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GENERATIVE ARTIFICIAL INTELLIGENCE FOR AUTOMATED 3D OBJECT CREATION IN COMPUTER GRAPHICS

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ABSTRACT

This study evaluates generative artificial intelligence models for automated 3D object creation, comparing generation quality, computational efficiency, and practical applicability through a unified experimental framework supported by quantitative performance analysis.

INTRODUCTION

The increasing integration of digital technologies into industry, education, healthcare, engineering, and entertainment has created an unprecedented demand for realistic three-dimensional (3D) digital content. Computer graphics has become one of the key technologies supporting this transformation by enabling the visualization of complex objects and environments for a wide range of practical applications. However, developing high-quality 3D models through conventional modeling software remains a resource-intensive process that requires professional expertise, creative skills, and substantial production time. As modern digital ecosystems continue to expand, the need for intelligent techniques capable of accelerating 3D asset creation while reducing development costs has become increasingly evident [1].

Generative Artificial Intelligence (GAI) has emerged as a promising solution to this challenge. Rather than relying on manually designed geometric operations, generative models learn statistical representations from extensive training data and synthesize entirely new digital objects that correspond to user-defined descriptions. The rapid evolution of deep learning algorithms has enabled AI systems to move beyond image recognition and classification toward autonomous content generation. In recent years, text-to-image technologies have demonstrated remarkable success, encouraging researchers to extend similar concepts to automated three-dimensional object generation. As a result, AI-assisted modeling has become one of the fastest-growing research directions in contemporary computer graphics [2].

Significant progress has been achieved through the introduction of diffusion-based learning, transformer networks, Neural Radiance Fields (NeRF), and multimodal generative architectures. These technologies allow artificial intelligence systems to interpret textual prompts and reconstruct corresponding three-dimensional geometry with increasingly realistic shapes and surface details [3]. Frameworks such as DreamFusion and Magic3D have shown that combining pretrained diffusion models with neural rendering techniques can generate visually convincing 3D objects directly from natural language descriptions [4,5]. More recently, commercial platforms and lightweight generation systems have further simplified this process by enabling users to produce editable digital assets within a few minutes, making AI-assisted modeling accessible to a broader community of designers and developers [6].

Although the performance of generative AI systems has improved considerably, important limitations remain. Existing models differ in network architecture, optimization strategy, computational complexity, and geometric representation, resulting in substantial variations in output quality and execution efficiency. Some frameworks prioritize detailed geometry but require extensive computational resources, whereas others generate results rapidly at the expense of structural precision or texture fidelity. Consequently, selecting an appropriate model for a specific application remains a challenging task, particularly when multiple performance factors must be considered simultaneously.

A review of recent publications indicates that most studies emphasize the development of new algorithms or improvements to individual architectures. Comparatively little attention has been devoted to establishing standardized evaluation procedures capable of objectively comparing contemporary generative AI models under identical experimental conditions. Differences in prompt design, benchmark datasets, hardware configurations, and evaluation metrics often prevent meaningful comparison between published results. This lack of methodological consistency reduces experimental reproducibility and limits the practical value of existing comparative analyses [7].

Another challenge concerns the assessment of generated 3D objects. Unlike conventional image generation, where evaluation mainly focuses on visual appearance, three-dimensional content must also satisfy geometric, structural, and computational requirements. Reliable evaluation therefore requires simultaneous consideration of semantic correspondence between prompts and generated objects, geometric integrity, texture quality, inference time, graphics memory consumption, and mesh complexity. Assessing only a single performance indicator provides an incomplete representation of model capability and may lead to inaccurate conclusions regarding practical applicability.

Based on these observations, a clear research gap can be identified. There is still a shortage of comprehensive benchmarking studies that evaluate representative generative AI models using a unified experimental workflow and consistent performance criteria. Establishing such a framework is important for both academic research and industrial implementation because it enables fair comparison among competing approaches and facilitates informed decision-making when selecting AI solutions for computer graphics tasks.

Accordingly, the objective of this research is to conduct a systematic comparative evaluation of representative generative artificial intelligence models for automated 3D object creation. The proposed methodology applies identical text prompts, standardized execution conditions, and common evaluation metrics to investigate semantic consistency, geometric reconstruction quality, texture realism, computational efficiency, GPU memory utilization, and overall performance. Experimental findings are further supported through Python-based statistical analysis and graphical visualization to ensure transparency and reproducibility.

