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Generative vs. Non-Generative AI: Analyzing the Effects of AI on the Architectural Design Process

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Abstract: The rapid advancements in artificial intelligence (AI) and machine learning (ML) have led to numerous practical applications across various fields. Architects and researchers have also begun exploring the potential of applying AI & ML to enhance their work. The advent of generative AI led to new opportunities for the architects who started using image generation models to aid in the concept phase as well as visualizing projects, plans generation, etc. Moreover, more experiments were done with non-generative AI in planning, predicting materials, and classification to serve architectural design and analysis purposes. However, existing applications often fail to provide precise and readily usable architectural models within the standard design software used by architects. Moreover, architects started to rely on generative (gen) AI models to generate designs in the form of rendered photos and many experimentations with such tools are being done with little focus on the use of non-generative (non-gen) AI models. In this paper, we analyze the mechanism and technology behind different gen-AI models as well as the product of these models to give insights on the authenticity of these products and the effects of applying such technologies on the architectural design process. This analytical study is supported by reviewing different applications from researchers and architects regarding both types of algorithms. The research concludes with a strong suggestion to rely more on non-gen AI models which aid in a more human-centered design approach. The findings also suggest that gen-AI models could affect the design process negatively, especially if the design concept is purely generated using text or even undetailed photos. And finally, possible applications of both gen and non-gen AI models are suggested as a result.

Keywords: Architectural design process – artificial intelligence – machine learning – generative AI – non-generative AI – image generation.

1. Introduction

In January 2021, a breakthrough in AI creative abilities was announced when DALL-E was open for the public to experiment with. DALL-E is a platform that converts text to images through generative AI. In July 2022, another breakthrough in AI creative abilities was announced when MidJourney was open for the public to experiment with. MidJourney is another text-to-image generative AI model, but it was resulting in more realistic generated images with more options [1, 2].

Since then, DALL-E and MidJourney were developed, and new versions were published gradually with more options including inpainting, outpainting, and image-to-image generation reaching DALL-E v3 and MidJourney 5 at the time of writing this research. Also, other image generation models were developed including Adobe Firefly and stable diffusion [3].

Of course, Many fields have leveraged the power of such models and capabilities and the architectural field is no exception.

In fact, the advent of both generative and non-generative AI has significantly transformed the architectural design process. Generative AI, with its prowess in divergent thinking and algorithmic creativity, has become a catalyst for idea generation. Furthermore, generative AI facilitates collaboration between architects and machines, fostering a symbiotic relationship that leverages the strengths of both. On the other hand, non-generative AI excels in analytical support, aiding architects in data analysis, simulation, and visualization. It contributes to realistic renderings, project management optimization, and quality assurance. However, the integration of AI in architecture poses challenges, including ethical considerations regarding biases, the delicate balance between technological efficiency and human creativity, and the need for architects to adapt to evolving workflows. In navigating these challenges, architects can harness the benefits of AI to enhance their design processes, ensuring a harmonious integration of technological advancements with traditional practices.

In this paper, we question the authenticity of Gen-AI products with a focus on generated images. We analyze Gen-AI as a concept and how it could affect the design process, proposing a theory on how Gen-AI could fit in the process rather than dramatically changing it in a way contradicting with the essence of architectural design. After that, we discuss architectural visualization field and whether it directly affects the design process or not. Finally, we explain how non-gen- AI could be integrated to the design process.

1.1 Non-Gen-AI

Non-generative AI includes AI models that do not have the inherent capability to generate new content but excel in tasks such as classification, regression, pattern recognition, or prediction which are considered the base role of ML algorithms. ML algorithms include supervised, unsupervised, and reinforcement learning as well as artificial neural networks (ANN) specified for such tasks and deep learning (DL) [4]. This type is typically trained on a dataset of labeled data learning the relationship between the features and the labels [5]. This kind of application does not include creative generation of new outputs such as images, text, 3d models, etc. The abilities of non-Gen-AI suggest a broad spectrum of applications that could aid in the design process as well as management of architectural projects during documentation and construction phases.

ML is defined as a type of AI which excels at discovering intricate patterns within data, utilizing good generalization on unseen data with very precise predictions [6]. In ML several disciplines meet such as database, data mining, pattern recognitions, etc. This process does not require explicit programming of ML algorithms and meanwhile, many explorations in applying ML are being widely conducted in different fields. ML algorithms could be categorized as supervised learning, unsupervised learning, and enforcement learning. Supervised learning is where the data fed to machine is labeled whereas in unsupervised learning the data is fed to machine without any labels and so, the machine can cluster the data into groups [7]. Specific types of data are used with ML algorithms including images, text, numbers, and sounds. However, all these types require the ability to be transformed into numerical values so that they can be processed by machines. And in architectural form design, numerical predictions require being labeled to be used in their predefined parameters afterwards to generate a model.

