

Ai Mension 2.2: A Comparative Evaluation Framework for Print-Ready 3D Model Generation from 2D Images

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Abstract

This article presents AI Mension 2.2 as a comparative evaluation framework for converting 2D images to printable 3D models via a unified AI-to-3D workflow. The study addresses a key limitation of current AI-to-3D systems: while many tools can generate realistic 3D outputs, the resulting models often lack consistency in terms of geometry, structure, size, and manufacturability. AI Mension 2.2 solves this by integrating four stages—input, image preparation, AI-powered 3D visualization, and printability/customer availability verification—within a modular system comprising engine connector layers, Blender-based standardization and quality assurance modules, and proof-based branding logic. The framework is designed to compare different build regimes, specifically single- and multi-image workflows, under a collaborative evaluation environment, rather than identifying a generally superior 3D modeling tool. The research highlights how varying input conditions impact geometric integrity, printability, and manufacturability. This article further suggests that AI-to-3D output should be evaluated at the workflow level, where build quality, technical validation, and usability in subsequent stages are collectively assessed. Instead of being separate, in this sense, AI Mension 2.2 offers a comparative manufacturing framework, a printability-focused quality assurance workflow, and a foundation for the future digital certification of verified AI-generated 3D assets.

Keywords: AI-to-3D, Image-to-3D, Print-ready Model, Blender QA, Additive Manufacturing.

Introduction

Artificial intelligence (AI) has significantly expanded the reach of 3D asset creation, enabling workflows that previously relied on specialized modeling expertise to start from sketches, concept art, photographs, or multiple-perspective references. This transformation impacts digital design, product prototyping, manufacturing, cosplay production, game assets, animation, and virtual media. Thai research also indicates that AI should not be viewed merely as a facilitating tool, but rather as a system that transforms learning, creativity, ethics, and workflow design through AI literacy, ethical governance, and human-AI collaboration (Madee, 2025; Nakburi & Leknoi, 2025; Porweerasunthorn & Phalasondhi, 2025). From this perspective, the importance of AI lies not only in accelerating content creation but also in transforming how creative and technical processes are organized, reviewed, and evaluated.

However, despite these advancements, a significant limitation of AI in 3D modeling remains unresolved. Realistic models often fail to produce or be modified in subsequent stages due to imperfect geometry, open surfaces, inconsistent scaling, unstable structures, weak wall thickness, excessive protrusions, or output incompatibility. Thai research on 3D printing design and optimization using Blender shows that successful implementation depends not only on modeling quality but also on design-informed preparation, mesh tuning, and technical readiness before deployment (Rasmidatta, 2022; Rangsoongnern et al., 2024; Charoensuk, 2026). In other words, the main problem is not whether AI can create three-dimensional shapes, but whether those shapes can be validated, standardized, and transferred to a practical manufacturing or delivery context with minimal modifications. The gap between visual realism and usability in the following stages is a significant research problem for both AI-to-3D studies and applied digital manufacturing.

This article addresses this problem by proposing AI Mension 2.2 as a comparative evaluation framework for creating printable 3D models from 2D images. Instead of replacing external AI tools, this framework creates a collaborative evaluation environment where results from various AI-to-3D systems are processed under the same conditions of input preparation, tool routing, technical standardization, printability evaluation, and output validation. Key features include a tool connector layer for linking multiple build tools. Blender's standardization and quality assurance modules for evaluating geometric and manufacturing readiness, and proof-based branding logic for linking verified results to future digital certifications, make AI Mension 2.2 function less as a standalone builder tool and more as a manufacturing and evaluation architecture designed to bridge the gap between built-only models and usable models.

Comparison is central to this study. Official documentation states that Meshy supports both single-image to 3D and multi-image to 3D transformation workflows, while Hyper3D Rodin Gen-2 supports both single-image and multi-image processing via coupling and merging modes (Meshy, n.d.; Hyper3D, n.d.). These capabilities make the use of both single-image and multi-image conditions within a shared evaluation framework appropriate. Therefore, this article argues that the value of AI-to-3D should be judged on next-stage readiness, such as geometric completeness, printability, output reliability, cleanup effort, and suitability for customer delivery, rather than solely on the novelty of the build itself. By positioning AI-to-3D comparative analysis within the general inspection

pipeline, AI Mension 2.2 offers a framework that can fairly, systematically, and more realistically evaluate different build regimes in a manner relevant to real-world production.