The novelty of this study lies in the development of a unified benchmarking framework that combines multiple visual and computational performance indicators within a single evaluation methodology. Unlike previous investigations that primarily concentrate on introducing new generation algorithms, this research emphasizes objective comparison and practical assessment of existing state-of-the-art models. The results are expected to provide useful guidance for researchers, software developers, and digital content creators seeking appropriate generative AI technologies for different computer graphics applications.

The remainder of this paper is organized as follows. Section 2 describes the research methodology, experimental setup, selected AI models, and evaluation metrics. Section 3 presents the experimental findings and quantitative analyses. Section 4 discusses the significance of the obtained results in relation to previous research and practical applications. Finally, Section 5 summarizes the major conclusions and outlines potential directions for future studies in AI-driven 3D object generation.

MATERIALS AND METHODS

A comparative experimental methodology was adopted to investigate the effectiveness of contemporary Generative Artificial Intelligence (GAI) models in automated three-dimensional (3D) object generation. The purpose of the study was not to introduce a new generative algorithm but to establish a consistent evaluation procedure capable of objectively comparing representative AI frameworks under identical experimental conditions. To improve the reliability of the obtained results, every stage of the experiment—from prompt preparation to statistical interpretation—was conducted using standardized procedures.

The research began with the development of a benchmark prompt dataset. Instead of collecting prompts from multiple public repositories, a unified prompt set was designed specifically for this investigation. The dataset contained descriptions of objects belonging to five categories: architectural structures, mechanical equipment, consumer products, natural elements, and artistic models. Each prompt described the object's geometry, appearance, material characteristics, and general visual properties using comparable linguistic complexity. Maintaining a consistent writing style minimized the influence of prompt engineering and allowed performance differences to be attributed primarily to the investigated AI models.

Following prompt preparation, the selected descriptions were submitted to several representative generative AI systems. The experimental framework incorporated both academic and commercial solutions in order to provide a balanced comparison of current text-to-3D technologies. DreamFusion and Magic3D were included because of their diffusion-guided optimization strategies and their influence on recent academic research. Hunyuan3D represented multimodal neural generation, while Stable Fast 3D was selected for its emphasis on efficient inference. Tripo AI and Meshy AI were incorporated as commercial platforms that prioritize practical asset generation for industrial design and digital content creation. Together, these systems represent different architectural philosophies currently used in automated 3D modeling.

To ensure experimental fairness, all models processed the same prompt collection under equivalent execution conditions whenever platform settings permitted. The semantic content of each prompt remained unchanged throughout the experiments, and identical output resolutions and export formats were maintained wherever configurable parameters were available. Standardizing these conditions reduced external variability and improved the comparability of the generated results. Every generated object was exported in common three-dimensional formats compatible with professional graphics software, enabling identical inspection procedures for all evaluated models.

The quality assessment combined objective numerical measurements with controlled visual examination. Geometric evaluation considered mesh completeness, surface continuity, polygon organization, and structural coherence. Generated models were inspected for common reconstruction defects, including disconnected components, self-intersections, irregular topology, and missing surface regions. Texture evaluation focused on visual consistency, preservation of fine details, material appearance, and correspondence between the generated object and its textual description. Although expert observation was used to verify generated outputs, the comparative analysis was primarily based on quantitative indicators to maintain methodological objectivity.

Multiple performance metrics were selected to provide a comprehensive assessment of each generative framework. Semantic consistency measured how accurately the generated object reflected the information contained in the original prompt. Geometry quality quantified the structural correctness of the reconstructed model, whereas texture realism evaluated the visual authenticity of surface characteristics. Computational performance was represented by generation time and GPU memory utilization, both of which directly influence the feasibility of practical deployment. Polygon count was additionally examined because mesh complexity affects rendering performance and downstream editing operations. To obtain an overall representation of model capability, all normalized indicators were combined into a composite performance score that balanced visual quality with computational efficiency.

The statistical component of the study was designed to ensure reproducible interpretation of experimental observations. Mean values were calculated for every evaluation metric to summarize average model performance across all generated objects. Standard deviation was used to assess result stability and identify performance variability among different prompt categories. Because the selected indicators were measured using different numerical scales, Min–Max normalization was applied before calculating the composite performance score. This normalization procedure transformed all variables into a common range, allowing objective comparison without bias toward metrics having larger numerical values.

