AI-driven image generation for enhancing design in digital fabrication: urban furnishings in historic city centres

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Abstract

Artificial Intelligence (AI) technologies, such as deep learning and neural networks, are being widely used across various sectors with an unprecedented acceleration in recent years, particularly in the field of image generation. Indeed, such innovation is becoming a paradigm-shifting technology in the Architecture, Engineering, and Construction (AEC) sector specifically for the generation of highly detailed and visually compelling images of architectural projects. The AI algorithms, trained on vast datasets, enable users to automatically generate realistic representations of buildings, interiors, and urban landscapes starting from a text string. The potential of these technologies is significant, but the current literature lacks well-defined processes for effectively utilizing these techniques to achieve implementable projects.
This paper proposes a novel design approach based on AI-driven Image Generation to support design for digital fabrication, consisting of three steps. Firstly, the conceptual design is defined along with a set of keywords. Secondly, the application of AI in image generation allows designers to efficiently explore a multitude of design possibilities. The AI-based tools facilitate the automatic generation of diverse design variants, aiding professionals in evaluating different options and enhancing their visualizations. Thirdly, by leveraging a synergistic set of techniques including image processing, 3D CAD design, and additive manufacturing, it is possible to transform the images suggested by AI into an actual project that can be effectively fabricated.
Finally, the potential of the proposed approach is applied to the case of urban furnishings in historic city centers in southern Italy.

Keywords
AI-driven Image Generation, Urban Furnishings, Digital Fabrication, Historic City Centres, Technical Architecture

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1. Introduction

The first experiments in image processing and generation using artificial intelligence (AI) date back to the 1980 when researchers began exploring the use of neural networks to generate simple figures [1,2,3]. However, significant progress in generating realistic images using AI has occurred more recently with the development of deep learning algorithms and the increase in computing power. Thanks to the advancements made in recent years, the utilization of AI in image generation has experienced a significant rise. This growth can be attributed to the application of deep advanced generative models like Generative Adversarial Networks (GANs) and Recurrent Neural Networks (RNNs) employing capabilities of Deep Learning (DL). These last techniques have opened up new possibilities for generating photorealistic and detailed images.
It is possible to attribute the origin of the generative capability, specifically for DL-driven algorithms, to the work of Ian Goodfellow [4] which conceptualized GANs for the first time. In this technology, two opposing DL agents challenge each other: a discriminator network, working to detect whether an image is real or synthesized by the second network, and the generator network, in charge of learning to create synthetic images not recognizable by the discriminator.
In works as [5,6] it is possible to identify many research fields that are widely investigated nowadays, such as image generation, image inpainting, text generation, medical image processing, semantic segmentation, image colorization, image-to-image translation, art generation and text-to-image (T2I). These numerous applications differ in their final aim (e.g. the generation of a new synthetic image vs the modification of an input image) but also in the input or starting point of their usage (e.g. an image or a text). In this context, T2I is gaining noticeable interest because of the immediacy and straightness of its usage also for non-specialized users [7].

AI-driven Image Generation has found a wide range of applications in the AEC sector. In fact, this new technology is capable of supporting designers and technicians in speeding up design processes, improving visualization capabilities, fostering sustainable practices, and facilitating effective communication between stakeholders [8]. In this context, it is possible to resume the evolution of this technology by referring to [9], in which authors also investigate the different underlying DL architectures of the technologies. The first T2I application was identified with AlignDRAW [10], followed by Text-conditional GAN [11] which has been followed by many other GAN-based methods [12,13,14] featuring applications on small-scale datasets. Parallel to GAN-based ones, autoregressive models [15] allowed large-scale dataset training in exchange for high computational costs. Examples of these architectures are the famous DALL-E [16] from OpenAI and Parti [17] from Google. Among the most widely adopted and considered models to perform T2I, we can list DALL-E2 [18], Stable Diffusion [19] and Midjourney [20].
A recent literature review has demonstrated that in the past five years, the utilization of AI methods to address conceptual design challenges in architecture has grown significantly, experiencing a remarkable 85% increase [21,22]. In this context, various applications of AI-driven image generation can be found in the AEC sector, including:

- Design Exploration where AI algorithms can generate multiple design variations based on specified parameters, allowing architects and designers to explore numerous options quickly [23];
- Realistic Visualizations with AI-driven image generation producing photorealistic renderings, enabling stakeholders to visualize projects in great detail before construction begins [24];
- Virtual Reality (VR) and Augmented Reality (AR) where AI-generated images can be integrated into VR and AR applications, enhancing immersive experiences for clients and facilitating virtual walkthroughs of architectural designs [25];
- Interior Design, as AI-generated images assist interior designers in visualizing different layouts, colour schemes, and furniture arrangements, helping clients make informed decisions about their living or working spaces [25];
- Historical Restoration where AI-driven image generation aids in the restoration of historic structures by recreating missing elements or visualizing how they might have looked in the past.

1.1. Current applications of AI-driven image generator

This work falls within the applied contexts of Design Exploration and Realistic Visualizations, specifically focused on historic city centres. In this section, to illustrate how this technique is currently being applied in the literature and to showcase its potential, the authors present two sets of figures obtained using an AI-driven generator. In particular, Figure 1 shows a set of images generated by the software Midjourney (an AI-driven image generator) [20] depicting glass structure systems in historic city centres, considering a typical architectural context of Apulia (southern Italy). This application serves as a demonstration of how the AI system can achieve highly effective Realistic Visualizations of the structure's facade, providing valuable insights for designers, engineers, and architects.

Figure 1: AI-driven image generation to create glass structure systems in historic city centres of southern Italy.

Another example is provided by Figure 2, where the same software is used to create images of possible interventions for the restoration, renovation, and expansion of historic buildings with new volumetric elements (still within the historical context of Apulian architecture). In this case, AI approaches can be an effective tool to provide immediate suggestions to the designer for visualizing the aesthetic impact of the intervention. By generating numerous realistic renders quickly, it allows for a rapid overview of different types of interventions with varying materials, techniques, and visual impacts.
It is important to note that the evolution of AI technologies for image generation is still ongoing, and new developments and improvements continue to emerge. In this context, although several applications are being developed worldwide, the use of this approach is currently limited to providing suggestions for designers, engineers, or stakeholders. To the best of our knowledge, there are no existing literature applications that aim to structure a procedure for translating AI-generated images into physically realizable objects. However, this possibility can be achieved by combining AI-generated images and digital fabrication, which enables greater freedom in form and facilitates the execution phases of complex shapes.

Figure 2: AI-driven image generation to create renovation and expansion interventions in historic buildings.

1.2. The work proposal

The present research proposes a new methodological approach based on the synergistic integration of AI-driven image generation, image processing, and digital manufacturing. The approach consists of three main steps.

Firstly, the designer defines the conceptual design, accompanied by a set of keywords. Secondly, the application of AI in image generation enables designers to efficiently explore a wide range of design possibilities. AI-based tools facilitate the automatic generation of diverse design variants, assisting professionals in evaluating different options and enhancing visualizations. Thirdly, by leveraging a synergistic combination of techniques including image processing, 3D CAD design, and additive manufacturing, it becomes possible to transform the AI-suggested images into tangible projects that can be effectively fabricated [26, 27, 28].

Lastly, the potential of this proposed approach is demonstrated through a comprehensive case study that specifically focuses on the design and implementation of AI-driven urban furnishings in historic city centres of southern Italy. The study examines how the combination of AI-driven image generation, advanced fabrication techniques, and a deep understanding of the local architectural context can result in innovative and aesthetically pleasing urban furniture solutions that seamlessly integrate with the historical surroundings. By showcasing practical examples and evaluating their impact on the urban environment, the case study highlights the effectiveness and applicability of the proposed approach in enhancing the design and functionality of urban spaces while preserving their historical significance.

The rest of the paper is structured as follows. Section 2 describes the architecture of AI-driven image generators; Section 3 presents the proposed novel AI-driven methodological approach; Section 4 proposes an application in historic city centres of southern Italy. Finally, Section 5 draws conclusions.