ML supervised learning algorithms can perform both regression and classification tasks. In regression, the relationship between input and target variables is quantified to allow predictions based on this relationship, meaning that data are fed as numerical values and predictions return as numerical values as well [8]. In an architectural design model, and when predicting parameters that involve lengths, widths, heights, distances, etc., regression analysis will suit such problems very well. Classification tasks involve dealing with classes where the target of the task is to categorize every input into one of the classes [9]. It is a form of data mining techniques. This could be used in an architectural model in case a boolean value (true/false) is required to take decisions on problems like whether there are windows in a wall or not, whether an element is added to the façade or not, etc.

Non-Gen AI Applications in Architecture

Numerous studies within sustainable architecture have leveraged Machine Learning (ML) techniques to optimize building energy efficiency and consumption. For instance, Tsanas and Xifara developed a statistical ML framework to scrutinize the influence of variables like wall area and glazing area on residential building heating and cooling loads, emphasizing the accuracy of ML predictions aligned with the training data [10]. Also, Chou and Bui utilized various AI techniques to estimate heating and cooling loads, with the ensemble approach and Support Vector Regression standing out [11]. In addition, Robinson et al. found that gradient boosting regression models excelled in predicting commercial building energy consumption [12]. Roy et al. delved into advanced ML techniques for residential buildings, while Deng et al. cautioned about the nuanced performance of ML algorithms compared to linear regression for US commercial building energy use [13]. Additionally, Studies by Rahman and Smith showcased ML's capability, including Neural Networks and Gaussian process regression, in predicting fuel consumption in commercial buildings [14].

Yazici, S., 2020, experimented with integrating ML and ANN algorithms with geometry, material, and structural performance simulation data to aid in the decision making. They collected the data from a structural performance simulation and the data were applied to train an ANN, non-linear regression model (NLR), and a gaussian mixture model (GM) to predict materials based on structural performance, points on architectural geometry, and panel clusters on the shell model. Fig 1 shows the result of applying the GM model. The results yielded fast solutions and accurate values according to the author [15].

Mandow et al. (2020) used shape grammars and reinforcement learning to generate habitable and energy-efficient sketches for small single-family dwellings. They defined diverse shape grammar rules, applied reinforcement learning to ensure compliance, and presented experimental results demonstrating convergence and comparisons with real designs. Validation was conducted using an energy simulation program [16]. Also, Cudzik and Radziszewski (2018) used an artificial neural network (ANN) to predict Roman Corinthian order capitals, turning it into a co-designer for spatial variations. Trained on 28,900 samples, the ANN successfully generated three-dimensional variations (fig 2) based on input parameters, enhancing architectural design with computer-generated solutions [17].

The integration of machine learning into the architectural design process holds immense potential across all planning phases, transforming both repeatable and predictable activities. Machine learning tools can effectively replace certain tasks, particularly those involving decision-making, by learning from the work performed by architects. This evolution introduces complex machine learning methods, bringing artificial intelligence to the forefront of architectural and product design. This shift has the power to redefine the value of algorithmic design, moving beyond being a mere computational tool to becoming an equal collaborator in the design process. This collaborative synergy between human designers and machine learning systems has the capacity to revolutionize the architectural design landscape, fostering efficiency, creativity, and the exploration of novel design paradigms.

