TOBB UNIVERSITY OF ECONOMICS AND TECHNOLOGY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

FROM BLACK BOX TO TRANSPARENCY: ADVANCES IN AI-DRIVEN CO-CREATION IN ARCHITECTURAL DESIGN

MASTER OF ARCHITECTURE

Sevda BAŞAR

Department of Architecture

Thesis Supervisor: Asst. Prof. Dr. Zelal Çınar

AUGUST 2024

DECLARATION OF THE THESIS

I hereby declare that all the information presented in this thesis has been obtained and presented in accordance with ethical conduct and academic rules. Proper citations have been provided for the sources referenced sources, and the references have been accurately stated. Furthermore, I confirm that this thesis has been prepared in compliance with the thesis writing guidelines of the TOBB ETU Graduate School of Natural and Applied Sciences.

Sevda BAŞAR

TEZ BİLDİRİMİ

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Sevda BAŞAR

ABSTRACT

Master of Science

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This thesis examines the integration of artificial intelligence (AI) into architectural design processes and explores the impact of these technologies on creative practices, while also addressing the limitations that arise from the "black box" nature of AI tools. AI technologies, particularly those using machine learning and deep learning algorithms, are increasingly being utilized in architecture, providing new tools for design generation, analysis, and optimization. However, the opaque nature of these technologies can make it challenging for users to understand and control these tools, creating barriers to their effective use as collaborative partners in the design process. As an alternative to this, a "gray box" approach is suggested.

The research explores various AI-supported methods for both 2D and 3D production, including tools such as Stable Diffusion, Midjourney, ZoeDepth, GhPython, Blender, ChatGPT, Tripo AI, and Comfy UI. Experimental studies using these tools highlight their strengths, such as visualization and modeling capabilities, while also revealing weaknesses like lack of transparency and limited user interaction. The study provides an assessment of the current state of co-creation between AI and human designers in practice. It emphasizes the need for more interactive and explainable AI systems (XAI) to give architects a better understanding and influence over the outputs of AI tools, thus enabling a more effective co-creation process.

This work advocates for the development of AI tools specifically designed for architectural purposes and suggests that integrating methodologies like XAI could enhance transparency and user engagement, making AI more creatively useful within design workflows. XAI could increase trust by making AI systems' decision-making processes more understandable to architects and could enable AI to serve as a more effective co-creator in design processes. Additionally, the thesis explores the potential for AI to evolve from a passive tool to an active co-creator, where AI not only generates design options but also interacts dynamically with human designers in a feedback-driven process.

Keywords: Artificial intelligence, Black box, Gray box, Explainability, Co-creation, 2D/3D generation, Design tools.

ÖZET

Yüksek Lisans

KARA KUTUDAN ŞEFFAFLIĞA: MİMARİ TASARIMDA YAPAY ZEKA DESTEKLİ ORTAK YARATIMDAKİ İLERLEMELER

Sevda BAŞAR

TOBB Ekonomi ve Teknoloji Üniversitesi
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Bu tez, yapay zekanın (AI) mimari tasarım süreçlerine entegrasyonunu ve bu teknolojilerin yaratıcı uygulamalar üzerindeki etkilerini incelerken, aynı zamanda yapay zeka araçlarının "kara kutu" doğasıyla ilgili ortaya çıkan sınırlamaları da ele almaktadır. Özellikle makine öğrenimi ve derin öğrenme algoritmaları kullanan yapay zeka teknolojileri, mimarlık alanında giderek artan bir şekilde kullanılmakta ve tasarım üretimi, analiz ve optimizasyon gibi alanlarda yeni araçlar sunmaktadır. Ancak, bu teknolojilerin opak yapısı, kullanıcıların bu araçları anlamasını ve kontrol etmesini zorlaştırmakta ve onları tasarım sürecinde etkin bir ortak olarak kullanmanın önünde engeller yaratmaktadır. Bu duruma bir alternatif olarak "gray box" yaklaşımı önerilmektedir.

Araştırma, Stable Diffusion, Midjourney, ZoeDepth, GhPython, Blender, ChatGPT, Tripo AI ve Comfy UI gibi araçları içeren, hem 2D hem de 3D üretim için yapay zeka destekli çeşitli yöntemleri incelemektedir. Bu araçlar üzerinde yapılan deneysel çalışmalar, görselleştirme ve modelleme yetenekleri gibi güçlü yönleri vurgularken, aynı zamanda şeffaflık eksikliği ve sınırlı kullanıcı etkileşimi gibi zayıf yönleri de ortaya koymaktadır. Çalışma, AI ile insan tasarımcılar arasındaki ortak yaratımın

güncel durumuna dair bir değerlendirme sunmaktadır. Daha etkileşimli ve açıklanabilir yapay zeka sistemlerine (XAI) duyulan ihtiyacı vurgulayarak, mimarların yapay zeka araçlarının çıktıları üzerinde daha fazla anlayış ve etkiye sahip olmalarının sağlanması ve böylece daha etkili bir ortak yaratım sürecinin mümkün kılınması gerektiğini belirtmektedir.

Bu çalışma, mimari amaçlar için özel olarak tasarlanmış yapay zeka araçlarının geliştirilmesini savunmakta ve XAI gibi metodolojilerin entegrasyonunun şeffaflığı ve kullanıcı katılımını artırarak yapay zekanın tasarım iş akışlarında daha yaratıcı bir şekilde kullanılmasını mümkün kılabileceğini öne sürmektedir. XAI, yapay zeka sistemlerinin karar verme süreçlerini mimarlara açıklayarak ve anlamalarını sağlayarak güveni artırabilir ve yapay zekanın tasarım süreçlerinde daha etkin bir ortak yaratıcı olarak yer almasını sağlayabilir. Tez ayrıca, yapay zekanın pasif bir araçtan aktif bir ortak yaratıcıya dönüştüğü bir rolü tartışmakta; bu senaryoda yapay zekanın yalnızca tasarım seçenekleri üretmekle kalmayıp, aynı zamanda insan tasarımcılarla dinamik ve geri bildirim odaklı bir etkileşim sürecine girebileceği vurgulanmaktadır.

Anahtar Kelimeler: Yapay zeka, Kara kutu,Gri kutu, Açıklanabilirlik, Ortak yaratım, 2D/3D üretim, Tasarım araçları

To the human desire for explanation

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1 INTRODUCTION

Since architects have been creating their designs in the digital environment, a new language has developed between the computer and the designer. Recently, architecture has entered a paradigm shift with the widespread use of artificial intelligence (AI) (Chaillou, 2020). This shift has led AI tools to develop a new language with designers as they move beyond simple automation and take on a more active role in the design process. These AI tools are referred to as "co-creators" (Gmeiner et al., 2023).

According to Gordon Pask, co-creation is a process where humans and machines learn and develop together through continuous interaction (Pask, 1969). Pask envisioned a dynamic partnership in which both machines and humans engage in a reciprocal learning process, enhancing each other's knowledge and capabilities through active participation and feedback (Werner, 2019). However, current AI technologies have inherent limitations that restrict the depth and scope of co-creation, lacking the feedback loops necessary for deeper engagement. (Werner, 2019).

While tools like DALL-E and Midjourney have advanced creative collaboration by generating consistent visual content from text or visual inputs, they still require human guidance to refine and improve outputs, highlighting the necessity for a collaborative approach in creative endeavors (S. Wang et al., 2024). The designer's involvement often remains limited to providing prompts, and the capacity to revise generated visuals is constrained, posing significant challenges to the co-creation process.

Despite these constraints, AI continues to influence the design process significantly (Leach, 2022), prompting a reevaluation of many conventional beliefs in the design community. Understanding the changes AI brings to design thinking is crucial to unlocking the potential of co-creation. To achieve this, it is essential to address the concept of the "black box"—a metaphor for the opaque computational processes in architectural design (Fricker et al., 2020). These processes can obscure understanding and limit trust, making it challenging for designers to fully engage with AI tools.

To enhance transparency, various methods of model interpretation and visualization have been developed to clarify the decision-making processes of these models (McGovern et al., 2019). The "black box" nature of some computational tools can hinder innovation and experimentation, which Kotnik and Fricker (2020) argue is a significant issue. They suggest developing new tools and methods that provide architects with better understanding and control over the computational processes they use (Fricker et al., 2020).

Current AI tools often function with an input-output logic that exacerbates the 'black box' effect, limiting user understanding and intervention. To address these issues, this thesis explores the 'black box' problem and introduces the "Gray Box" approach proposed by Prof. Andrew Witt (Witt, 2018), which involves integrating designers throughout the entire design process to improve output quality.

To effectively collaborate with AI tools, designers must develop both participatory skills and technical competencies, becoming familiar with these tools as co-creators in the design process. Given the current limitations and the 'black box' nature of AI in architecture, this thesis seeks to evaluate how these tools can function as "co-creators" and what extent they can be used effectively as collaborative partners in design.

Currently, many visualization tools generate outputs from text or image inputs without creating such a feedback loop, limiting co-creation. However, this scenario is rapidly evolving as new tools and methodologies are developed to facilitate more interactive and collaborative processes.

Figure 1.1 shows a design schema proposal where the design control is maintained through intermediate stages rather than a single final product. In certain instances within these tool groups, the feedback loop has been optimized, thereby enhancing the co-creation process.

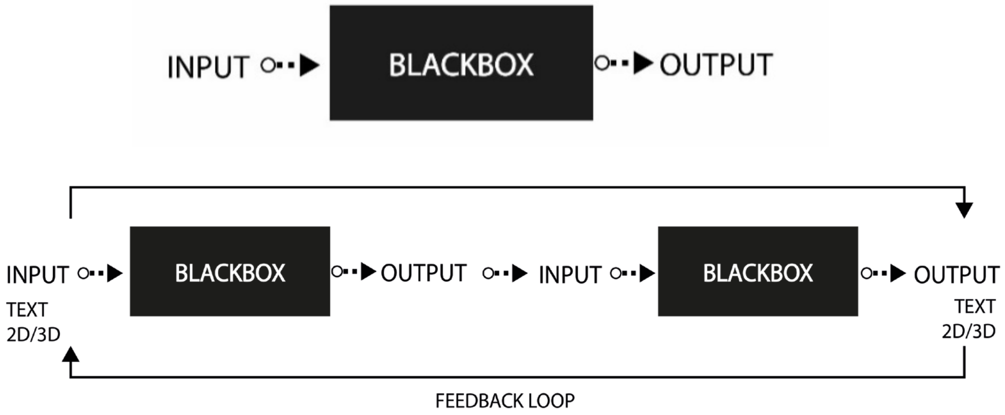


Figure 1.1: Feedback Loop (created by the author)

Given this, it can be stated that the term "co-creation tools" is used to denote the various instruments and methodologies that facilitate production processes leveraging artificial intelligence.

Explainability is a critical aspect of using AI tools, especially as these tools become more complex. Understanding the decision-making processes of AI systems is increasingly challenging, which raises concerns about safety, reliability, and bias. Explainable AI (XAI) aims to address these concerns by increasing transparency, helping users understand the underlying decision-making factors (Das & Rad, 2020). In architecture, XAI can provide architects with greater control over AI tools, enhancing their effectiveness and trustworthiness. However, XAI has not yet been widely applied to tools that generate visual outputs, indicating a significant area for future research and development.

1.1 Problem Statement

AI tools are increasingly being used to support design processes in the field of architecture. However, existing AI tools often function as "black boxes," meaning their internal workings are difficult for users to understand. This lack of transparency hinders architects' ability to effectively collaborate with AI tools and fully engage in the creative process. Additionally, while current AI tools have made significant strides in generating 2D images, the development of robust and reliable 3D modeling capabilities remains a work in progress, indicating that further advancements are necessary to achieve similarly high-quality outcomes in the 3D domain.

The opaque nature of these tools means that while text inputs can significantly alter outputs, direct modifications to the visuals are not possible. This limitation restricts the co-creation process, as designers cannot interactively refine generated visuals. This lack of transparency and control creates a barrier, making it difficult to achieve precise or desired outcomes. To enhance co-creation capabilities, more transparent and interactive interfaces are needed.

1.2 Research Question

Given the current limitations and the 'black box' nature of existing AI tools in architecture, this thesis seeks to answer the following research question:

How can the capacity of existing black box tools (particularly in the context of 2D and 3D generation) to function as "co-creators" in architectural design processes be evaluated, and to what extent can these tools be effectively used as collaborative partners in the design process? To what extent is co-creation possible with these black box tools? What are the limitations, potentials, and future development prospects of these tools?

To address the research question above, this thesis examines the state of the art in AI tools in terms of their black box nature and co-creation potential. In this regard, this study provides insights for the development of future tools.

1.3 Objectives and Scope

This study aims to investigate the use of AI tools in architecture, focusing on transparency and explainability while examining the potential and limitations of these tools. The experiments conducted encourage architects to engage with AI tools, while also providing data scientists with a foundation for further research in this field.

The primary goal is to evaluate AI's role as a co-creator in architectural design by exploring current tools and methodologies. Key objectives include identifying the limitations of existing AI tools, understanding the principles and applications of explainability, and proposing a framework for more effective integration of AI in the design process. Furthermore, the thesis delves into the potential of 2D and 3D AI tools to enhance collaboration and advance architectural practices. It also considers how the concept of co-creation can be redefined with contemporary tools, examining AI's potential to become more explainable and collaborative in the future. This framework aims to provide insights into how AI tools can be more effectively used as 'co-creators' in architectural design, laying the groundwork for strategic recommendations that could be developed moving forward.

1.4 Methodology

This thesis employs a mixed-methods approach to explore the potential of AI tools in the field of architecture. The methodology involves both qualitative and quantitative analyses to comprehensively examine the capabilities and limitations of various AI-driven methods in 2D and 3D content generation. The primary focus is on their applications in architectural design and the explainability of these tools.

Data Collection and Analysis: The initial phase involves a comprehensive review of existing literature on AI and design, with a focus on machine learning, deep learning, and their applications in generation methods. This includes an examination of both 2D and 3D generation methods, as well as a discussion on the "black box" nature of deep learning models and the importance of explainability in AI tools. Additionally, datasets used for training 2D and 3D generation methods are collected to support the experimental framework.

Experimental Framework: The second phase involves the selection and application of various 2D and 3D AI tools, including Stable Diffusion, Midjourney, ZoeDepth, Tripo AI, Blender, Grasshopper, and Comfy UI. These tools are chosen based on their relevance and capabilities in generating architectural visuals and models. Blender and Grasshopper are not AI tools, but in this process, ChatGPT was used as an assistant, allowing for an experience of the co-creation process. Many of the 2D tools selected are widely recognized and commonly utilized for text-to-image and image-to-image generation. Their performance is tested using consistent input text, and the resulting outputs are systematically compared to evaluate their capabilities. The 3D tools identified during the literature review are gaining popularity in sectors such as gaming. These tools include both text-to-3D and 2D-to-3D generation methods. Furthermore, due to the script-writing capabilities of ChatGPT, an AI-assisted workflow involving Blender and Grasshopper is explored. Although the current application of these tools in architecture is limited, this study investigates their potential by conducting a series of experiments to assess their effectiveness and versatility in architectural design. Practical application of these tools involves generating 2D images and 3D models, and exploring the interconvertibility of text, 2D, and 3D methods. An iterative design loop process is employed where AI-generated outputs are reviewed, modified, and refined through user feedback. This process aims to understand the co-creation dynamics between AI tools and human designers. However, the design loop is implemented only with tools that allow for user input and interaction.

Evaluation and Comparison: The third phase includes a detailed analysis of the outputs generated by the AI tools, focusing on their transparency and controllability. This includes examining the tools' ability to handle complex geometries, generate high-quality visuals, and produce detailed 3D models. Additionally, an assessment of the transparency and explainability of the AI tools is conducted, particularly focusing on the "black box" problem. This involves evaluating how the tools' internal mechanisms can be understood and controlled by architects.

Discussion and Recommendations: The final phase identifies the key challenges and opportunities associated with the use of AI tools in architecture. This includes discussing the limitations of current tools and proposing potential solutions to enhance their effectiveness. Recommendations for future research and development in the field of AI-driven architectural design are provided, suggesting improvements in tool design, data collection, and the integration of explainable AI (XAI) methodologies.

The thesis aims to offer a systematic overview of 2D and 3D generation methods and their applications in architecture, providing insights into the co-creation process between AI tools and human designers. By highlighting the current limitations of these tools and offering recommendations to enhance their potential, the thesis seeks to improve the collaborative capabilities of these technologies, ultimately contributing to the advancement of architectural design practices.

2 LITERATURE REVIEW

The literature review aims to explore various facets of AI and its influence on design, with a particular focus on architecture. It considers the potential of AI to transform architectural practices, examining how new technologies might reshape creative processes and workflows. By covering topics like machine learning and deep learning, the review seeks to offer insights into the algorithms and models that drive AI tools, exploring their ability to generate, evaluate, and optimize architectural designs.

The review also examines the "black box" nature of AI tools, which can obscure the processes behind specific outcomes. This lack of transparency has the potential to limit creative collaboration between architects and AI. Therefore, the review emphasizes the importance of methods that enhance transparency and explainability, such as Explainable AI (XAI), which aims to provide insights into the decision-making processes of AI systems.

Additionally, the review looks into current AI applications in design, from generative design tools to predictive analytics that could support decision-making. It considers the practical implications of these technologies, discussing their advantages and limitations, and how they may influence the role of architects in the design process. By presenting an overview of AI's current involvement in design, the literature review identifies gaps in existing research and proposes future directions for potentially incorporating AI as a collaborative partner in architectural design. This approach could encourage a more interactive and iterative design process, where AI acts as an intelligent assistant, potentially enhancing the creativity and efficiency of architects.

2.1 AI and Design

Artificial intelligence (AI), first introduced in the 1940s, can generally be defined as the science of creating intelligent machines or computer programs that mimic human intelligence (Baduge et al., 2022). According to Russell and Norvig (Norvig & Russell, 2016), studies consistently highlight AI as one of the most intriguing and fast-evolving fields. AI expert Kai-Fu Lee suggests that AI could have a more profound impact than any other development in human history. Recently, artificial intelligence has made significant strides in various domains, such as computer vision, robotics, language translation, gaming, medical diagnosis, and generative design.

In architecture, the application of AI is continuously expanding. As new applications emerge, designers are increasingly gaining a deeper understanding of AI's potential and limitations. This growing understanding is forming a clearer picture of how AI might affect and transform the field of architecture. According to Thomas Lane (Matoso, 2023), AI has the potential for up to 37% of the jobs currently performed by architects and engineers. Similarly, Chaillou (Chaillou, 2020), argues that AI may significantly enhance architects' daily practice in the near future. However, this automation is currently utilized to handle routine and less creative tasks, thereby allowing professionals to dedicate more time to the strategic and creative facets of their work. In the same way that Revit, CAD, or other 3D software do not replace architects but rather modify workflows and possibly enhance their creativity, the same can be said for artificial intelligence solutions. Additionally, AI has the potential to revolutionize the way architects operate. Tools such as Midjourney, DALL-E, and ChatGPT, widely recognized today, illustrate the advancements in AI language models and visualization models. However, these advancements are accelerating rapidly, with new capabilities continuously emerging.

Primarily, all AI tools rely on data and machine learning algorithms to function effectively. In this context, conceptualizing AI as a design partner in a co-creative process, one of the potential avenues for enhancing our familiarity with this partner might be to explore the inner workings, production, and learning processes of these tools. Gaining this understanding could improve our ability to collaborate more effectively with AI in the design process.

In the subsequent stages of this thesis, topics such as machine learning and deep learning are discussed to provide a better understanding of this paradigm and its inner mechanisms. Following this, the reasons why these tools often appear as a 'black box' to users are explored.

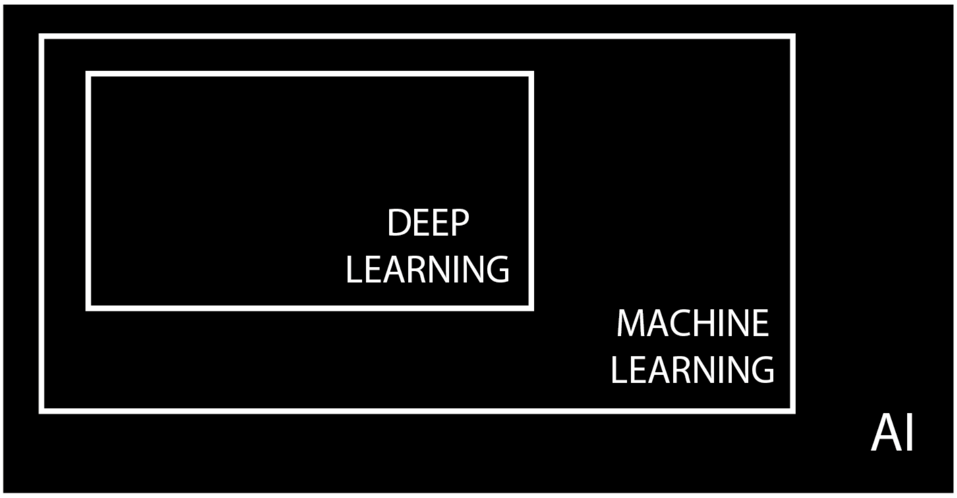


Figure 2.1: Machine learning, Deep learning, and AI relationship, redrawn by the author. (Kuntz & Wilson, 2022)

Accordingly, deep learning models are a subset of machine learning models, which in turn are part of the broader field of artificial intelligence. This relationship can be likened to a set of Russian dolls, where each layer is nested within the other. Specifically, 'deep learning' is a subset of 'machine learning,' and 'machine learning' is encompassed within the broader domain of AI (Figure 2.1). This hierarchical structure illustrates the interconnected layers, where deep learning techniques represent a more specialized form of machine learning. Machine learning constitutes a subset of the broader field of artificial intelligence. (Leach, 2022). This nested structure highlights how advancements in deep learning contribute to the broader field of machine learning and AI as a whole.

To comprehend the creative capabilities of AI in both 2D and 3D contexts, it is imperative to first address the concepts of machine learning and deep learning. As these tools are employed in a multitude of disciplines, their utilization in the field of architecture is set to extend beyond the mere inspiration of the design. For those working in the field of architecture, AI represents a new tool, which can be utilized in a ‘co-creative’ capacity. However, there is a possibility that we may not have a comprehensive understanding of this partner or be fully acquainted with its operational mechanisms. An understanding of the background and learning mechanisms of these tools can provide insight into their future evolution, highlighting both their strengths and limitations.

2.1.1 From data to design; ML/DL algorithms

Machine learning and deep learning, as subfields of artificial intelligence, have the potential to revolutionize design. This section details the fundamental principles of these technologies, their applications in design, and the solutions they offer. Specifically, it addresses how these technologies transform design processes and enhance creative potential. The opportunities presented by machine learning and deep learning elucidate their role and future impact on architecture.

Traditional programming involves a manual process where the programmer creates the program. This means that, besides programming the logic, the programmer must manually decide the rules or write the code. With traditional programming, we have input data, and the programmer writes the program or rules that use this data and executes it on a computer to generate the output or answer, as depicted in Figure 2.2 (Hiran et al., 2021). In contrast, machine learning takes both the data and the desired output as inputs and produces the learning models as the output, as depicted in Figure 2.2. This approach is of particular importance because it allows computers to learn and adapt new rules within complex and sophisticated environments that are challenging for humans to comprehend (Hiran et al., 2021).

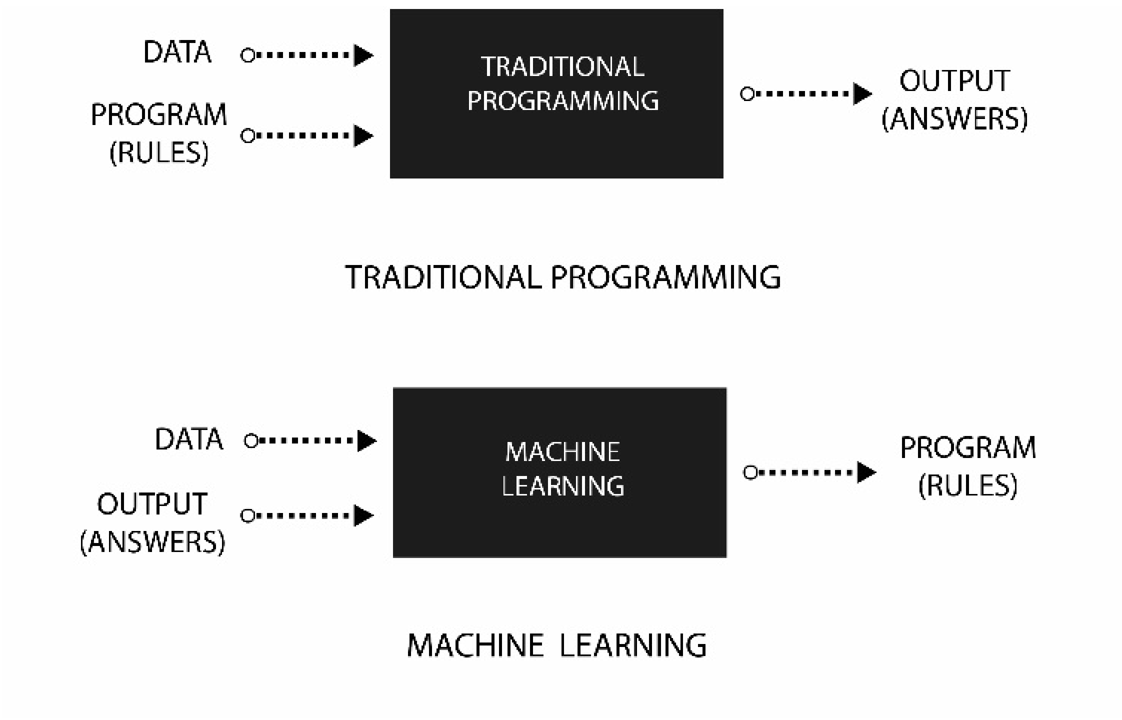


Figure 2.2: Traditional Programming vs. Machine Learning (Hiran et al., 2021), redrawn by author.