2. Architecture of AI-driven Image Generation

This section introduces the typical architecture of AI-driven image generators such as DALL-E2, Stable Diffusion and Midjourney. The tool Midjourney used in the proposed work is a commercial product whose model architecture specifications have not been shared with the community. Consequently, the following description refers to a generic architecture, similar to that of DALL-E2 [18], which enables us to understand the process of generating images from texts implemented by all these different models. A high-level description of the internal behaviour of the network implies the following steps:

i) Contrastive Language-Image Pre-training (CLIP) [29] (Figure 3). This is the fundamental building block of these technologies, creating a link between textual semantics and their visual representation. It is pre-trained on big dataset of image/captions couples and is used in his pre-trained version inside the DALL-E2 model by applying it processing capability on the input text snippet: it is not trained during DALL-E2 model. CLIP is essential because determines how much a natural language snippet and an image is semantically related. It allows the training of both the image encoder and text decoder to obtain image and text embeddings respectively.

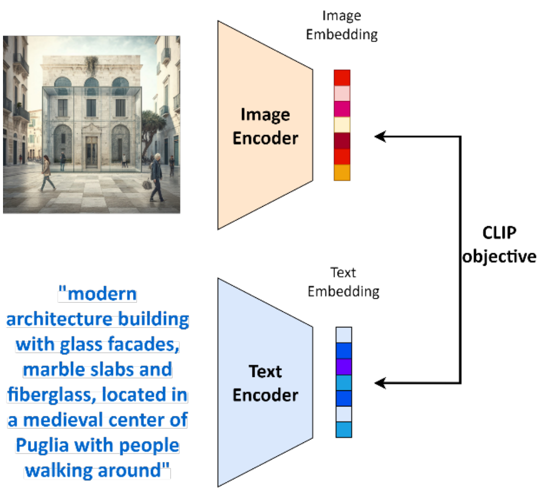

Figure 3: CLIP training procedures (already performed by authors in [65]) used as a building block in DALL-E2 model.

ii) Theprior and decoder training. During the training phase, the model in Figure 4 is trained on a dataset consisting of pairs of images and their corresponding captions. By using the already trained CLIP, the text and image encoders are used to obtain text and image embedding respectively of each image/caption pair to train a prior and a decoder:

a. the prior learns to produce an image embedding starting from the caption and its related text embedding;
b. the decoder learns to produce a stochastic image, starting from the image embedding, featuring the semantic fundamental information of the caption.

Examples of available architectures for the prior are autoregressive or diffusion models, while the decoder is often modelled with diffusion models [18].

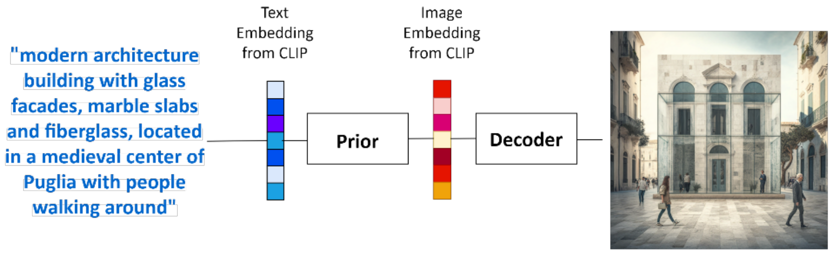

Figure 4: DALL-E2 architecture.

3. The proposed AI-driven approach

As already mentioned, the proposed approach is based on three steps (Figure 5): i) *Conceptual design*, ii) *AI-driven image generation*, and iii) *Digital manufacturing*.

The **first step** of *conceptual design* focuses on defining the initial draft of the project along with the relevant keywords that will guide the subsequent stages.
The **second step** utilizes *AI-driven image generation*, employing specialized software like Midjourney [10], to generate images and visual representations based on the provided conceptual design and keywords (as shown by the authors in the introduction). After an iterative process of refining the generated image by adjusting the input text string, it is possible to achieve the desired project outcome. Finally, in the **third step**, image processing techniques are utilized to transition from the AI-generated image to a two-dimensional CAD (Computer-Aided Design) representation. Subsequently, the designer performs suitable 3D modelling, resulting in the creation of a digital model that can be effectively fabricated using *digital manufacturing* technologies. The following subsections provide a detailed description of the three defined steps.