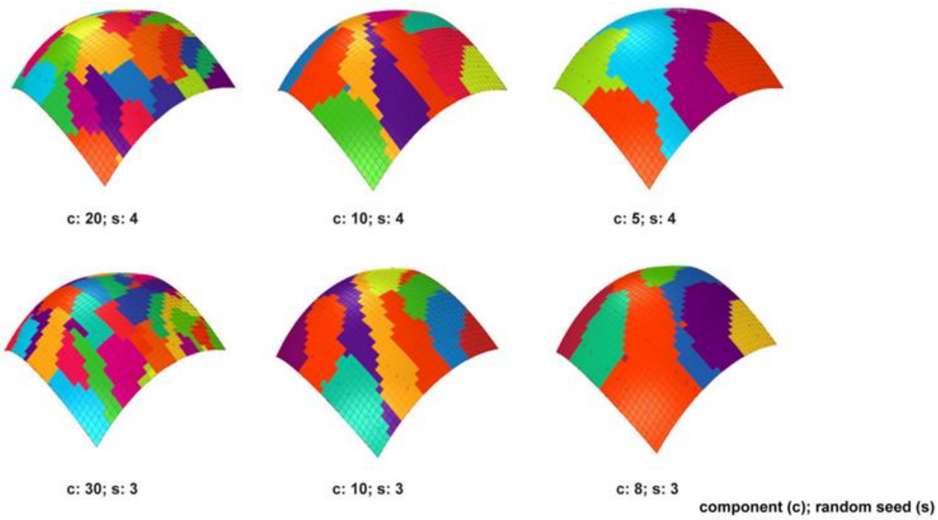

FIGURE 1 - GM algorithm implemented towards prediction of panel clusters based on the area size and planarity of panels. - Yazici, C., 2020, A machine-learning model driven by geometry, material, and structural performance data in architectural design process

FIGURE 2 - Designed capitals with ML - Cudzik, J., 2018, Artificial Intelligence Aided Architectural Design

Also, and more importantly, such collaboration could be described as 'human-centered' where the machine aids in automating the process rather than interfering in creative and aesthetic aspects of the design which we argue that they are the essence of an architectural product. These aspects along with many others require the architect to be the center of the process seeing the whole picture and taking decisions that respect the complicated network of all design aspects.

Recently, many AI applications have been introduced to the architectural design process including encompassing modeling, classification, rendering, and more. However, getting predictions that aid in form modeling was not experimented with deeply. Also, the basic knowledge of a framework to codify a building to retrieve its parameters and to create efficient data sets remains crucial for the success of such applications.

1.2 Gen-AI

Generative AI refers to systems that have the ability to generate similar new content, often in the form of images, text, sound, 3d models, speech, code, video, etc. These systems can create outputs that are not explicitly present in their training data by understanding the distribution of data. Gen-AI applications involve generating new content, ideas, or solutions based on input data or predefined parameters. In the context of architectural design, generative AI can play a significant role in creating, modifying, or optimizing designs by leveraging algorithms and computational models.

Text generation techniques involve the use of algorithms and models to produce coherent and contextually relevant textual content. These techniques have applications in various domains, including natural language processing, chatbots, content creation, and more. Additionally, and more important to architects, image generation AI works by using algorithms to create new and realistic images. These algorithms are trained on large datasets of images and learn to generate novel content by capturing patterns and features present in the training data. Image generation AI often relies on deep learning architectures, such as Generative Adversarial Networks (GANs) and Variational

Autoencoders (VAEs). It involves various models and algorithms, each with its own approach to creating realistic and diverse images. Some prominent models and algorithms in the field of image generation are GANs, VAEs, CNN, RNN, CLIP, and Diffusion.

In image generation, GANs generator creates images, and the discriminator evaluates their authenticity [18]. GANs use algorithms such as DCGAN (Deep Convolutional GAN), StyleGAN, BigGAN, and CycleGAN. StyleGAN introduces style-based generators that allow control over the style and content of generated images. CycleGAN is designed for unpaired image-to-image translation. It learns mappings between two domains without requiring paired training data and is useful for tasks like transforming images between different artistic styles [19]. And BigGAN is an extension of GANs designed for large-scale image generation. It utilizes a conditional GAN architecture and is known for generating high-quality images and is commonly used for large-scale image synthesis tasks [20].

VAEs are probabilistic models that learn a latent representation of images. They consist of an encoder, a decoder, and a loss function that ensures the generated images match the input distribution. VAEs use algorithms such as β-VAE which introduces a hyperparameter for better disentanglement of features. These models are autoregressive and generate images pixel by pixel [21]. PixelCNN and PixelRNN capture dependencies between pixels in the generation process. They are suited for high-resolution image generation but can be computationally expensive. Such models use algorithms including PixelCNN++ and PixelRNN [22].

While primarily a multimodal model, CLIP can also generate images based on textual prompts, demonstrating a unique approach to image generation. It is used in associating images and text, enabling tasks like image captioning and text-based image retrieval [23].

DALL-E is a generative model designed for image generation within the GPT architecture family, specifically based on a variant of GPT-3. Unlike traditional language models, DALL-E is trained to generate images from textual prompts by learning intricate relationships between text and visual elements. It undergoes extensive pre-training on a dataset of images paired with text, enabling it to associate textual descriptions with visual features. Users input a textual prompt, and DALL-E leverages its learned associations to create diverse and novel images. The generation process involves sampling from a latent space for output variation. While DALL-E does not explicitly use a noising and denoising mechanism, it may handle uncertainties internally, allowing it to produce creative and varied outputs based on the same textual input. The model showcases the adaptability of large language models for image generation, demonstrating its proficiency in translating textual descriptions into visually compelling content [24].