According to Ford (2018), machine learning refers to the development of algorithms that can improve their own performance through data analysis. These algorithms autonomously enhance their performance by processing and learning from information, thereby becoming better at specific tasks. In the context of architecture, this capability offers immense potential for automating and optimizing various design processes.

There are several types of learning in AI, including supervised learning, reinforcement learning, and unsupervised learning (Ford, 2018). Of these, supervised learning is the most widely used. This technique involves training an algorithm on carefully prepared, categorized, or labeled data, which helps the algorithm to understand the data (Ford, 2018). For example, in the field of architectural design, supervised learning can be employed to identify and categorize a range of architectural styles or features within a substantial corpus of building images. By providing the system with a vast number of labeled images, ranging from thousands to millions, the system is able to learn to differentiate between images that contain specific architectural elements and those that exhibit different features. Once trained, the system is capable of evaluating new images and classifying architectural styles or features with a level of accuracy that may surpass that of the average human observer (Ford, 2018).

The primary objective of reinforcement learning is to facilitate the acquisition of knowledge through practice or trial and error. Unlike supervised learning, where the correct outcomes are provided, reinforcement learning enables the system to identify solutions autonomously. Successful attempts are rewarded, similar to training a dog to sit and offering it a treat when it succeeds. However, a significant disadvantage is the considerable number of practice runs required for the algorithm to perform effectively (Ford, 2018).

Conversely, unsupervised learning entails machines acquiring knowledge directly from unstructured data in their surrounding environment, akin to human learning (Ford, 2018). For example, children primarily acquire language through observation of their surroundings. While supervised and reinforcement learning also play roles in human learning, the human brain's exceptional capacity to learn through unsupervised interaction with the environment is particularly noteworthy.

In the context of architectural design, an understanding of and ability to leverage the various types of machine learning can significantly enhance the design process. The incorporation of machine learning algorithms enables architects to automate repetitive tasks and explore new design possibilities through data-driven insights. The integration of machine learning in architecture has the potential to facilitate the creation of more efficient, innovative, and sustainable designs, which could ultimately transform the field and expand the boundaries of what is possible in architectural design.

Additionally, Deep learning, a subfield of machine learning that falls under the wider domain of AI, employs neural networks, particularly deep neural networks, to model and interpret intricate patterns in data (Ford, 2018). The term "deep" is used to describe the multitude of layers that are present within these neural networks, through which data is processed.

Significant progress in artificial cognition can be attributed to recent advancements in deep learning and the exploitation of large datasets. The role of Graphics Processing Units (GPUs) has been crucial, along with the abundance of data available for training neural networks. This combination has dramatically sped up the training process, allowing neural networks to identify intricate patterns within vast datasets, marking a major leap in the field of artificial cognition (Siemens et al., 2022).

Deep learning models are frequently viewed as "black boxes" because of the complexity and lack of transparency in their internal mechanisms (Fong & Vedaldi, 2017). This perception stems from the difficulty in interpreting the decisions made by deep neural networks, particularly when they handle complex tasks or high-dimensional data.

AI models typically contain stochastic (random) elements that can lead to different outputs from the same input. Random factors are present during the training and operating phases of the model, resulting in different results each time. Models are trained on large datasets containing trillions of images and learn specific features and patterns from these datasets; however, they may form a different combination each time when selecting which images and features to use. Deep learning models navigate a high-dimensional latent space, and even small changes in this space can cause the model to produce different results. The model can interpret the same input in different ways and produce different results by navigating different regions. In addition, the models' internal selection mechanisms and the complex network structures and weights that determine which data to use are learned automatically during training and cannot be tracked in detail. Therefore, the fact that different images are obtained from the same prompt is due to factors such as the stochastic nature of the model, the diversity of the dataset, the navigation in latent space, and the uncertainty of the internal selection mechanisms. Exactly how these processes work may be unclear even to those who develop the algorithms, and this is one of the main reasons why the model is referred to as a 'black box'.

Generative Adversarial Networks (GANs), a subfield of deep learning, take this complexity and potential even further. GANs consist of two neural networks—the generator and the discriminator—that compete against each other. This competitive structure allows GANs to produce high-quality and realistic visual content. Understanding the fundamental mechanisms and decision-making processes of GANs can help elucidate how these deep learning models operate.

2.1.2 AI-based generation methods

With an understanding of the fundamental mechanisms and complexities of AI models, particularly in the context of deep learning, we can now delve into the various generation methods utilized in architectural design. These methods leverage the capabilities of AI to produce innovative and efficient design solutions, offering new possibilities in the field of architecture. This section explores different generation methods, highlighting their applications, benefits, and limitations in architectural practice.

GANs are an integral part of deep learning. GANs are examined in this section due to their significant advancements in generating high-quality, realistic visual content, which is particularly valuable for architectural visual production. By leveraging the generative capabilities of GANs, architects can experiment with innovative design concepts and generate new architectural forms. This exploration aims to uncover the potential of AI not just as a tool, but also as an active partner in the creative process of architectural design. Specifically, examining the use of GANs in deep learning for visual production can provide insights into their applications and benefits in architecture.

Goodfellow et al. (2014) introduced the concept of GANs, a novel architecture comprising two competing neural networks. The first network, known as the generator, creates images, while the second network, called the discriminator, evaluates these images to determine whether they are real or generated by the first network. This adversarial process drives the generator to produce increasingly realistic images. Due to their effectiveness in reducing deceptive outcomes, GANs have become highly popular and have been applied across various fields, including creative practices. Karras et al. (2017) demonstrated that GANs are capable of creating photorealistic, high-resolution images of people who do not exist. Their capability to generate highly realistic visuals has made them valuable in areas such as graphic design, art, fashion, game development, and medical imaging, offering innovative solutions and enhancing the realism and significance of results. Also, Goodfellow and colleagues describe GANs as a type of generative neural network model used for unsupervised machine learning (Goodfellow et al., 2014). These models have garnered substantial attention in the arts and design sectors due to their capacity to learn and produce creations that are generally considered to be products of human creativity.

Since their introduction by Goodfellow et al. in 2014. Initially, GANs gained attention due to their innovative approach, where two networks (a generator and a discriminator) compete to produce images indistinguishable from real ones (Figure 2.3).

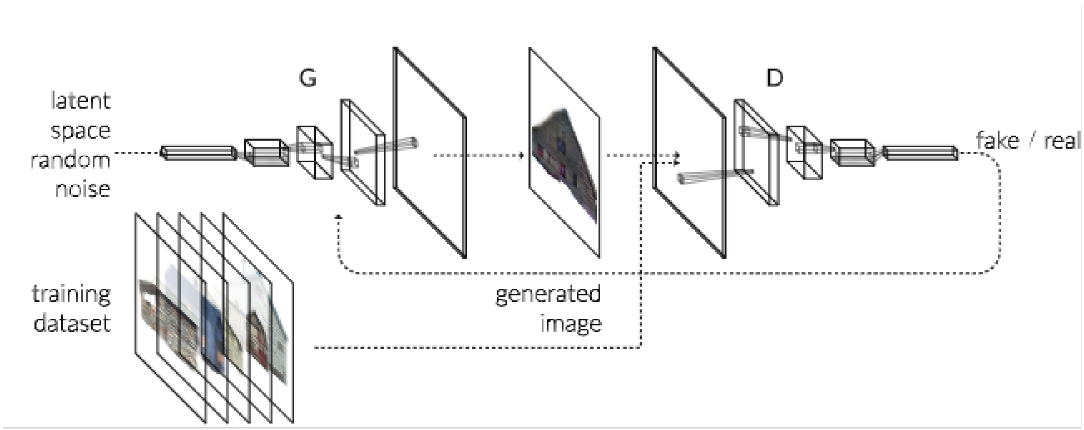


Figure 2.3: The basic architecture of GANs, comprising two competing networks: generator G and discriminator D. (Huang et al., 2021)

In architectural design, it has been found that GANs are particularly effective for generating 2D images, such as building facades and floor plans, due to the significantly higher computational demands involved in applying GANs to 3D model generation (Huang et al., 2021). However, despite these challenges, GANs can still be adapted to handle three-dimensional data representations, such as meshes and voxel grids, to create intricate 3D models. By utilizing techniques like mesh generation, GANs can generate detailed 3D models applicable in various domains, including architecture, gaming, and virtual reality. This capability to create both 2D and 3D content underscores the flexibility and strength of GANs in advancing digital content creation across multiple dimensions, despite the higher computational costs associated with 3D model generation.

The following section presents AI methods relevant to generating 2D and 3D content, showcasing advancements in both areas.

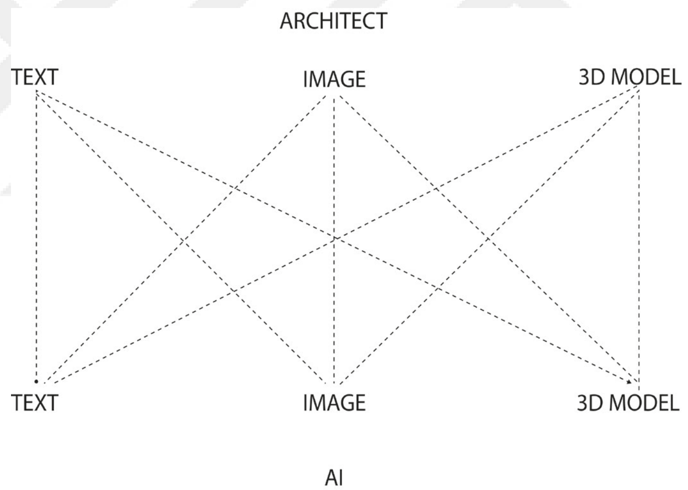


Figure 2.4: Collaborative exchange between the designer and AI. Redrawn by the author (Guida & Escobar, 2023).

In this thesis, a co-creation process between AI and designers is envisioned, where text, 2D, and 3D methods are interconvertible. As illustrated in Figure 2.4, the process involves a collaborative exchange between the designer and AI, enabling iterative development. To better understand this dynamic, the thesis explores both 2D and 3D methodologies, investigating how they can be integrated and transformed within the co-creation framework. In this process, text can be transformed into images or 3D models using text-to-image or text-to-3D generation methods. Similarly, images can be converted into 3D models or described textually, and 3D models can be generated from text descriptions or 2D images. The continuous interaction between the architect and AI allows for iterative refinement, where each type of data influences the others. This flexible integration demonstrates the potential of AI in architectural design, fostering a dynamic exchange of ideas and continuous improvements between the human designer and the AI system.

2.1.2.1 2D generation methods

In recent years, advancements in generative models for 2D content generation have steadily improved the capabilities for image creation and editing, leading to increasingly diverse and high-quality outcomes. Pioneering research on generative adversarial networks (GANs), variational autoencoders (VAEs), and autoregressive models has demonstrated impressive results (Li et al., 2024). Additionally, the advent of generative artificial intelligence (AI) and diffusion models has brought about a significant shift in image manipulation techniques, with tools like Stable Diffusion, Imagen, Midjourney, Copilot, and DALL-E 3 revolutionizing the field. These generative AI models can create and edit photorealistic or stylized images, and even videos, using minimal inputs such as text prompts. Consequently, they often produce imaginative content that transcends the boundaries of the real world, pushing the limits of creativity and artistic expression. With their newfound capabilities, these models have redefined what is possible in content generation, expanding the horizons of creativity and artistic expression.

According to Patrick Schumacher of Zaha Hadid Architects states that text-to-image generation tools are now employed in almost every project during the early phases of concept creation (Barker, 2023). In addition, other prominent architectural firms have also adopted various generative technologies and have employed image-to-image generators developed within their own offices for conceptual design in recent years. Additionally, Hickock Cole has displayed a building designed using the text-to-text generator ChatGPT, This concept was later developed in conjunction with the Midjourney platform, which facilitates the generation of text-to-image outputs. (Barker, 2023).

Text-to-image generators have demonstrated significant promise for rendering and visualization. However, further experimentation is needed on prompt creation and the correlation between prompts and visual outputs. It has been proposed that the most effective utilization of AI frameworks in architectural design entails the training of these systems with architectural data by the architects themselves (Horvath & Pouliou, 2024). Therefore, there is a necessity to explore how these tools can be specifically adapted for architectural design applications.

In the context of GAN applications, it is evident that image-to-image translation models, such as CycleGAN, Pix2Pix, and GANimorph, exhibit a notable degree of variation. These models are designed to transfer features from one dataset to another, a process often referred to as style transfer. Recently, alternative approaches for image-to-image translation, including Stable Diffusion models (Rombach et al., 2021), have gained importance. These methods aim to enhance the quality and flexibility of image transformation processes (Lataifeh et al., 2024).

Text-to-image tools create visual representations of a written text, description, or keyword while preserving the semantic context of the text (Hanafy, 2023). These tools interpret the meaning of the input text to generate corresponding images accurately.

Tools like Midjourney and DALL-E primarily utilize deep learning algorithms, specifically variations of GANs and transformer-based models. Although these tools can generate architectural visuals, their primary purpose was not specifically for architecture. Consequently, their internal workings are often unknown to users, limiting the extent to which architects can control the final output. Therefore, their use is typically restricted to providing inspiration rather than detailed design work. AI can generate architectural visuals using tools that convert text to image or image to image. These tools operate on an input-output system, where text-to-image tools create visual representations based on written descriptions, and image-to-image tools transform one image into another while maintaining the semantic context.

However, despite involving the user in a co-creation process, the designer—specifically the architect in the context of this thesis—has limited control over the final product. The designer is confronted with the “black box” nature of the tool. While the designer can modify the output by changing the input text, image, or other parameters, they do not have a comprehensive understanding of the internal mechanisms that generate the output. This lack of transparency creates a barrier between the designer and the tool.

To further investigate this issue, this thesis explores 3D tools and their applications. The subsequent chapters examine various 3D methods, their advancements, and their impact on the design process.

2.1.2.2 3D generation methods

The emergence of advanced neural representations and generative models is driving rapid development in the field of 3D content generation, enabling the creation of increasingly high-quality and diverse 3D models. However, this process is generally more complex than the creation of 2D content. Collecting two-dimensional image data is significantly more straightforward compared to acquiring three-dimensional assets. The creation of 3D assets typically necessitates a considerable investment of time and effort from 3D artists or designers utilizing specialized software (Li et al., 2024). Moreover, the diverse range of use cases and the individual creative styles of the asset creators result in considerable variation in the scale, quality, and style of these 3D assets, which in turn adds to the complexity of 3D data. In order to normalize this diverse 3D data and render it more suitable for production methods, it is necessary to establish specific guidelines. A large-scale, high-quality 3D dataset remains a highly sought-after resource in the field of 3D generation. Furthermore, an investigation into the extent to which 2D data can be employed in 3D generation may offer a potential solution to the shortage of 3D data.

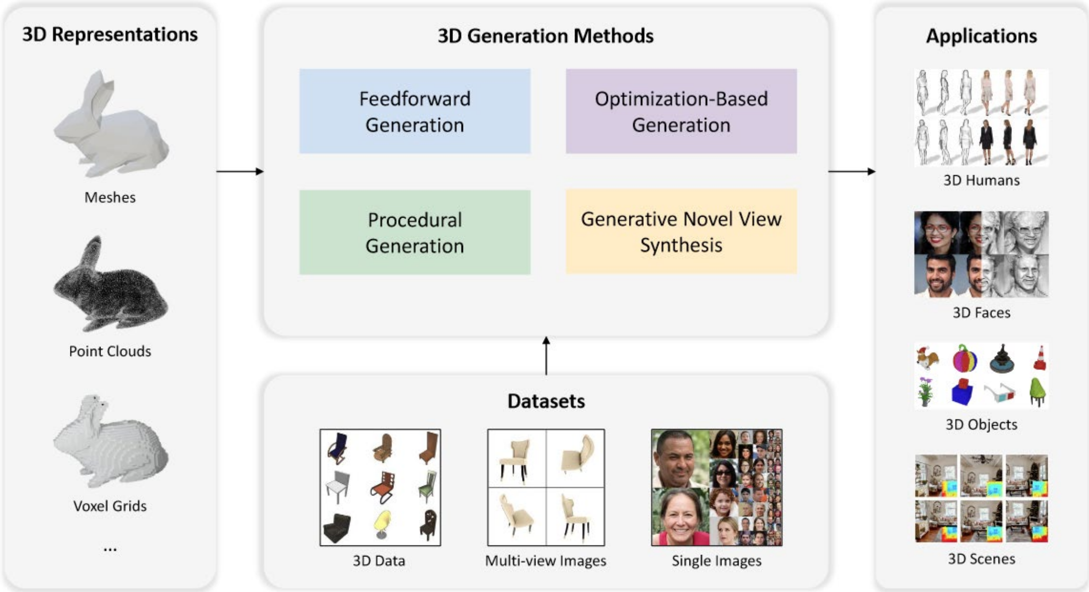


Figure 2.5: Overview of 3D Representations,3D Generation Methods, Datasets and Applications (Li et al., 2024)

In Figure 2.5 3D generation methods can be categorized into four types based on their algorithmic approaches: feedforward generation, optimization-based generation, procedural generation, and generative novel view synthesis (Li et al., 2024).

According to the survey by Li et al. (2024) on Advances in 3D Generation, Figure 2.5 provides an overview of 3D generation methods, datasets, and applications. This survey highlights that 3D representations serve as the backbone for 3D generation. It also offers a comprehensive review of the rapidly growing literature on generation methods, categorized by algorithmic paradigms such as feedforward generation, optimization-based generation, procedural generation, and generative novel view synthesis. Additionally, the survey discusses popular datasets and available applications in the field.

This thesis explores 3D tools and their applications to further investigate this issue. The subsequent chapters examine various 3D methods, their advancements, and their impact on the design process. Over the past decade, 3D generation has achieved remarkable progress and has recently garnered considerable attention due to the success of generative AI in images and videos.

In Figure 2.6, based on the provided survey, here is an overview of the 3D generation methods:

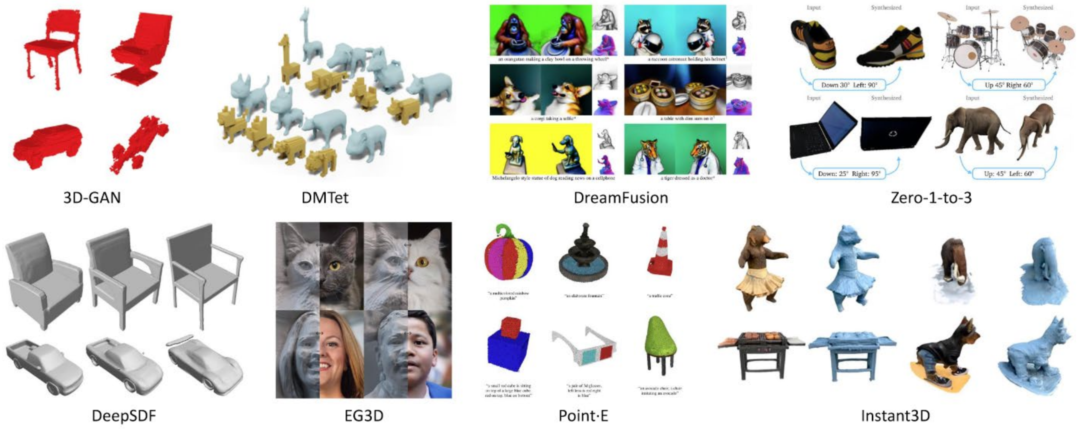


Figure 2.6: 3D Generation Methods

3D-GAN (Generative Adversarial Networks): The system employs GANs to generate three-dimensional shapes from a latent space, thereby providing a framework for the creation of diverse and realistic three-dimensional models.

DeepSDF (Signed Distance Functions): The employment of signed distance functions enables the representation of three-dimensional shapes, thereby facilitating high-quality shape reconstruction and interpolation.

DMTet (Differentiable Tetrahedral Meshes): A method for the generation of three-dimensional tetrahedral meshes that supports differentiable rendering, thereby enabling optimization-based three-dimensional shape generation.

EG3D (Explicit Geometric Representations): The combination of GANs with explicit geometric representations results in an improvement in the quality and realism of generated 3D models.

DreamFusion (Diffusion Models): It employs a combination of diffusion models and three-dimensional generation, providing an innovative methodology for synthesizing three-dimensional content from noise via a progressive refinement process.

PointE (Point Clouds): This approach is geared towards generating three-dimensional point clouds, thereby enabling the creation of detailed and complex 3D shapes with fine-grained control over the underlying geometry.

Zero-1to-3 (Zero-shot Learning): A zero-shot method that employs pre-trained models to generate three-dimensional content from two-dimensional inputs, obviating the necessity for supplementary three-dimensional data for training purposes.

Instant3D (Real-time Algorithms): The utilisation of real-time algorithms enables the rapid generation of 3D models, making it an appropriate choice for interactive applications and fast prototyping.

These developments illustrate the diverse methodologies and substantial advancements in the field of 3D content generation. The methodologies employed encompass the utilisation of GANs, diffusion models, and signed distance functions, in addition to point cloud generation and zero-shot learning. The objective is to address the challenges associated with the creation of 3D models by offering a range of techniques for the generation of high-quality, detailed, and diverse 3D assets.

These methods are used in areas such as video games, movies, virtual characters, and immersive experiences, which typically require a wealth of 3D assets. However, it is also anticipated that tools utilizing these methods produce excellent results in the field of architecture.

Table 2.1: Summary of the 3D Generation Methods

METHOD	Generative Model	Generation Space	Reconstruction Space	Rendering Technique	Supervision
DeepSDF	Autoencoder	SDF	SDF	Surface Rendering	3D
3D-GAN	GAN	Voxel Grid	Voxel Grid	Voxel Rendering	3D
DMTet	Implicit Surface	Hybrid Surface	Mesh	Mixed Rendering	2d and 3D
EG3D	Hybrid Explicit-Implicit	Tri-plane	Tri-plan	Mixed Rendering	2D
DreamFusion	Diffusion	NeRF	NeRF	Volume Rendering	Text
Point-E	Diffusion	Point Cloud	Point Cloud	Point Rendering	Text
Zero-1-to-3	Diffusion	Pixel	Pixel	Image-based	Image

Table 2.1 provides a summary of the methods. In the context of machine learning and artificial intelligence, “supervision” refers to the manner in which a model is trained. The type of supervision determines the characteristics of the data utilized during the model’s training phase.

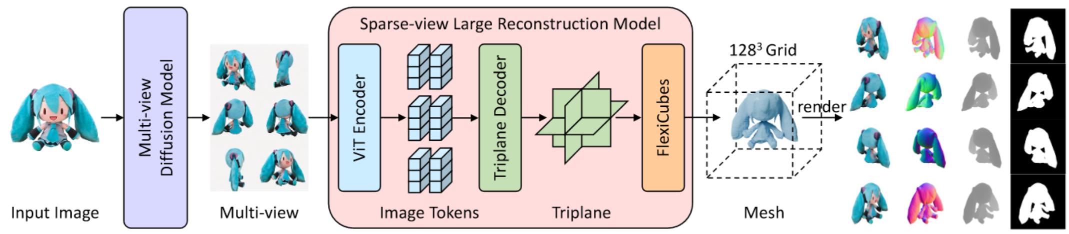


Figure 2.7 Overview of InstantMesh Framework (J. Xu et al., 2024)

Figure 2.7 illustrates the InstantMesh model, which is capable of generating three-dimensional representations from a single image. As stated by J. Xu et al. (2024), the InstantMesh framework employs a multi-view diffusion model to generate six novel views from a single input image at fixed camera positions. Subsequently, the images are fed into a transformer-based sparse-view large reconstruction model, resulting in a high-quality 3D mesh within approximately 10 seconds (J. Xu et al., 2024).

Figure 2.8 illustrates the 3D meshes generated by analogous algorithms. As this study was conducted by the InstantMesh developers, a comparison is provided between their results and those produced by other tools.

Figure 2.8: InstantMesh Tools Comparison (J. Xu et al., 2024)

Similarly, image-to-3D and text-to-3D tools are advancing, as demonstrated in studies involving tools like Tripo AI, which is utilized as a case study in this research and can generate 3D models from visual or textual inputs.