Research Objectives

This article has four objectives:

First, to develop AI Mension 2.2 into a structured comparative evaluation framework for transforming two-dimensional data into printable three-dimensional results within a shared AI-to-3D workflow. Second, to create a collaborative evaluation environment for comparing single and multiple AI-to-3D workflows under identical preparation, standardization, validation, and result evaluation conditions. Third, to assess the technical readiness of AI-generated 3D models by defining evaluation criteria related to geometric integrity, printability, and production readiness for use in manufacturing processes or customer delivery. Finally, to propose an evidence-based structure that can link verified technical results to digital certificates, micro certifications, or future AI-assisted 3D manufacturing capability certificates.

Literature Review

Generative Artificial Intelligence, Workflow Design, and Ethical Governance

Current Thai research views generative AI as a system requiring knowledge, ethical awareness, and process design, rather than its uncritical application. Madi (2025) emphasizes that integrating AI into Thai language learning should be understood through contemporary learning theories and ethical considerations. Meanwhile, Nakburi and Noknoi (2025) demonstrate that the ethical use of generative AI in research and academic writing depends on an understanding of AI, evaluative decision-making, and responsible practice. In a related approach, Porweerasunthorn and Phalasondhi (2025) propose the concept of embedding AI throughout the pre-production, production, and post-production stages, rather than using it as a separate technical tool. These studies are significant for current research because they affirm that AI should be considered as part of a systematic workflow, subject to human oversight, decision-making, and accountability.

This perspective directly supports the AI Mension 2.2 concept, which is not designed as a standalone output-generating tool but as a comparative evaluation framework operating within a structured workflow. This framework also assumes that the value of AI-generated results depends on how they are prepared, overseen, validated, and integrated into subsequent production stages. Beyond simply generating results, Thai research on AI literacy, ethical governance, and workflow design provides a conceptual foundation for understanding why AI-to-3D systems should be evaluated not only on the quality of their output but also on the structured processes and responsible implementation.

Research on 3D Modeling and Blender Use in Thailand

Thai research on 3D modeling supports arguments from both technical and production perspectives. Rangsoongnern et al. (2024) found that Blender add-ons can improve the performance of 3D models for metaverse applications by reducing file size, mesh complexity, material load, and rendering load, while simultaneously increasing productivity. Phattanapiphat and Choithongmun (2024) demonstrated that 3D modeling for

Bayonetta cosplay costumes requires careful asset development, technical refinement, and expert review before the results are suitable for use. Charoensuk (2026) also highlights the historical evolution of 3D modeling technology through CAD, NURBS, subdivision methods, and AI integration, while identifying ongoing challenges in linking digital modeling processes to actual production.

Overall, this research suggests that 3D results should not be evaluated solely on their appearance, but should also consider performance, structure, adaptability, and practical usability. This concept is highly relevant to AI Mention 2.2, as this framework is designed based on the same assumption: that AI-generated 3D results must be standardized, verified, and prepared before being considered ready for printing or delivery to the customer. Therefore, Thai research on Blender and 3D manufacturing directly supports the framework's emphasis on post-construction evaluation and technical readiness.

Printability and Additive Manufacturing

Printability is a key issue in AI Mention 2.2, particularly in the PR4 phase. Rasmidatta (2022) argues that successful 3D printing depends more on design constraints, manufacturing awareness, and systematic preparation than on image quality alone. This is supported by Sayin et al. (2025), who show that even if 3D models can be successfully generated from image data, dimensional inaccuracies and manufacturing sensitivity still require post-processing, validation, and parameterized evaluation. Their molten deposition modeling workflow demonstrates that nozzle diameter, layer thickness, wall thickness, printing speed, and fill ratio all influence the final usability of the printed model. Furthermore, industry evidence reported by PR Newswire (2026) indicates that 3D printing from photos remains susceptible to geometric instability, segmentation irregularities, brittle structures, and unreliable support behavior.

These studies are directly relevant to the current research because they confirm that printability is not guaranteed by successful model building alone. Conversely, manufacturing-oriented evaluation should be considered a post-process requiring explicit verification and correction. This is why AI Mention 2.2 features a standardization and quality assurance workflow using Blender. Therefore, the literature on additive printing and manufacturing supports the argument that evaluating AI for 3D should encompass manufacturability, export readiness, and real-world application conditions as key components of the research framework.