Diffusion algorithms, such as Diffusion with Denoising Priors (DDPM) and Noise-Contrastive Estimation for Stable Density Ratio (NCSN), are examples of stable diffusion models used in image generation. DDPM employs denoising priors to guide the generation process, enhancing the robustness of generated images to noise. NCSN combines noise-contrastive estimation with stable diffusion to address challenges in training generative models [25]. In the diffusion model, the image generation process unfolds through controlled steps, gradually transforming a clean image into a more complex and noisier version (fig 3). Trained on clean images, the model learns parameters governing the diffusion process, with optional denoising priors to encourage specific properties. Once trained, the diffusion model can sample from the learned distribution to generate synthetic images, aiming to produce stable and realistic samples resembling the training dataset. Controlled diffusion proves valuable for generating diverse and high-quality images while maintaining stability in the generation process [26].

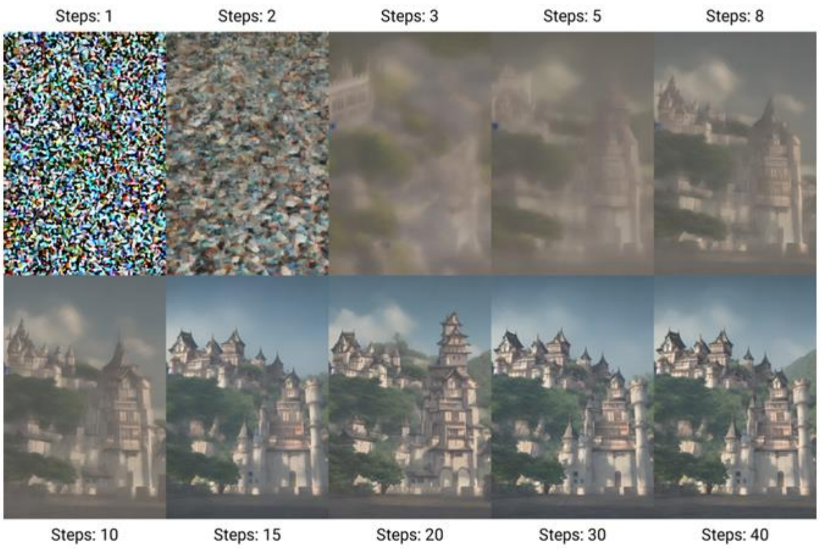

FIGURE 3 - The denoising process used by Stable Diffusion. https://en.wikipedia.org/wiki/Stable_Diffusion#/media/File:X-Y_plot_of_algorithmically-generated_AI_art_of_European-style_castle_in_Japan_demonstrating_DDIM_diffusion_steps.png

The addition of noise to images, followed by denoising, serves as a valuable technique for data augmentation and regularization in both human and machine learning processes. This approach introduces variations to the learning process, fostering a more robust understanding of visual content. Noise functions as a regularization method, preventing overfitting and encouraging generalization beyond specific training instances. Denoising then focuses the learner on essential features, enhancing generalization and promoting a stable representation. This interplay of noise and denoising encourages creativity, adaptability, and a broader understanding of images, improving performance in recognition tasks and potentially aiding in the generation of new visual content. In stable diffusion models, crucial visual details like textures and shapes are encoded as numerical pixel values. The model processes images through its neural network, adjusting weights and biases during training to recognize patterns. The objective is to learn representations that effectively capture salient details, enabling the model to simulate the introduction and removal of noise, ultimately generating and denoising images with precision [27].

Additionally, image generation models allow different functions like inpainting and outpainting which are image generation techniques that involve filling in or extending parts of an image. They are often used in the context of generative models and computer vision applications. Inpainting is the process of reconstructing missing or damaged parts of an image, commonly used for image restoration and object removal. Outpainting, on the other hand, involves extending the content of an image beyond its original boundaries, useful for image expansion and creative content generation. Both techniques leverage generative models, such as GANs and VAEs, trained on large datasets to fill in missing areas or generate content beyond the observed image space. Inpainting and outpainting find applications in image editing, restoration, and creative visual generation.

Gen AI Applications in Architecture

In 2019, Chaillous employed nested GANs to generate diverse floor plans, utilizing Boston's building footprints database for training. The pipeline involved sequential steps, including layout generation, room count assignment, furniture placement, and building finalization as shown in fig 4. The model addressed architectural complexities and incorporated style transfer for specific architectural aesthetics. The approach facilitated architect-centered design exploration by allowing user intervention in the pipeline [28].