The illustrated example represents a sample model generated by Tripo AI using the prompt, "Cute little humanoid figure with raccoon ears and tail, cartoon style (Figure 2.9). (Platform of Tripo AI, n.d.)" This tool demonstrates proficiency in creating animations with accurate textures, colors, and intricate details. Unlike traditional 2D image tools, Tripo AI employs a 3D prediction mechanism, enabling it to output a comprehensive point cloud representation of the model from various perspectives.

Figure 2.9: Prompt: "Cute little humanoid figure with raccoon ears and tail, cartoon style" (https://www.tripo3d.ai/app?tab=create) Retrieved at: 20.05.2024

These tools are used for various applications, including quick prototyping and conceptual development in architectural projects. The Tripo AI provides a full set of tools for creating and manipulating 3D models. It comprises draft model generation for rapid prototyping from text or image inputs, refinement of draft models into high-resolution versions, and automatic animation to bring static models to life. It also offers advanced stylization options, such as transforming models into Lego-style or voxel-based versions, and format conversion to common formats such as USDZ or FBX, ensuring compatibility and versatility across several platforms and applications. These tools are not currently used for generating architectural models but can support the conceptual development processes in architectural projects through draft model creation. They also provide quick prototyping capabilities and highlight the potential of AI in architectural design (Platform of Tripo AI, n.d.).

Another tool to be used in this study is ComfyUI. The ComfyUI is a node-based graphical user interface (GUI) designed specifically for use with Stable Diffusion. The software enables users to construct image generation workflows by connecting a variety of blocks, or nodes, in a network. The ComfyUI platform offers a range of features, including text-to-image, image-to-image, SDXL workflow, inpainting, and ComfyUI Manager for the management of custom nodes within the GUI (Andrew, 2024).

Figure 2.10 depicts the default image-to-image workflow. In addition to the input image, positive and negative prompts can be used to make intermediate adjustments to the output. ComfyUI's workflow can be quite advanced, depending on the user's proficiency with the tool. For this, some workflows are presented in Figure 2.11.

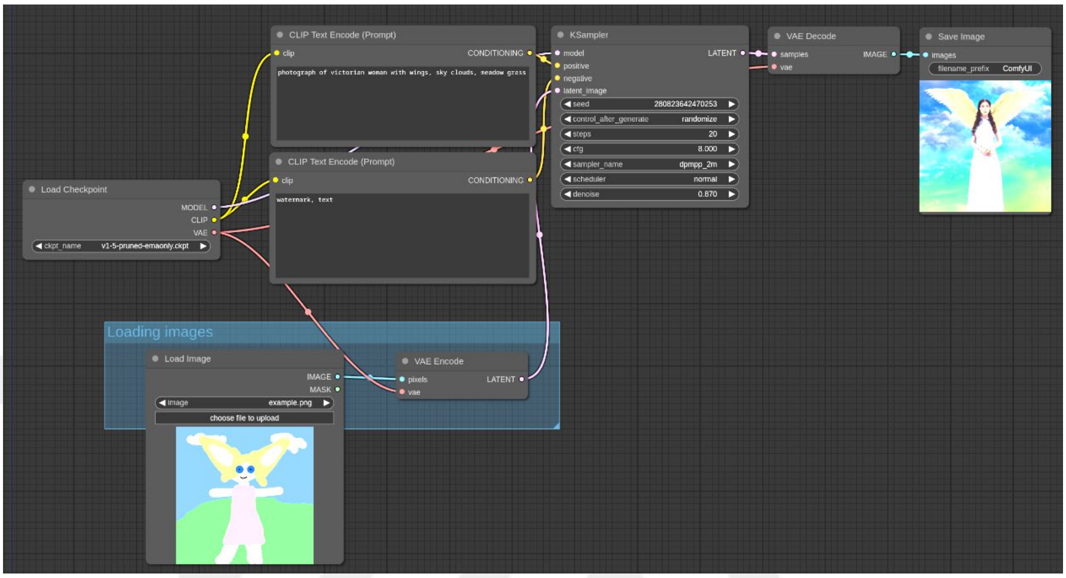


Figure 2.10: Image-to-image workflow (https://stable-diffusion-art.com/comfyui/#What_is_ComfyUI)

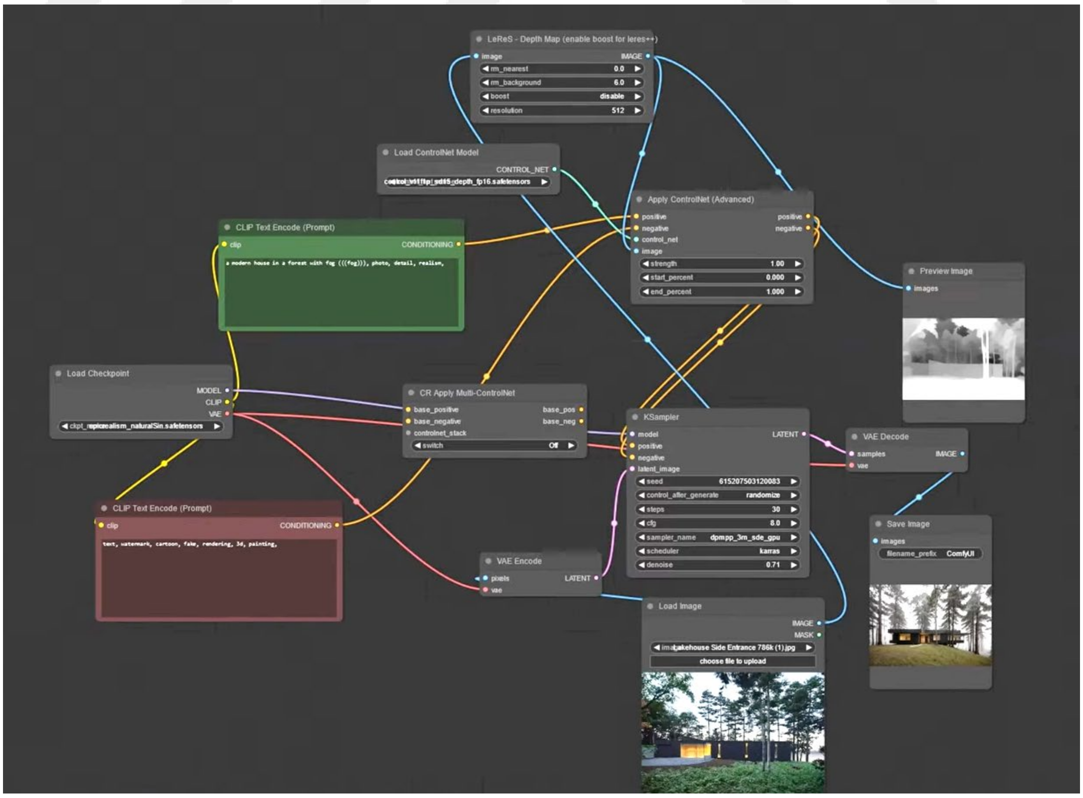


Figure 2.11: A workflow created with ComfyUI (Appendix1)

The image-to-image workflow represents a pivotal process in Stable Diffusion, whereby an image is generated based on both a prompt and an input image. The denoising strength may be adjusted to control the extent to which Stable Diffusion should adhere to the base image.

The advancements in generative models, 3D representations, and algorithmic approaches have led to significant improvements in the quality and variety of 3D generation outcomes. The recent success of large-scale models in fields like natural language processing and image generation has brought considerable attention to 3D generation. Despite these advances, there are still many hurdles to overcome before 3D models can achieve the high standards necessary for applications in video games, movies, and immersive digital experiences in VR/AR. This thesis examines some of the current challenges and explores potential future directions in this area, with a particular focus on their implications for architecture.

In the following sections, case studies are conducted using tools that include these methods, and general assessments are made about the explainability, opacity, and usage conditions of the tools. Before these case studies, the literature review continues to focus on the concepts of black box and explainability to better classify the tools.

2.2 Black Box to Gray Box

The term "black box" is used to describe the lack of transparency in understanding how an algorithm arrives at its conclusions. This opacity can result in unintended outcomes, as algorithms often optimize based on their training data rather than the intended objectives, leading to results that lack clear, explainable logic (Ahramovich, 2023). When AI tools are used in architecture, it often means that architects do not understand how the AI reached a specific design solution. This absence of transparency can hinder the effectiveness and the ability to refine and improve design solutions. Therefore, it is important to develop the skills to critically evaluate and adjust AI outputs. Fundamentally, a significant portion of AI applications in the field of architecture follow a two-step approach. This involves inputting relevant data into an AI model and then receiving the final designs as output. This process causes architects to not fully understand the intermediate processes that support the creation of the designs.

A related definition of a "black box" is provided by Gmeiner and colleagues. Artificial intelligence (AI) tools employ a range of methodologies to develop designs by specified objectives and criteria. These include constraint-based solvers, style transfer, simulation and optimization, and genetic algorithms. These techniques are becoming increasingly accessible in commercial 3D CAD design software, including SolidWorks and Autodesk Fusion 360. A significant proportion of these tools operate in a manner that may be described as analogous to a 'black box'(Gmeiner et al., 2023). In this context, the designer inputs their objectives and then assesses the resulting designs. This process can obscure the tool's inner workings, making it challenging for designers to rapidly comprehend its functionality, which can impede their creative abilities. (Gmeiner et al., 2023)

According to Kotnik and Fricker, the term "black box" metaphorically illustrates the opacity of certain automated systems, such as AI-enhanced design generators. While the inputs and outputs of these systems are visible, the internal processes remain largely obscure. This lack of transparency often leads to concerns about trust, accountability, and ethics in the deployment of AI. As architects, we are encouraged to focus on understanding these black boxes, aiming to enhance our intellectual knowledge to "open" them, thereby improving the interpretability and transparency of AI systems and further developing generative AI tools to benefit our field. (Kotnik & Fricker, 2024)

Kotnik suggests that one way to address this issue is to develop new tools and methods that allow architects to better understand and control the computational processes that they are using (Fricker et al., 2020). Similarly, Kousoulas (2018) suggests that in today's digital era of architectural thinking, there's a common acceptance of a mysterious 'black box' (Kousoulas, 2018). This metaphorical box takes in digital inputs and produces the spatial outputs desired by architects.

According to Zhi Chen, the capacity of deep neural networks (NNs) for image recognition represents a significant strength (Li et al., 2024). However, the opacity of the knowledge acquired in the hidden layers presents a challenge due to the intricate nature of NNs. The lack of interpretability in these networks not only renders them difficult to trust but also presents obstacles in terms of resolving any issues that may arise.

There are various definitions of the term ‘black box’. In his article, "Shattering the Black Box: In "Technicities of Architectural Manipulation," Stavros Kousoulas (2018) offers a critique of the commonly accepted view in architectural theory that treats architectural processes as a simple input-output system. This perspective reduces the architectural creation process to a mere input-output system, whereby design parameters are fed into a system and the resulting built environment is obtained (Kousoulas, 2018).

Kousoulas presents a challenge to this deterministic view by proposing an alternative, more dynamic and manipulative approach to the discipline of architecture. In developing his argument, Kousoulas draws upon the theories of prominent philosophers, such as Simondon, Leroi-Gourhan, Deleuze and Guattari, in order to propose that architecture should be conceptualised as a reticular technicity. This approach emphasises the reciprocal relationship between technical objects and their users.

In order to "shatter" the black box, Kousoulas proposes a shift away from the rigid input-output model and the adoption of an abductive heuristic approach. This approach emphasises the active and iterative engagement with materials and techniques throughout the design process. This enables a transformation in architectural practice from the mere translation of preconceived ideas into physical forms, to a more experimental and process-oriented methodology.

In Bruno Latour's 1987 article "Opening Pandora’s Black Box," he explains that the term "black box" is used by cyberneticists to refer to a machine component or a set of commands that are too complex to fully understand. Instead, they simplify it to a small box, focusing only on its inputs and outputs. According to Latour, the black box is not inherently inaccessible but represents something that can be deciphered by experts (Latour 1987).

Andrew Witt adds to this by stating that the black box's dubious epistemic reputation is inevitable due to the user's partial ignorance and lack of knowledge about its contents. Black boxes also serve as shortcuts to the effects of methods without requiring content knowledge. This makes them appealing because they can be used 'unconsciously' as functional surrogates for the information they contain (Witt, 2018).

Within the scope of this thesis, the black box can be examined from two perspectives: one being the opacity of the tool's operation, and the other, which we can term "extending the black box." Prof. Andrew Witt has addressed this concept as the "Gray Box"(Chaillou, 2020). This approach contrasts with the traditional black box method, where user input is only considered at the beginning, and the machine generates design options independently, without further user involvement. The gray box method, however, keeps the designer engaged throughout the entire design process (Witt, 2018). By maintaining the designer's continuous contribution and oversight, this approach ensures that the quality of the design is higher, as the designer can continually influence and refine the machine's outputs. This continuous interaction allows for a more dynamic and responsive design process, leading to outcomes that better meet the designer's intentions and standards.

2.2.1 The Opaque Nature of the Tool (Black Box):

When generating visuals from given text, the changes made to the text significantly alter the output, but direct modifications to the visual itself are not possible. This highlights the tool's opaque nature. Users do not have access to or understanding of the training dataset that underlies the visual creation process. The tool does not provide interfaces that allow for detailed intervention or adjustments in the design. As a result, the co-creation process is limited.

This lack of transparency and control creates a barrier between the user and the tool, making it difficult to achieve precise or desired outcomes. The inability to understand or access the inner workings of the tool means that users cannot see how the tool processes input data to produce the final visual output. Consequently, the collaborative potential of these tools is significantly diminished, as users cannot engage in an iterative and interactive design process.

Figure 2.12 exemplifies this situation. When the input text is highly detailed and the correct keywords are chosen, the tool produces better results. However, achieving these optimal outcomes often requires trial and error. We are unable to intervene directly with the tool or make modifications to the final output. One of the ways to use such tools effectively is through prompt engineering (J. Wang et al., 2023). The process of prompt engineering entails the creation of detailed and refined prompts that direct the AI in the generation of the desired output. By developing this skill further, users can markedly enhance the quality of the results generated by these tools, thereby optimizing the process and increasing its efficiency and productivity. This approach has the potential to result in the generation of designs that are more accurate and of a higher quality.

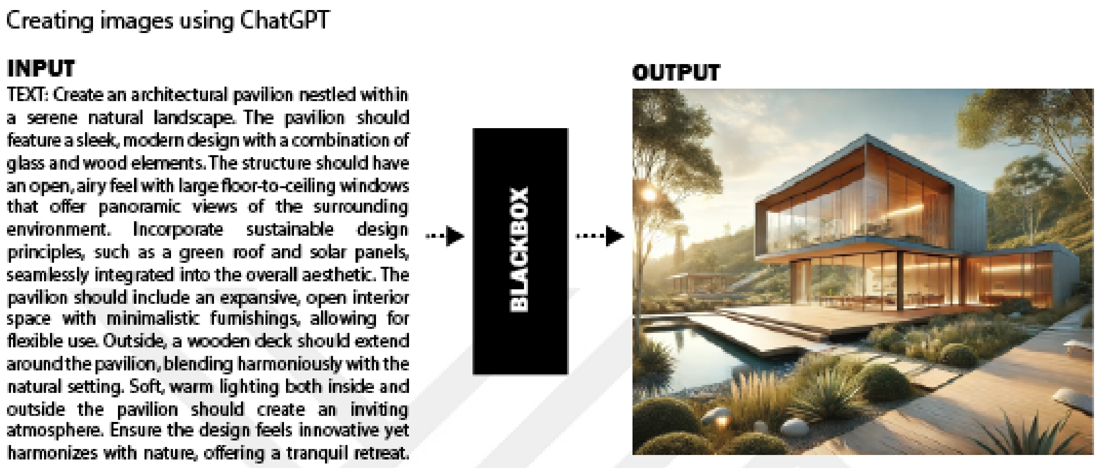


Figure 2.12: Text-to-Image Schema: The Black Box Nature of the Tool

Exploring solutions to this limitation, such as developing more transparent and interactive interfaces, could enhance the co-creation capabilities of these tools, making them more effective and user-friendly for designers and other creative professionals.

2.2.2 Gray Box Approach

Using AI to optimize a set of variables doesn't fully leverage its potential. However, co-creating with AI, relying on it, and integrating it throughout the design process reveals its true capabilities and signifies a paradigm shift (Chaillou, 2020). As previously mentioned, it needs to provide more opportunities for feedback loops.

In architecture, visualization tools, often used for inspiration, are evolving from 2D to 3D capabilities. This evolution indicates that AI can make three-dimensional predictions. Yet, given the current state of development, we also encounter tools that do not yet produce consistently successful outcomes. I have conducted a study related to this topic. This study was carried out using ChatGPT (Figure 2.13) and ComfyUI (Figure 2.14).

ComfyUI, as an interface, offers more intervention capabilities compared to 2D tools. This can help to demystify the black box because it allows designers to track options and outcomes at each step of the design process. However, the 3D output quality in this tool is still insufficient.

As demonstrated in the visuals, a 3D model was generated from a 2D image using ComfyUI. Yet, when examining other facades of the model, it becomes clear that while it does create a three-dimensional structure, its ability to accurately predict the details of the building's facades is not yet fully developed (Figure 2.15).

Text: "*Architectural photography of an ocean-side house into a landscape on the hill, overlooking the ocean, huge windows, curve-linear forms undulating roof, shape allows access from the building terrace, nature and architecture intimately interconnected, Highly textured, Color Grading, Ultra HD, wide angle, Global Illumination, octane rendering, hyperrealism, high resolution, rule of thirds, volumetric lighting, shadows, misty, intricate detail, photorealistic, cinematic lighting, 4K.*"

Figure 2.13: Input image, created with ChatGPT

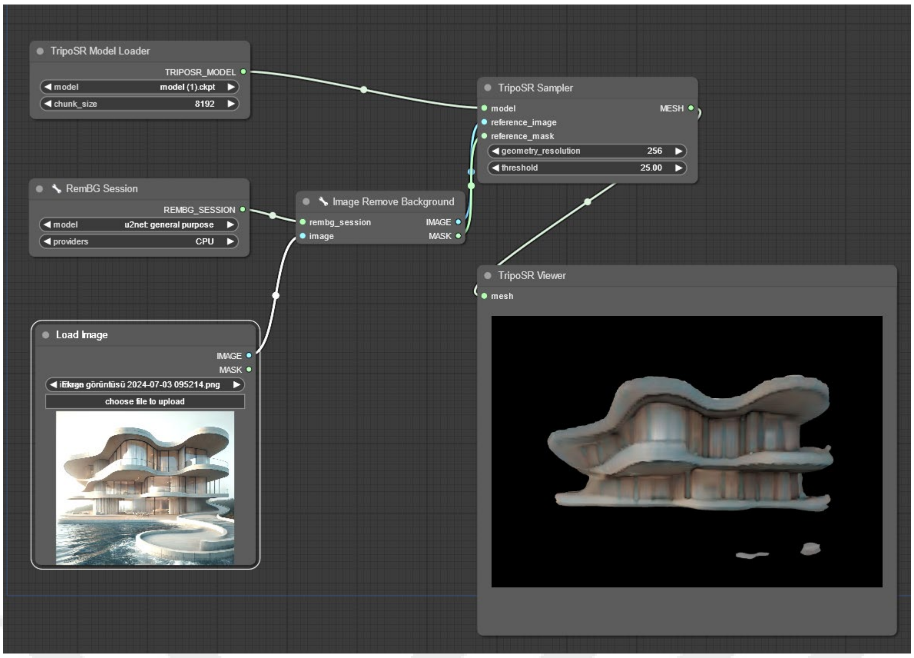


Figure 2.14: Comfy UI image creation process (Appendix2)

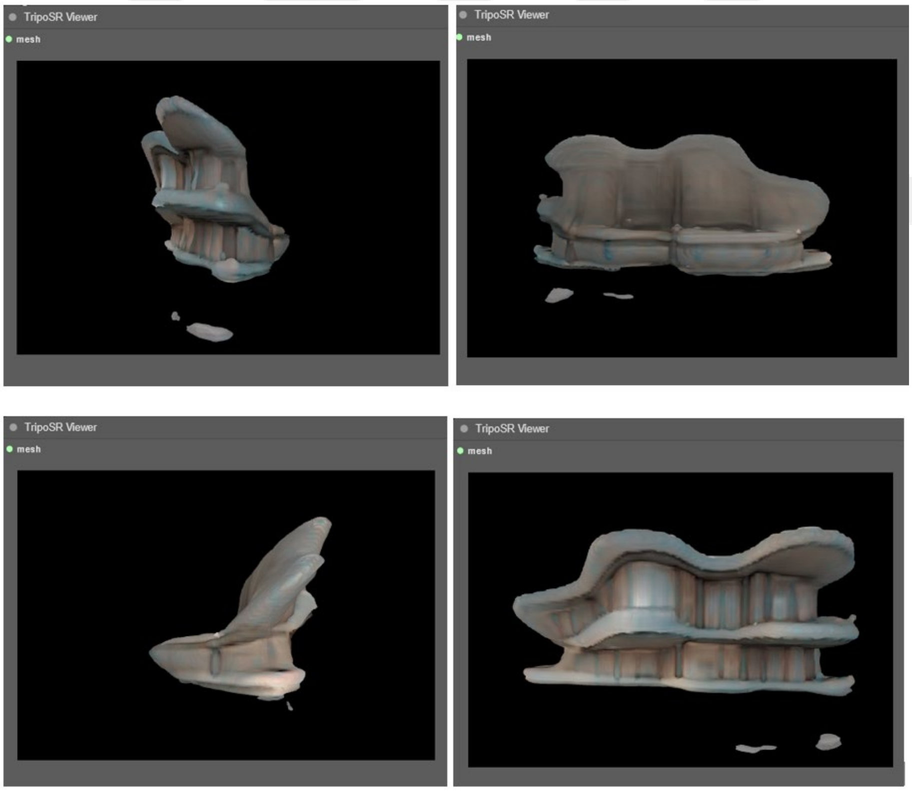


Figure 2.15: View from each side of the created model

This situation presents a significant challenge. When using an AI tool during the design phase, we lack control over the final output it produces. Additionally, since we cannot track the production stages of the generated output, we cannot fully utilize the tool as a co-creator. In this sense, architects will need to gain a deeper understanding of AI to experiment with it and enhance their creative potential, thereby gaining more control over the design process.

One strategy for enhancing the transparency of the black box is to incorporate explanation methods. This involves integrating techniques and approaches that allow for a more understandable and interpretable view of the decision-making processes of complex AI systems.

2.3 Explainability

In recent years, advancements in artificial intelligence have rendered explainability a necessity for data scientists, developers, and researchers to comprehend the models they create, extending beyond a mere requirement. The human-centered explainable AI framework seeks to address the question of what users require to be made aware of in order to understand AI systems. Explainability must extend beyond the mere technical descriptions of how an algorithm functions, as this narrow focus could compromise the consistency and accuracy of the generated content (Sun et al., 2022).

To illustrate, conversational AI models such as ChatGPT have the potential to generate 'hallucinations', whereby the model produces factually inaccurate outputs with a high degree of confidence, thereby undermining their reliability for critical decision-making processes (Maslej et al., 2023).

The term "explainability" was coined in 2004 by Van Lent to describe their system's ability to clarify how AI-controlled entities behave in simulation games (Van Lent et al., n.d.). Although the term is quite recent, the challenge of explainability dates to the mid-1970s when researchers were looking into explaining expert systems (Swartout and Moore 1988). However, progress in solving this challenge slowed down as AI made big leaps in machine learning. Since then, AI research has mainly focused on creating models and algorithms that are great at predicting outcomes, with less emphasis on explaining how decisions are made (Adadi & Berrada, 2018).

As AI tools become increasingly complex and sophisticated, understanding how specific decisions are made becomes more challenging. In some cases, it is impossible to discern the internal workings of a neural network that results in a particular output. As AI systems take on more decision-making responsibilities, this opacity raises concerns about safety, reliability, accountability, fairness, and bias. These issues are being tackled by a growing body of explainability research spanning multiple disciplines, including human-computer interaction, computer science, design informatics, ethics, and law. 'Black-box' models can erode trust in AI, particularly in fields where AI decision-making has significant real-world implications.

It can be stated that explainability refers to the ability of an artificial intelligence system's decision-making processes and outcomes to be understood and traced. This is particularly important for architects, as understanding how AI tools work and how they arrive at specific results is crucial for the safe and effective use of these tools. As mentioned in the previous section, AI tools are driven by specific algorithms and are trained on specific datasets. However, as it is highlighted by Chaillou (2020), especially in the context of 3D production, the lack of sufficient 3D model inputs can pose a significant problem. To develop a good architectural production tool, it is essential to first establish a robust data pool.

2.3.1 The Potential of Explainable Artificial Intelligence (XAI)

Explainable AI has become a new research topic in the context of modern deep learning. Without completely new explanatory mechanisms, the output of today's Deep Neural Networks (DNNs) cannot be explained, neither by the neural network itself, nor by an external explanatory component, and not even by the developer of the system. We know that there are different architectures of DNNs designed for different problem classes and input data, such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM). All of them have to be considered as black boxes - whose internal inference processes are neither known to the observer nor interpretable by humans (F. Xu et al., 2019).