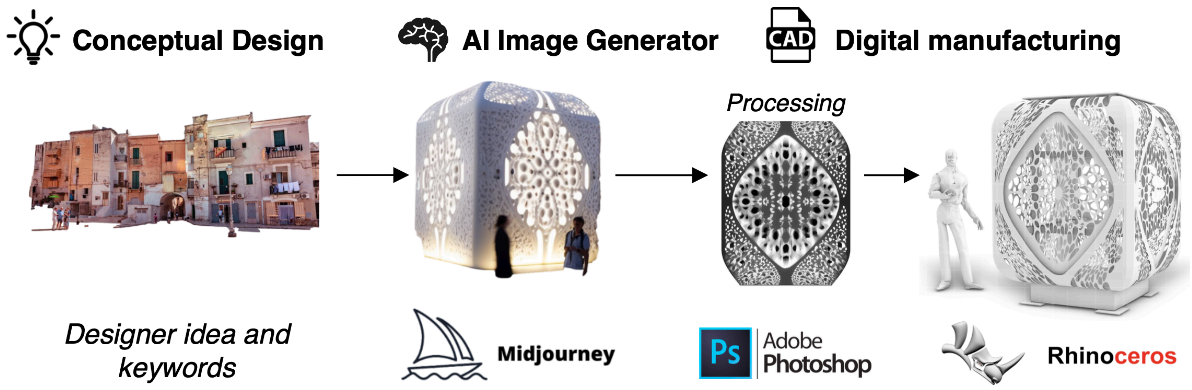

Figure 5: The three steps to achieve a Digital Fabricated component starting from an AI-driven Image Generation

3.1. Conceptual design

Conceptual design in the AEC (Architecture, Engineering, and Construction) sector involves the initial phase of developing a design concept for a building or infrastructure project. It focuses on capturing the overall vision, functional requirements, and aesthetic intent of the project. During this stage, architects, engineers, and other stakeholders collaborate to explore design ideas, establish project goals, and define key parameters. The conceptual design phase lays the foundation for further development and refinement of the project, guiding subsequent stages such as detailed design, engineering analysis, and construction planning. In the proposed approach, the final step of the conceptual design entails defining a set of keywords that will be used in the text to generate subsequent AI images.

3.2. Text to image AI generator

The model developers provide end users with guidelines to obtain better possible results using T2I algorithms. Because of their internal architectures, the fundamental semantic concepts (consisting of the keywords identified in the previous step) must be always specified in the text snippets. In addition, a set of parameters added to the text helps the user to gather the desired specification for the final resulting image. In the case of Midjourney, the main parameters are available for consultation on the online documentation and consist mainly of:

- Aspect ratios, to set the image proportions;
- Chaos, to set a measure of the variation of the final result;

- Quality, to set the render quality of the image;
- Repeat, to define the number of final images created;
- Style, to suggest a visual style for the image.

By iterative refining and adjusting the textual input, designers can gradually steer the AI-driven image generation towards the desired project vision and ultimately obtain the desired design outcome.

3.3. From AI image to digital manufacturing

Once the AI-driven image reflecting the desired conceptual design has been obtained, the first operation of the third step in the approach is to convert the image into a CAD file. To accomplish this, the image is imported into a specific image processing software such as Photoshop [30] where it can be edited and modified if necessary. This may include adjusting colours, removing backgrounds, or enhancing details. Next, the image is traced or vectorized to create a digital representation of its shapes and lines. This process involves using specific tools to trace the important elements of the image or utilizing automated tracing functions. Once the image is vectorized, it can be exported as a suitable file format for CAD software, such as DXF or DWG. These formats allow the vectorized image to be imported into CAD software, where it can be further refined, scaled, manipulated and rendered in three dimensions to create an accurate and editable 3D CAD design. The final step involves selecting the most suitable digital fabrication technology, such as laser cutting, CNC milling, or 3D printing, to produce the component. The 3D CAD file is then adapted to be compatible with the chosen technology for further development and fabrication.