Also, in 2023, Aalaei et al. explored architectural layout generation using graph-constrained conditional GANs. They introduced a vectorized workflow (fig 5) for handling high-level constraints, utilizing a convolutional message passing (CMP) approach considering both topological and geometric conditions. The study presented a distinctive network architecture and an iterative pipeline with three GAN models for varied objectives [29].

FIGURE 4 - Resulting Furnished Units (Chaillous, S, 2019., AI & Architecture – An Experimental Perspective – Harvard University GSD)

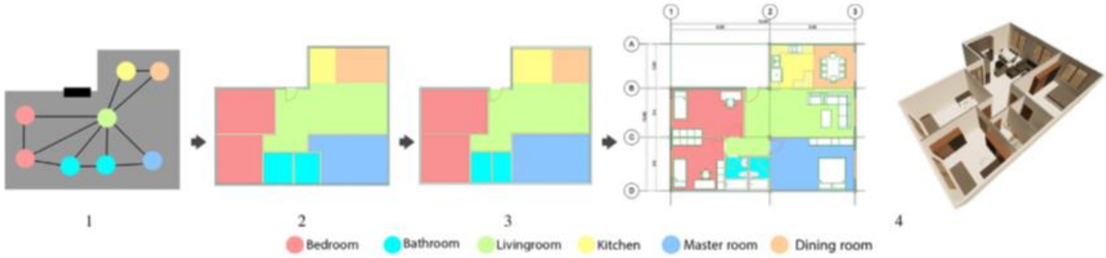

FIGURE 5 - Iterative and collaborative human–machine workflow for architectural floor plan generation. (Aalaei, M., et. Al., 2023, Architectural layout generation using a graph-constrained conditional Generative Adversarial Network (GAN))

Moreover, Bao and Xiang, 2023, focused on AI platforms like Stable Diffusion, MidJourney, and DALL-E 2 as smart assistants in preliminary design. These platforms optimized conceptual design by transforming hand-drawn sketches into rendering photos and improving massing diagram visualization. The study, based on a survey with AI-generated images (figs 6 and 7), revealed AI's potential to assist architects effectively, optimizing various aspects of architectural design [30].

Gen-AI models and algorithms contribute to the field of image generation, each with its unique strengths and applications. Researchers and practitioners often choose or develop models based on the specific requirements and characteristics of the images they aim to generate.

FIGURE 6 - Base input sketch for AI generation (Bao, Y and Xiang, C., 2023 - Exploration of Conceptual Design Generation based on the Deep Learning Model-Discussing the Application of AI Generator to the Preliminary Architectural Design Process)

FIGURE 7 - Rendering generation results made by MidJourney, Stable Diffusion and DALL-E 2 (from left to right respectively). (Bao, Y and Xiang, C., 2023 - Exploration of Conceptual Design Generation based on the Deep Learning Model-Discussing the Application of AI Generator to the Preliminary Architectural Design Process)

2. GENERATIVE AI ARCHITECTURAL DESIGNS AUTHENTICITY

Today, the field of architecture has seen many experiments with generated designs in the form of images. Recently, some architects have started to generate design ideas through image generation gen-AI models either by providing a prompt expressing the project requirements, some certain ideas, etc. in the form of text, or by providing sketches.

Gen-AI's impact on the authenticity of designs is a pivotal aspect of this evolution. The authenticity of generative AI architectural designs is a nuanced consideration, encompassing both the innovative potential of AI-generated creations and the preservation of unique human expression in design. Generative AI excels at exploring diverse design possibilities, pushing the boundaries of conventional architecture, and fostering creativity. However, questions arise regarding the authenticity of designs when algorithms autonomously generate solutions. Critics argue that reliance on generative AI might lead to a homogenization of designs, with the risk of overlooking the distinct cultural, historical, and contextual nuances that human architects often incorporate into their work.

Millet et. Al, 2023, revealed an anthropocentric bias in art appreciation, suggesting a prevailing human-centric viewpoint in assessing creativity, particularly in the context of AI-generated art. Their experiments, encompassing over 1,700 participants, unveiled a consistent bias against AI-created art, perceived as less creative and awe-inspiring compared to human-made counterparts [31]. Similarly, Ragot et. Al., 2020's extensive study involving 565 participants identified a preference bias toward human-made creations, with art perceived as AI-generated receiving less favorable evaluations [32]. These findings underscore a persistent negative perception bias towards AI in the realm of art, reflecting a broader inclination to view creativity as an exclusively human trait. As AI continues to advance in the creative domain, these biases pose challenges to fostering an inclusive perspective that recognizes and appreciates the unique contributions of both human and machine creativity. Addressing these biases is essential for cultivating a more open-minded appreciation of AI's potential as a tool for artistic expression.