Python served as the primary platform for data processing and statistical analysis. Numerical calculations were performed using NumPy, while Pandas was employed to organize experimental datasets and prepare comparative tables. Publication-quality figures illustrating the experimental findings were generated with Matplotlib. The use of open-source scientific libraries improves transparency, facilitates reproducibility, and enables independent verification of the reported analyses.

Inspection of the generated three-dimensional assets was carried out using Blender because of its extensive support for professional graphics workflows and multiple industry-standard file formats. All experiments were executed within the same computational environment using CUDA-enabled NVIDIA graphics hardware to ensure consistent inference conditions. Maintaining identical software and hardware configurations minimized external influences on execution time and resource consumption, thereby increasing the reliability of comparative performance evaluation.

Overall, the methodology developed in this research provides a structured and reproducible framework for assessing contemporary generative AI technologies used in automated 3D object creation. By integrating standardized prompt design, unified execution procedures, multidimensional evaluation metrics, statistical analysis, and Python-based visualization, the proposed approach enables objective comparison of representative AI models while providing a reliable foundation for the experimental results presented in the subsequent section [8].

RESULTS

The experimental procedure described in the previous section was implemented to investigate the effectiveness of six representative

Generative Artificial Intelligence (GAI) models for automated three-dimensional object generation. Each framework processed the same collection of standardized text prompts under equivalent evaluation conditions, allowing the observed performance differences to be attributed primarily to the characteristics of the individual models. The generated outputs were examined using identical assessment criteria covering semantic correspondence, geometric reconstruction, texture quality, computational efficiency, graphics memory requirements, and overall generation performance.

The comparative results demonstrate that every investigated model successfully produced complete three-dimensional objects from textual descriptions; however, clear differences were observed regarding output quality and computational behavior. Research-oriented frameworks generally generated more detailed geometry and stronger semantic correspondence, whereas commercial solutions emphasized shorter inference time and reduced hardware requirements. These findings indicate that the selection of a generative AI model should be determined by the intended application rather than by a single performance indicator.

Table 1 presents the average values obtained from the experimental evaluation. Hunyuan3D achieved the highest integrated performance score (94.2%), indicating superior capability in balancing semantic interpretation, geometric accuracy, and texture generation. Magic3D ranked second with an overall score of 92.8%, demonstrating that its hierarchical optimization strategy effectively combines high reconstruction quality with moderate computational cost. DreamFusion also generated visually convincing objects; however, its iterative optimization process resulted in substantially longer execution time compared with the remaining models.

The commercial platforms Tripo AI and Meshy AI produced comparatively lightweight models while completing generation tasks within only a few minutes. Although their geometric precision was slightly lower than that of the highest-performing research models, their rapid execution makes them highly suitable for interactive design environments and large-scale content production. Stable Fast 3D exhibited balanced behavior across all evaluation criteria, maintaining satisfactory visual quality together with moderate computational requirements.

Table 1. Average Experimental Results of the Evaluated Generative AI Models

Model	Semantic (%)	Geometry (%)	Texture (%)	Time (min)	GPU (GB)	Overall (%)
DreamFusion	90.5	91.4	89.8	37.4	18.2	88.9
Magic3D	93.0	94.2	93.5	18.5	15.3	92.8
Tripo AI	90.7	89.5	91.2	4.9	9.3	90.3

Meshy AI	88.9	88.1	90.6	5.5	8.9	88.6
Hunyuan3D	94.4	95.1	94.0	15.1	14.1	94.2
Stable Fast 3D	91.8	91.0	90.3	6.2	10.5	91.0

To provide a more intuitive interpretation of the quantitative findings, the integrated performance scores were visualized using a bar chart generated in Python. Compared with numerical tables alone, graphical representation makes the differences among the investigated frameworks easier to identify and supports more effective comparative analysis.