4. An application for the historic centers in Puglia (Southern Italy)

The proposed approach is applied to achieve architectural urban furnishings in the historic city centres of Apulia (southern Italy). In this region, the construction technique of the old town is characterized by the use of local limestone, known as "pietra leccese," which gives the buildings their distinctive white appearance. Furthermore, the architecture is enriched with decorative elements such as ornate carvings, arches, and balconies that are often incorporated into the design. These details reflect the historical influences of various civilizations that have shaped the region's architecture over the centuries.
In this context, the paper intends to apply the proposed 3-step procedure based on AI-driven image generation to obtain a cubic pavilion to be placed in the squares of Apulian historic city centres.
With this purpose, the **first step** of *conceptual design* defines the geometry and shape that should be coherent with the existing architectural elements. Indeed, the design is inspired by the traditional textile craftsmanship of the area to achieve the pattern of the object. In order to finalize the conceptual design and obtain useful data for subsequent steps, the following set of keywords is identified: white, cubic pavilion, relief lace tracery, and historic square in Puglia.
In the **second step**, the text snippet is defined starting from the semantic concept summarized in the conceptual design phase. In particular, the most effective text researched and refined is:
white cubic pavilion with relief lace tracery on the walls with led lights located in a historic square in Puglia with people walking around with the night sky.
Figure 6 shows the results of the image generation. It is possible to notice that the main characteristics of the image remain constant during the exploration of the model: the position of the pavilion in the middle of the square, the perspective of the two buildings in the background, people walking around, the night sky and lights on the pavilion. The exploration mainly focuses on the laces geometries on the surface of the pavilion, in different color intensities of the blue sky, on lights on the background buildings and their architectural details.
At the end of the second phase, the design of the cubic pavilion was selected among the various objects generated by the AI and was refined through iterative adjustments of the textual input.