Das and Rad (2020) define XAI as a field within AI that supports a range of tools, techniques, and algorithms. The primary goal of XAI is to generate explanations for AI decisions that are not only of high quality but also interpretable, intuitive, and easily understandable for humans (Figure 2.16) (Das & Rad, 2020).

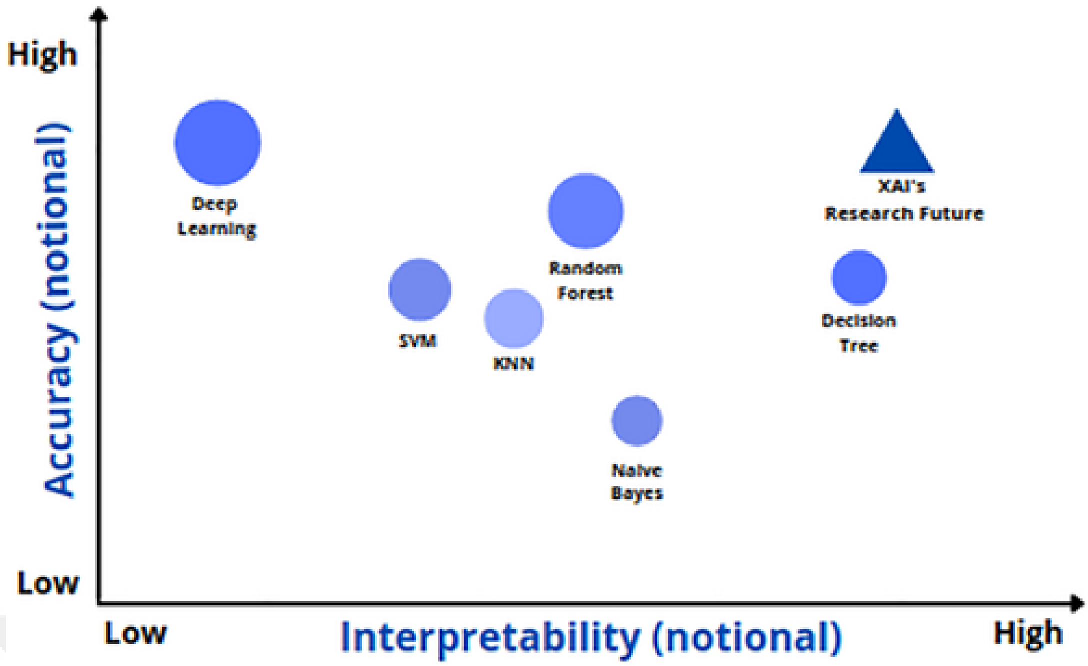


Figure 2.16: Accuracy versus interpretability for different machine learning models (Das & Rad, 2020)

As shown in Figure 2.16, XAI is considerably more predictable compared to deep learning models in AI methods. This situation, in a way, helps break the unpredictability of the Black Box. By providing insights into decision-making processes, XAI aims to make AI models more transparent and understandable. This increased interpretability fosters trust, facilitates integration into applications, and allows for easier analysis and validation of model decisions.

To help people trust and feel confident in AI decisions, it is important to explain how the algorithm works in a way that is easy to understand. This transparency ensures fairness and builds trust in the machine-learning system. In simpler terms, clear explanations make AI decisions more reliable and understandable for everyone (Das & Rad, 2020).

Lately, AI researchers have been focusing on unveiling the inner workings of neural networks, transforming them from opaque structures into transparent systems. Figure 2.17 illustrates two primary parts within Explainable AI: transparency design and post-hoc explanation (F. Xu et al., 2019).

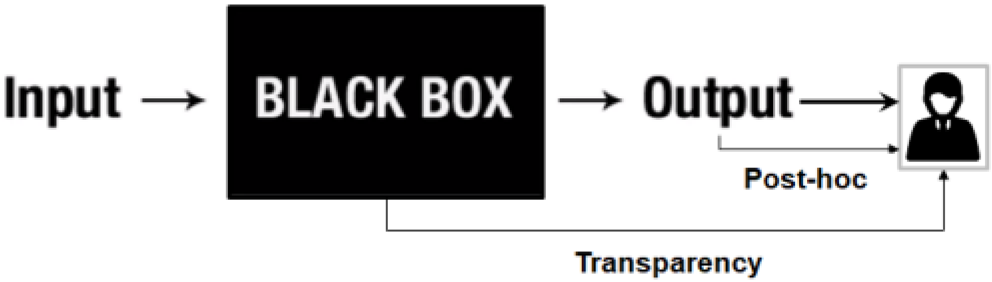


Figure 2.17: Two categories of Explainable AI: Transparency and post-hoc explanations (F. Xu et al., 2019).

Transparency design reveals how a model works for developers, helping them understand the model's structure, individual components, and training algorithms. Post-hoc explanation, on the other hand, explains why a result is inferred for users, providing analytic statements, visualizations, and explanations through examples (Figure 2.17) (F. Xu et al., 2019).

As it can be seen, XAI can play a crucial role in enhancing transparency and understanding in architectural design processes, fostering trust and acceptance. One effective strategy is "explainability by design," which involves integrating explanation features into the AI model early in its development. By incorporating XAI, architects gain a deeper understanding of AI-generated design recommendations, ensuring alignment with their expertise and intentions (Huynh, n.d.). This integration facilitates more informed and collaborative decision-making, ultimately improving the efficiency and quality of architectural design. The overall integration of XAI in architectural design holds significant potential, contributing to the development of AI-powered building design platforms that deliver optimal and compliant solutions in a shorter timeframe. In essence, XAI transforms and enhances the architectural design process by making AI-driven insights transparent, comprehensible, and in harmony with human expertise and intent.

As studies in the field progress, a critical aspect of the investigation involves assessing the interpretability of products produced by AI tools, using the principles of Explainable AI (XAI). The examination of several tools has been a focal point of the research thus far, and a subset of these tools is presented below for reference.

Using XAI in generation tools can be seen as an innovative approach with the potential to fill existing research gaps and make the use of these tools more transparent. However, the success of this approach depends on the development of new methodologies and overcoming implementation challenges. Chapter 6 aims to provide insights into this development by analyzing current tools and their outputs.

2.4 The Concept of Co-Creation

Artificial intelligence systems like ChatGPT gather knowledge from the web and can interpret this information, engaging with humans on various levels, from addressing complex inquiries to simply having a conversation (Cooper, 2023). The relationship between an AI engine and a human is inherently asymmetrical. Humans see the outcome of the AI's processing but are often unaware of the specific inputs or reasoning that led to that outcome. Sometimes, the results may even surpass what the AI's creators anticipated. In contrast, the AI engine utilizes all the information provided to it to formulate solutions and continuously enhances its training and capabilities.

Co-creation should be seen as a process where new technologies enable machines and humans to work together, pushing the limits of creativity as we currently understand it. This approach requires a new perspective on technology and different development models. To achieve these results, a new generation of AI technology that fosters a more balanced relationship between humans and AI is required. This would mean that just as knowledge is provided to AI, the system reciprocates by sharing what it has learned and the new methods it has developed for learning—facilitating a mutual co-creation process (Arbizzani et al., 2023).

According to Candy et al. (2002), co-creativity involves multiple parties contributing to the creative process in an integrated manner. Unlike situations where tasks are divided and the outcome is merely the sum of individual efforts, co-creativity enables collaborative and synthetic contributions(Candy et al. 2002).

As AI is integrated into architectural and design processes, the relationship between explainability and co-creation becomes increasingly important. Co-creation in AI-enhanced design transcends simple collaboration; it represents a dynamic partnership where humans and machines learn and adapt together. This process requires a high level of explainability, ensuring that human participants can fully understand and trust the AI systems they interact with. By fostering transparent interactions and continuous feedback loops, more robust and innovative design solutions can be developed, thereby the field of architecture will be advanced through integrated design cybernetics.

Gordon Pask believed that co-creation goes beyond merely working together to create something; it is a collaborative partnership where humans and machines learn and evolve through their interactions. (Werner, 2019). The machine is designed to "learn" from its interactions, adapting its responses based on feedback from human participants, which in turn enhances the collaborative creativity process. (Werner, 2019). In Gordon Pask's work, co-creation refers to a dynamic interaction between humans and machines. This interaction allows human participants to engage with the machine, which then adjusts and responds to their inputs. Such interaction creates a feedback loop where both humans and machines influence each other, resulting in a shared creative process. (Werner, 2019).

Gordon Pask and Ranulph Glanville were instrumental in introducing a cybernetic perspective to architecture and design. Pask viewed architecture as a form of conversation, suggesting that there is a fundamental link between the two. Central to his work is the concept of learning environments, which involve humans as integral components of a resonant system interacting with the environment or tools. Glanville furthered Pask's ideas, asserting that cybernetics and design activities are essentially conversations. The integration of human feedback into intelligent digital systems represents the next advancement towards Integrated Design Cybernetics.

Davis (2021) introduced the concept of human-computer co-creativity, which integrates a computer as an equal partner in the creative process. In this model, the computer collaborates with the user in various ways, adapting to user input and generating responses based on creative algorithms. This real-time improvisation between human and computer produces a creative product through their interaction, rather than through a distribution of labor. The contributions of both human and computer are mutually influential, reflecting true collaboration and improvisation (Davis, 2021).

Human-AI co-creativity, a subfield of computational creativity, focuses on the collaboration between humans and AI in creating shared creative outputs. This area of study is gaining importance as AI is increasingly utilized in various collaborative environments, such as music creation, design, and even healthcare, where AI functions as a virtual nurse(Rezwana & Maher, 2022). In many current co-creative systems, only humans can communicate with AI, typically through buttons, sliders, or other user interface components. However, in these systems, AI often lacks the ability to communicate back to users, which is crucial for AI to be regarded as a true partner in co-creativity. In human collaborations, partners exchange feedback and share information, a dynamic that should be mirrored in human-AI interactions (Rezwana & Maher, 2022).

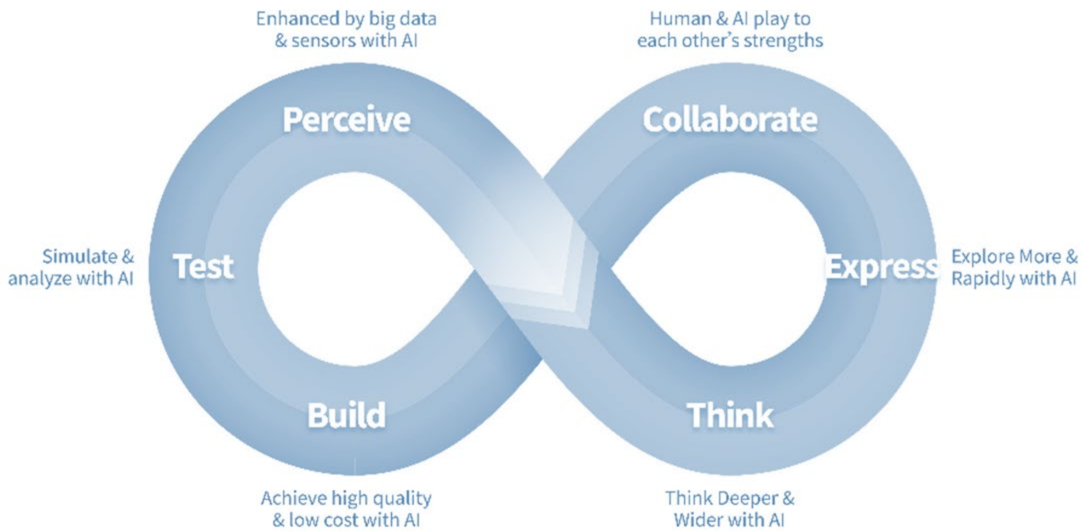


Figure 2.18: The Human-AI co-creation model (Davis, 2021)

According to Davis, The "Human-AI Co-Creation Model" is a circular process model (Figure 2.18) including 6 major phases: perceiving, thinking, expressing, collaborating, building, and testing (Davis, 2021).

The initial step is "perceive," during which human senses are enhanced by artificial intelligence through the analysis of vast data sets and the use of sensors. In addition to the conventional human senses, AI employs a multitude of sensors and networks to transform vast quantities of data into useful information and insights. This enables humans to gain a more comprehensive understanding from both perceptual and rational perspectives.

In the second phase, the "think" function of AI enables humans to engage in more profound and expansive forms of thought. The inspiration and exploration that AI offers extend beyond the limitations of the human mind, allowing for deeper and more comprehensive thinking. This collaboration has the potential to facilitate the overcoming of resource constraints, thereby enabling the achievement of innovative and unexpected outcomes.

The third phase, known as the expression phase, enables people to explore and create with the help of AI quickly. Individuals from various backgrounds, equipped with diverse ideas, can discover the most effective ways to express themselves. This can be achieved through creative activities like painting, design, composing music, writing, performing, programming, or developing prototypes. The use of AI tools empowers individuals to express their creativity without being limited by a lack of skills or formal training. In this phase, creativity becomes more important than technical expertise. The fourth phase focuses on fostering collaboration between humans and AI, allowing both to harness their unique strengths to achieve greater outcomes. Individuals can work alongside AI, whether they are operating independently or as part of a group. It is of the utmost importance to gain an understanding of the respective strengths and limitations of both humans and AI to assign tasks optimally. The fifth and sixth phases entail the construction and examination of prototypes. The deployment of AI for simulation and analysis can facilitate the production of superior-quality items at a reduced cost. Rehearsing enables the anticipation of outcomes and the preparation for real-world scenarios. The detailed simulation and computation capabilities of AI facilitate more efficient and effective construction and testing processes. Throughout this creative process, humans and AI can be seen to complement each other, thereby unlocking the potential of both. Dai et al. (2023) also present a framework for human-AI collaboration in the architectural design process. It combines the use of semantic AI models, 2D and 3D modeling, and neural networks. The users can iteratively explore and transform conceptual forms by combining prompts, 2D images, and 3D models utilizing the Rhinoceros/Grasshopper interface. The framework is validated through a case study involving early concept exploration for a museum, demonstrating its practical application in design scenarios.

Co-creation is utilized in various fields within the literature, including architectural design, where it is employed in collaboration with AI. The following section explores co-creation processes using different AI tools. It addresses the co-creative capacities of these tools in terms of their transparency and interpretability, as well as how the establishment of feedback loops can enhance the co-creation processes.

Currently, many visualization tools (such as 2D image tools) generate one or several outputs from a text input without establishing a feedback loop, which limits our ability to fully engage in co-creation. While this situation is rapidly changing, it is still too early to reach the definition of co-creation as proposed by Pask. There are limitations in these tools that constrain the extent of co-creation possible. However, these experiments aim to serve as an introduction to co-creation, demonstrating early efforts in this collaborative process.

In an environment lacking feedback, co-creation can be seen as a desired goal; however, it remains limited in its current form. While there is potential for humans and AI tools to collaborate, a true co-creation process has not yet been fully realized. AI can process human inputs and generate outputs, but due to the lack of mutual interaction and feedback, co-creation remains constrained. This represents a collaboration model that is aimed to be fully achieved in the future with more advanced tools.

Next section involves experimenting with different tools to experience co-creation. Evaluation of these tools based on specific benchmarks, assessments of explainability, and user interaction analysis is provided.

3 EXPERIENCES AND FINDINGS

In this study, various methods were employed to explore co-creation across different domains, including image-to-image, text-to-image, 2D to 3D, and text-to-3D (Figure 3.1). Through these methods, experiments with AI tools for co-creation were conducted, and observations were shared based on the outputs. For 2D tools, well-known and widely adopted options were selected. In contrast, for 3D tools, those that produce relatively higher quality outputs and have recently gained prominence were chosen. Tools with a higher level of user intervention were prioritized for this study.

When selecting 3D tools, an attempt was made to identify a common design problem. However, imposing a single design problem on tools with different usage purposes may not yield optimal results and could hinder our understanding of each tool's potential. Focusing on one problem might overlook other possible applications of the tools. If the chosen problem is too narrow, the full contributions of some tools might not be realized. Therefore, different usage scenarios were determined to test each tool's potential and progress.

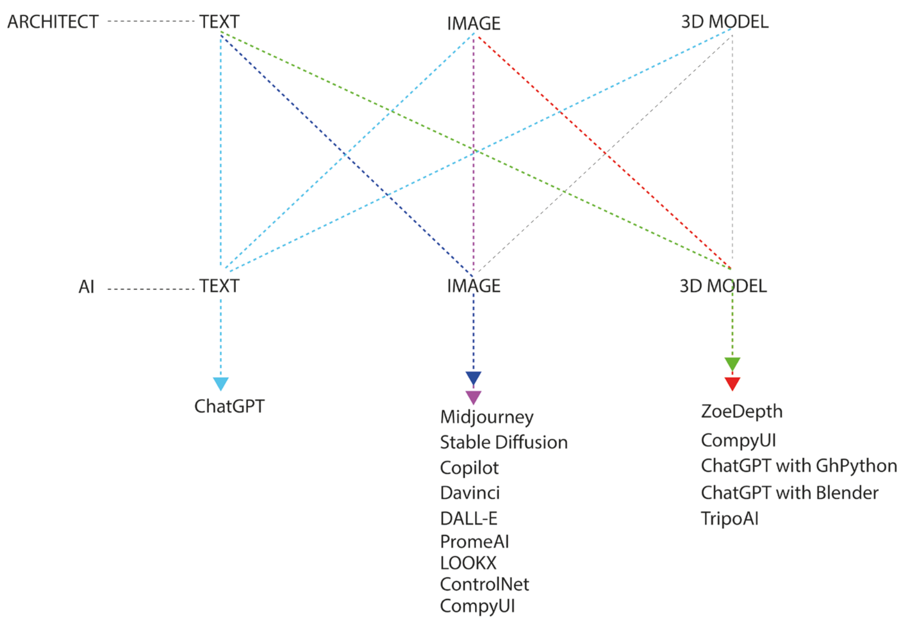


Figure 3.1: Selected Tools

Figure 3.1 tools selected for use in this study from among the many tools that were tested using the trial-and-error method.

3.1 2D Generation Tools

By experimenting with tools like Stable Diffusion and Midjourney, various visuals were generated to explore AI's capabilities in design. Simple prompts were initially used, revealing that specific keywords like "lighting" and "photorealistic" significantly enhance the visual output. Comparing the same prompt across different tools showed distinct variations due to their unique algorithms and training data, highlighting each tool's strengths and weaknesses.

The selected image acts as a reward to the AI, providing positive feedback. This positive reinforcement leads to the development of a specific visual language. Over time, our minds begin to synchronize with this evolving visual language.

This process underscored the "black box" nature of these AI tools, where the internal workings are opaque to users. Designers mainly influence outcomes by adjusting prompts or input visuals, which requires a deep understanding of how different prompts affect results. Despite the limited control over the intermediate stages of the generation process, these tools demonstrate significant potential for creative exploration and design innovation.

Figure 3.2 showcases the 2D production results using different tools. To enable comparison, they were generated using the same prompt.

TEXT: *Architectural photography of an ocean-side house into a landscape on the hill, overlooking the ocean, huge windows, curve-linear forms undulating roof, shape allows access from the building terrace, nature and architecture intimately interconnected, Highly textured, Color Grading, Ultra HD, wide angle, Global Illumination, octane rendering, hyperrealism, high resolution, rule of thirds, volumetric lighting, shadows, misty, intricate detail, photorealistic, cinematic lighting, 4K.*

The resulting images were as follows:


Stable Diffusion


Midjourney


Bing created Copilot


Davinci


LookX


PromeAI

Figure 3.2: Text-to-image tools outputs

The findings from this experiment show that, while opaque algorithms pose a challenge, they also open up previously unimaginable methods for creative expression. By learning how to use and manipulate prompt-based interactions with these AI tools, designers can push the boundaries of traditional design paradigms, developing a symbiotic relationship between human creativity and AI. This continual interaction between the user and the AI system, which requires prompt engineering, is critical for realizing the full potential of these tools in design creation.

3.2 3D Generation Tools

As AI tools for generating 3D models have advanced, their controllability has increased, allowing for more interactive co-creation beyond simple prompts. In this part of the study, it is demonstrated how designers can engage with 3D tools such as ZoeDepth, ChatGPT with GhPython, ChatGPT with Blender, TripoAI, and Comfy UI. These tools provide various levels of control and transparency, facilitating parametric design and quick prototyping, thus enhancing the interactive co-creation process in architectural and visual design.

When selecting these tools, an attempt was made to identify a common design problem. However, imposing a design problem on tools with different usage purposes may not yield good results and could affect our understanding of the tool's potential. Focusing on a single problem could overlook other potential applications of the tools. If the chosen problem is not broad enough, the contributions of some tools might not fully emerge. Therefore, different usage purposes were determined to test each tool's potential and progress. Table 3.1 shows the purposes of the tools and the specific areas in which they are used.

Table 3.1: 3D Generation Tools Class and Purpose.

TOOL	CLASS	PURPOSE
ZoeDepth	3D Scene Reconstruction/ Depth Estimation	Extracting depth maps from 2D images and 3D scene reconstruction
ChatGPT with GhPython	AI-Enhanced Procedural Generation	Automating and speeding up architectural design and modeling processes
ChatGPT with Blender	AI-Enhanced 3D Modeling	Guidance and automation in 3D modeling, and rendering processes
TripoAI	Generative Design	Creating 3D models from images or text in seconds
Comfy UI	Node-based graphical user interface (GUI)	Making AI tools more accessible

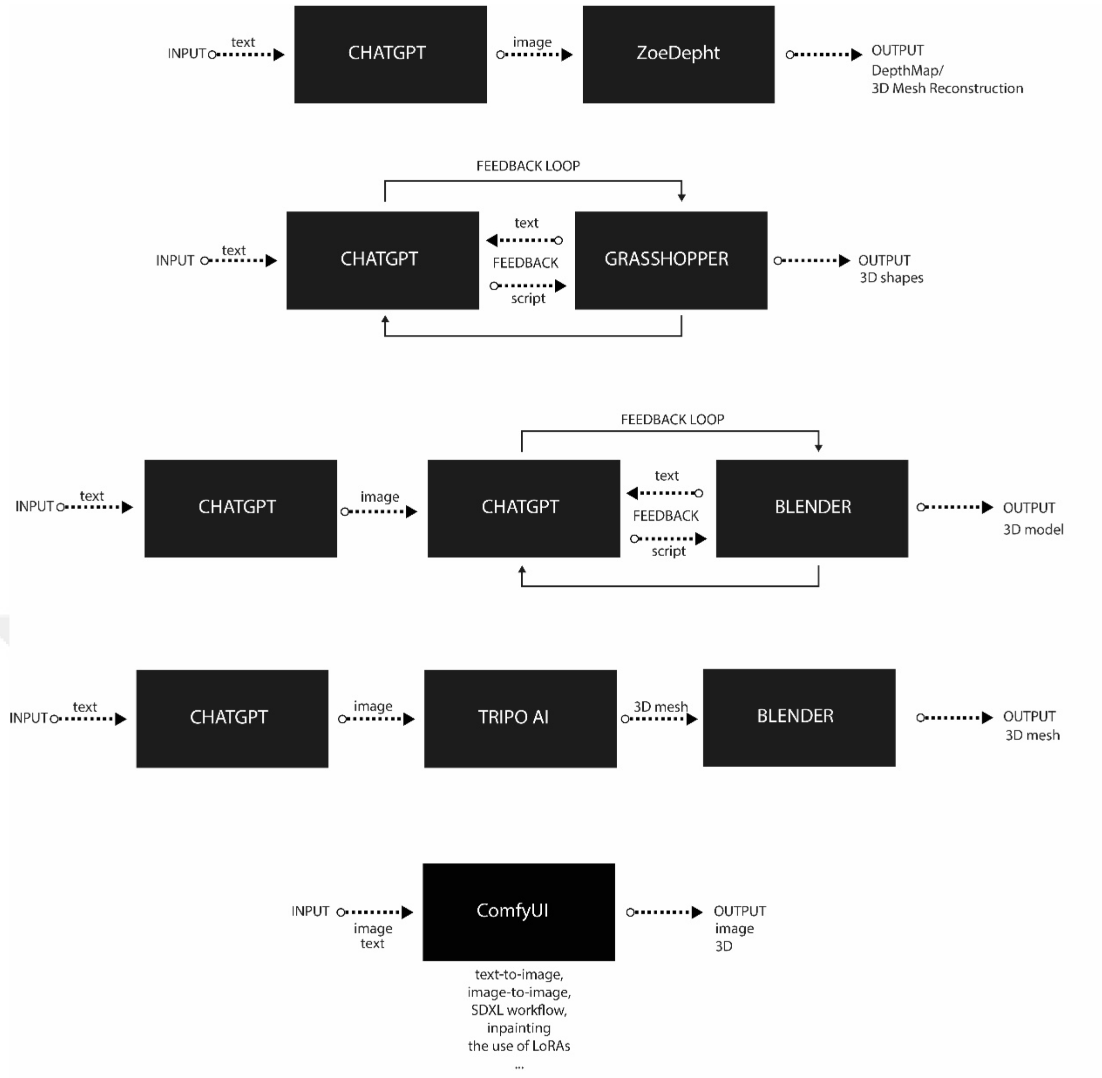


Figure 3.3: Co-Creation Scheme

In Figure 3.3, the workflows of tools with potential for co-creation are illustrated. Some tools facilitate collaboration between different tools, while others establish a feedback loop, allowing for an interactive co-creation process between the user and AI.

