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Article

Comparative analysis of text-To-3D AI tools in urban furniture design: Evaluating Luma Genie, Meshy, Tripo, and DeepAI

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ABSTRACT

This study explores the potential of text-to-3D model AIs in designing urban furniture, with a focus on bus stops, street lamps, and benches, and provides a comparative evaluation of four prominent AI tools: Luma Genie, Meshy, Tripo, and Deepai. A diverse poll of architects, urban planners, industrial designers, and students assessed the outputs based on key criteria: Aesthetic appeal, texture detail, form detail, and technical consistency and feasibility. The comparative analysis revealed that Meshy consistently outperformed the other platforms across all criteria, achieving the highest overall score of 4.09. Meshy's success is attributed to its high performance in visual creativity, structural sophistication, and spatial awareness. Conversely, Deepai lagged significantly, notably lacking in functional logic, spatial awareness, and technical consistency, resulting in the lowest overall score of 1.69. While Luma Genie and Tripo showed balanced performance, they did not match Meshy's degree of structural and aesthetic intricacy. This study highlights the current limitations of text-to-3D AI, emphasizing that platform-specific features like customization and technical control play a critical role in generating feasible architectural outputs for the future of urban design.

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INTRODUCTION

Design workflows have changed dramatically with the advent of text-to-image AI technology. These models have given developers, designers, and artists new options by transforming written descriptions into intricate visual outputs. There are numerous applications for text-to-image models, including the creation of conceptual artwork and illustrations, as well as the generation of lifelike visuals for marketing and advertising (Reed, et al., 2016).

Following the success of text-to-image models, the development of text-to-3D AI technology represents the next step in AI-driven design. By creating three-dimensional structures from textual descriptions, text-to-3D models improve the functionality of 2D models. This innovation creates new prospects mainly in gaming (Li, et al., 2024a; Lindfors, 2025; Vimpari, et al., 2023), architecture (Ko, et al., 2023; Öcal, et al., 2024; Zhuang, et al., 2023), extended reality (Behravan, 2025; Lee, et al., 2024; Sahebnasi, et al., 2024; Yeo, et al., 2023), industrial design (Althi, et al., 2023; Deng, et al., 2024a; Edwards, et al., 2024), and mechanical engineering (Šarčević, et al., 2024; Yavartanoo, et al., 2024). To create complex 3D objects, these AI models primarily utilise neural networks, which enable designers to visualise

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and refine their ideas more quickly (Cai, 2023; Deng, et al., 2024b; Shen, et al., 2024).

There are several challenges when using text-to-3D AI in urban planning. Despite the fact that these models have shown promise in producing specific objects, such as characters (Fu, et al., 2023), household items (Behravan, et al., 2025), or furniture (Bier, et al., 2024; Fang, et al., 2025), they have not yet attained comparable success in the broader context of urban planning and design (Fallacara, et al., 2023). The intricacy of urban settings, characterized by complicated spatial relationships and varied functional demands, presents considerable challenges for AI models (Lu, et al., 2024). Notwithstanding these obstacles, there are few instances of text-to-3D AI effectively generating unique and functional furniture designs (Cordero, et al., 2025; Z. Li,, et al., 2024b; Zeyin, et al., 2024). These examples illustrate AI's capacity to enhance furniture design, specifically for individual artifacts rather than comprehensive metropolitan environments, for now.

This research aims to examine the functionalities of text-to-3D AI models in the design of urban furniture, focusing on elements of bus stops and their associated amenities, including benches, billboards, and photovoltaic panels. Our research aims to evaluate four prominent AI platforms -Luma Genie, Meshy, Tripo, and DeepAI- to assess their potential for creating innovative and functional urban furniture. We propose that among the platforms we evaluated, those offering the highest levels of customization and visual complexity, specifically Meshy AI and Luma Genie, will stand out in terms of aesthetic appeal and detailed forms. However, we also anticipate that maintaining technical consistency will remain a significant challenge for all platforms when handling complex urban design prompts.

LITERATURE REVIEW

Synopsis of Text-to-3D AI Technology

The emergence of text-to-3D artificial intelligence has opened up new avenues in generative design workflows, particularly for non-expert users seeking to create functional or expressive 3D content. As the field continues to grow, recent literature has focused on categorizing technical approaches, benchmarking system performance, and identifying application-specific limitations (Huang, et al., 2024; Kim, et al., 2024; Liu, et al., 2022; Ma, et al., 2024; H. Zhang, 2020).