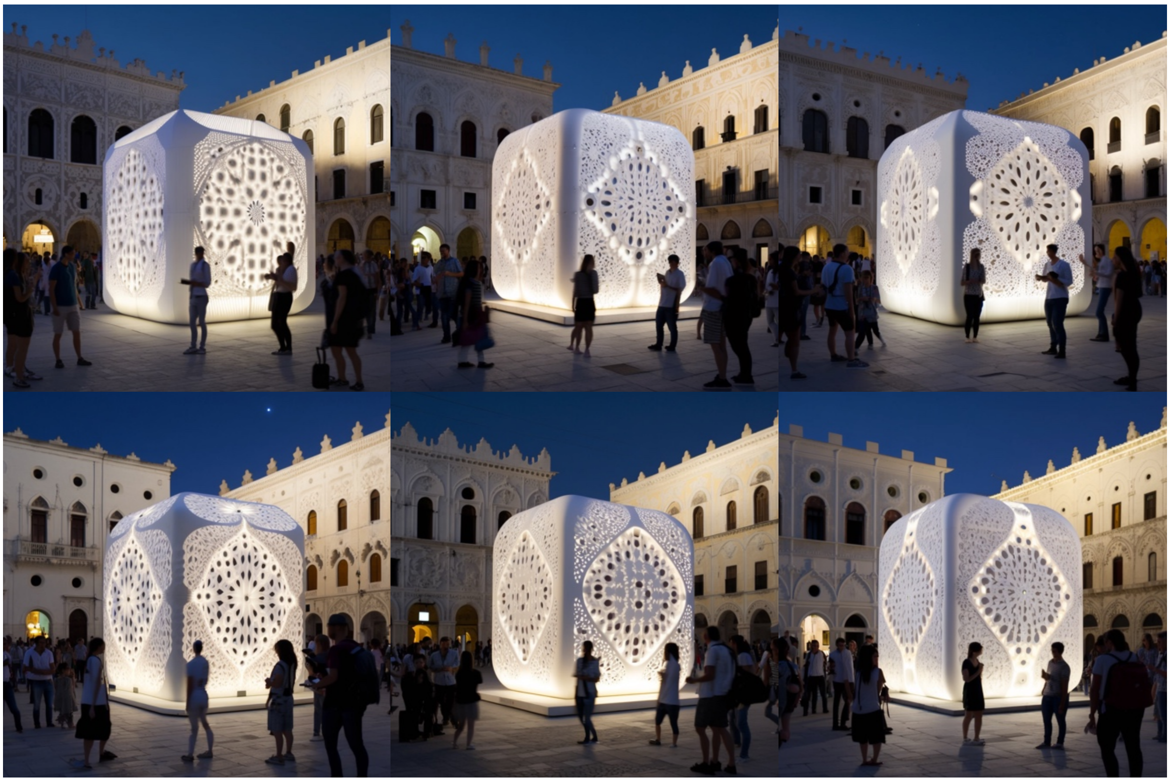

Figure 6: Generation of the conceptualised cubic pavilion through AI-driven image.

In the **third step**, the visual representation of the cubic pavilion achieved by using AI-driven image generation is converted into a 3D model with features suitable for *Digital manufacturing*. To accomplish this, firstly, the image is imported into Adobe Photoshop© (2020 v21.1.0) [30]. In this software, a set of tools and filters are used to modify colours, remove backgrounds, enhance details and straighten the AI-generated image to remove perspective distortion and achieve a frontal perspective view of the pavilion. Secondly, the perspective view obtained can be easily converted into a bidimensional DXF or DWG CAD file to be further refined, scaled, and manipulated. Figure 7 illustrates the conversion process from an image generated by the AI system to CAD. Specifically, on the left side of the image, the image generated by the AI system is shown. In the centre, the grayscale image obtained after a series of tools and filters in Photoshop is displayed, and on the right side, the resulting CAD file is shown. Finally, a 3D model is generated starting from the two-dimensional CAD by using specific software for 3D modelling such as Rhinoceros (Version 7, 7.28.23058.03002, 2023-02-27) [31]. The final 3D model must observe specific criteria to be successfully produced using a specific digital fabrication technology. In this case, additive manufacturing is the technique chosen to achieve the prototype, and the 3D CAD file is modelled with specific features to ensure its suitability for 3D printing [32]. Indeed, the 3D CAD model is modelled to have a manifold geometry, ensuring it is watertight with no gaps or intersecting surfaces. The model is accurately scaled to match the desired physical size. It also features sufficient resolution and detail to faithfully represent the intended object. Moreover, the model is optimized for 3D printing, taking into consideration factors such as support structures, orientation, and material considerations to ensure successful and high-quality printing. Figure 8 shows the achieved 3D CAD file.

The achieved 3D model has been printed in scale with fused deposition method (FDM) technology to show the potential of the approach Figure 9. It is worth noting that, the increasing effectiveness of technology, also supported by modern artificial intelligence techniques, is making 3D printing increasingly efficient for this type of realization [33,34]. Currently, there are several technologies (such as gantry systems, cable-suspended solutions, or robotic arms) that are considered effective for printing prototypes at full size (which would be approximately 3m x 3m x 3m) [35].

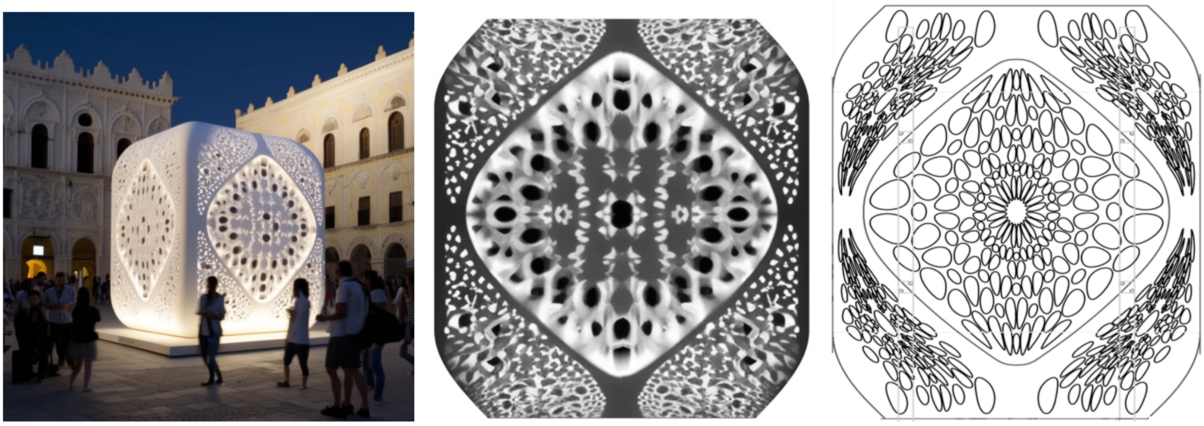

Figure 7: Image processing techniques are utilized to transition from the AI-generated image to a two-dimensional CAD.