3.2.1 ZoeDepth

ZoeDepth is an advanced deep learning model designed for metric depth estimation from single images, showcasing significant potential in the realm of 3D modeling and computer vision. Depth refers to the perception of the distance between objects and the viewer. It adds a sense of dimension, as well as realism, to a scene. While depth is inherent to three-dimensional rendering, achieving or replicating it in two-dimensional matte paintings or background plates can be challenging. To overcome this difficulty, ZoeDepth addresses the issue by effectively calculating depth. This enables artists to transform two-dimensional backgrounds into realistic three-dimensional meshes. Figure 3.4 shows that the depth prediction is based on the given input image (Bhat et al., 2023).

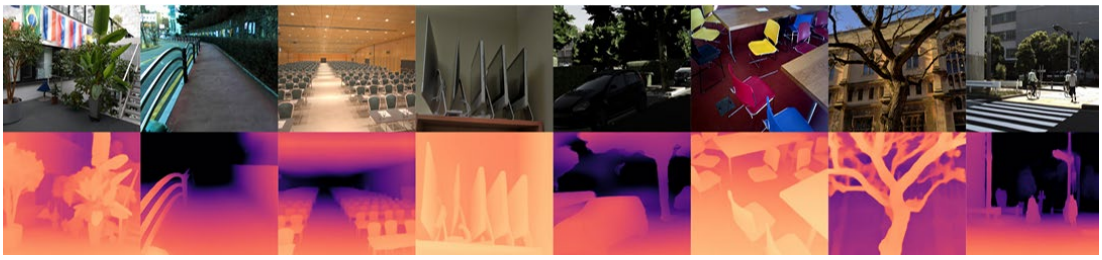


Figure 3.4 Top: Input RGB. Bottom: Predicted depth (Bhat et al., 2023)

Accordingly, this tool has the ability to transform depth estimations into 3D mesh models, facilitating the transition from 2D imagery to 3D models. Additionally, ZoeDepth can convert 360-degree panoramas into comprehensive 3D representations, enhancing its utility across various applications. The demonstration of ZoeDepth's depth prediction capabilities underscores the transformative role of AI in creating 3D models from depth maps.

Despite current limitations, particularly in accurately predicting the back facades of buildings, the model's ongoing development promises improvements in precision and reliability. This iterative enhancement reflects a broader trend in AI research where continuous refinements lead to progressively better performance, paving the way for more accurate and practical applications in fields such as architecture and virtual reality. As ZoeDepth evolves, it is expected to overcome its initial challenges, thereby solidifying its role as a crucial tool in the seamless integration of 2D and 3D digital environments.

Figure 3.5 shows the image created using Stable Diffusion XL, and the given image was first reprocessed in the ZoeDepth tool for depth map estimation (Figure 3.6). In the subsequent stage (Figure 3.7), the 3D shape derived from the depth estimation is presented.

Figure 3.5: Image created with Stable Diffusion XL

Figure 3.6: Depth map of the same image

Figure 3.7: 3D mesh reconstruction of the same image. That is a 3D model shown on one side.

However, the three-dimensional effect achieved in this step is not entirely accurate. It provides an approach to transforming a 2D image into a 3D model. To compare the 3D predictions of the final products, more examples have been included. From these examples, it can be inferred that the simpler the visual background, the cleaner the resulting 3D shape. Nevertheless, since the predictions are based solely on depth estimation, the visual backgrounds do not always translate into successful 3D productions. Despite this limitation, the tool demonstrates a method for converting 2D images into 3D models, offering insights into the future possibilities of 3D generation.

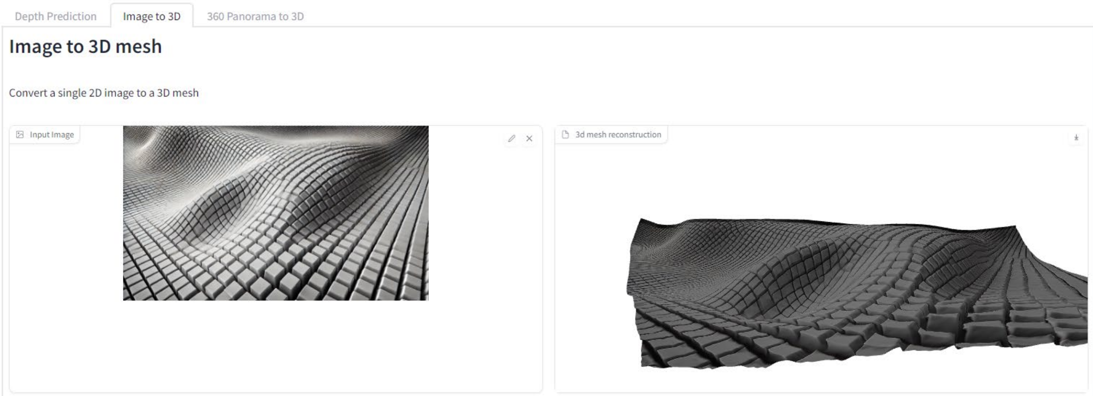


Figure 3.8: 2D to 3D Example

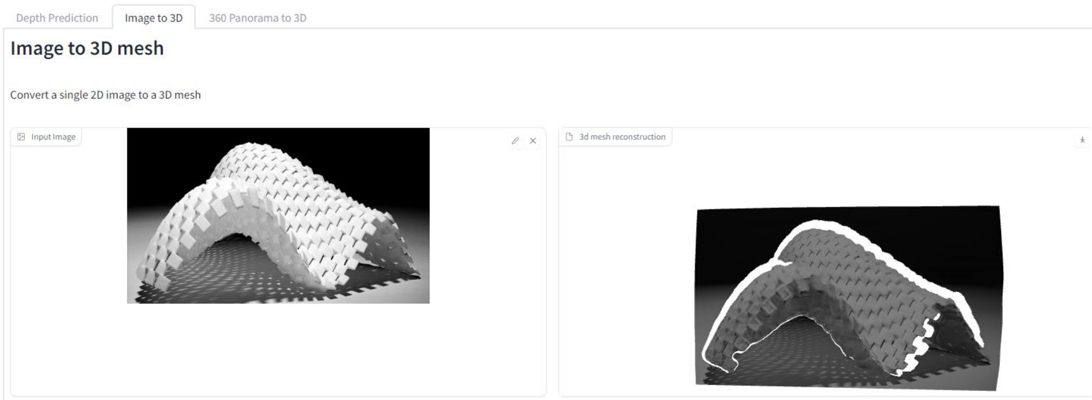


Figure 3.9: 2D to 3D Example

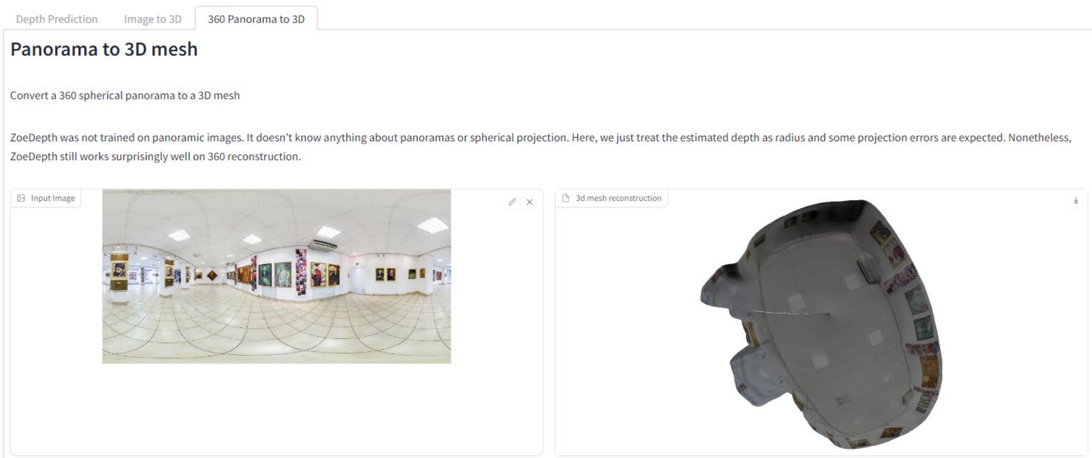


Figure 3.10: 3D Panorama to 3D

In Figures 3.8, 3.9, 3.10 examples demonstrate a method employed by ZoeDepth for 3D production. Unlike traditional 2D visuals, this method utilizes a panorama of a scene. Although ZoeDepth was not specifically designed for generating panoramic images, it handles depth estimation well, despite some expected projection errors.

Nonetheless, ZoeDepth performs effectively in 360-degree reconstructions, showcasing its capability in this domain.

In this stage of the thesis, the outcomes derived from utilizing the Python coding capabilities of ChatGPT through different tools are examined. During this phase, Grasshopper's GhPython and Blender's scripting features are employed. Blender and Grasshopper are both powerful tools for 3D modeling and design, yet they serve different purposes and offer distinct APIs.

Grasshopper is a visual programming plugin for Rhino, utilizing the GhPython component to integrate Python. GhPython provides access to Rhino. Geometry and RhinoScriptSyntax libraries, though it is not as comprehensive as Blender's bpy API. Blender offers a fully integrated programming environment through its bpy API. The bpy library grants access to all Blender functionalities, allowing for direct control over complex 3D modeling processes.

3.2.2 ChatGPT - Grasshopper's Python interface

In this study, specific scripts were generated using ChatGPT and then transferred to Grasshopper's Python Interface (GhPython), a graphical algorithm editor integrated with Rhino's 3D modeling tools, to create certain parametric shapes. This co-creation process was facilitated using Python code, written with the assistance of ChatGPT.

The process began by instructing ChatGPT to write Python code to create a Torus Knot. A Torus Knot is a complex geometric shape that wraps around and through the central hole of a torus (a doughnut-shaped surface) without intersecting itself. This specific task was chosen to test the capabilities of AI-assisted design in generating intricate shapes.

Once ChatGPT provided the code, it was pasted into the GhPython interface in Grasshopper (Figure 3.11). This integration allowed the script to be executed within the 3D modeling environment, resulting in the creation of the visual model of the Torus Knot (Figure 3.12).

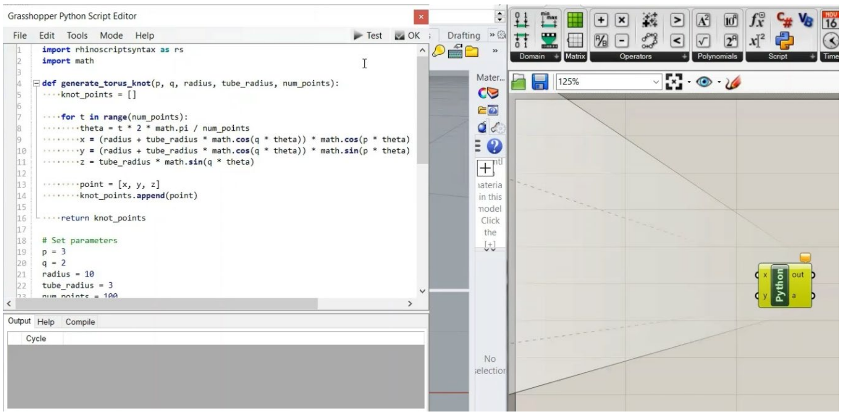


Figure 3.11: GhPython in Grasshopper

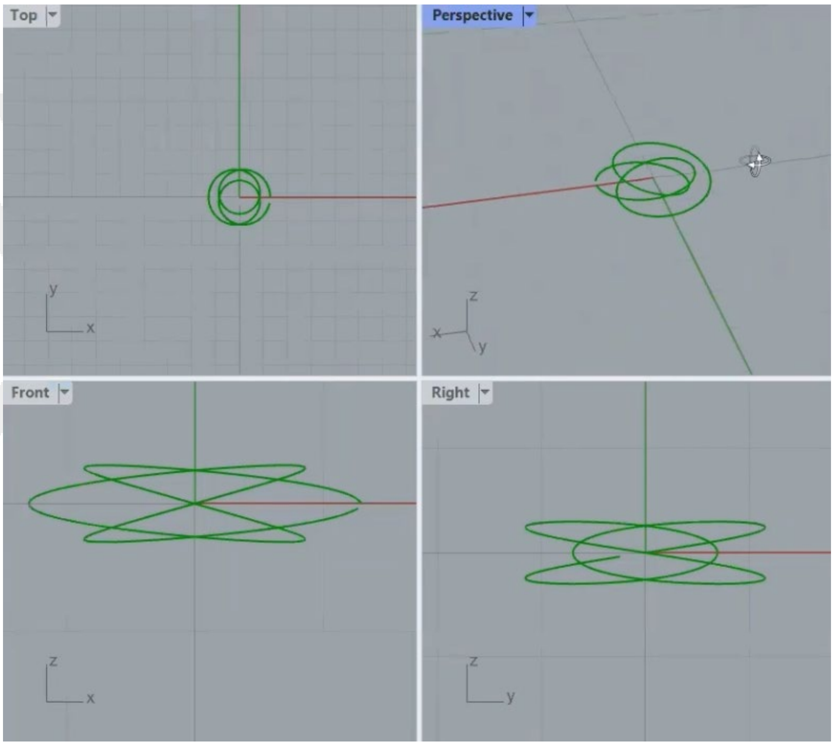


Figure 3.12: Torus Knot shape produced with Ghpython

The generated shape was initially a basic representation, but its parameters could be adjusted directly within the script or through Grasshopper sliders, providing a flexible approach to modifying the design. Figure 3.13 illustrates the Torus Knot shapes after adjusting its parameters. This iterative process of adjusting parameters and rerunning the script highlighted the trial-and-error nature of working with AI-assisted design tools. Despite the designer's lack of coding knowledge, they were able to achieve the desired 3D model by utilizing ChatGPT as a co-creator to assist the process. By experimenting with different parameters and observing real-time changes, the designer successfully obtained the desired outcome.

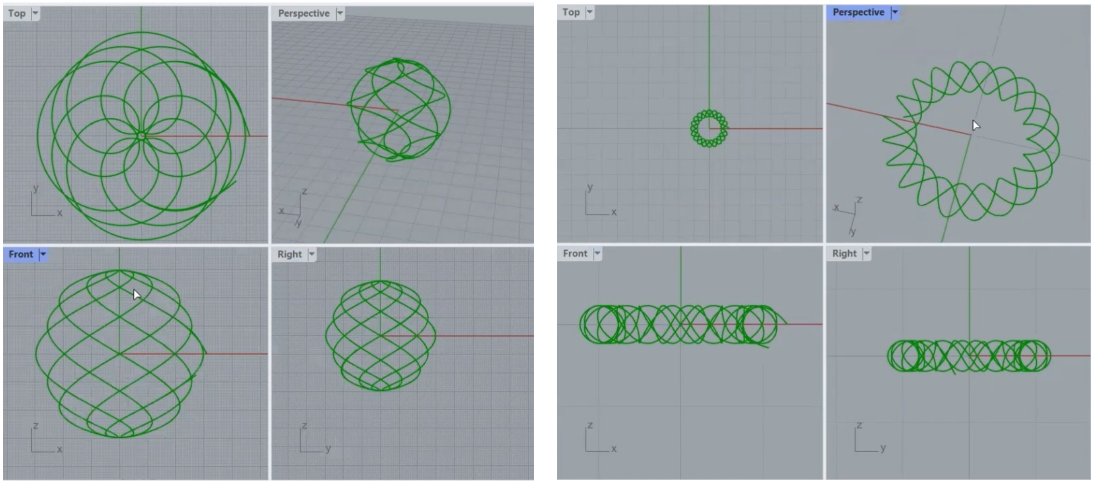


Figure 3.13: Torus Knot shape produced with Ghpython

This experience demonstrated the potential of AI in assisting the design process, particularly in generating shapes without requiring extensive prior coding knowledge. AI showcased its capability as a co-creator, enabling designers to explore and realize designs effectively. However, despite the current integration's limitations in producing complex shapes, it highlighted the hope that AI's presence could simplify the design process.

In this experiment, consistent success was not achieved while working with GhPython. For each encountered error, the reason was presented to ChatGPT to devise a solution, and the revised script was reprocessed. This created a design loop that continued until a successful outcome was achieved.

Overall, the integration of ChatGPT with GhPython in Grasshopper presents a promising avenue for architectural and design innovation. By leveraging AI tools, designers can expand their creative capabilities and simplify the development of models, thereby enhancing the transparency of the design process. The design loop established in the AI co-creation process can lead to better results.

3.2.3 ChatGPT- Blender

In this part, an AI-assisted co-creation process using ChatGPT was employed to create a parametric 3D model in Blender. Initially, ChatGPT was asked to generate a parametric visual based on the following prompt (Figure 3.14). This design is the first step in guiding the creation of the model in Blender.

TEXT: " *Create an image of a structure that is an example of parametric design. The structure should be composed of repeating geometric units in white, capturing attention both visually and structurally. These units should be shaped like square prisms and arranged in a regular grid pattern, forming a curved surface. The curved form should be achieved using parametric data such as the radii and centers of curvature at specific points on the surface."*

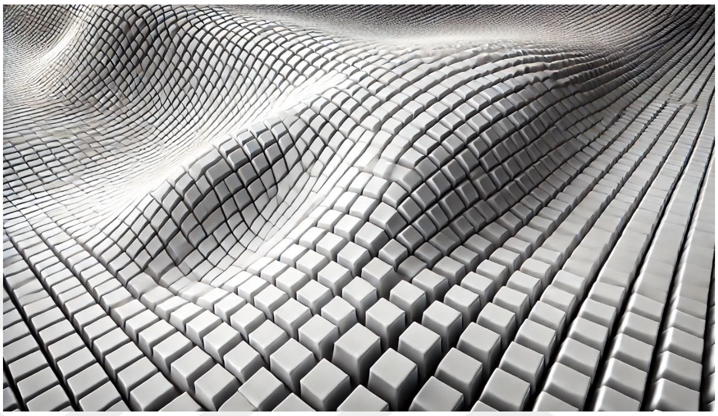


Figure 3.14: The parametric image generated with ChatGPT.

Subsequently, I requested ChatGPT to write a Python code that could create this visual in Blender. The response from ChatGPT is as follows (See scripts in Appendix 3).

ChatGPT: *"Sure! Here is a Blender script that helps in creating a parametric design similar to the one shown in the image, using repeating geometric units. The script uses Blender's Python API to automate the creation of a grid of square prisms arranged on a curved surface."*(Figure 3.15).

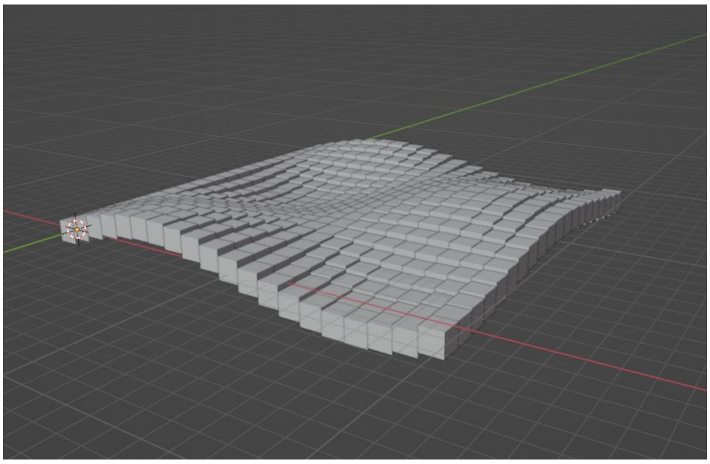


Figure 3.15 Grid of square prisms arranged on a curved surface obtained using a Blender script.

Subsequently, a duplication of the resulting shape was requested (Figure 3.16). Then, it was requested to add a circular opening in the center of one of the units (Figure 3.17). and then this modified shape was duplicated (Figure 3.18).

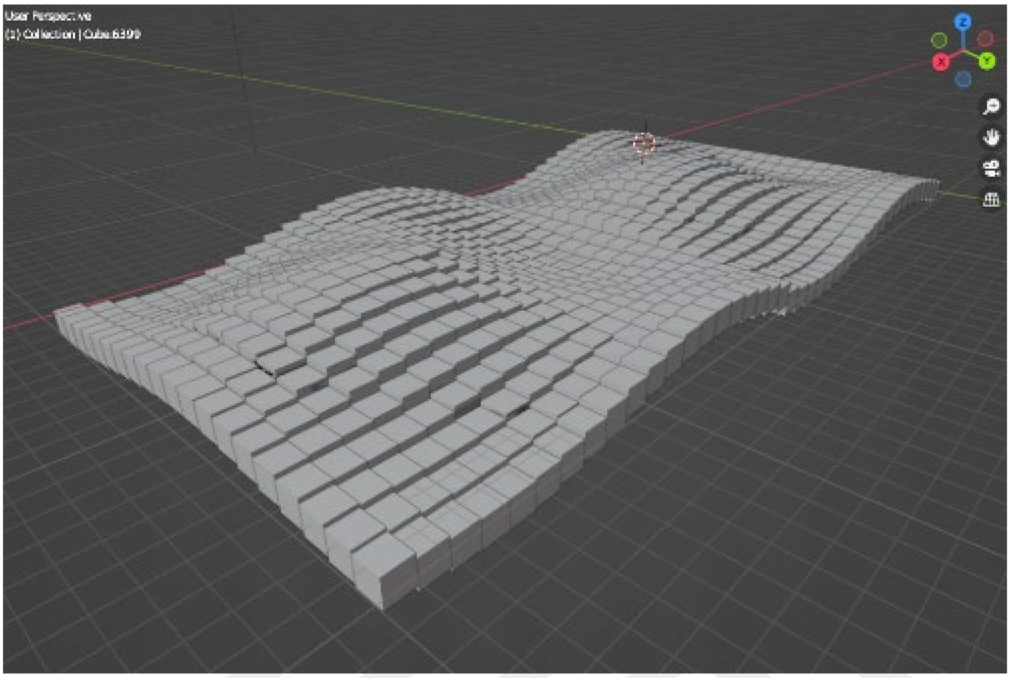


Figure 3.16: Duplication of the previous stage

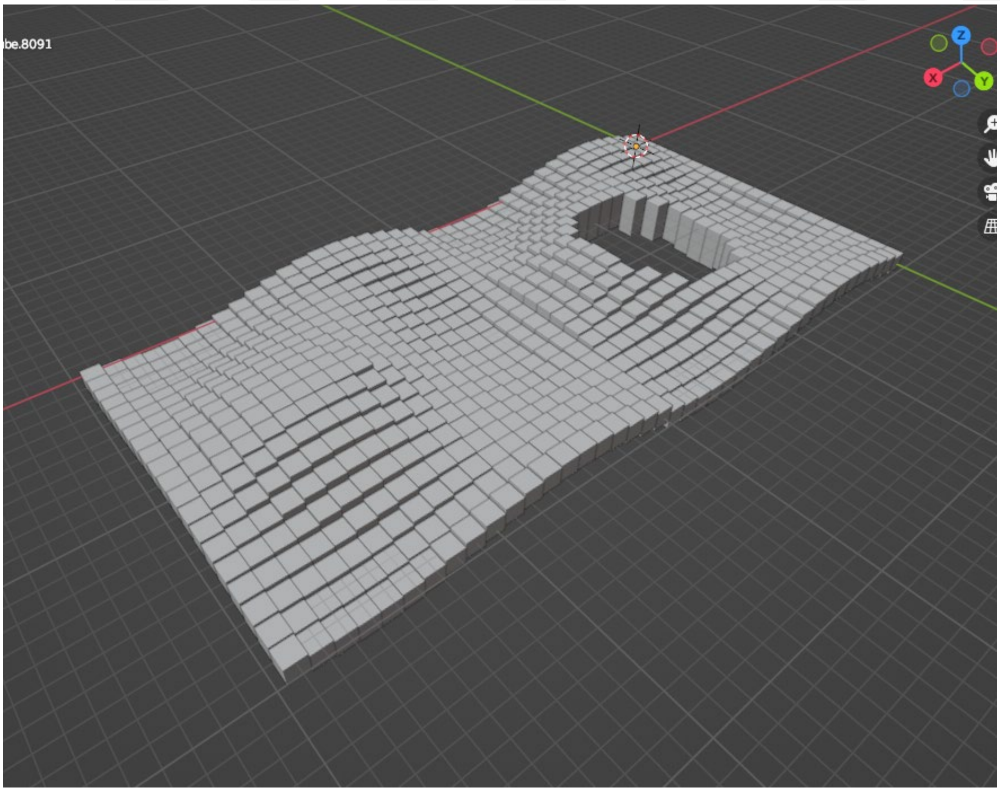


Figure 3.17: requested to add a circular opening

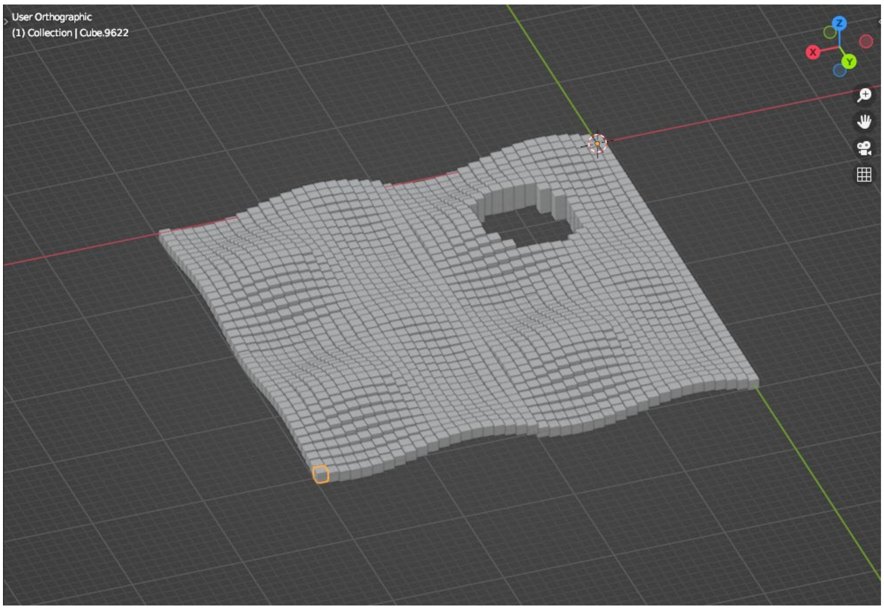


Figure 3.18: Duplication of the previous stage

The primary goal of this process was to design a parametric roof model by utilizing principles of parametric design. Initially, a basic script was developed using Blender's Python API to generate surfaces and geometries. This script allowed the model to be shaped based on user-defined parameters such as curvature, dimensions, and other relevant attributes.