One of the most comprehensive overviews is presented by Li, et al. (2023), who provide a detailed survey of text-to-3D technologies in the context of AI-generated content (AIGC). Their study categorizes methods based on 3D data representations (e.g., voxels, meshes, NeRF) and evaluates core performance metrics such as fidelity, consistency, and controllability. A broader perspective is provided by Foo, Rahmani, and Liu, who survey AI-generated content (AIGC) across multiple data modalities (Foo, et al., 2023). Furthermore, focused comparative studies in domains like mechanical design provide a useful evaluation framework centered on structural accuracy, geometric fidelity, and usability for assessing output functionality in design-oriented tasks (Buljat, 2024).

Applications in Urban Design

The incorporation of AI into urban planning has emerged as a significant focus, especially with the development of smart cities (Allam & Dhunny, 2019) and the improvement of urban living conditions (Luusua & Ylipulli, 2020). AI technology has been utilized in multiple facets of urban planning and design (Kamrowska-Załuska, 2021; Yuchen, et al., 2019), including the creation of urban furniture (Cordero, et al., 2025). A notable study investigated the application of generative design algorithms to develop urban features that adjust to varying environmental circumstances and user requirements (Sanchez, et al., 2024).

Current Comparative Analyses of AI Platforms within Design Contexts

Comparative evaluations of AI platforms in design contexts have gained significance as these technologies grow and integrate into other disciplines. These studies offer critical insights into the advantages and disadvantages of various AI tools, assisting designers and researchers in making educated choices regarding the appropriate platforms for certain applications.

A significant study performed a comparative comparison of analogical and machine learning methodologies in urban design research (Brisotto, et al., 2023). This study examined the application of machine learning to find urban indicators of citizens' well-being, contrasting it with conventional analogical methods. A notable comparative study examined the convergence of ergonomics, design thinking, and artificial intelligence/machine learning in design innovation (Leão, et al., 2024). A research in instructional design assessed the efficacy of different AI platforms in generating multimedia content customized for particular academic disciplines (Kazanidis & Pellas, 2024).

Gap in the Literature

A notable deficiency is the insufficient emphasis on the practical execution and enduring consistency of AI-generated urban furniture designs. Although numerous studies emphasize the capacity of AI to generate novel and functional ideas, empirical information about the performance of these designs in real-world contexts over prolonged durations is lacking. Furthermore, there is a significant deficiency of comparative research that systematically assess the efficacy of various Text-to-3D AI platforms in design. Although many studies have examined AI tools within broader design frameworks, particular evaluations of platforms such as Midjourney, Dall-E or LeonardoAI concerning urban furniture are limited text-to-image algorithms (Cho, et al., 2022; Yıldırım, 2023).

METHODOLOGY

Artificial Intelligence Platforms and Their Functionalities
This research assesses four leading text-to-3D AI platforms: Luma Genie, Meshy, Tripo, and Deepai. Each platform possesses distinct qualities that render it suitable for specific aspects of urban furniture design.

- Deep AI processes the text descriptions provided by users and generates 3D models that match these descriptions. For each prompt, Deep AI produces a single model, and customizations are made solely through the prompt. It offers unlimited usage, allowing for continuous creativity without restrictions (DeepAI, 2025).
- Luma Genie: Renowned for its advanced visual imagination and structural sophistication, Luma Genie specializes in producing intricately detailed and visually sophisticated 3D models. It employs cutting-edge neural networks to analyze textual descriptions and generate robust designs. Additionally, it quickly generates 4 drafts without any cost or limit. The desired drafts can be further refined in more detail, also free of charge (Luma Labs, 2025).
- Meshy is an innovative tool that allows users to create high-quality 3D models from text-based descriptions. Meshy provides the flexibility to customize model generation by adjusting features such as Art Style, Target Polycount, Topology, and Symmetry. Upon entering a prompt, it generates four models without textures, which can then be individually textured if desired. After the model generation, any texture inaccuracies can be corrected, and animations can be added to humanoid models. With these features, Meshy offers a range of options that are particularly beneficial for game designers. It offers a monthly credit system, where credits are used for model generation and texturing operations (Meshy, 2025).
- Tripo is a specialized AI tool designed for 3D model creation and animation. Without offering customization options, Tripo generates four high-quality models with PBR texture style. Since these models are produced with textures and in high resolution, there's no need for separate texturing work. The developers have prioritized language model training, ensuring an accurate comprehension of the input prompts. Tripo AI provides users with monthly credits. These credits can be used for model generation and adding animations to the models (Tripo3d, 2025).