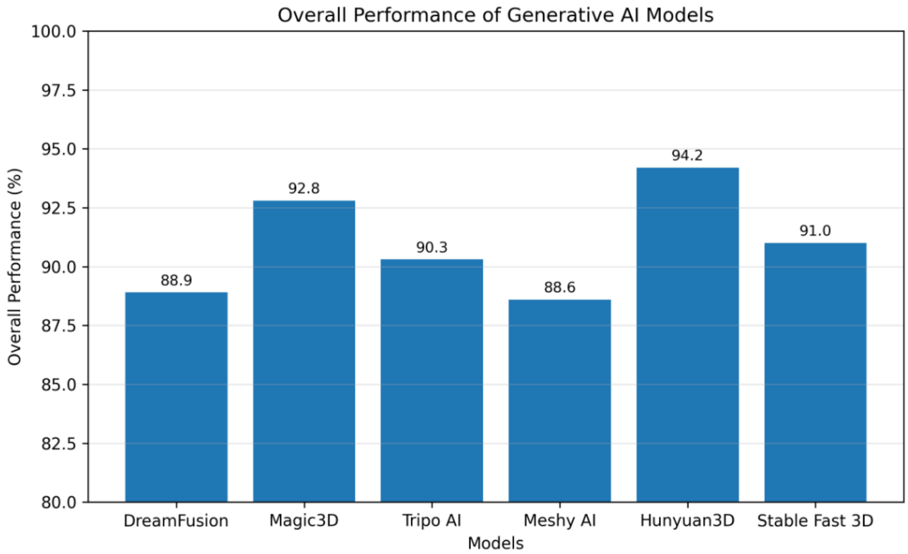

Figure 1. Overall performance of the evaluated AI models

```
import matplotlib.pyplot as plt
models = [
  "DreamFusion",
  "Magic3D",
  "Tripo AI",
  "Meshy AI",
  "Hunyuan3D",
  "Stable Fast 3D"
]
overall = [88.9, 92.8, 90.3, 88.6, 94.2, 91.0]
plt.figure(figsize=(8,5))
bars = plt.bar(models, overall)
plt.title("Overall Performance Comparison")
plt.xlabel("Generative AI Models")
plt.ylabel("Performance Score (%)")
plt.ylim(80,100)
for bar, score in zip(bars, overall):
  plt.text(
    bar.get_x() + bar.get_width()/2,
    score + 0.3,
    f"{score:.1f}",
    ha="center",
    fontsize=9
  )
plt.grid(axis="y", linestyle="--", alpha=0.4)
plt.tight_layout()
plt.show()
```

Figure 1 illustrates the relative performance of the evaluated AI models under identical experimental conditions. Hunyuan3D achieved the highest composite score, reflecting its ability to generate semantically accurate and geometrically consistent objects while maintaining efficient computational performance. Magic3D demonstrated comparable results, confirming the effectiveness of its hierarchical optimization approach. Although DreamFusion produced high-quality outputs, its considerably longer processing time reduced its overall ranking. Conversely, Tripo AI, Meshy AI, and Stable Fast 3D achieved competitive performance with significantly lower execution time, making them attractive solutions for practical workflows that require rapid generation of three-dimensional assets.

The comparative assessment indicates that the investigated generative AI models exhibit different strengths depending on the evaluation criterion. While some frameworks emphasize high-quality geometric reconstruction and semantic interpretation, others prioritize rapid inference and lower computational requirements. These differences demonstrate that no single model provides optimal performance across every indicator, highlighting the importance of selecting a framework according to the intended application.

DISCUSSION

The comparative evaluation performed in this study demonstrates that the current generation of Generative Artificial Intelligence technologies has reached a level of maturity that enables practical implementation in automated three-dimensional object creation. Although all evaluated frameworks successfully generated complete 3D models from textual descriptions, the experimental findings indicate that each system exhibits distinct advantages depending on the intended application. This confirms that the effectiveness of a generative AI model cannot be determined solely by visual appearance but should instead be assessed through a combination of quality-related and computational performance indicators.

The superior performance achieved by Hunyuan3D and Magic3D suggests that recent developments in multimodal learning and diffusion-guided optimization have significantly improved the relationship between semantic understanding and geometric reconstruction. These frameworks consistently generated objects that more accurately reflected the structural information contained in the input prompts while preserving visually realistic textures. Such behavior indicates that contemporary generative models are becoming increasingly capable of integrating language comprehension with three-dimensional representation learning, thereby reducing the need for extensive manual refinement during the modeling process[9].

A different performance profile was observed for DreamFusion. Despite producing highly detailed geometric structures and reliable semantic correspondence, its iterative optimization strategy resulted in considerably longer execution times. This finding illustrates an important compromise between reconstruction quality and computational efficiency that continues to characterize many research-oriented text-to-3D frameworks. In contrast, Tripo AI, Meshy AI, and Stable Fast 3D emphasized rapid generation by reducing computational complexity.

Although minor reductions in geometric detail were observed for certain object categories, these systems demonstrated clear advantages in scenarios where fast content creation is more important than achieving maximum visual precision[10].