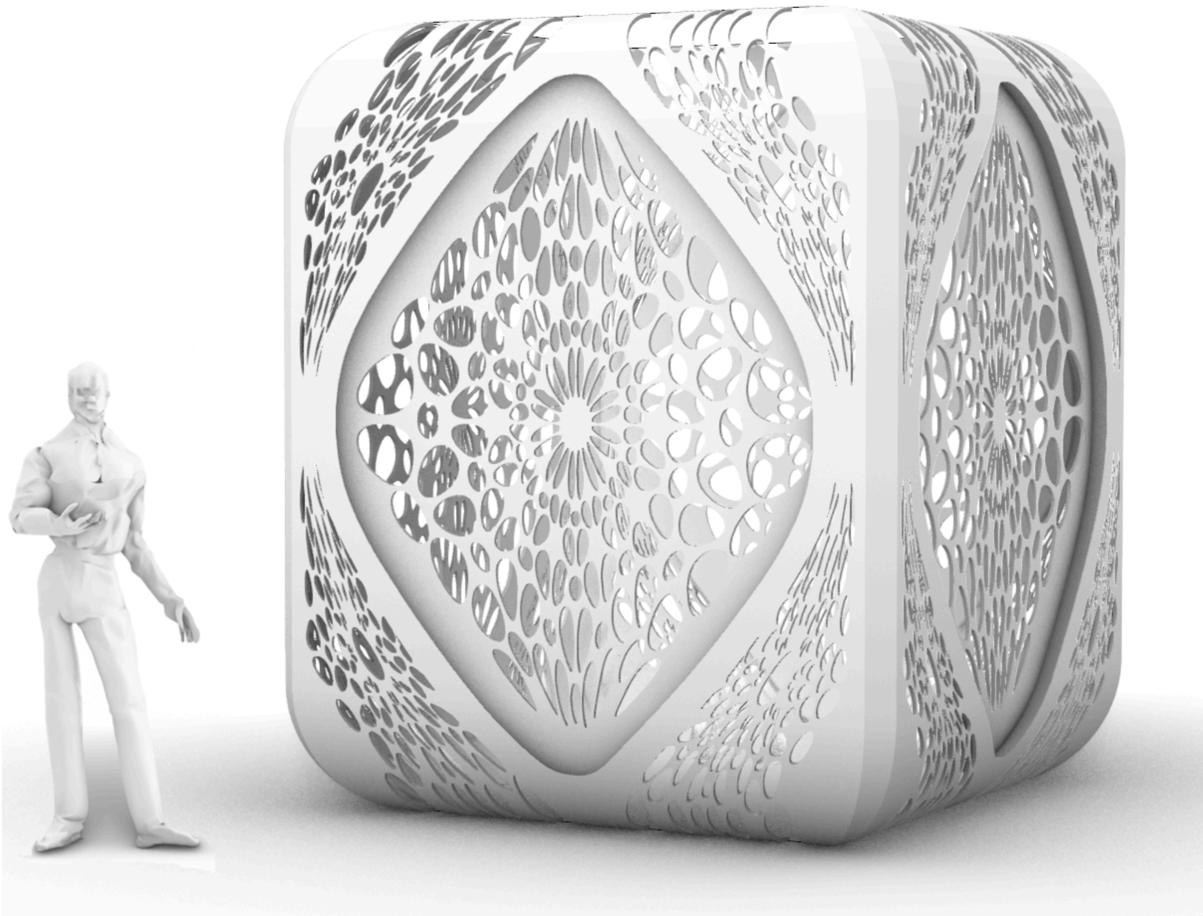

Figure 8: Development of the 3D model that can be manufactured with 3D printing technology