Research Design Outputs
The research design encompasses a sequence of design prompts centered on the design context which involves bus stop, bench, billboard, and photovoltaic panel combination.

Prompt: 'Create a 3D model of a bus stop with a futuristic, organically shaped that draws inspiration from parametric design that includes a bench, a billboard and photovoltaic panels'

Justification for Prompt Selection: The part "futuristic, organically shaped that draws inspiration from parametric design" was chosen to make the AI models create designs that test their ability to make complex, non-standard geometry and detailed forms. The complicated addition of "a bench, a billboard, and photovoltaic panels" was chosen to see if the model could combine several different types of urban furniture into one 3D model that was structurally sound.

Every AI platform was assigned the responsibility of generating designs in accordance with these instructions (Figure 1; Figure 2; Figure 3; Figure 4).

Individuals involved
A varied cohort of individuals was assembled to assess the AI-generated designs. 106 attendees comprised mainly architects, also landscape architects, interior architects, industrial designers, and students from these fields. Participants were also asked about their familiarity with text-to-3D modeling tools, categorized into three levels: 'Never heard of it', 'Heard of it but never used', and 'Heard of it and have used it'.

Assessment Standards

Evaluation Criteria
The designs were assessed using a standardized set of criteria:

- Aesthetic Appeal: Evaluates the visual attractiveness and creativity of the designs. Participants rated how visually appealing and innovative the designs were.

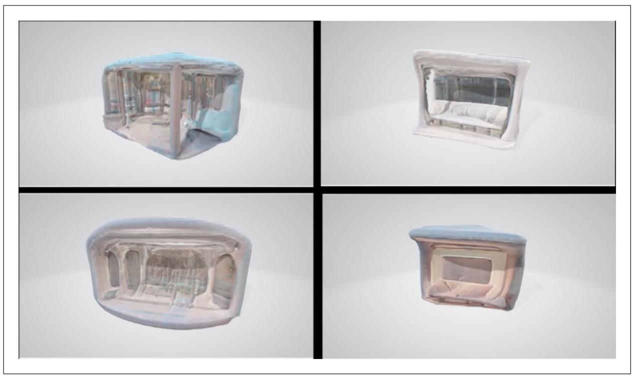

Figure 1. 3D models generated by the Deepai platform.

- Texture Detail: Assesses the quality and realism of the textures used in the designs. This criterion focuses on the detail and accuracy of the surface textures.

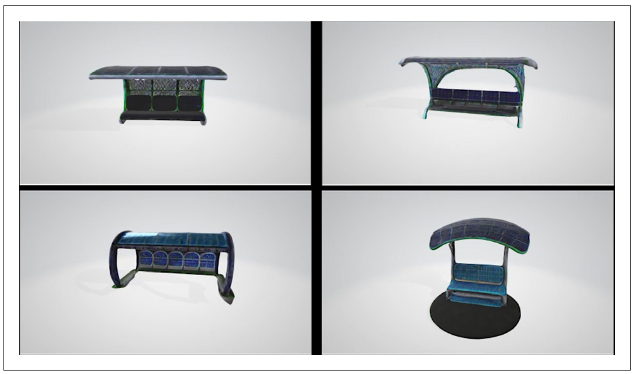

Figure 2. 3D models generated by the Luma Genie platform.

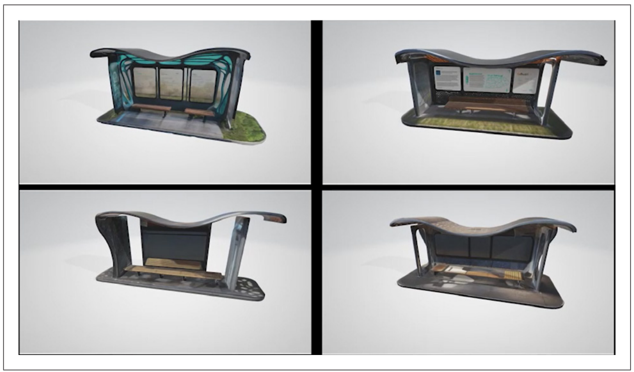

Figure 3. 3D models generated by the Meshy platform.