Multimodal and Multi-Perspective 3D Reasoning

Research on multi-format and multi-perspective reasoning provides strong support for the comparative logic of AI Mention 2.2. Biehler et al. (2025) considered 3D modeling as a multi-format fusion problem, demonstrating the ability to recreate 3D shapes from 2D images along with diverse process information in the context of additive manufacturing. Their work is relevant because it shows that robust 3D modeling benefits from integrating image inputs with structured supplemental information rather than relying on isolated single signals. Hu et al. (2025), although working more in the field of medical image segmentation than consumer 3D AI modeling, showed that multi-perspective swarm learning preserves richer spatial semantics and improves structural understanding

compared to single-perspective estimation. Sun et al. (2025) extended this concept industrially by incorporating neural network rendering and model extraction for digital twin scene modeling, demonstrating that multi-angle RGB capture and subsequent geometric matching can be integrated into an efficient scene reconstruction pipeline.

Overall, this research supports the core methodological hypothesis of AI Mension 2.2: different input regimes should be evaluated as different analysis conditions. Instead of categorizing them into a single, indistinct category of AI creation, this also supports the idea that more complete input structures and post-construction justifications can improve the reliability of 3D results. This is why the present study compares single- and multiple-image workflows within a collaborative evaluation environment. Multimodal and multi-view literature is therefore fundamental both for comparative design and interpretation at the workflow level of this framework.

Digital Badges and Microcredentials

AI Mension 2.2 also incorporates evidence-based badge logic, an aspect supported by Thai research on digital qualifications. Thammametha (2025) demonstrates that Thai MOOCs have begun integrating microcredentials and digital badges into lifelong learning pathways, reflecting a broader shift towards more flexible and adaptable certification systems. Hencharoenlert et al. (2023) propose a blockchain-based microcredential model for secure and verifiable certification, highlighting how evidence-based certification can be made more transparent and trustworthy through digital systems. This research indicates that qualifications are no longer limited to traditional degree structures but can be linked to specific competencies, verified results, and more portable digital records.

This literature is relevant to AI Mension 2.2 because the framework aims not only to validate 3D models but also to verify the user's competence through evidence-based results. By linking verified technical results to a badge-focused structure, AI Mension 2.2 extends the logic of quality assurance to the realm of digital certification. Thus, documentation on microcredentials and digital badges explains why the framework includes a layer of evidence beyond the creation and verification components, and why such a structure may be critical to future professional recognition in AI-assisted 3D manufacturing.

Conceptual Framework of AI Mension 2.2

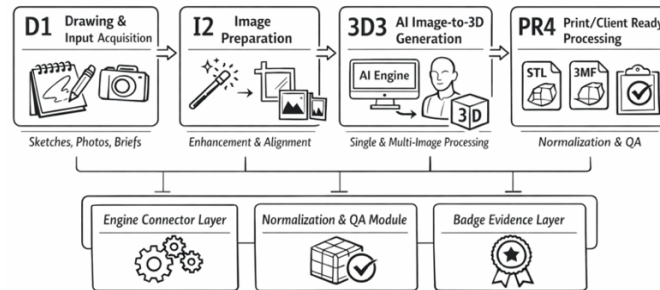


Figure 1. Conceptual Framework of AI Mension 2.2 Workflow

The AI Mension 2.2 framework is based on the assumption that the quality of AI-to-3D implementations should be evaluated at the workflow level rather than just at the fabrication stage. This framework is derived from a synthesis of knowledge from four complementary domains: AI literacy and ethical workflow design (Madee, 2025; Nakburi & Leknoi, 2025; Porweerasunthorn & Phalasondhi, 2025), 3D modeling and fabrication studies using Blender (Rangsoongnern et al., 2024; Charoensuk, 2026), printability verification and additive manufacturing (Rasmidatta, 2022; Sayin et al., 2025), and evidence-based digital authentication (Thammametha, 2025; Hencharoenlert et al., 2023). These domains are combined to create a framework that does not view AI-generated 3D outputs as separate visual results, but as an integral part of a traceable manufacturing process. Comparable and technically verifiable.