Yet when it comes to the originality of ideas in image generation models like diffusion models, it is important to note that these models are trained on existing data. The originality of generated samples depends on the diversity and complexity of the training data. If the training data includes a wide range of unique and novel examples, the model has the potential to generate original outputs. However, diffusion models, like other generative models, do not inherently generate truly novel ideas in the creative sense—they synthesize new examples based on patterns learned from the training data.

Moreover, gen-AI models could be eclectic. The term "eclectic" in the context of image generation refers to the ability of a model to combine diverse elements from its training data to create novel and varied images. If a diffusion model has been trained on a diverse dataset containing images with different visual styles, objects, and scenes, it may be capable of generating images that incorporate elements from various sources. In the case of diffusion models, the process typically involves iteratively adding noise to an input until it transforms into a sample from the target distribution. The ability to create eclectic images could arise from the model's capacity to blend and remix features it has learned from disparate examples in its training data. Thus, proponents of generative AI emphasize its capacity to reinterpret and combine design elements in novel ways, challenging traditional notions of authenticity. AI-generated designs can be seen as a reflection of the data they are trained on capturing and reinterpreting architectural styles and features from various sources. This dynamic process can result in unexpected designs that embody a new form of randomness rooted in computational creativity.

Navigating the authenticity of generative AI architectural designs requires a careful balance. Architects and designers must actively engage with AI tools, guiding the algorithms to align with their vision while also embracing the serendipity and novelty that AI can introduce. The synthesis of human insight and machine-generated possibilities can lead to truly authentic designs that are both innovative and deeply connected to human sensibilities. As the field continues to evolve, a thoughtful and critical approach to the integration of generative AI will be essential in preserving and redefining the authenticity of architectural design.

3. CAN GEN-AI FIT IN A PROFESSIONAL ARCHITECTURAL DESIGN PROCESS?

Among many researchers and architects, Chaillou, S., 2019 had beliefs which are rooted in the assertion that a statistical approach to design conception profoundly shapes the potential of AI in the field of architecture. The departure from deterministic methodologies toward a more holistic, less-prescriptive character is seen as a unique opportunity within the architectural domain. Rather than viewing machines solely as tools for optimizing predefined variables, Chaillou advocates relying on AI to extract significant qualities and emulate them throughout the entire design process, marking a paradigm shift toward a more dynamic and exploratory design experience [28].

Furthermore, according to Chaillou, the conviction lies in the pivotal role of designing the right pipeline to ensure the success of AI as a new architectural toolset. The preference for the "Grayboxing" approach, as introduced by Witt, A., is considered strategic and likely to yield optimal results. Chaillou contrasts this with the "black box" model, where users input information upfront and receive finished design options at the end, without influence over intermediate generation steps [28]. The "Grayboxing" approach, as advocated by Chaillou, involves breaking down the pipeline into discrete steps, empowering the user to intervene at various stages.

This hands-on control over the machine ensures the user's ultimate guarantee of the quality of the design process, offering a more collaborative and iterative interaction between human insight and AI capabilities. This deliberate approach, as expressed by Chaillou, underscores a commitment to a thoughtful integration of AI into architectural practices, emphasizing user agency and creativity within the technological framework.

The gray box approach seems logical especially with today’s mathematical applications in architectural generative designs which includes optimization and simulation techniques for instance. Also, AI applications in architectural design could involve such an approach. Especially, that it includes different applications (APIs) that could be learnt and used in the form of an internal black box operation in the design process without needing to learn what is behind -as users and not as developers-.

In fact, while strongly agreeing with Chaillou that AI should be dealt with as a ‘toolset’ for the architect that involve many advantages, we strongly believe that today’s Gen-AI applications which generates images (used as designs) -at least till the time of writing this research- are as far as possible not only from what architectural design profession is about but also from what an architectural design methodology could be and could propose as a solution to a problem. I believe that an architectural design product is not just drawings. It is rather an experience and a process. And this process most likely -if not always- includes problem solving of a handful of issues from a handful of other disciplines as well as architectural rules (form, commodity, and delight). Those other disciplines include structural, societal, psychological, philosophical, humanitarian, and environmental, to name a few. All of these issues could never be diminished to whatever a generated architectural drawing image could encompass because every project should be designed with a whole new character and new thoughts.