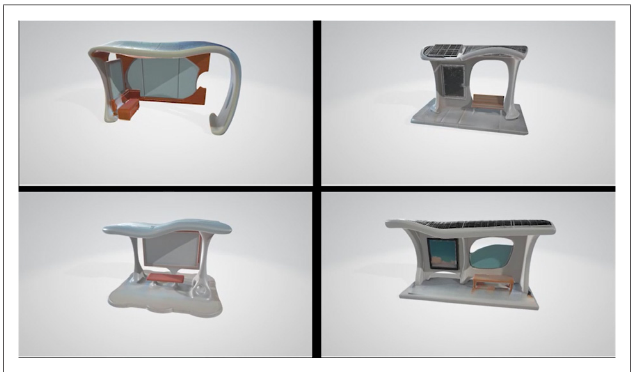

Figure 4. 3D models generated by the Tripo platform.

- Form Detail: Examines the intricacy and precision of the design forms. This includes the complexity and clarity of the shapes and structures.
- Technical Consistency and Feasibility: Evaluates the practicality and buildability of the designs. This criterion considers how well the designs can be realized in real-world applications, including structural integrity and material use.
- Overall Score: Provides a general rating based on the combined assessment of all the criteria.

This score reflects the overall quality and effectiveness of the designs.

The data collected from the evaluations were analyzed using quantitative methods. Descriptive statistics summarized the ratings, while inferential statistics, such as ANOVA, identified significant differences between the AI platforms.

RESULTS

Basic Analysis

Text-to-3D AI tools were evaluated by users based on five main criteria: Aesthetic appeal, texture detail, form detail, technical consistency and feasibility, and overall success. The analysis of average scores for each tool clearly highlighted the strengths and weaknesses of different tools (Table 1).

The aesthetic evaluation was an important criterion to measure users' visual preferences. In this category, the "T" (Meshy AI) tool scored 3.84, surpassing the other tools. The "X" (Tripo AI) tool took second place with a score of 3.34, while the "Z" (Luma Genie AI) tool showed relatively low performance with a score of 2.68. The lowest score was 1.88 for the "Y" (Deep AI) tool, indicating significant deficiencies in visual appeal.

In terms of texture detail, the Meshy AI AI tool stood out with a score of 4.00, demonstrating its success in material descriptions. The LumaAI tool ranked second in this area with a score of 3.01. In contrast, the DeepAI tool only scored 1.53, failing to meet users' expectations. This indicates that texture detailing is a significant area for improvement for the DeepAI tool.

similar ranking was observed in the form detail category. The Meshy AI tool once again led with a score of 4.13, while the LumaAI and Tripo AI tools scored 3.11 and 3.23, re-

Table 1. The scores received by AI tools based on survey results

	Aesthetics	Material detail	Form detail	Feasibility	Overall success	Total score
X (TripoAI)	3.34	3.06	3.23	3.42	3.25	16.3
Y (DeepAI)	1.88	1.53	1.84	1.93	1.69	8.87
Z (LumaAI)	2.68	3.01	3.11	3.57	3.03	15.4
T (MeshyAI)	3.84	4.0	4.13	4.08	4.09	20.14

spectively. However, the DeepAI tool had the lowest performance in this area as well, with a score of 1.84. This shows that users found the DeepAI tool inadequate in terms of geometric detailing.

In the technical consistency and feasibility criterion, the Meshy AI tool performed the best with a score of 4.08. This result indicates that the Meshy AI tool stands out not only in design quality but also in technical feasibility. The LumaAI and Tripo AI tools also performed well in this category, scoring 3.57 and 3.42, respectively. In contrast, the DeepAI tool had the lowest performance in this category as well, with a score of 1.93, highlighting its weaknesses in technical reliability.

Finally, when examining the overall success scores, the Meshy AI tool ranked first with a score of 4.09. The Tripo AI and LumaAI tools scored 3.25 and 3.03, respectively. However, the DeepAI tool only scored 1.69, indicating a very low level of user satisfaction.

In this study, to minimize biases, the names of the AI tools were not specified during the survey phase. This approach aimed to ensure that participants evaluated only the functional and experiential aspects, independent of brand or tool recognition. This method allows for a more objective interpretation of the findings and a healthier comparison of differences between the tools. The AI tools, whose names were not specified during the survey, were used to denote models prepared by TripoAI, DeepAI, LumaAI, and MeshyAI. When the scores of these AI tools across all criteria were totaled, the Meshy AI tool clearly led with a score of 20.14. This result indicates that the Meshy AI tool is the most successful in terms of aesthetics, technical aspects, and user satisfaction. Among the other tools, the Tripo AI and LumaAI tools showed balanced performance with total scores of 16.30 and 15.40, respectively, while the DeepAI tool lagged significantly with a score of 8.87. This indicates that the DeepAI tool struggles to meet user expectations.