During the second phase, one corner of the model was parametrically elevated, and the location of the created void was adjusted to align with the center of the mass (Figure 3.19). The script underwent continuous refinement and updates according to user feedback, ensuring the evolving model met the desired specifications.

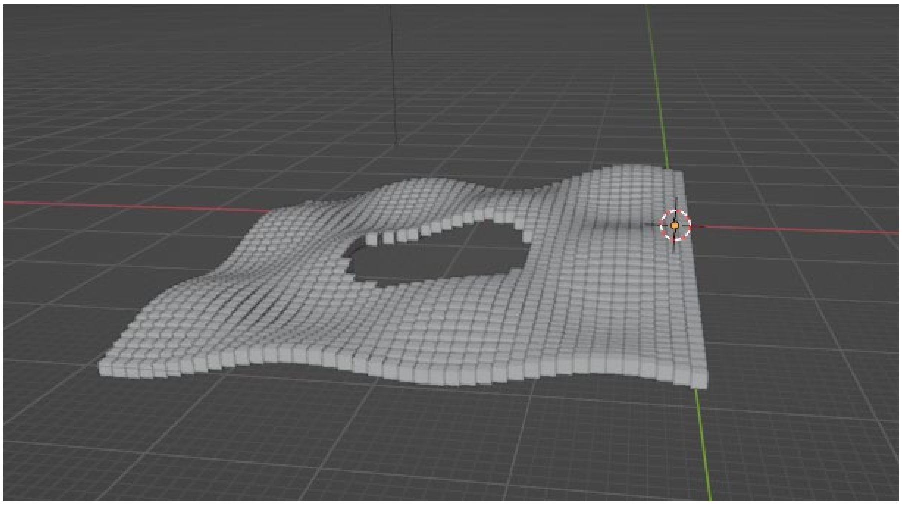


Figure 3.19: Elevated Mass

In the third stage, columns were systematically added to the roof model at equal intervals, extending down to the ground level. Despite these efforts, the anticipated effect was not fully realized. This highlighted the limitations of the AI-assisted co-creation process and emphasized our mastery over the design language crafted in collaboration with AI, underlining the importance of our experiential knowledge.

It may be worth noting that prompt engineering is one of the important topics currently being discussed. The language we use with AI has its limitations in terms of words, and it is possible to describe a situation from many perspectives. For this reason, the design evolves by moving back and forth within a loop.

Moving to the fourth stage, roofing and facade materials were applied (Figure 3.20); however, at this point, the entire model was assigned a glass material. As a result, a parametric roof model was successfully created through the AI-assisted co-creation process. However, it should be noted that the facade was not successfully obtained. This is because the AI treated all units as columns and lowered them to a plane designated as the ground level. While this did create a facade-like impression, it was formed independently of the intended design.

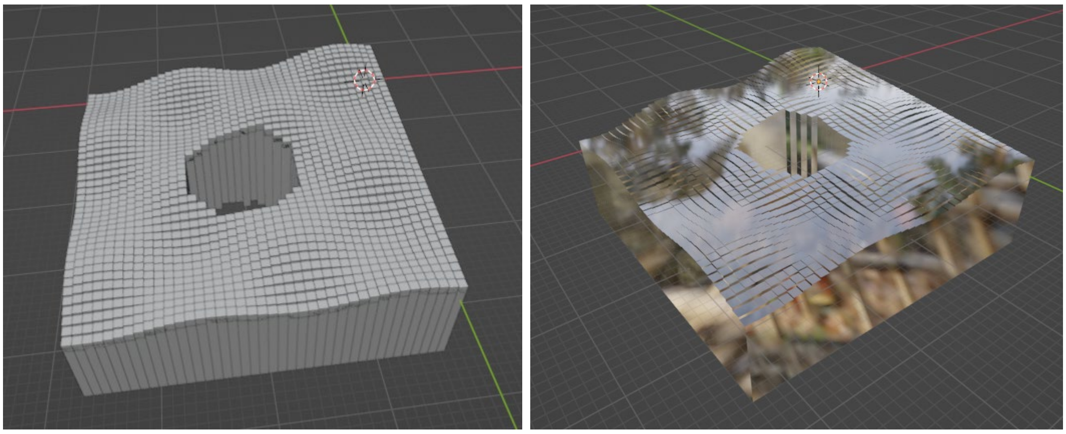


Figure 3.20: Roofing and facade materials

This journey provides valuable insights into how AI-assisted co-creation processes might function in the future. Although there are current limitations in effectively communicating with AI, it has demonstrated the ability to guide complex parametric design processes and swiftly integrate user inputs, thus enhancing the efficiency and creativity of the design process. This experience showcases the potential of AI in 3D modeling and parametric design, suggesting a promising direction for future developments in collaborative design technologies.

While creating this design, some results were not achieved on the first attempt. Specifically, when raising the roof parametrically from one point, it was necessary to emphasize to ChatGPT that this should be done by elevating the units along the z-axis rather than extending them along the z-axis. The outputs before making this clarification were as follows:

ChatGPT: "*We can revise the script to create an entrance by raising the units on one edge of the model. This involves increasing height from one side to the other, creating the entrance effect.*"

This included the information that the intention was to create an entrance by lifting one corner; however, the desired result was not achieved, as shown in Figure 3.21, this height increase was achieved by altering the height of the units at the desired corner. After clarifying that the units should be elevated along the z-axis rather than extended along the z-axis, the result is shown in Figure 3.19.

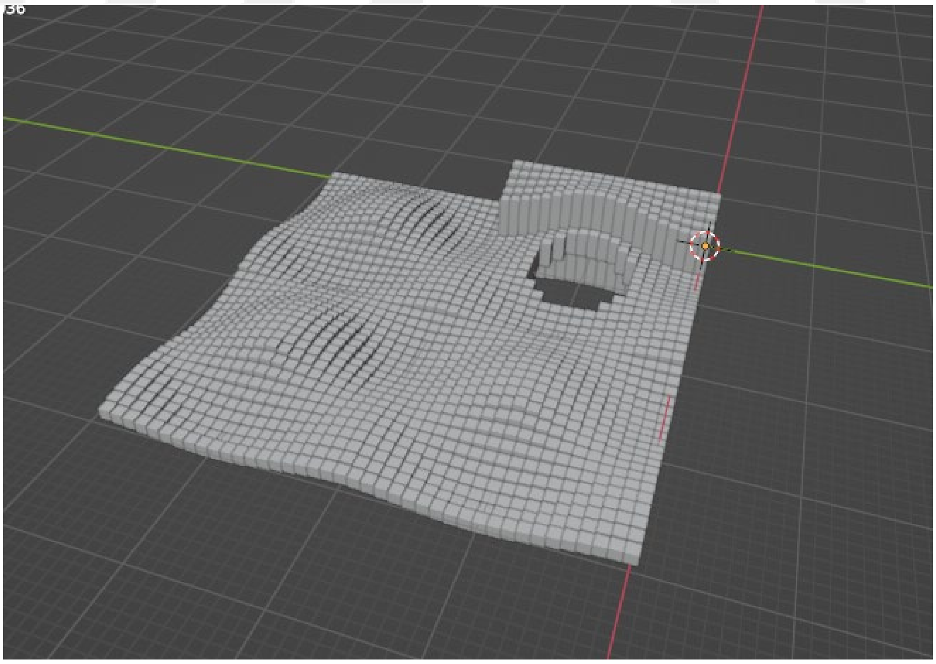


Figure 3.21: Lifting one corner

In this example (Figure 3.22), it was expected to randomly add 2 or 3 units on top of the existing units at specified locations. This allowed us to experience the tool's capability to make random decisions and generate outputs. A total of 1725 objects were created in the model.

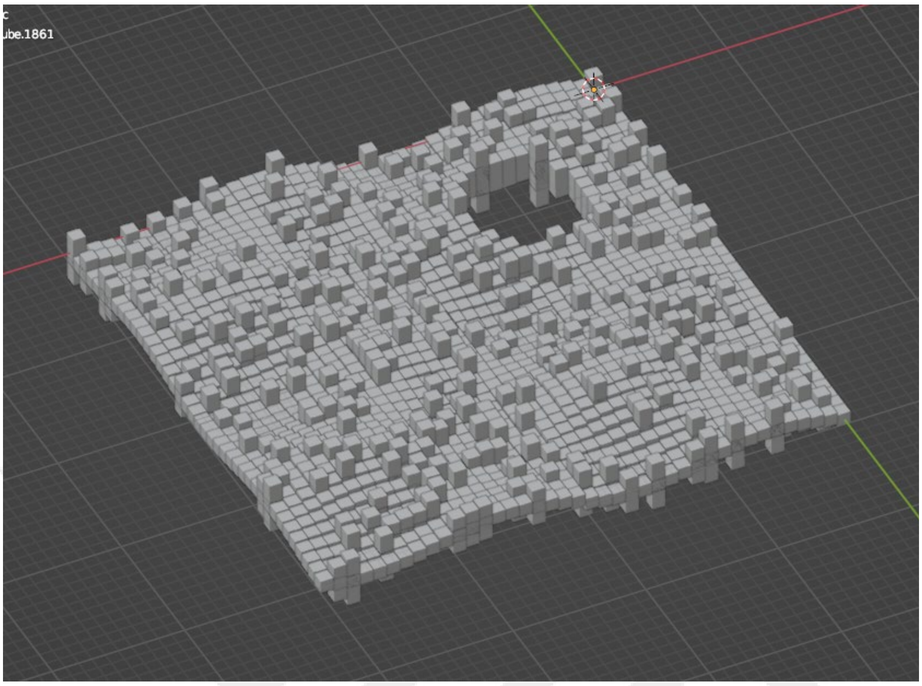


Figure 3.22: Randomly adding 2 or 3 units

Another example was tested, as shown in Figure 3.23, where design approaches to create a courtyard were explored using ChatGPT. This example demonstrates how the AI tool can be integrated into the architectural design process and facilitate more effective collaboration between the user and the AI.

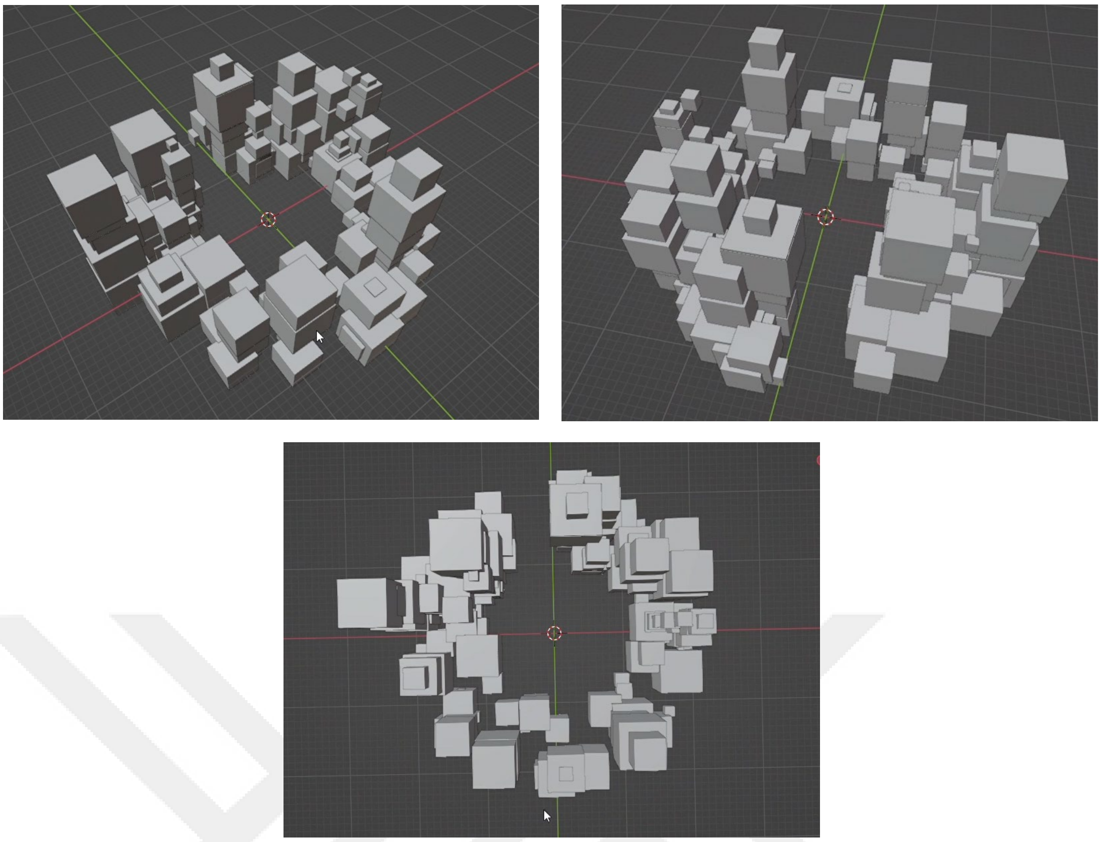


Figure 3.23: creating a courtyard

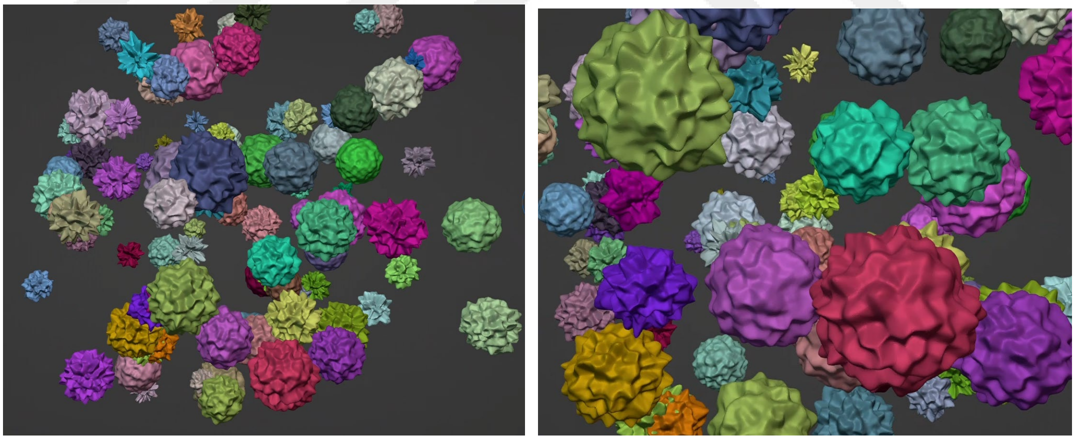


Figure 3.24: 100 icospheres of varying sizes

In Figure 3.24, 100 icospheres of varying sizes and deformations were randomly positioned in Blender to create complex volumes. Additionally, each object was assigned a random color. A light source and a camera were added to the scene, which was then rendered. This process, similar to the previous example, was assisted by ChatGPT.

3.2.4 TripoAI

Tripo AI is an online tool offering free features, utilizing the TripoSR model. TripoSR is a three-dimensional reconstruction model that employs transformer architecture for rapid feed-forward three-dimensional generation. It is capable of producing a three-dimensional mesh from a single image in under 0.5 seconds (Tochilkin et al., 2024). The objective of TripoSR is to provide researchers, developers, and creative professionals with access to the most recent developments in 3D generative AI.

In the example, AI was used to produce a 3D model following a similar logic used in ZoeDepth. The initial work involved using ChatGPT to process the desired image (Figure 3.25), which converted to 3D using TripoAI (Figure 3.26).

Initially, the process started with providing a text description to ChatGPT, which generated an image based on the input. It has been found through experiments that TripoAI produces better results with images that have a simple background. Additionally, it has been observed that lighting and shadows that create depth in the image result in better outcomes on the model. Therefore, the text and image that yielded relatively better results among other experiments are as follows:

Text: *A modern, multi-story concrete building at night, composed of interlocking cubic structures. The building features large windows with warm, glowing lights inside, creating a stark contrast against the dark exterior. The design is complex, with various levels and cantilevered sections, showcasing an innovative architectural style. The surrounding area is dimly lit, highlighting the building as the focal point in an urban environment.* (Figure 3.25)

Figure 3.25: Image created with ChatGPT

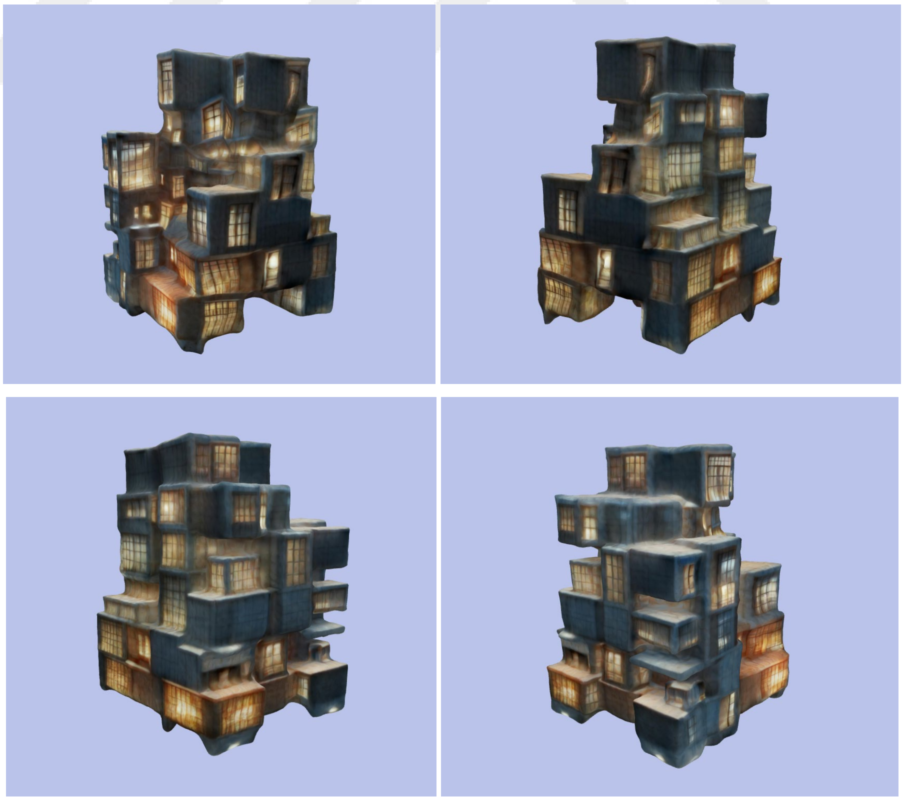


Figure 3.26: 3D model created with Tripo AI

Figure 3.26 served as the basis for creating a 3D model using TripoAI. TripoAI is equipped with advanced algorithms that can interpret 2D images and predict their 3D alternatives. The generated model was detailed and structurally coherent, displaying AI's capability to understand and extrapolate complex geometries from simple inputs.

The patterns of voids on the facades of the obtained example, along with the mass and voids on the rear facades designed based on the input image, could indicate that AI has advanced one step further in 3D creation. In Figure 3.27, side views of the model are provided for a more detailed examination.

Figure 3.27: Side views of the model

The model obtained from TripoAI could be exported as a mesh, a collection of vertices, edges, and faces that define the 3D structure of the model. This mesh data could then be imported into design programs like Blender and Sketchup, making it open to further modifications. In these programs, users could refine the model, adjust parameters, and enhance details, allowing for greater customization and precision. The exports are available in formats such as GLB, OBJ, FBX, STL, and USD.

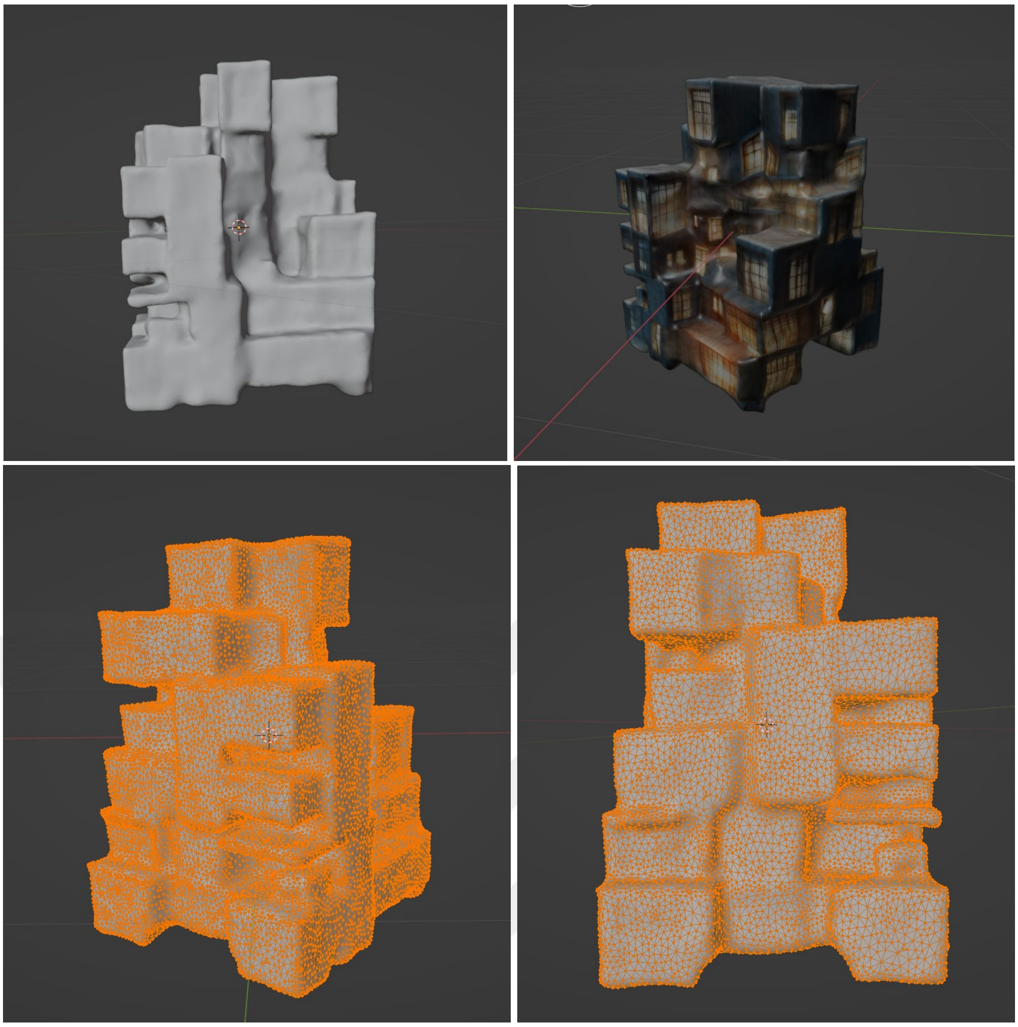


Figure 3.28: Model on Blender

Figure 3.28 shows the images of the FBX output imported into Blender. It is possible to perform UV modeling and sculpting on the model. While the model output is successful and editable, there are still deficiencies. The points that make up the mesh units are not on the same plane, causing surfaces that appear flat to not be completely flat. It is anticipated that better output production and a more advanced knowledge of Blender can correct this issue.

