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EXPLAINABLE ARTIFICIAL INTELLIGENCE IN GENERATIVE DESIGN FOR CONSTRUCTION.

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Abstract

As artificial intelligence rapidly advance, their growing complexity enables more sophisticated applications across sectors, including construction. However, the opaque nature of algorithms, such as generative AI, reduces human interpretability and trust. While providing benefits like enhanced efficiency, generative design's black-box processes hamper adoption. Explainable AI can elucidate how AI algorithms generate outputs, thereby improving understanding and confidence. Despite explainable AI's potential, construction has given it limited focus. This research systematically reviews the application of explainable AI in generative design in construction, with an aim to allay risks and enable wider utilization of these emerging technologies for improved engineering design.

Introduction

The expanding integration of artificial intelligence (AI) in the field of architecture and construction, driven by the exponential growth in data, is reshaping traditional practices. The manual analysis of vast datasets and reliance on rule-based computing methods pose challenges, prompting the adoption of AI for systematic data analysis through predictive modeling. This transformation influences various facets of the industry, including architectural and structural design, construction safety, sustainability, affordability, speed, return on investment, and operational performance. Generative design, a departure from traditional methods, empowers computers to semi-autonomously explore design spaces, presenting designers with diverse options for analysis and consideration (Baduge at al., 2022; Junk and Burkart, 2021; Krish, 2011).

While the adoption of AI in construction is gaining recognition, challenges arise in understanding and interpreting AI model outputs, often considered "black boxes". Concerns about bias, fairness, trust, and reliability, particularly in critical domains such as recruitment, real-time progress monitoring, cyber-security, risk management, and safety, warrant attention. Human decision-making in these domains is also susceptible to bias, and the reluctance to embrace AI is often rooted in a lack of understanding. Establishing trust in AI models, crucial for widespread acceptance, is explored through explainable artificial intelligence (XAI). This involves methodologies and processes to enhance comprehension and confidence in the outcomes and outputs of AI algorithms, addressing the industry's need for transparency and reliability (Matthews et al., 2022; Gunning et al., 2019; Sokol et al., 2022; Love et al., 2023). While XAI has gained traction in fields like law and medicine , its exploration in construction remains limited despite the rise of generative AI.

This study aims to fill this gap by providing a thorough exploration of XAI for generative design in construction. Through a systematic review, this paper advocates for generative AI in construction, raises awareness of XAI limitations and gaps, and harnesses its advantages. To achieve this, the study provides comprehensive answers on how XAI tackles transparency and bias, differentiates generative AI, elucidates the mechanisms of XAI for generative design in construction, and examines how XAI influences the generative design framework in this industry.

Methodology

The methodology employed in this study aims to provide a comprehensive analysis of the research objectives. In essence, this paper begins by elucidating the fundamentals of AI followed by a systematic review of 31 academic papers on generative design and the emerging field of generative AI design. In essence, drawing from the mentioned comprehensive review, this section has been concluded by presentation of a categorization of generative design techniques, methods, and models. Subsequently, the concept of XAI is introduced and to enhance the clarity, terminologies are provided, outlining its significance and methodologies. This section derives from an analysis of 30 academic papers to establish a taxonomy for the preliminary stages of applying XAI. Moving forward, the paper conducts a critical review of the construction industry, focusing on the potential applications of generative AI within this domain. Illustrative examples of generative processes in architectural design further enrich the discussion. Finally, the paper proposes a comprehensive taxonomy titled "Explainable Generative AI Design," defining various approaches to render generative design algorithms interpretable and transparent. The mentioned taxonomy was developed by exploring major types of GENAI models based on their mechanisms. They were then categorized according to AI models. Finally, post-hoc expandability techniques were provided for these GENAI models. Each step of the methodology is meticulously created to provide a comprehensive understanding of the intersection between generative AI and construction, elucidating the theoretical underpinnings and practical implications for future research and applications.

Artificial Intelligence

Over the past decade, the construction sector has lagged in adopting transformative AI advancements that have revolutionized other industries. Notably driven by machine learning and its specialized subset, deep learning, these breakthroughs harness historical data to predict patterns, enabling automated generative design and analysis processes. Deep learning techniques, exemplified in Baduge et al. (2022), facilitate automated structural evaluation and design, emphasizing prestressed components. AI in construction promises generative and optimized layouts, safety risk prediction and mitigation, energy cost reductions, accelerated project timelines, enhanced financial returns, and sustainable building practices. The replicative capabilities of AI address feasibility and scalability challenges posed by big data in the construction sector. Despite being in an experimental stage, the rapid evolution of AI applications in construction, supported by expanding research and consistently impressive results, anticipates widespread integration and commercial viability in the near future (Love et al., 2023; Angelov et al., 2021).