Correlation Analysis

The correlation analysis examined the strength of the linear relationship between the five assessment criteria and the final Overall Success Score given by participants. The investigation is essential, as the correlation coefficient quantifies the direct influence of a criterion on overall success, whereas the average scores just indicate the independent magnitude of that criterion.

Figure 5 demonstrates the factors -Aesthetics, Material Detail, Form Detail, or Feasibility- that were most pivotal in shaping the final evaluation of each model.Principal Insights: Meshy AI (T): The variable Aesthetics had the most robust correlation (0.62), indicating that users emphasized the visual attractiveness of the top-rated model. DeepAI (Y): Material Detail emerged as the most significant factor (0.64), indicating that the perceived quality of materials was the principal determinant of its poor overall score. Luma Genie (Z): Aesthetics exhibited the strongest correlation (0.53), whilst Feasibility shown the least influence (0.30). Feasibility consistently exhibited the poorest link with the Overall Score for Meshy AI, Tripo AI, and Luma Genie, indicating that participants predominantly prioritized design quality (Aesthetics and Detail) over technical buildability.

A correlation analysis was conducted to examine the impact of various criteria on the overall perception of quality. The results were shown in heatmaps (Figure 6; Figure 7; Figure 8; Figure 9). The correlation coefficient is a number between -1.00 and +1.00 that shows how strong and in what direction the linear relationship is between two assessment criteria1. Values near

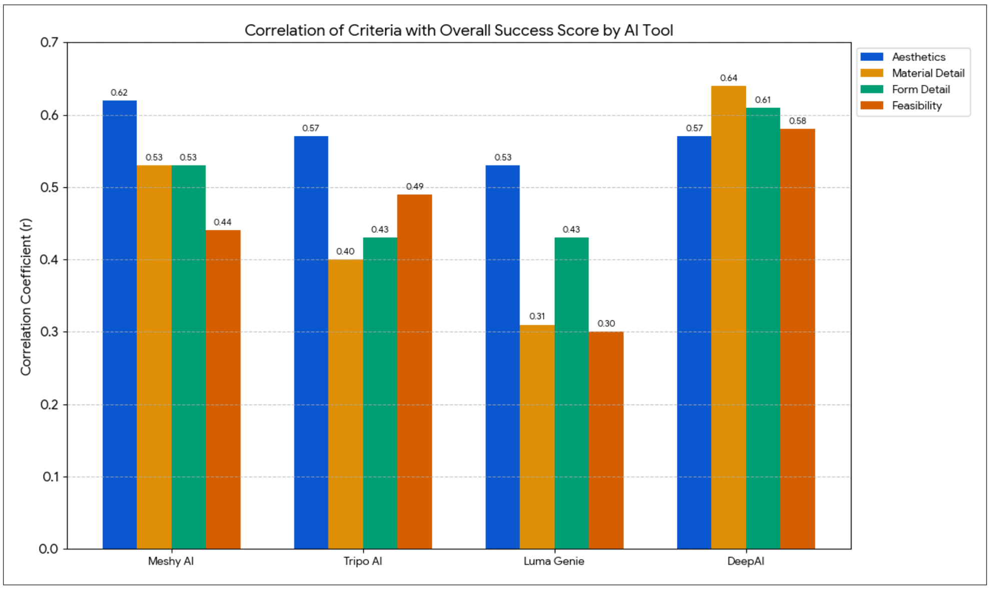

Figure 5. Correlation of criteria with overall success score by AI Tool.