3D model creation (Figure 3.29) was also attempted using the prompt feature:

Prompt: *A large, organic architectural structure resembling a modern, abstract art form. The building has flowing, wavy surfaces with irregular openings and windows that blend seamlessly into the curvilinear facade. Its appearance mimics natural rock formations with smooth, undulating contours. The color palette is warm and earthy, with shades of beige and tan. Surrounding the building are minimalist landscape elements such as pathways, benches, and sparse vegetation. The structure is situated in an open, desert-like environment with distant hills in the background. The overall aesthetic is futuristic and harmonious, integrating natural and modern design elements.*

Figure 3.29: Tripo AI Experience 2

Prompt: *Create an image that features a highly contrasted organic architectural design for the front facade of a multi-story building. The facade includes bold, curvilinear forms and deeply shadowed surfaces, with brightly illuminated windows that create a drama.* (Figure 3.30)

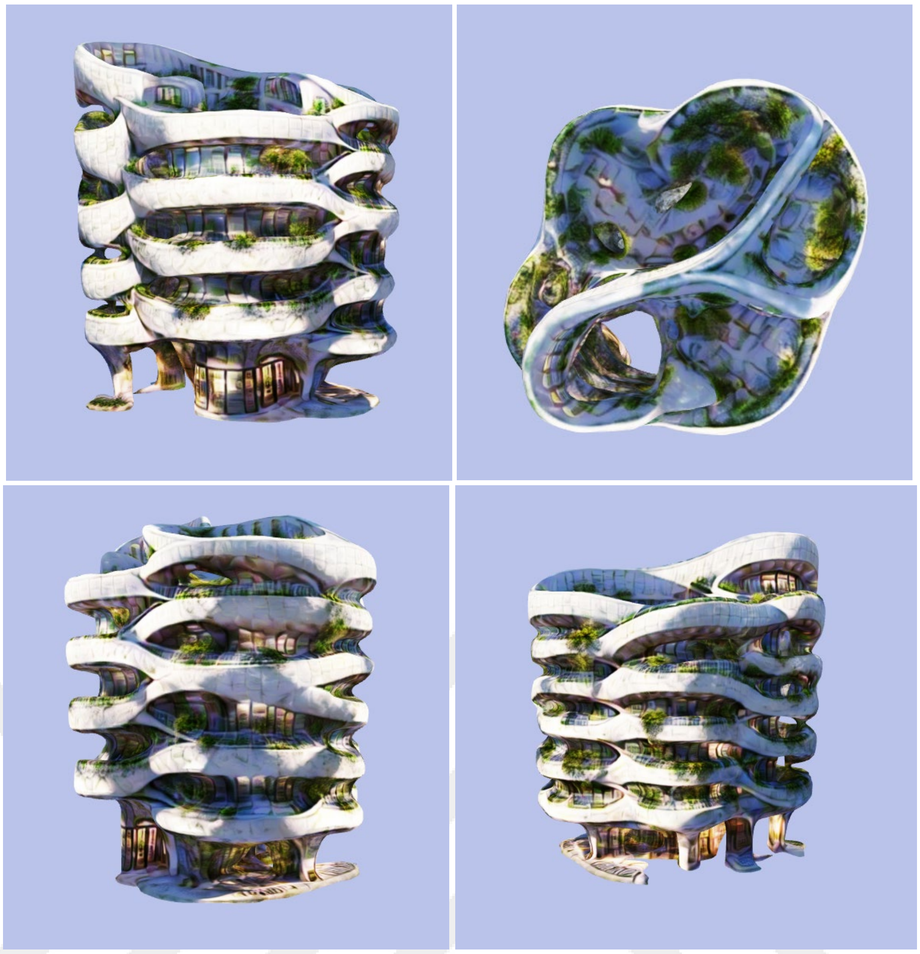


Figure 3.30: Tripo AI Experience 3

TripoAI examples demonstrated AI's capability to predict 3D models and the importance of providing a user interface for editing these models, enhancing both explainability and controllability. The ability to export and modify the model in traditional design software bridges the gap between AI-generated concepts and practical, usable designs. It allows designers to retain control over the final output, making adjustments as needed based on their expertise and preferences.

Since Tripo AI is not an architectural program, it does not generate controllable surfaces in its applications. However, it currently produces good outputs in terms of figure creation. When interpreted spatially, it creates areas with depth, but it should be remembered that it is not a tool designed specifically for architectural purposes. For it to produce designs that yield good results from an architectural perspective, it is necessary to incorporate architectural thinking into the design processes of these tools. Either the "black box" nature of these tools needs to become more transparent, or it will be necessary to work with tools specifically designed for architectural purposes.

3.2.5 Comfy UI

In Figure 3.31, the same visual used in Tripo AI has been employed to obtain a 3D output. The resulting product is a 3D model, but the 3D estimation is weaker compared to Tripo AI. This could be due to the workflow used. More advanced workflows could be utilized. Although in ComfyUI, seeing some intermediate stages makes the process more transparent, it has not necessarily improved the final product in this specific example.

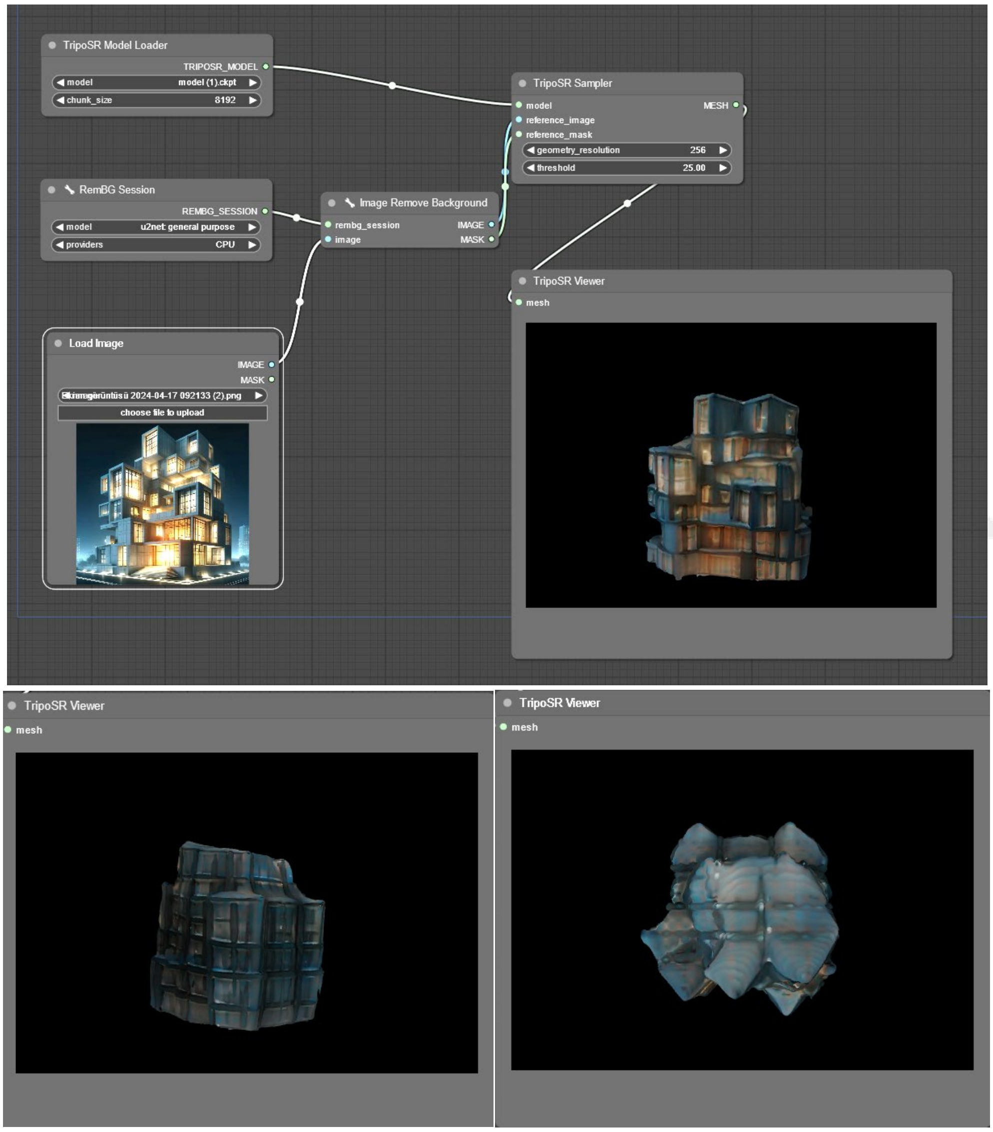


Figure 3.31: Experience 1 (Appendix 3)

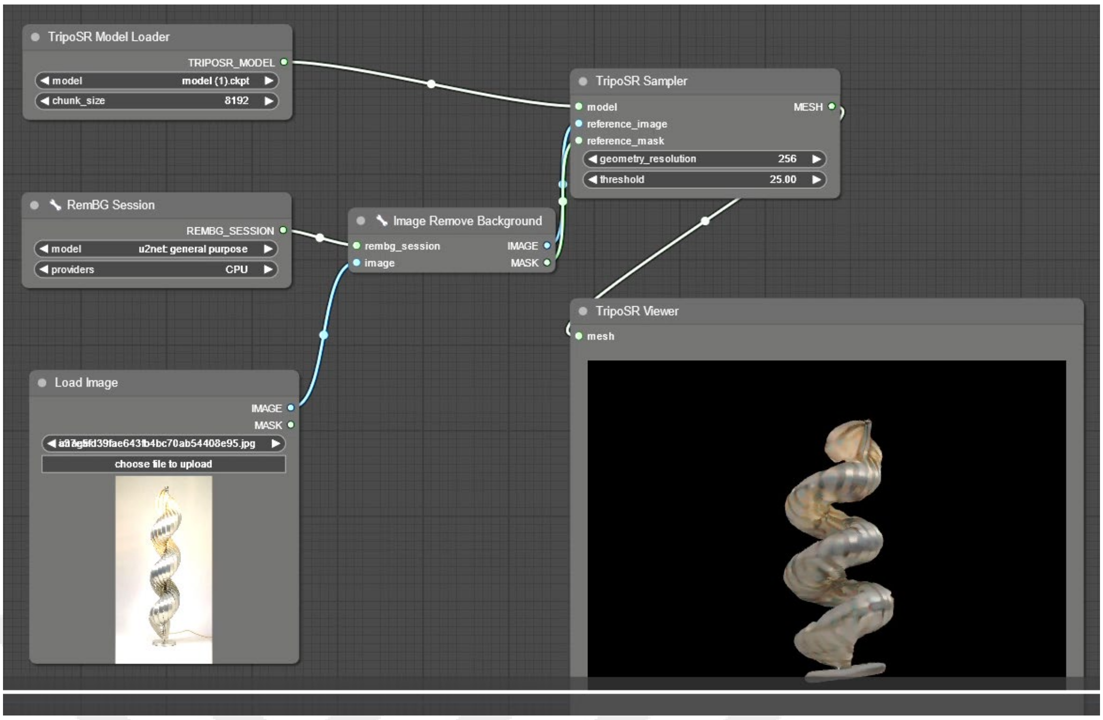


Figure 3.32: ComfyUI Experience 2

Figure 3.32 demonstrates a workflow for creating a 3D model from a different object.

The ComfyUI image creation process is designed to be both user-friendly and highly customizable. Users begin by entering a textual description or keywords to define the visual content they want. They can then modify parameters such as style, color palette, and resolution to influence the image generation. The tool uses natural language processing to interpret the input and employs deep learning models to produce an initial visual representation.

After the preliminary image is generated, it is shown to the user for review. Users can provide feedback and iteratively adjust the text and parameters to refine the image. Advanced users have the option to fine-tune specific details using detailed controls and editing tools. Once the image meets the user's expectations, it can be finalized and exported in various formats.

Nevertheless, some reviews suggest that the node-based interface, despite its considerable versatility and robustness, may prove initially challenging for those new to the system, requiring a certain degree of familiarity with the manner in which different nodes connect and interact to form complex workflows (Andrew, 2024) .

Despite its extensive capabilities, users often encounter difficulties when initially setting up and configuring the system, particularly if they lack prior experience with similar systems. Nevertheless, the comprehensive documentation and active user community that accompany ComfyUI can mitigate these issues, gradually enhancing the tool's usability and accessibility.

This process highlights Comfy UI’s comprehensive and user-centric approach, ensuring active user involvement throughout the image creation journey and enhancing the co-creation experience by effectively bridging user input and machine-generated output.

4 CONCLUSION

This mixed-method study, through comprehensive readings and hands-on tool experiences, has demonstrated that AI-based design processes hold significant potential in the field of architecture. The data collected from both research and practical applications indicate that AI tools substantially enhance architectural visualization and modeling capabilities, but also reveal some opacity issues that limit user understanding and control. The findings of this study emphasize the necessity of focusing on transparency and explainability to effectively integrate AI tools in architectural design.

Table 4.1 evaluates the explainability levels and user interactions of tools used in architecture. Each tool has its strengths and weaknesses, offering various advantages and limitations in architectural applications. As seen, the explainability of 2D tools is opaquer in both process and output, with limited user interaction. This limitation hinders the full realization of the co-creation process. As Pask highlighted, tool groups that create a feedback loop enhance co-creation (Werner, 2019). The explanations provided to the user can currently remain as understandable text information from ChatGPT. In tools like ComfyUI, although familiarity with the tool is required, control at each stage makes it more explainable.

Creating 3D content is more complex and time-consuming than creating 2D content. While 2D image data is easier to collect, 3D assets require significant effort from artists using specialized software. The diversity in use cases and creative styles leads to variations in the scale, quality, and style of 3D assets, adding to the complexity of managing 3D data. To standardize this diverse data and make it more suitable for production, specific guidelines need to be established. A large-scale, high-quality 3D dataset is still highly desired in the field of 3D generation. Additionally, exploring how 2D data can be utilized in 3D generation might help address the shortage of 3D data. Therefore, the tools currently used for 3D creation are not yet highly advanced, but they do demonstrate the potential of these technologies.

Table 4.1: Explainability of AI Tools.

TOOL NAME	LEVEL OF EXPLAINA BILITY	USER INTERACTION	GENERAL EVALUATION
2D TOOLS	Low	Limited	Opaque process, limited user interaction
ZOEDEPTH	Medium	Limited	Generates depth maps but has limited detail and control
COMFY UI	High	High	Workflow-based stages are experienced by the user, but can be challenging to use.
CHATGPT - BLENDER	High	High	Providing more control and transparency through coding. Feedback loop, higher quality outputs
CHATGPT - GHPYTHON	High	High	Feedback loop, greater user involvement

This research also demonstrates that by using ChatGPT as a translator and guide within AI's decision-making mechanism, a feedback loop is created that provides user feedback and strengthens the co-creation process. However, for designers to effectively utilize this shared language, they need to have at least a basic understanding of coding to interpret and guide the outputs. In design tools like ComfyUI, creating workflows requires users to gain experience and become familiar with the tool. In summary, AI is taking on a co-creative role as a new design partner, but for the architects to adapt to this paradigm shift in design language requires gaining experience in this language.

Table 4.2 provides a general overview of these tools. Since their primary use is not in the field of architecture, the results produced by these tools come with both advantages and disadvantages. While their usage in many areas is currently limited, they also showcase numerous potentials.

Table 4.2: Comprehensive Features and Applications of AI Tools

Tool Name	Application Area (for this experiment)	Features	Advantages	Disadvantages	Explanation
2D TOOLS	Visual Generation	Text-to-image generation	High-quality visuals	Black box nature	Generates high-quality visuals from text descriptions but operates as a black box with limited transparency.
ZOEDEPTH	3D Model Generation	Depth map generation	Fast 3D modeling	Limited back facade details	Generates depth maps from images, useful for creating 3D models but lacks detail control for back facades.
CHATGPT	Text-Code Assistance	Python integration	Speeds up the coding process	Limited for complex codes	Assists in writing Python code, and streamlining the coding process, but may be limited for complex code generation.
CHATGPT - GHPYTHON	Parametric Design	Parametric 3D modeling	Direct control over 3D models	Requires Python proficiency	Enables detailed parametric design with Python scripts, offering high control over 3D shapes and models.
CHATGPT - BLENDER	Parametric Design	3D model creation with code	Complex shape generation	Requires Blender proficiency	Facilitates complex parametric designs using Python scripts in Blender, providing high control and transparency.
TRIPO AI	3D Model Generation	2D to 3D model conversion	Quick prototyping	Not optimized for architecture yet	Converts 2D images to 3D models, ideal for quick prototyping but lacks optimization for architectural purposes.
COMFY UI	2D-3D Generation, Workflows	Interface Workflow	Flexible creation	Complex	Offers an interface for generating visuals but requires advanced control for detailed adjustments.

To briefly evaluate the tools used in the experiments, ZoeDepth, provides more input compared to 2D tools as it generates depth estimations. However, the quality and capacity of its productions are currently limited. ZoeDepth has current limitations in accurately predicting the back facades of buildings, but ongoing development promises improvements. Similar to 2D tools, ZoeDepth does not allow for user interface intervention during the production process.

Tripo AI is useful for quick prototyping and conceptual development in architectural projects. It supports the creation and manipulation of 3D models with advanced stylization options. This tool demonstrates significant potential in architectural design through draft model creation and rapid prototyping capabilities.

Grasshopper and Blender, in contrast, offer higher levels of explainability and create a feedback loop, allowing greater user involvement in the process. While Blender and Grasshopper are both powerful tools for 3D modeling and design, they serve different purposes and offer distinct APIs. GhPython provides access to Rhino. Geometry and RhinoScriptSyntax libraries, though it is not as comprehensive as Blender’s bpy API. Therefore, the outputs generated using Blender were superior. More complex commands requested from Grasshopper often went unanswered.

ComfyUI, operating through workflows, allows users to experience each stage of the process. However, the tool's structure can be challenging for those not familiar with this language. Nevertheless, there are many platforms available to learn how to use this tool.

These tools have also been compared using specific benchmarks. Figure 4.1 provides a comparative evaluation of different AI tools based on usability, process time, detail level, algorithm success rate, and integration capacity with other tools. These values are derived from the author's experiences and observations during the experiments conducted, reflecting practical insights into the performance and capabilities of each tool.

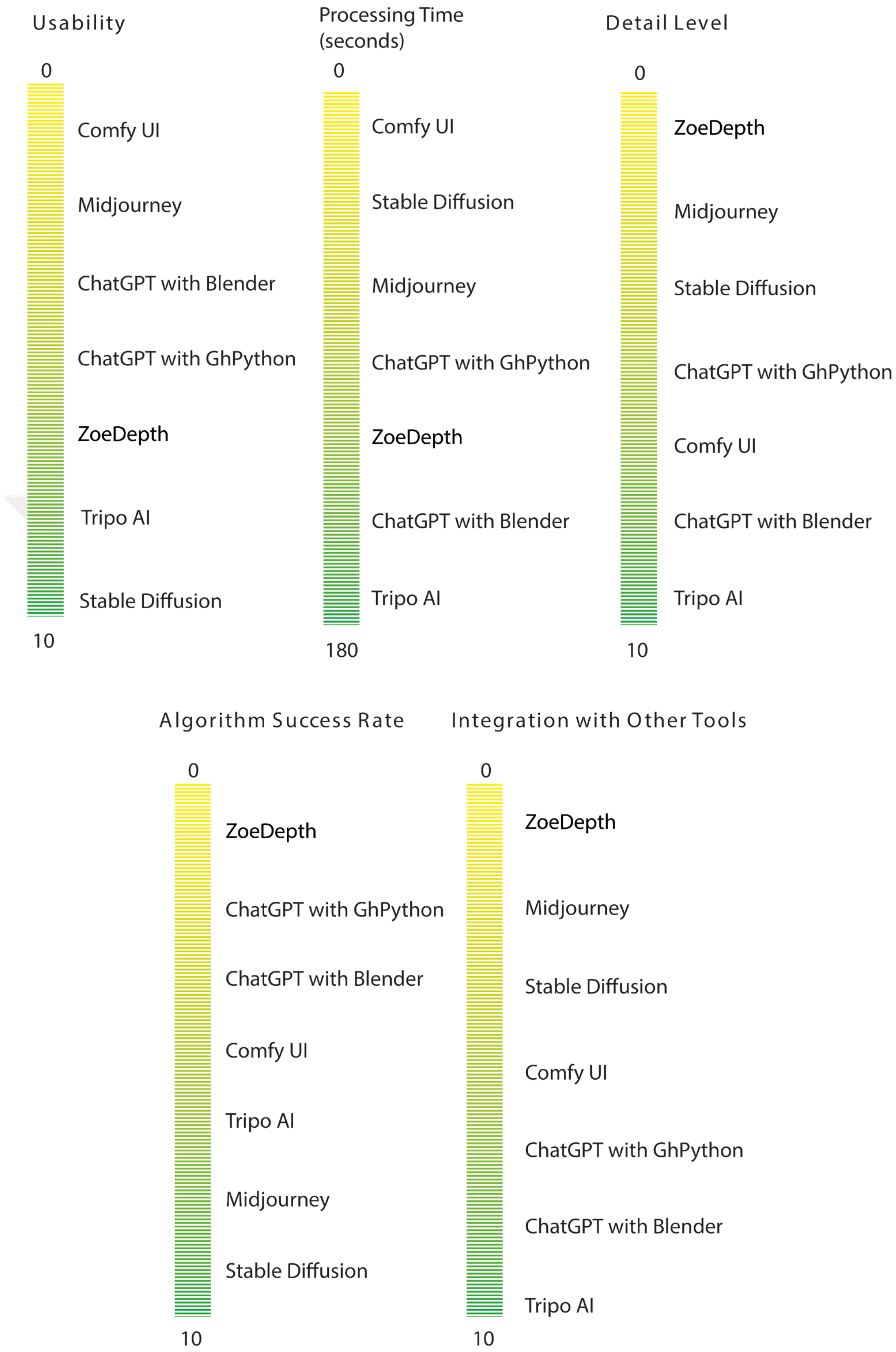


Figure 4.1: Tools Benchmarks Comparison

Usability: Usability refers to how easily and effectively a tool can be used by a user. Tools like Stable Diffusion and ZoeDepth generally offer higher usability due to their accessibility on online platforms and user-friendly interfaces. In contrast, tools like Midjourney may present a more complex usage experience because they operate through external platforms (e.g., Discord) and require a subscription model, which can limit accessibility and ease of use. Tools used in conjunction with ChatGPT, which require interaction with script-based environments, demand more technical knowledge and skills, making them less user-friendly. Meanwhile, Comfy UI provides a more complex user experience because it requires all functionality to be built within its own interface.

Processing Time: Processing time refers to the duration required for a tool to complete a specific task and can vary depending on the computing power of the hardware used. According to Figure 4.1, some tools offer shorter processing times, while those that generate 3D models and provide more detailed results may require longer processing times. For example, ChatGPT with Blender and Tripo AI have longer processing times compared to other tools because they produce more complex and detailed models.

Detail Level: Detail level indicates the degree of detail in the content produced by the tools. 3D modeling tools generally have a higher level of detail due to the more complex structures they produce. For example, ChatGPT with Blender and Tripo AI demonstrate superior performance in 3D modeling with high levels of detail.

Algorithm Success Rate: The algorithm success rate measures a tool's ability to produce the desired output. Tools that produce 2D content generally have high success rates; however, these tools can limit user interaction as they do not allow direct modification of the outputs. When a design loop is created with ChatGPT, successful outcomes have been achieved through user feedback and adjustments. However, this process also involves trial and error and the correction of errors that arise. As work in this area increases and usage practices are developed, it is expected that the success rate of the outputs will improve over time. Currently, the success of prompt or image-based tools in generating the desired output is as shown in Figure 4.1.

Integration with Other Tools: Integration capacity with other tools reflects how well a tool can integrate with different software and platforms. 3D modeling tools generally have more flexible integration capabilities. For instance, Tripo AI and ChatGPT with Blender have strong integration capabilities with various 3D tools, making them more versatile and functional.

In conclusion, Figure 4.1 provides an overview of how AI tools perform across different criteria, helping users evaluate which tool is most suitable based on their needs and usage scenarios.

The findings from this study reveal that, as previously discussed, AI tools have made significant strides in supporting creative tasks but often operate as "black boxes," limiting user understanding and control over the design process. This lack of transparency hinders architects' ability to fully engage and collaborate effectively with these tools. The study also shows that a more "Gray Box" approach is present in the co-creation process with AI, highlighting the importance of getting to know the co-creation partner better. It underscores the need for more transparent and interactive interfaces that enhance co-creation capabilities, making AI tools more effective and user-friendly for designers.

In this context, future research and development should focus on enhancing the explainability of AI tools to strengthen human-AI collaboration. The implementation of Explainable AI (XAI) methodologies holds significant promise in making AI-driven design processes more transparent and controllable.

Additionally, the development of AI tools specifically tailored for architectural design will be crucial. These tools should incorporate user feedback mechanisms, allowing for iterative design loops that enhance the co-creation process.

In conclusion, this study paves the way for future research and development aimed at overcoming current limitations and unlocking the full potential of AI as a co-creator in architectural design.