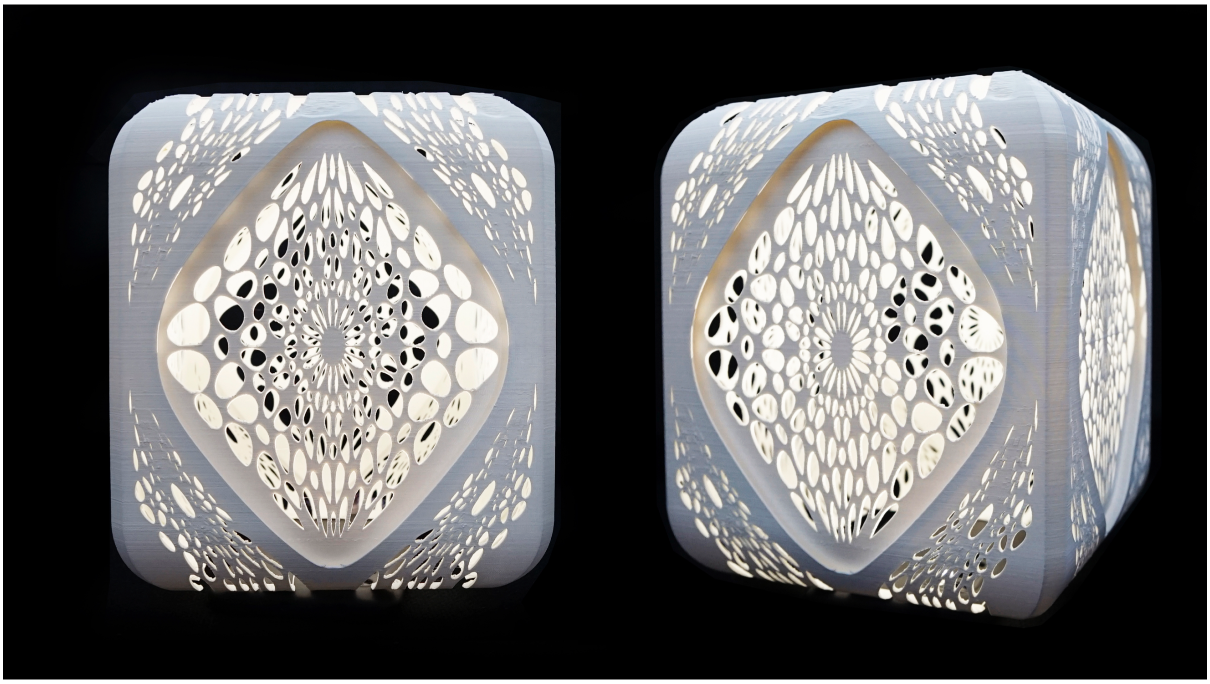

Figure 9: Prototype of the AI-generated pavilion (Photo taken in a black photo studio)

5. Concluding remarks

This paper has presented a novel approach based on AI-driven image generation for supporting architectural design and digital fabrication. We proposed a three-step process, comprising conceptual design, AI-driven image generation, and digital manufacturing, and we has demonstrated its effectiveness in generating diverse design variations, refining them iteratively, and transforming them into realizable objects.

The approach has been applied to achieve a cubic pavilion in the historic city centres of Apulia, showcasing the potential for integrating AI technologies with traditional architectural contexts. Indeed, considering the local construction techniques and materials specific to the region, such as the renowned "pietra leccese", the AI is able to integrate elements in the architectural landscape inspired by traditional textile craftsmanship within the local context, through the generation of an image. Furthermore, the seamless transition from AI-generated images to CAD files, followed by the adaptation of the 3D model for 3D printing, ensures the practical feasibility of the proposed designs. This paper highlights the power of AI and digital fabrication in enhancing the design process. In addition, the proposed approach unlocks new possibilities for engineers, architects, and designers to explore creative avenues, visualize concepts accurately, and ultimately bring their vision to life by harnessing the power of artificial intelligence. Future research will employ the suggested approach to achieve a more complex project, wherein a collection of functional attributes for the intended object will be delineated.

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