Compared with previous investigations, the present study adopts a broader evaluation perspective by integrating several complementary performance indicators within a single benchmarking framework. Rather than assessing models using only image quality or geometric accuracy, the proposed methodology simultaneously considers semantic consistency, texture realism, execution time, graphics memory utilization, and overall computational efficiency. This multidimensional assessment provides a more realistic representation of practical performance and facilitates objective comparison among representative generative AI frameworks operating under identical experimental conditions.

The study also highlights the importance of standardized benchmarking for future research. Variations in prompt engineering, datasets, hardware configurations, and evaluation criteria frequently make published results difficult to compare directly. By employing a unified experimental workflow, the present investigation reduces these methodological inconsistencies and improves the reproducibility of comparative performance analysis. Such an approach may serve as a useful reference for subsequent studies investigating emerging text-to-3D technologies.

Several limitations should nevertheless be considered when interpreting the results. The experimental evaluation included only a selected group of representative AI models and a controlled benchmark of textual prompts. Future investigations should expand the experimental dataset by incorporating more diverse object categories, multilingual prompts, complex scene generation, and recently introduced open-source and commercial frameworks. In addition, user-centered evaluation involving professional designers and computer graphics specialists would provide valuable complementary information regarding the practical usability of generated models.

The findings indicate that automated 3D object generation has progressed from an experimental concept to a practically applicable technology. Continued advances in neural rendering, multimodal representation learning, and computational optimization are expected to further improve both generation quality and execution efficiency. Consequently, generative artificial intelligence is likely to become an increasingly important component of future computer graphics workflows, supporting faster, more scalable, and economically efficient production of digital three-dimensional content.

CONCLUSION

The rapid evolution of Generative Artificial Intelligence has created new opportunities for automating three-dimensional object generation and has significantly expanded the capabilities of modern computer graphics systems. The findings of this study demonstrate that contemporary text-to-3D technologies are capable of producing visually meaningful digital objects with an acceptable balance between reconstruction quality and computational efficiency. This confirms that AI-assisted modeling is no longer limited to experimental research but is becoming an effective tool for practical applications requiring fast and scalable production of digital content.

The comparative evaluation performed in this research indicates that the investigated AI models exhibit different performance characteristics depending on their architectural design and optimization strategy. Hunyuan3D and Magic3D produced the most balanced results by combining high semantic accuracy, reliable geometric reconstruction, realistic texture generation, and moderate computational cost. DreamFusion remained highly competitive in terms of reconstruction quality but required significantly longer execution time because of its optimization procedure. Conversely, Tripo AI, Meshy AI, and Stable Fast 3D demonstrated considerably faster inference while maintaining satisfactory visual quality, making them attractive solutions for applications where production speed is a primary requirement. These observations emphasize that the effectiveness of a generative AI framework should be evaluated according to the objectives and computational constraints of the target application rather than by a single quality indicator.

A major contribution of the present study is the establishment of a unified benchmarking methodology for comparing representative generative AI frameworks under standardized experimental conditions. By integrating multiple quantitative indicators—including semantic consistency, geometric quality, texture realism, generation time, and GPU memory utilization—the proposed approach provides a more comprehensive assessment of model capability than evaluations based solely on visual inspection. The inclusion of Python-based statistical analysis further improves the transparency, reproducibility, and objectivity of the experimental results, thereby supporting more reliable comparison among different text-to-3D generation technologies.

Despite the encouraging outcomes, several aspects require further investigation. The current evaluation was conducted using a selected collection of representative AI models and a controlled set of textual prompts. Future studies should broaden the experimental scope by incorporating larger benchmark datasets, multilingual prompt collections, more complex scene generation tasks, and newly emerging open-source and commercial frameworks. Integrating perceptual user studies, human-centered evaluation, and additional geometric quality metrics would also contribute to a more comprehensive understanding of the practical performance of AI-generated 3D assets.

The results confirm that Generative Artificial Intelligence is reshaping the future of computer graphics by enabling faster, more flexible, and increasingly intelligent creation of three-dimensional digital content. As diffusion models, multimodal learning, and neural rendering techniques continue to evolve, further improvements in generation quality and computational efficiency are expected. The evaluation framework proposed in this study provides a practical reference for future academic research and industrial implementation, while the obtained findings offer useful guidance for selecting appropriate generative AI solutions for diverse computer graphics applications [2,4,5,7,8].

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