Generative Design and Generative AI

The architectural design process is conventionally divided into three integral phases: the initial conceptual or scheme design, the detailed preliminary design incorporating optimization, and the creation of construction drawings. The conceptual phase holds paramount significance as it molds the ultimate design and heavily relies on the designer's expertise. Addressing prevalent issues in structural design, such as inefficiencies, data underutilization, and knowledge transfer challenges, has prompted a growing emphasis on smart design strategies. Leveraging historical design data, architectural concepts, and various forms of knowledge, the evolving approach employs generative AI to efficiently produce new designs (Kanyilmaz et al., 2022). The GD process comprises three components: a design schema, creating variations, and selecting desirable outcomes (Krish, 2011).

Generative design, rooted in facilitating innovation, utilizes algorithmic software driven by parameters set by designers, including materials, geometric shapes, and loads. The incorporation of artificial intelligence into generative design processes utilizes metaheuristic search algorithms, such as genetic algorithms, to explore and identify efficient solutions within predefined design frameworks. This transformative approach comprises three core elements: a generative geometry model, criteria defining design objectives, and a metaheuristic search algorithm. Generative AI has emerged as a pivotal technological development, prominently featured in intelligent design to overcome inefficiencies in the structural design industry (Avital, 2007; Junk and Burkart, 2021; Liao et al., 2024). This article delves into data feature representation, intelligent structural design creation, and robust design outcome assessment within the realm of generative AI for architectural design.

Singh's explorations in 2012 of generative design techniques, detailed in Table 1, encompasses SG, CA, GA, LS, and SI, considering their technical, design, and system development characteristics. Integrating these computational systems poses challenges due to the necessity for a common language across diverse generative design (GD) techniques. Singh envisions an interactive expert system, placing the designer at the core of the GD process. Meanwhile, Krish (2011) proposes generative design methods (see Figure 1 and outlined at the top of Table 1). Contemporary research emphasizes adapting generative AI models, employing deep learning methods like CNNs, GNNs, and RNN/LSTM for domain-specific problem-solving, as elucidated by advanced algorithms in the last section of the table (Liao et.al, 2024). Generative AI holds the potential to revolutionize data management in architecture, engineering, and construction (Ghimire et al., 2023). However, its transformative impact in the construction industry is hindered by issues, including a gap between research and industry, hesitancy due to interpretability, feasibility, reliability concerns, and ethical considerations (Arrieta et al., 2020).

Explainable Artificial Intelligence

Explainable artificial intelligence (XAI) is a collection of methodologies designed to enable human users to understand and trust the outcomes of artificial intelligence systems. The objective of any XAI method is to make the decision-making of AI models transparent and interpretable. Anand et al. (2020) have persuasively argued that AI algorithms often resemble inscrutable "black boxes" due to their intricate, nonlinear structures that are hard to elucidate, even for their creators. The inability to fully understand machine learning and deep learning models entails risks when relying on their unexplained outputs. XAI has thus been developed to help users grasp the rationale behind the specific outputs of AI systems. The diminished explainability of AI models has led Gerling et al. (2021) to assert that the inability to elucidate algorithms means we cannot contest, validate, enhance, or derive knowledge from them. Therefore, generating explanations that clarify the functioning of DL and ML models, as well as the basis for their decisions or predictions, is crucial for fostering trust in these technologies. Arrieta et al. (2020) have characterized XAI to provide insights or justifications that render the operations of a model transparent and easily comprehensible. While a consensus on the definition remains elusive, it is widely accepted that XAI systems ought to articulate their capabilities, recount their past actions, describe their current activities, predict future outcomes, and disclose the pertinent data upon which they operate. To achieve these ends, XAI addresses concerns related to interpretability and transparency.

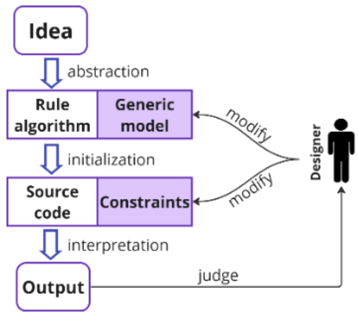

Figure 1: Generative design process (Krish, 2011)

Table 1: Generative design methods and techniques and generative AI models.