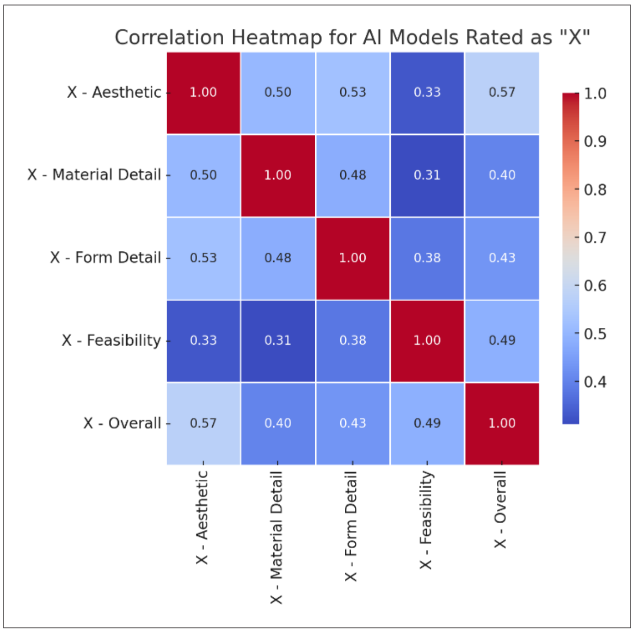

Figure 6. Correlation heatmap for Tripo AI.

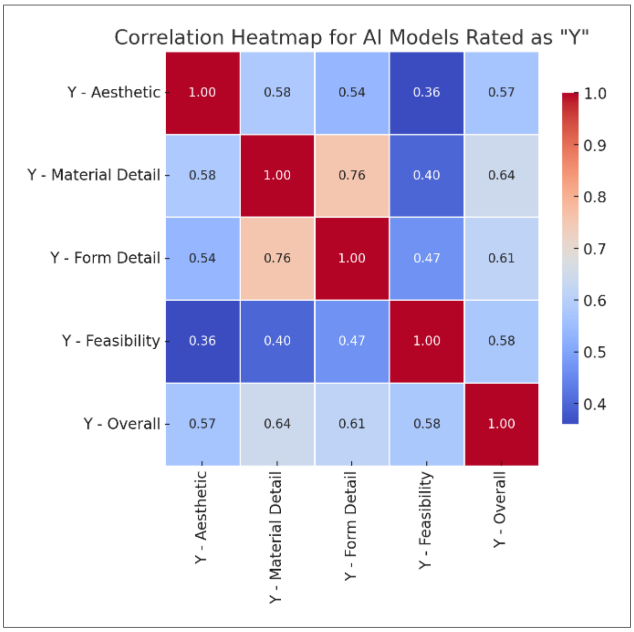

Figure 7. Correlation heatmap for DeepAI.

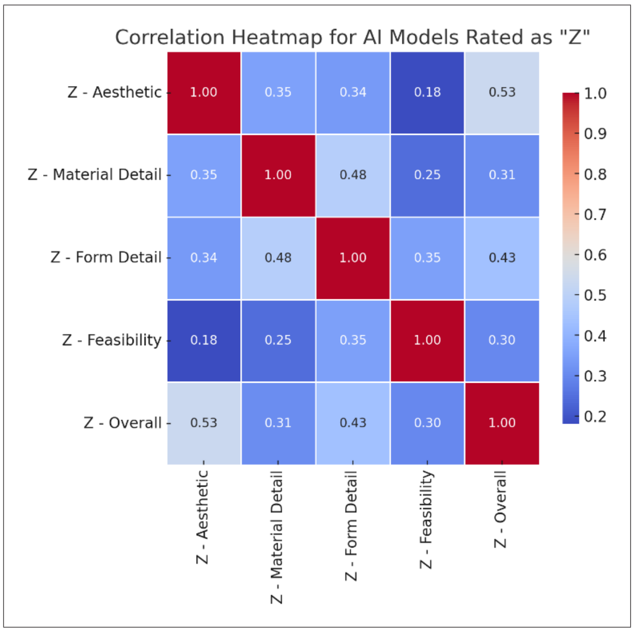

Figure 8. Correlation heatmap for LumaAI-Genie.

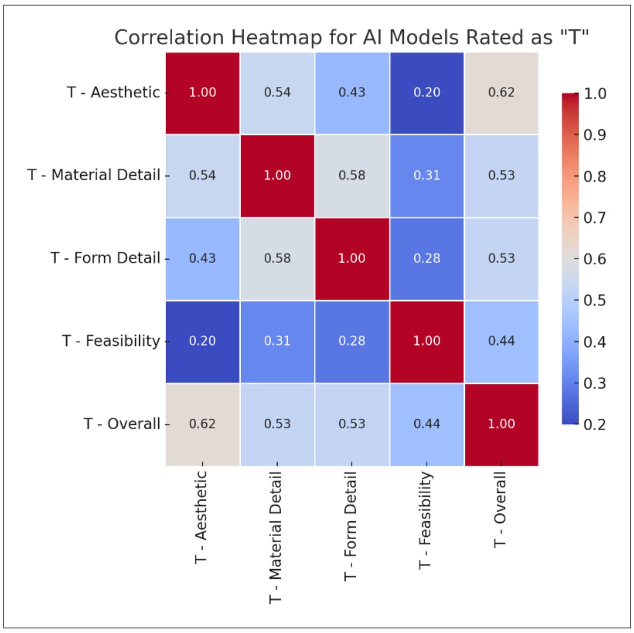

Figure 9. Correlation heatmap for Meshy AI.

