Experience via AR

Deploying restored geometry within the artifact's original physical context activates spatial memory and grounds interpretation in site-specific materiality. This spatial alignment confirms that AR visualization improves user engagement and comprehension relative to static displays. Grounded in embodied presence theory, the framework demonstrates AR's efficacy for spatial heritage communication.

3. Design as Methodological Inquiry

Rather than presenting a static system, this study frames the iterative design process as a locus of knowledge production. Scenario modeling and practical prototyping demonstrate how interdisciplinary methodologies reconcile computational algorithms with curatorial constraints. Ultimately, this design-led inquiry provides a framework for deploying intelligent, immersive systems that transform passive heritage viewing into active interpretation.

The qualitative evaluation of the AR prototype supports Hypothesis 2 (H_2) by demonstrating the seamless visualization of isolated restored components. However, this finding should be interpreted within the scope of a technical proof-of-concept, as empirical user testing with end-users was outside the present study's scope and is recommended for future work

8. Conclusion and Design Implications

Through the design and implementation of an AI-AR digital restoration system, this study addressed the underlying research questions and evaluated two primary hypotheses.

The empirical results fully supported **H1**: the integrated AI pipeline (Scenario 6) significantly reduced restoration duration compared to manual or hybrid workflows, demonstrating that targeted automation achieves computational efficiency without sacrificing geometric fidelity.

Conversely, **H2** received preliminary support; initial user feedback indicated that context-aware AR presentations enhanced audience engagement and spatial comprehension relative to static displays, though conclusive validation requires formal quantitative user testing.

By aligning computational capabilities with curatorial governance, this work establishes a framework for scalable and ethically grounded digital preservation. The resulting design implications emphasize automating technical pre-processing to lower operational barriers for museum personnel, maintaining algorithmic transparency to uphold artifact integrity, and embedding restored geometries within context-aware AR environments.

Integrating AI directly into the 3D capture phase marks a fundamental shift toward real-time, automated artifact restoration, significantly reducing post-processing overhead and expanding scalability for conservation and exhibition. This aligns with recent advancements by Kachkine et al. (2025), whose AI-driven restoration framework demonstrated rapid reconstruction of age-damaged artworks within hours.

Building on these findings, future heritage preservation frameworks should adopt smart scanning protocols featuring on-device AI inference to detect, complete, and isolate damaged geometry during capture—a capability particularly critical for field conservation in resource-constrained environments. Museums are further advised to pair AR-rendered restorations with interactive, context-aware annotations detailing artifact provenance, historical usage, and cultural significance. This layered visual presentation enhances spatial comprehension and educational engagement across diverse visitor demographics without compromising curatorial authenticity.

Regarding Hypothesis 2 (H_2), the developed workflow successfully offers a qualitative proof-of-concept for deploying AI-restored models within interactive AR environments. While the technical integration via Vuforia demonstrates clear potential for enhancing user experience, formal empirical validation with museum audiences remains a direction for future research.

9. Limitations and Future Research

While this study presents a functioning system and a theoretically grounded strategy for digital restoration, it does not include empirical user testing or behavioral evaluation. The focus was placed on the design process, technical feasibility, and conceptual contribution rather than measuring user perception or cognitive impact.

Future research should:

- Conduct controlled experiments to validate **H2** and measure the impact of AR-based presentations on visitor engagement, learning outcomes, and perceived authenticity.
- Refine AI models to improve visual fidelity, particularly for complex or symbolically significant artifacts.
- Explore user feedback loops and community-based annotation to strengthen interpretive legitimacy

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