Also, and more importantly regarding text-to-image applications specifically, ‘can we diminish all the aspects of an architectural design in words?’. Architects who mostly follow the ‘black box’ approach find it hard to clearly express their ideas and how the form is generated. And worse, even those who apply the ‘glass box’ approach either by following function, relying on generative design various techniques, etc., still have hard time realizing the process and the reasons of the resulting product which is usually hard to explain to a machine. A gen-AI photo generation model cannot understand the orientation of the building, or the parametric approach taken to stabilize the structure, or the best façade pattern or form manipulation to reduce solar gain. Instead, Gen-AI models generate responses based on patterns learned during training. And of course, such manners are taken into consideration from day one in the design process and are ‘applied directly’ more than ‘thought of’. If architects skip such techniques in the process and start with a generative design (created by AI-Gen models), it is most likely that the end product will be as far as possible from these images, and then the architects should ask themselves, ‘what was the benefit?’ Even with newly introduced models including LoRA and ControlNet. Still, the ‘control’ they provide the architect with, is more control of an outline or a boundary of the building or getting closer results to the words descriptions. Still, this whole process deals with an architectural product as a 2-dimensional product.

In addition, architectural design is about understanding what a user desires, and not only the architect’s aesthetic and creative parts. If this part of the architect’s job is well perceived, they would most probably find themselves in need of designing something that is unseen before, even if some details/techniques are reused. In this sense, relying on a dataset of previously designed projects could contradict this theory.

And in this manner, we would strongly suggest differentiating between the product of Gen-AI models and the product of a generative design as there are no contradictions if we apply the previous theory on generative design. Generative design is still controlled by the architect who defines the parameters and the goals for which a machine searches the solutions to achieve. Even if we imagine a generative design based on a simulation analogy. Still, there are goals defined that spark the simulation. And even the parameters affected by the simulations are defined by the architect.

So, after all, answering the question 'can gen-AI fit in a professional architectural design process', of course. But it could be integrated into some phases of the process rather than starting the process. In the next section, we suggest some applications of gen-AI that could possibly add value to the process.

4. GENERATIVE AI POSSIBILITIES IN ARCHITECTURAL DESIGN

AI technology could be seen and thought of as a great tool for automating the design process which includes by nature visualization of ideas. And in section 1 we exhibited some of these applications where a Gen-AI could generate a plan after defined boundaries (regardless of the idea that those boundaries were decided by AI in those examples).

Ali, S., 2020, argues that architectural visualization plays a crucial role in augmenting the comprehension of knowledge by minimizing cognitive load. The utilization of visualization tools enables individuals to grasp information more efficiently and to a deeper extent. By representing data in visual formats such as charts, graphs, or diagrams, complex concepts are simplified, aiding in quicker assimilation and enhanced retention [33]. This visual approach leverages the brain's capacity to process and interpret images rapidly, allowing individuals to extract meaningful insights with greater ease. Whether conveying intricate datasets or illustrating abstract ideas, visualization serves as a powerful cognitive aid, facilitating a more intuitive and expedited understanding of information. Ultimately, the integration of visualization tools proves instrumental in optimizing the communication of knowledge across diverse fields. However, and according to the author visualization in architecture has become a target more than a tool especially in architectural education. In fact, visualization could be misleading or deceptive. The beauty of a 'hyper-realistically' and aesthetically rendered glass box could mislead the client's preferences. In this regard, visualization should be carefully dealt with by architects as a tool rather than as a product.

In terms of visualization, the idea of transforming sketches is seen very powerful and with more development it could make a great tool for visualizing plans, sections, other drawings, and perspectives when the machine has a 100% ability to generate images which apply exactly what is defined in a sketch. This application is seeing many developments today especially with the introduction of techniques like inpainting, outpainting, and LoRA. The more datasets to be fed to the generative algorithm, the more precise it will be in visualizing the architect's sketch instead of generating new ideas.

Also, such technology could aid a lot in a phase of the design process called the 'mood board' in which architects search for inspirational designs and show it to the client in order to be on the same ground during the design phase. Such a phase is important before starting the concept design and is usually related to aspects like façade elements, aesthetical elements, and design style. However, this step is not meant to have a significant impact on the core of the form making/finding process. Gen-AI image generation in this case, could have an added value based on the data it is trained on, and it is believed to have the same result as collecting the inspirational images from the web.

Additionally, Gen-AI applications regarding transforming images into 3D-models could have a huge impact on automating design tasks. Especially, if 3d-model gen-AI models developed to generate surfaces and clean meshes rather than point clouds or voxels. Such an application is not far from reality. It could develop through integrating the gen-AI model to a pipeline which exhibits an automated way to segment images and extract the main points' coordinates. Such an application could be exhaustive at first, but if better data sets are collected and engineered, it could not be regarded as impossible.