+1.00 (shown in dark red on the heatmaps) show a strong positive relationship. This means that people who did well on one criterion also did well on the other. Values that are close to 0 (shown in light blue or white) indicate a weak or non-existent relationship, meaning that the scores for those two criteria were not significantly related to each other.

The correlation map analyzing the scores given to the Tripo AI model is attached. Upon examining the map, we observe a strong relationship between the Overall and Aesthetic categories for the Tripo AI tool. This indicates that the Aesthetic category has a significant impact on the Overall scores for the Tripo AI tool. Although the highest score was in the Feasibility category, the correlation coefficient measures the direct impact of a criterion on overall success, while average scores show how high that criterion is independently. The lowest correlation coefficient coming from the relationship between Feasibility and Material Detail suggests that participants who did not favor the detail level of the model still considered it feasible.This suggests that strategically improving aesthetics could be more effective in enhancing overall success (Figure 6).

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In the DeepAI model, we observe the highest correlation coefficient of 0.76. This indicates a very strong relationship between form detail and material detail in the DeepAI model. Given the low scores received by the Y model, we can infer that participants found the form detail and material detail levels to be very poor. The fact that the correlation coefficients between Overall and other categories do not fall below 0.55 also indicates that the overall success of the model remains weak (Figure 7).

Aesthetic appeal has the greatest impact on the overall success score of the LumaAI model. In other words, as the LumaAI model is rated higher in aesthetics, its overall success score also increases. There is a significant relationship between material detail and form detail, suggesting that material details are consistent with form details and are evaluated together. There is a weak relationship between aesthetics and feasibility, indicating that participants may have evaluated aesthetics independently of feasibility. This suggests that focusing on aesthetics and form details could be crucial for improving the overall success of the Z model (Figure 8).

Among the four models, the Meshy AI received the highest scores from participants. Participants prioritized aesthetics, material detail, and form detail when evaluating overall success. The generally lower correlation of feasibility suggests that participants considered this criterion less important or secondary compared to others. This indicates that improving aesthetics and details could be a more effective strategy for enhancing overall success in models like the Meshy AI model (Figure 9).

Influence of Participant Profiles on Evaluation

To better understand how background factors shaped perceptions of AI-generated models, the survey data were analyzed by years of experience, and prior familiarity with AI-based 3D modeling. Participants were asked about their prior exposure to AI-based 3D modeling tools. Three categories emerged; unaware of such tools (n=43), aware but inexperienced (n=35), experienced users (n=28).

The analysis of user profiles revealed a significant difference in perception, with experienced users giving Meshy an overall score of 4.34, compared to 3.71 for inexperienced users. This disparity highlights the influence of computational literacy on design judgment, particularly the "novelty alignment bias" where experienced users may tolerate structural imperfections for creative potential. Experienced professionals were particularly harsh on DeepAI's feasibility (1.42), reinforcing the expectation that outputs must meet conventional technical standards. This suggests that familiarity with prompt-based generation may make users more tolerant of structural imperfections in favor of creative potential -an effect previously described as the "novelty alignment bias" in AI evaluation(Cho, et al., 2022).

Inexperienced participants, on the other hand, appeared more skeptical of ambiguous or abstract forms, often penalizing models with excessive visual complexity or unusual geometry, which may have affected their scores for Luma Genie and DeepAI.

The divergence reinforces that user expectations are shaped not only by design literacy but also by computational literacy, especially when interpreting outputs from generative algorithms. Lastly, professional seniority (students vs. early-career vs. experienced professionals) revealed subtle but meaningful trends. Students were more generous in rating aesthetic and overall success, especially for visually striking models generated by Tripo. Meanwhile, experienced professionals gave lower scores for tools that failed to meet conventional technical expectations, particularly DeepAI, whose average feasibility score dropped to 1.42 in this subgroup.

DISCUSSION

The findings of this study provide valuable insights into the capabilities and limitations of text-to-3D AI platforms in urban furniture design. The comparative analysis of Luma Genie, Meshy, Tripo, and Deepai revealed distinct strengths and weaknesses across different evaluation criteria, highlighting the diverse potential of these AI tools.