The framework comprises four operational steps: D1: Drawing and Input. Record initial input such as sketches, concept art, photographs, or structural outlines to maintain design intent and workflow traceability. I2: Image Preparation. Refine 2D input for subsequent creation through processes such as enhancement, masking, perspective alignment, style alignment, and orientation preparation. In a single-image workflow, this step emphasizes clarity and object separation, while in a multi-image workflow, it focuses on perspective consistency and structural consistency. 3D3: AI 3D Visualization. Send the prepared input to an external engine via an engine connector layer. In the current comparative design, Single-image workflows are represented by Meshy image-to-3D, while multi-image workflows are represented by Hyper3D Rodin Gen-2. Official documentation states that Meshy supports both image-to-3D and multi-image-to-3D conversion workflows, while Hyper3D Rodin Gen-2 supports multi-image processing via concat mode for capturing multiple views of the same object and fuse mode for unified feature extraction (Meshy, n.d.; Hyper3D, n.d.).

A prominent step in the framework is PR4: Print-Ready/Customer-Ready Processing, where a headless Blender-based workflow performs calibration, scaling, and axis correction, origin adjustment, mesh validation, geometry validation, wall thickness analysis, overhang inspection, spacing estimation, and output file generation. The goal is to convert the raw AI output into usable files such as GLB for previewing and STL/3MF for additive manufacturing. Beyond these four steps, AI Mension 2.2 also includes three

additional support modules: the Engine Connector Layer, the Calibration and Quality Assurance Module, and the Seal Proof Layer. These components together create a collaborative evaluation environment where results from various AI-to-3D tools are processed under identical preparation, verification, and evaluation conditions in subsequent steps. In this sense, AI Mension 2.2 serves as an AI-to-3D framework focused on comparison, production, and validation, rather than a single, specialized modeling tool.

Research Method and Design

Research Design

This research employs a comparative design framework combined with a mixed evaluation approach. The empirical design is divided into two stages. The first stage is a use-based comparison, which aligns single-image and multi-image generation processes with actual implementations, reflecting the real-world scenarios where different AI tools are selected based on the completeness and structure of the provided image data. The second stage is a control comparison, using the same data type for more than one tool to mitigate bias caused by data asymmetry. This step is necessary because both Meshy and Hyper3D formally support multiple input modes (Hyper3D, n.d.; Meshy, n.d.).

To ensure clarity and validity in the comparisons, the same end-evaluation environment was used for all samples. The process involved the following steps: (1) collecting and classifying 2D input images; (2) assigning samples to single- and multi-image workflows; (3) generating preliminary 3D outputs via the chosen AI engines; (4) processing all outputs through the same standardization and quality assurance procedures using Blender; (5) recording relevant evaluation metrics related to geometry, printability, and production readiness; and (6) interpreting the findings in relation to the four research objectives. This design allows for comparative studies of different AI-to-3D conditions without changing the validation criteria in the next step.

Sample Design

The proposed benchmark comprises four object categories: character and distinctive forms; solid-surface objects; household products and utensils; and decorative or collectible models. These categories were chosen because they represent different geometric and manufacturing challenges. Characters emphasize natural form and continuity; solid-surface objects emphasize structural accuracy; products emphasize proportion and manufacturability; and collectibles often combine aesthetic detail with printability. The inclusion of these categories allows this study to reflect a wider range of use cases in AI-powered 3D modeling, rather than relying on a single object type or geometry.

Comparative Arms

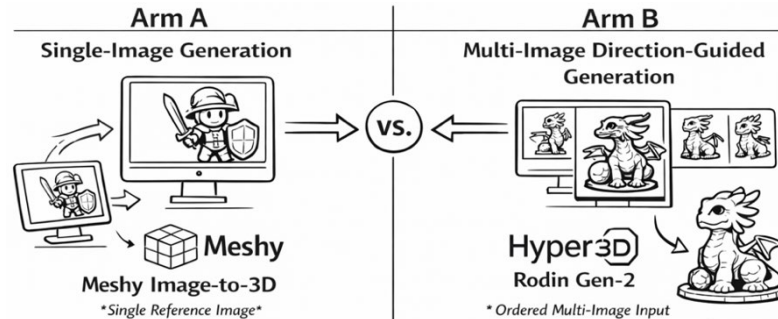


Figure 2. Two main comparative arms

This research defines two main comparison groups: Group A, representing single-image rendering using Meshy image-to-3D; and Group B, representing oriented multi-image rendering using Hyper3D Rodin Gen-2 with multiple images sequenced as input. Where necessary, additional fairness control conditions may be added by using both platforms with the same input format, whether single or multiple images (Hyper3D, n.d.; Meshy, n.d.). This structure aims to clarify whether differences in output quality arise from the engine itself, the input conditions, or the interaction between the two factors.