Finally, another bright application of Gen-AI is the video Gen-AI which could create animations and walkthroughs which are considered an architectural output in some projects. The idea of generating videos through photos collected from around a 3D-model using diffusion is now present and could be applied in such tasks.

5. NON-GENERATIVE AI POSSIBILITIES IN ARCHITECTURAL DESIGN

While non-gen-AI models do not generate data such as images, text, 3d-models, they are capable of predicting and generalizing on unseen data based on the pattern they learn during their training process. In this regard, non-gen-AI will not produce an image, but may predict numbers, or classes. These numbers and classes could be projected to the architectural field as parameters which could be used by the architects themselves or automated systems to generate products. This particular description aligns well with the approach taken to deal with the architectural process as a holistic system rather than a process of processes.

The idea of dealing with a building as a set of parameters which are interrelated and strongly connected in the design phase, could make good use of non-gen-AI applications. Accordingly, turning a building's design parameters to data sets which could be used to train AI and ML algorithms could yield many possibilities. Training a model with parameters either numerical or text to predict design decisions is thought to be an automation process saving time and effort for architects in the future. Imagine designing a cluster of buildings (a residential or administrative compound). Such projects could take months to create variations or prototypes of the building with different areas, functions, etc. but with the same architectural style and theme or either days but with more manhours or architects. With the aid of coding in extracting all the parameters and generating a data set including many designs with different areas that is used to train ML models for example, this could automate the 3d modeling tasks of different prototypes with different characteristics. Also, and looking from the same perspective, non-gen-AI models could be used to predict spatial relations and to detect proper spaces' areas based on learned data. Moreover, the models could predict and make decisions based on other aspects such as environmental and legislative aspects. For instance, they could predict a length parameter that defines the spacing between two staircases based on firefighting code or the tilt angle of louvers which reduce solar gain, or minimum required spacing that respects setbacks, etc. However, such decisions require neat and precise data sets so that predictions are mirroring real decisions based on real data. Those models are guaranteed to have learnt data directly from the architect.

In general, non-gen-AI models could be thought of the same way as generative-design techniques like optimization and simulations in the sense that the product is unknown, but it is still respecting certain rules controlled by the architect through the data sets they learn from which could be very specific to the details-of-every-parameter extent and unique rather than general and repetitive. Thus, the overall process is controlled by the architect against any random decisions that could be made by gen-AI models.

6. CONCLUSION AND FUTURE DIRECTION

The main aim of the present study was to evaluate the evolution of AI creative capabilities in the architectural field from a skeptical perspective, particularly focusing on image generation models, which have progressed through various models and techniques, each introducing more options like inpainting, outpainting, and image-to-image generation. The impact of both generative and non-generative AI on the architectural design process is highlighted.

Generative AI, known for its divergent thinking and algorithmic creativity, plays a pivotal role in idea generation and we questioned if it is reliable as a tool used in the architectural design process. Collaboration between architects and generative AI is emphasized as well as the architect's role in the process. In general, applying AI in the architectural field fits well with the gray box approach of design thinking. In a holistic design process composed of other processes that relate to each other cyclically, with today's design tools which benefit mainly from mathematics and physics, architects could think of some processes with a black box approach. In such processes, the embedded operations that happen form no concerns as the architect totally controls and directs them freely. In fact, the architect can direct and control Gen-AI systems, but we conclude that the architectural design process cannot be diminished in a 2D-space with an image that hardly involves other design aspects. Such a process could lead to laziness and stripping the architectural design of its meaning. Also, the authenticity of AI-generated designs was discussed. And from the understanding of how the models work, those models could be described as eclectic collage makers which present innovation through repeating elements that are learned from the training data set. Moreover, architectural visualization's direct influence is discussed as a useful tool using AI generative models.

Non-generative AI, on the other hand, excels in analytical support, aiding architects in data analysis, decision making, predicting, and classification tasks. The integration of AI in architecture, however, poses challenges, including ethical considerations, the balance between technological efficiency and human creativity, and the need for architects to adapt to evolving workflows to develop them rather than being a user. The research concludes by delving into benefits of using non-gen-AI models in the design process as automation assets to the architect in the decision making based on authentic and unique data provided by the architect themselves.

In future, the workflow of applying AI tools in architecture needs to be investigated in order to serve the architectural design process in a more human-centered approach where all design aspects are fully controlled. Future research could also include investigating AI models capability of being multi-tasking in a way that utilizes gen-AI as a rendering tool as well as non-gen AI as predictor of design parameters.

CONFLICTS OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of this article.

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