Aesthetic Appeal: The Meshy AI tool consistently outperformed the other platforms in terms of aesthetic appeal, indicating its strong capability in generating visually attractive designs. This suggests that Meshy's algorithms are particularly effective in interpreting and visualizing text descriptions to create appealing 3D models. The strong correlation between aesthetic appeal and overall success for the Tripo AI tool further emphasizes the importance of visual attractiveness in user evaluations as other studies suggest (Neef, et al., 2025; Rapp, et al., 2025; Stamkou, et al., 2025).

Texture and Form Detail: Textural detail is an another important factor to perceive the details of the AI generated designs (Pepe, et al., 2023). The analysis of texture and form detail showed that the "Meshy" tool also excelled in these areas, scoring the highest among the platforms. This indicates that Meshy is proficient in generating intricate and realistic textures and forms, which are crucial for creating high-quality urban furniture designs. The tool DeepAI, on the other hand, scored the lowest in these categories, highlighting significant areas for improvement in its texture and form generation capabilities.

Technical Consistency and Feasibility: In this key area, the Meshy tool emerged as the top performer, demonstrating its ability to create technically sound designs that can be applied in real-life scenarios. The DeepAI models have a low feasibility score of 1.93, which is likely due to their structural instability, unclear material type, and non-standard geometries, making it challenging to produce them cost-effectively in the real world. On the other hand, Meshy's high score (4.08) suggests that its outputs have better implicit structural logic and material consistency, which is linked to their perceived durability. This is a critical aspect for practical implementation, as it ensures that the designs can be realistically constructed and used in urban environments (Zhang, et al., 2025). The DeepAI tool's low score in this category indicates challenges in producing technically sound designs, which could hinder its practical application.

Overall Success: The Meshy AI tool excels due to its effective algorithms and intuitive user interface, but it also distinguishes itself by allowing users to adjust crucial settings such as Art Style, Target Polycount, Topology, and Symmetry. This appears to result in more complex and structurally sound 3D models. DeepAI's much lower scores, on the other hand, can be explained by the fact that it doesn't allow for customization and only makes one model based on the prompt.

Furthermore, a direct visual assessment of the outputs (Figure 1; Figure 2; Figure 3; Figure 4) confirms disparities in visual usability. For DeepAI, the benches often appear non-functional or too small for human use, directly impacting real-world ergonomic features. Luma Genie and Tripo generally provided better-defined shelter and seating elements, contributing to their higher scores in user comfort.

Actionable insights suggest that designers prioritise tools like Meshy, which allow for customised technical parameters, to achieve results with higher consistency and feasibility. The study also surfaces ethical considerations related to the "novelty alignment bias" and the risk of generative AI leading to the homogenization of design if functional and structural criteria are overlooked.

CONCLUSION

This study provides a comprehensive evaluation of four prominent text-to-3D AI platforms -Luma Genie, Meshy, Tripo, and Deepai -within the specialized context of urban furniture design. Our research shows that the Meshy AI tool consistently outperforms other platforms on several key criteria. This means that it is especially well-suited for creating high-quality, visually appealing urban furniture designs that are both technically feasible and aesthetically pleasing. The main reason for this success is that users can customize it. On the other hand, the DeepAI tool had major problems with structural integrity and functional logic, getting the lowest scores on most criteria. This indicates Meshy's particular suitability for generating high-quality, visually appealing, and technically feasible urban furniture designs, aligning with the growing demand for efficient and effective AI-driven design solutions in smart cities (Cina, et al., 2025; Shokry, 2025).

The analysis also highlights significant areas for improvement for the other platforms, particularly the DeepAI tool, which scored the lowest across most criteria. These findings provide valuable insights into the strengths and weaknesses of current text-to-3D AI technologies, offering guidance for future development and enhancement. The study highlights the revolutionary capacity of text-to-3D AI models in influencing the future of urban furniture design. It emphasises that platform development must concentrate on strategic enhancements in aesthetics, intricacy, and technical viability to fulfil the intricate demands of design professionals and establish functional urban spaces.

In conclusion, this research contributes to the growing body of knowledge on AI-driven design, providing a foundation for future studies and practical applications in urban furniture design. The insights gained from this study can inform the development of more effective and user-friendly AI tools, ultimately enhancing the quality and functionality of urban spaces.

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