Workflow Procedure

The evaluation was conducted in four dimensions. Geometric integrity comprised waterproofing, asymmetrical impact, open boundary detection, directional alignment, and standardization scaling. Printability comprised minimum wall thickness, protrusion risk, support requirements, assembly spacing, and successful STL/3MF file export. Production readiness comprised successful GLB file export, UV readiness, surface integrity, cleaning time, and first build time. Expert evaluation comprised visual accuracy, geometric consistency, printability, and suitability for customer delivery.

These dimensions directly align with the research objectives. Geometric integrity and printability are technical comparisons of AI-generated results. Production readiness reflects the practical usability of those results for production or delivery, and expert evaluation supports the interpretation of verified results relevant to future brand-focused certifications. Descriptive comparisons across these dimensions were used to systematically organize the findings, while expert judgments were employed to support interpretations beyond mere visual impressions. This structure aligns with the metric-based reconstruction evaluation in multi-faceted 3D modeling and with production-focused studies that rely on systematic measurement and expert verification. Instead of considering only visible characteristics (Biehler et al., 2025; Sayin et al., 2025).

Research Findings

The findings of this study are organized in relation to the four research objectives.

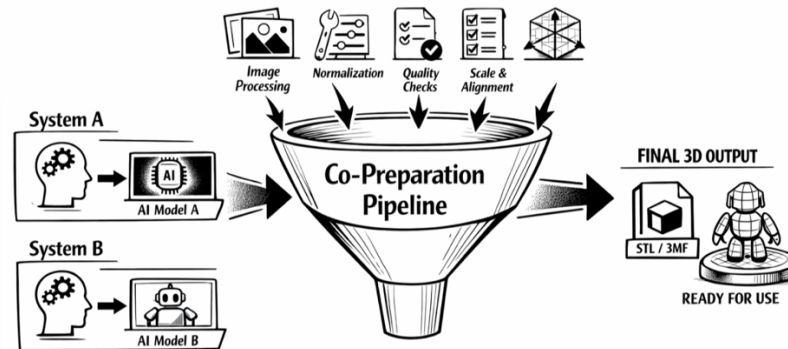


Figure 3. AI in 3D Pipeline Workflow

Firstly, this study confirms that AI Mension 2.2 can be described as a coherent comparative framework comprising four operational steps: input, image preparation, AI 3D visualization, and print-ready/customer-ready processing, supported by the Engine Connector Layer, Normalization and Quality Assurance Module, and Badge Evidence Layer. These components collectively form the framework's structural basis and clarify how diverse AI-to-3D outputs are processed within a shared evaluation environment, rather than being interpreted as separate generation outcomes.

Secondly, the comparative application of the framework demonstrates that single and multi-image workflows should be considered as distinct analysis conditions within a shared endpoint pipeline. Single-image conditions are better interpreted as a faster generation path, while multi-image conditions provide richer directional information for structural comparisons and reduce ambiguity in shape interpretation. This distinction is consistent with studies on multi-perspective reasoning, which suggest that directional inputs maintain richer spatial meaning and improve structural understanding (Hu et al., 2025; Sun et al., 2025). Therefore, a key finding of the study is that... AI-to-3D comparisons become more meaningful when performed within the normal workflow of preparation and standardization. And evaluation goes beyond considering visual results alone.

Thirdly, the findings suggest that technical evaluation must extend beyond build quality and include usability criteria in subsequent stages. The framework identifies four key evaluation dimensions: geometric integrity, printability, manufacturability, and expert evaluation, which are necessary to assess whether AI-generated 3D models are suitable for production or delivery to customers. In particular, printability cannot be assumed based solely on visual realism. Previous research has shown that even with successful 3D model creation from image data, dimensional inaccuracies and manufacturability persist, necessitating systematic post-processing and parameter evaluation (Sayin et al., 2025). Industry evidence also underscores the practical importance of wall thickness, slicer program stability, support construction, and geometric reliability for practical applications

(PR Newswire, 2026). These findings support the role of PR4 as a technical checkpoint within AI Mension 2.2.

Finally, the study suggests that evidence-linked certification is a practical extension of technical verification by documenting workflows, verification status, and technical outcomes of each model, giving rise to this framework which serves as the basis for linking model readiness to digital microcredentials. Or, in the future of competency certification, Thai research on digital and microcredential certification shows that validated badge systems are becoming more feasible in the educational and professional ecosystems (Thammametha, 2025; Hencharoenlert et al., 2023). In the context of AI Mension 2.2, this means that validated 3D results can not only be used as production assets but also as indicators of user competence. Overall, these findings demonstrate that this framework contributes not only to the evaluation of AI against comparative 3D models but also to the design of a broader production and certification environment for AI-generated 3D assets.