REFERENCES

Adadi, A., & Berrada, M. (2018). Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI). *IEEE Access*, *6*, 52138–52160. https://doi.org/10.1109/ACCESS.2018.2870052

Ahramovich, A. (2023, August 15). *Artificial intelligence in architecture: 10 use cases and top technologies* [Online post]. https://www.itransition.com/ai/architecture

Andrew. (2024, July 6). *Beginner's Guide to ComfyUI*. https://stable-diffusion-art.com/comfyui/#What_is_ComfyUI

Arbizzani, E., Cangelli, E., Clemente, C., Cumo, F., Giofrè, F., Giovenale, A. M., Palme, M., & Paris, S. (Eds.). (2023). *Technological Imagination in the Green and Digital Transition*. Springer International Publishing. https://doi.org/10.1007/978-3-031-29515-7

Baduge, S. K., Thilakarathna, S., Perera, J. S., Arashpour, M., Sharafi, P., Teodosio, B., Shringi, A., & Mendis, P. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Automation in Construction*, *141*, 104440. https://doi.org/10.1016/j.autcon.2022.104440

Barker, N. (2023, June 23). *Hickok Cole uses ChatGPT to design 24-storey mixed-use building*. https://www.dezeen.com/2023/06/23/hickok-cole-chatgpt-aitopia/

Bhat, S. F., Birkl, R., Wofk, D., Wonka, P., & Müller, M. (2023). *ZoeDepth: Zero-shot Transfer by Combining Relative and Metric Depth* (arXiv:2302.12288). arXiv. http://arxiv.org/abs/2302.12288

Chaillou, S. (2020). Archigan: Artificial intelligence x architecture. In *Architectural intelligence* (pp. 117–127). Springer.

Das, A., & Rad, P. (2020). *Opportunities and Challenges in Explainable Artificial Intelligence (XAI): A Survey* (arXiv:2006.11371). arXiv. http://arxiv.org/abs/2006.11371

Davis, N. (2021). Human-Computer Co-Creativity: Blending Human and Computational Creativity. *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, *9*(6), 9–12. https://doi.org/10.1609/aiide.v9i6.12603

Fong, R. C., & Vedaldi, A. (2017). Interpretable Explanations of Black Boxes by Meaningful Perturbation. *2017 IEEE International Conference on Computer Vision (ICCV)*, 3449–3457. https://doi.org/10.1109/ICCV.2017.371

Fricker, P., Kotnik, T., & Borg, K. (2020). *Computational Design Pedagogy for the Cognitive Age*. 685–692. https://doi.org/10.52842/conf.ecaade.2020.1.685

Gmeiner, F., Yang, H., Yao, L., Holstein, K., & Martelaro, N. (2023). Exploring Challenges and Opportunities to Support Designers in Learning to Co-create with AI-based Manufacturing Design Tools. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, 1–20. https://doi.org/10.1145/3544548.3580999

Guida, G., & Escobar, D. (2023, March 25). *Digital FUTURES world, AI Series 01—TUTORIAL 05: AI architectural toolkits—2D to 3D Techniques (Advanced Tutorial)*. https://www.youtube.com/watch?v=esUa_1g9578&t=949s&ab_channel=DigitalFUTURESworld

Hanafy, N. O. (2023). Artificial intelligence's effects on design process creativity: "A study on used A.I. Text-to-Image in architecture." *Journal of Building Engineering*, *80*, 107999. https://doi.org/10.1016/j.jobe.2023.107999

Hiran, K. K., Jain, R. K., Lakhwani, K., & Doshi, R. (2021). *Machine Learning: Master Supervised and Unsupervised Learning Algorithms with Real Examples (English Edition)*. https://books.google.com.tr/books?hl=tr&lr=&id=4VVDEAAAQBAJ&oi=fnd&pg=PT25&dq=supervised+learning,+reinforcement+learning,+and+unsupervised+learning+&ots=OMaaCAO7pF&sig=TWLJJuPvzcwABsGZVgwRw_OyiO4&redir_esc=y#v=onepage&q=supervised%20learning%2C%20reinforcement%20learning%2C%20and%20unsupervised%20learning&f=false

Horvath, A.-S., & Pouliou, P. (2024). AI for conceptual architecture: Reflections on designing with text-to-text, text-to-image, and image-to-image generators. *Frontiers of Architectural Research*, *13*(3), 593–612. https://doi.org/10.1016/j.foar.2024.02.006

Huang, J., Johanes, M., Kim, F. C., Doumpioti, C., & Holz, G.-C. (2021). On GANs, NLP and Architecture: Combining Human and Machine Intelligences for the Generation and Evaluation of Meaningful Designs. *Technology|Architecture + Design*, *5*(2), 207–224. https://doi.org/10.1080/24751448.2021.1967060

Huynh, T. D. (n.d.). *A Methodology and Software Architecture to Support Explainability-by-Design*.

Kotnik, T., & Fricker, P. (2024). *Architects Need to Learn to Embrace the Complexity of AI | ark*. https://www.ark.fi/en/2024/02/architects-need-to-learn-to-embrace-the-complexity-of-ai/

Kousoulas, S. (2018). Shattering the black box: Technicities of architectural manipulation. *International Journal of Architectural Computing*, *16*(4), 295–305. https://doi.org/10.1177/1478077118801937

Kuntz, D., & Wilson, A. K. (2022). Machine learning, artificial intelligence, and chemistry: How smart algorithms are reshaping simulation and the laboratory. *Pure and Applied Chemistry*, *94*(8), 1019–1054. https://doi.org/10.1515/pac-2022-0202

Lataifeh, M., Carrasco, X. A., Elnagar, A. M., Ahmed, N., & Junejo, I. (2024). Human–machine co-creation: A complementary cognitive approach to creative character design process using GANs. *The Journal of Supercomputing*. https://doi.org/10.1007/s11227-024-06083-z

Leach, N. (2022). *Architecture in the Age of Artificial Intelligence: An Introduction to AI for Architects*. Bloomsbury Academic. https://books.google.com.tr/books?id=9EOQzQEACAAJ

Li, X., Zhang, Q., Kang, D., Cheng, W., Gao, Y., Zhang, J., Liang, Z., Liao, J., Cao, Y.-P., & Shan, Y. (2024). *Advances in 3D Generation: A Survey* (arXiv:2401.17807). arXiv. http://arxiv.org/abs/2401.17807

Maslej, N., Fattorini, L., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Ngo, H., Niebles, J. C., Parli, V., Shoham, Y., Wald, R., Clark,

J., & Perrault, R. (2023). *Artificial Intelligence Index Report 2023* (arXiv:2310.03715). arXiv. https://doi.org/10.48550/arXiv.2310.03715

Matoso, M. (2023, October 18). *Will Artificial Intelligence Replace Architects? | ArchDaily*. https://www.archdaily.com/1007802/will-artificial-intelligence-replace-architects

McGovern, A., Lagerquist, R., John Gagne, D., Jergensen, G. E., Elmore, K. L., Homeyer, C. R., & Smith, T. (2019). Making the Black Box More Transparent: Understanding the Physical Implications of Machine Learning. *Bulletin of the American Meteorological Society*, *100*(11), 2175–2199. https://doi.org/10.1175/BAMS-D-18-0195.1

Norvig, P., & Russell, S. J. (2016). *Artificial intelligence: A modern approach*. Pearson. chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/https://dl.ebooksworld.ir/books/Artificial.Intelligence.A.Modern.Approach.4th.Edition.Peter.Norvig.%20Stuart.Russell.Pearson.9780134610993.EBooksWorld.ir.pdf

Pask, G. (1969). The Architectural Relevance of Cybernetics. *Architectural Design*, *7*(6), 494–496.

Platform of Tripo AI. (n.d.). Retrieved May 27, 2024, from https://platform.tripo3d.ai/docs/introduction

Rezwana, J., & Maher, M. L. (2022). *Identifying Ethical Issues in AI Partners in Human-AI Co-Creation* (arXiv:2204.07644). arXiv. http://arxiv.org/abs/2204.07644

Sun, J., Liao, Q. V., Muller, M., Agarwal, M., Houde, S., Talamadupula, K., & Weisz, J. D. (2022). *Investigating Explainability of Generative AI for Code through Scenario-based Design* (arXiv:2202.04903). arXiv. http://arxiv.org/abs/2202.04903

Tochilkin, D., Pankratz, D., Liu, Z., Huang, Z., Letts, A., Li, Y., Liang, D., Laforte, C., Jampani, V., & Cao, Y.-P. (2024). *TripoSR: Fast 3D Object Reconstruction from a Single Image* (arXiv:2403.02151). arXiv. http://arxiv.org/abs/2403.02151

Van Lent, M., Fisher, W., & Mancuso, M. (n.d.). *An Explainable Artificial Intelligence System for Small-unit Tactical Behavior*.

Wang, J., Liu, Z., Zhao, L., Wu, Z., Ma, C., Yu, S., Dai, H., Yang, Q., Liu, Y., Zhang, S., Shi, E., Pan, Y., Zhang, T., Zhu, D., Li, X., Jiang, X., Ge, B., Yuan, Y., Shen, D., … Zhang, S. (2023). Review of large vision models and visual prompt engineering. *Meta-Radiology*, *1*(3), 100047. https://doi.org/10.1016/j.metrad.2023.100047

Wang, S., Menon, S., Long, T., Henderson, K., Li, D., Crowston, K., Hansen, M., Nickerson, J. V., & Chilton, L. B. (2024). *ReelFramer: Human-AI Co-Creation for News-to-Video Translation* (arXiv:2304.09653). arXiv. http://arxiv.org/abs/2304.09653

Werner, L. C. (2019). Gordon Pask and the Origins of Design Cybernetics. In T. Fischer & C. M. Herr (Eds.), *Design Cybernetics* (pp. 65–84). Springer International Publishing. https://doi.org/10.1007/978-3-030-18557-2_3

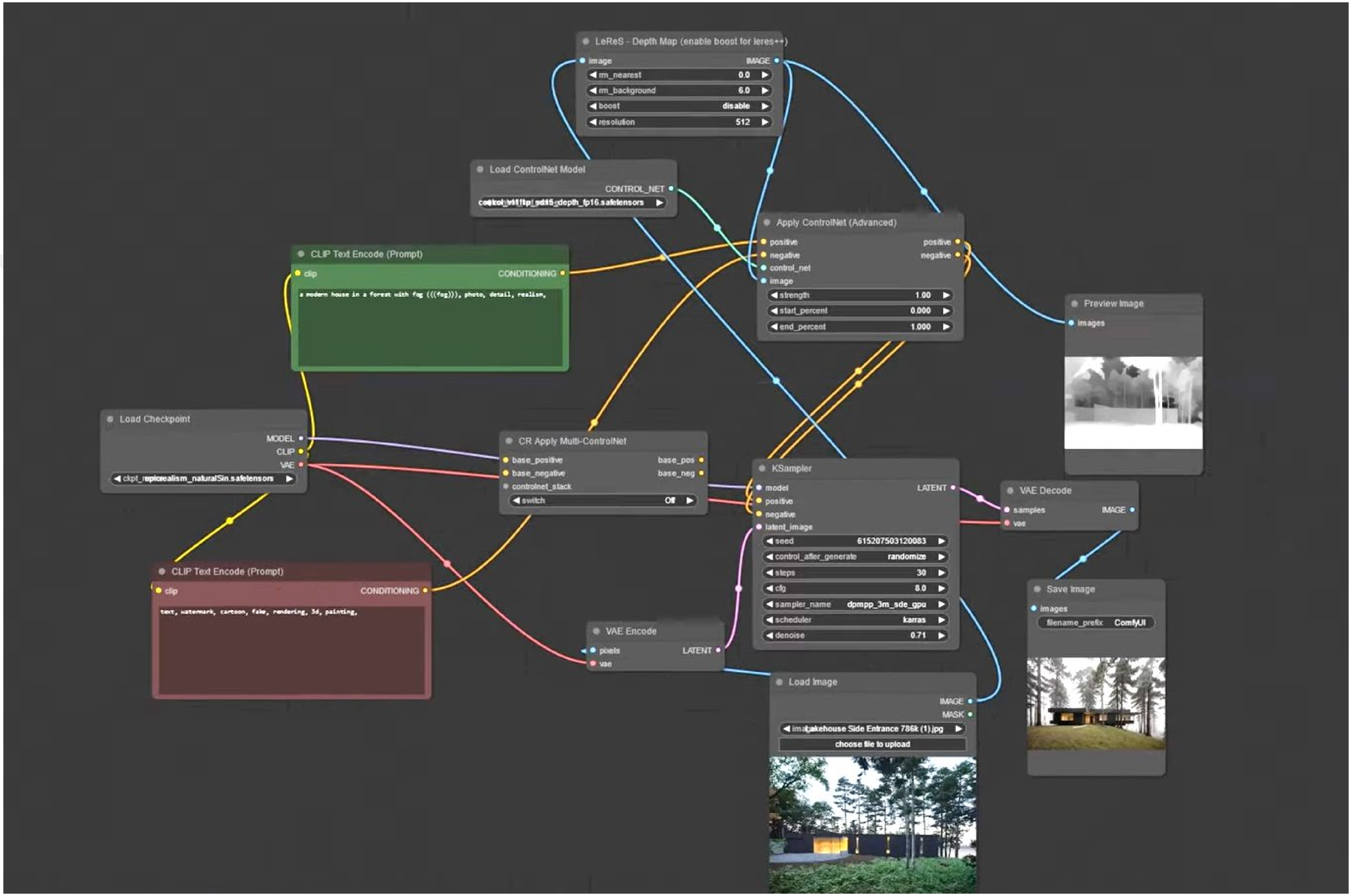
Witt, A. (2018). Grayboxing. *LOG*, *43*, 69–77.

Xu, F., Uszkoreit, H., Du, Y., Fan, W., Zhao, D., & Zhu, J. (2019). Explainable AI: A Brief Survey on History, Research Areas, Approaches and Challenges. In J. Tang, M.-Y. Kan, D. Zhao, S. Li, & H. Zan (Eds.), *Natural Language Processing and Chinese Computing* (Vol. 11839, pp. 563–574). Springer International Publishing. https://doi.org/10.1007/978-3-030-32236-6_51

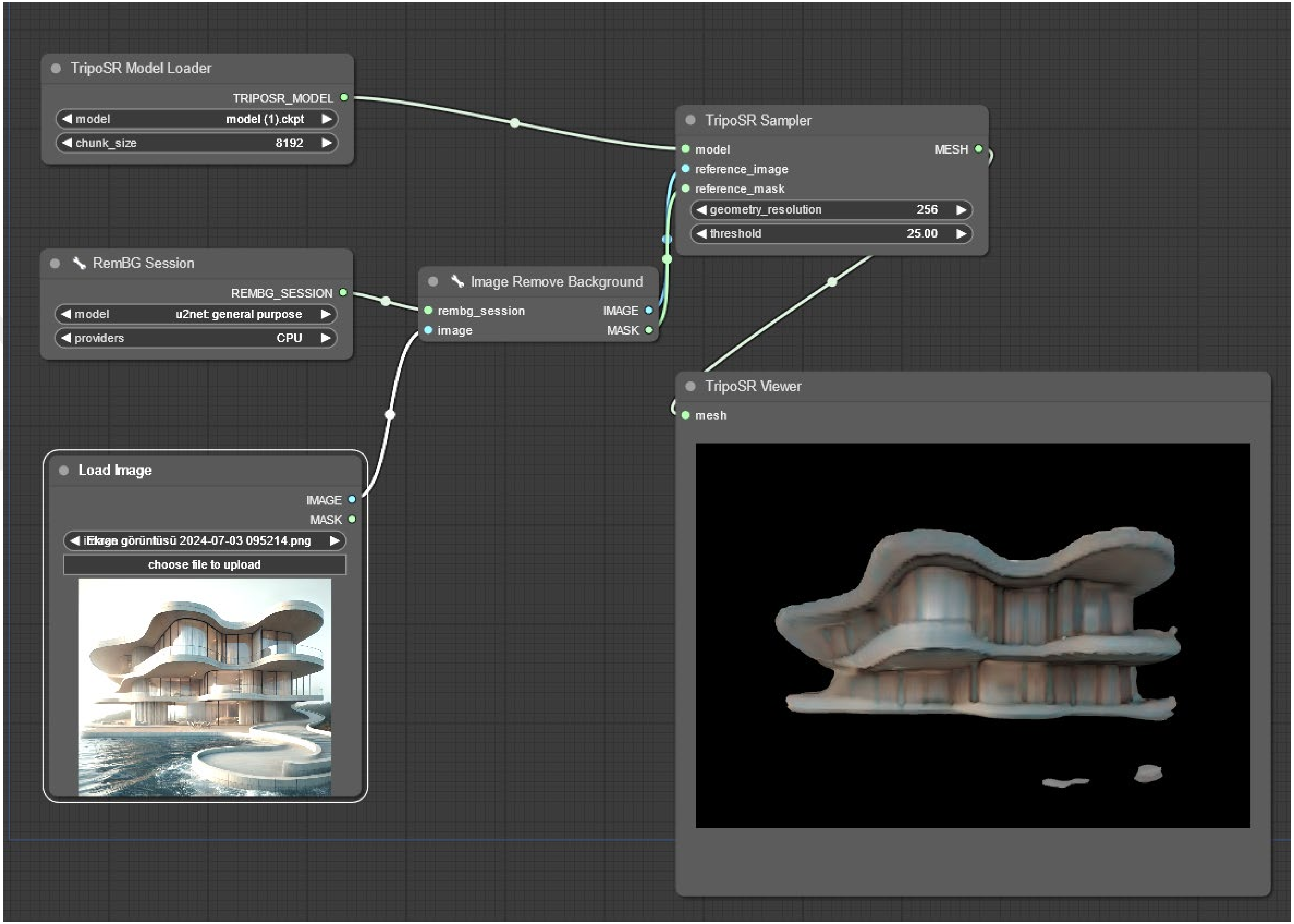
Xu, J., Cheng, W., Gao, Y., Wang, X., Gao, S., & Shan, Y. (2024). *InstantMesh: Efficient 3D Mesh Generation from a Single Image with Sparse-view Large Reconstruction Models* (arXiv:2404.07191). arXiv. http://arxiv.org/abs/2404.07191

APPENDIX

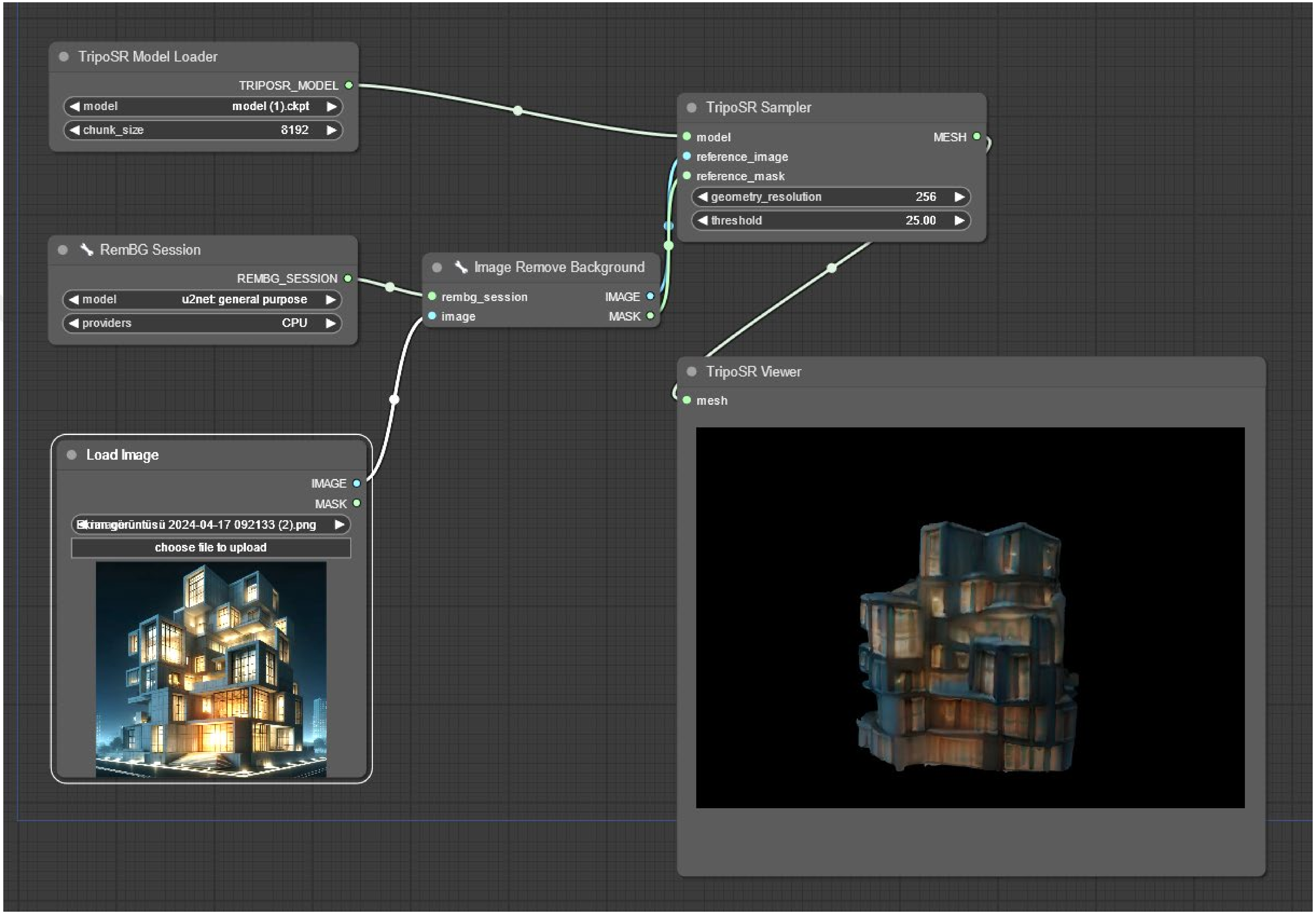
Appendix 1 Example script from ComfyUI



Appendix 2 Script from ComfyUI



Appendix 4 Script from ComfyUI



Appendix 3 Script from ChatGPT:

```
import bpy
import math

# Function to create a single square prism (cube) with a material
def create_square_prism(location, size, material):
    bpy.ops.mesh.primitive_cube_add(location=location)
    bpy.ops.transform.resize(value=(size, size, size))
    bpy.ops.object.transform_apply(scale=True)
    bpy.context.object.data.materials.append(material)

# Function to create a column under a square prism with a material
def create_column(location, size, height, material):
    bpy.ops.mesh.primitive_cube_add(location=location)
    bpy.ops.transform.resize(value=(size, size, height / 2))
    bpy.ops.object.transform_apply(scale=True)
    bpy.context.object.data.materials.append(material)

# Function to generate parametric curved surface with square prisms (cubes) and
columns
def generate_parametric_surface_with_columns(rows, cols, size, curvature_x,
curvature_y, global_offset_x=0, global_offset_y=0, hole_radius=7,
create_hole=True, raise_height=5):
    total_rows = rows * 2  # Since we are generating four surfaces, we consider
double rows and cols
    total_cols = cols * 2
    max_distance = math.sqrt((total_rows - 1)**2 + (total_cols - 1)**2)  # Max
distance for normalization
    ground_level = -10  # Adjust the ground level as needed

    # Create glass material
    glass_material = bpy.data.materials.new(name="Glass")
    glass_material.use_nodes = True
    bsdf = glass_material.node_tree.nodes["Principled BSDF"]
```

```
bsdf.inputs["Transmission"].default_value = 1
bsdf.inputs["Roughness"].default_value = 0
bsdf.inputs["IOR"].default_value = 1.45  # Index of Refraction for glass

for i in range(total_rows):
    for j in range(total_cols):
        # Calculate the distance from the top-left corner (0,0)
        distance_to_corner = math.sqrt(i**2 + j**2)

        # Calculate the position based on the curvature
        x = i * size * 2 + global_offset_x
        y = j * size * 2 + global_offset_y
        z = math.sin(i * curvature_x) * math.cos(j * curvature_y) * size * 2

        # Parametrically raise the corner
        raise_factor = (max_distance - distance_to_corner) / max_distance  #
Normalized distance
        z += raise_factor * raise_height  # Ensure cubes touch each other

        # Skip creating a prism if within the hole radius and if create_hole is True
        distance_to_center = math.sqrt((i - total_rows // 2) ** 2 + (j - total_cols // 2)
** 2)
        if create_hole and distance_to_center < hole_radius:
            continue

        location = (x, y, z)
        create_square_prism(location, size, glass_material)

        # Create a column under the square prism
        column_height = z - ground_level
        column_location = (x, y, (z + ground_level) / 2)
        create_column(column_location, size, column_height, glass_material)
```

```
# Parameters
rows = 20  # Number of rows per surface
cols = 20  # Number of columns per surface
size = 0.5  # Size of each square prism (cube)
curvature_x = 0.3  # Curvature factor in the x-direction
curvature_y = 0.3  # Curvature factor in the y-direction
hole_radius = 7  # Radius of the hole in the center, adjusted for a mid-sized hole
raise_height = 5  # Maximum raise height for the corner

# Generate the surfaces with raising effect applied to one corner and add columns
generate_parametric_surface_with_columns(rows, cols, size, curvature_x,
curvature_y, global_offset_x=0, global_offset_y=0, hole_radius=hole_radius,
create_hole=True, raise_height=raise_height)

# Adjust camera position
bpy.data.objects['Camera'].location = (40, -40, 40)
bpy.data.objects['Camera'].rotation_euler = (math.radians(60), 0, math.radians(45))

# Adjust light position
bpy.data.objects['Light'].location = (40, -40, 60)
```