Conclusion and Discussion

AI Mension 2.2 shifts the perspective on AI-powered 3D modeling from mere visualization to a process of creation, standardization, technical validation, printability, and usability with minimal manual modification. A key highlight is its proposed workflow structure, where the focus isn't on realistic model appearance, but on the ability to pass standardization, printability evaluation, and subsequent deployment with reduced manual correction. This aligns with Thai research on AI literacy and ethical use, 3D manufacturing using Blender, multifaceted and multi-perspective reasoning, and additive manufacturing studies emphasizing real-world manufacturing constraints (Madee, 2025; Nakburi & Leknoi, 2025; Rangsoongnern et al., 2024; Biehler et al., 2025; Hu et al., 2025; Sayin et al., 2025). In this sense, the novelty of AI Mension 2.2 lies not in introducing a separate, independent AI tool, but in the integration of creation, standardization, technical validation, printability, and evidence-based certification. Incorporating it into a shared comparative workflow:

The development of AI Mension 2.2 can be interpreted as four stages: receiving structured input, image preparation, AI 3D visualization, and checking for printability/customer readiness. Its performance is verified through a comparative workflow design, where different AI 3D creation conditions are processed under the same end-environment. This shared evaluation setup reveals that one of the major problems with AI-generated 3D content is the inconsistency between visual realism and technical usability. Raw results may appear credible but still fail in mesh integrity, printability, or production readiness. This framework addresses this by introducing Blender-based standardization and quality assurance as common checkpoints, reducing comparative ambiguity and improving the interpretability of the results.

From a technical perspective, the framework also clarifies how to resolve several recurring problems. Input asymmetry is addressed by separating single and multiple image workflows into different analysis conditions. Geometric instability is managed through standardization and mesh verification. And with print-focused validation in PR4, workflow fragmentation is mitigated by the Engine Connector Layer, enabling processing of different AI engines under comparable end-conditions. Finally, the difficulty in linking technical

results to user capabilities is addressed through the Badge Evidence Layer, providing the basis for evidence-based certification. The practical benefit of these solutions is the transformation of AI-generated 3D output from isolated experimental artifacts into assets that can be evaluated, improved, and potentially certified within a scalable manufacturing environment.

From a platform perspective, this framework is also commercially relevant. Research on evaluating additive manufacturing providers shows that the 3D manufacturing ecosystem increasingly relies on the availability of digital models, outsourcing decisions, and provider evaluation criteria, underscoring the need for reliable print-ready validation and structured service integration within scalable AI-to-3D systems (Pourhejazy et al., 2025). From an academic perspective, AI Mension 2.2 provides a clear foundation for future benchmarking by defining what should be compared, how comparisons should be conducted, and why workflow-level evaluation is important, rather than claiming one tool is superior in every case. This framework suggests that different AI tools may be better suited to different input conditions when evaluated within the same technical architecture and validation process.

At the same time, this study has limitations. The article develops and interprets the conceptual framework at a comparative and analytical level, but it does not present a large-scale empirical benchmark encompassing all possible tools, object classes, printers, and materials. Furthermore, printability may vary depending on slicing setup, production equipment, and production context. Therefore, the current findings should be interpreted as a structured conceptual framework with analytical support rather than a universal ranking of AI tools for final 3D modeling. Nevertheless, the study demonstrates that AI Mension 2.2 offers a meaningful approach to evaluating AI-generated 3D models through a shared, production-oriented, and validated workflow.

Suggestions

Future research should conduct more comprehensive empirical comparisons using the entire dataset across both comparison groups and incorporating real-world printing experiments for selected outcomes. Additional AI-to-3D tools should be added to test the usability and interoperability of the framework on a broader scale. Beyond tool comparisons, future research should refine the Badge Evidence Layer into a standardized identity structure compatible with the broader digital certification ecosystem. Furthermore, investigating how different manufacturing settings, materials, and cutting conditions affect the relationship between technical verification and actual production performance would be beneficial. These developments will strengthen the empirical foundation of AI Mension 2.2 and expand its relevance in both academic comparisons and practical applications.

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