Ref	Category						
Krish. 2011	**Generative Design Method (GDM)**						
Krish. 2011	**Genotype**	**Phenotype**	**Exploration envelope**	**Design Table**	**Design Generation Software**	**CAD system**	**Performance filters**
Krish. 2011	Is composed of a generic parametric CAD model, list of design parameters and their initial value and initial exploration envelope.	Generated CAD files (that may include build history, built-in relationships and built-in equations).	A list of minimum and maximum values of the driving parameters, specifying the limits of the design space to be explored.	A data table that stores the driving design parameters, their initial values and limits.	It generates random variations of the driving design parameters within limits set by the exploration envelope.	Is a parametric CAD engine with a transparent and editable build history.	A pass/fail software filter that is able to evaluate the performance of generated designs based on preset performance criteria.
Singh. 2012	**Generative design techniques across their technical, design and system development characteristics**						
Singh. 2012	**Cellular automata (CA)**	**Genetic algorithms (GA)**	**Shape grammars (SG)**	**L-systems (LS)**	**Swarm intelligence (SI) and multi-agent societies**		
Singh. 2012	A grid of cells that change over time based on predefined rules influenced by the states of adjacent cells.	Simulate natural selection by evolving a population of design solutions using a fitness function.	Rules for manipulating shapes to produce a variety of designs.	Create structures resembling natural growth patterns, resulting in self-similar forms.	Collective behavior of simple agents that interact with their local surroundings. Leading to the formation of organized, global patterns.		
Ghimire et.al. 2023	**Major types of GenAI models based on their generative mechanism**						
Ghimire et.al. 2023	**Generative Adversarial Networks (GAN)**		**Variational Auto Encoders (VAE)**		**Autoregressive models**	**Diffusion Models**	**Flow-based Models**
Ghimire et.al. 2023	Two neural networks, a generator, and a discriminator, compete with each other to generate realistic data.		Encodes data into a latent space and then decodes it back into the original space.		Generate data one step at a time, using the previously generated data as input.	Start with a noisy image and gradually refine it to a realistic image.	Transform data from one distribution to another using a series of invertible functions.

XAI is a complex concept encompassing intrinsic or post hoc nature, local or global scope, and model-specific or model-agnostic applicability (see Figure 2).

Defining XAI definitively demonstrates challenging due to context-dependent interpretability, varying across domains, as illustrated in Figures 2 and 3. Although these terms are frequently used interchangeably, they may convey distinct nuances in various settings. To enhance clarity, the distinctions and commonalities among terminologies frequently employed within the realms of ethical AI and XAI are elucidated in this section:

- Understandability refers to a model's inherent quality that enables a human to grasp its functionality—how the model operates—without necessitating an exposition of its internal architecture or the algorithmic processes it utilizes to manage data internally.

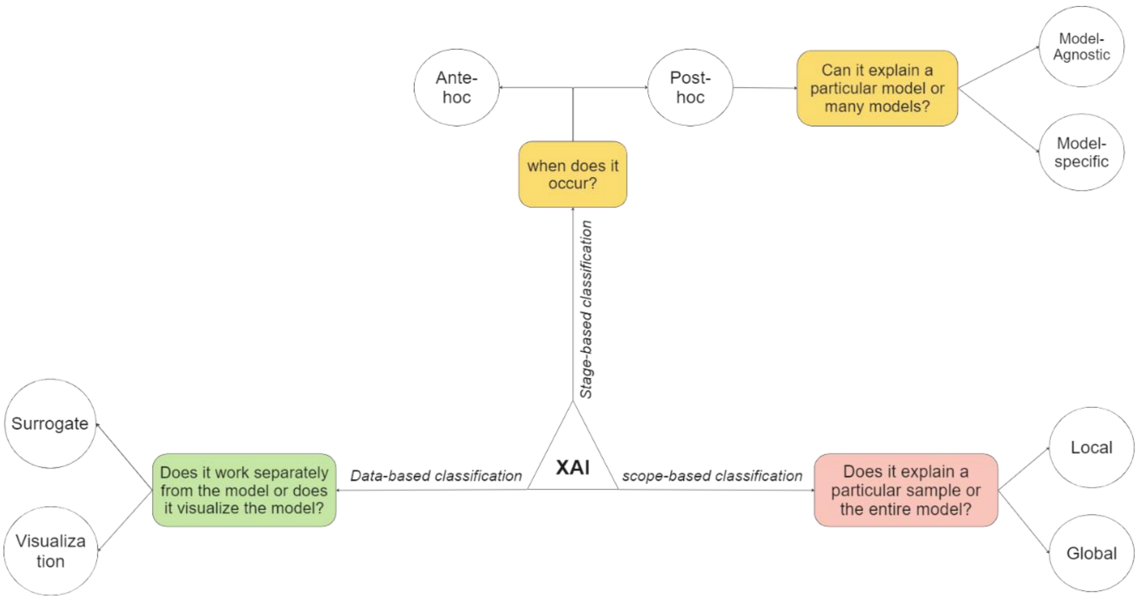

Figure 2. Preliminary stages in application of XAI (Source: Authors).

- Comprehensibility, when applied to machine learning models, pertains to the capacity of a learning algorithm to present its acquired knowledge in a manner that is intelligible to humans.
- Interpretability is described as the facility to convey significance in terms accessible and clear to a human observer.
- Explainability is crucial, acting as a bridge between humans and decision-making entities. It involves post-hoc methods to make opaque models intelligible. In this document, we prioritize explainability as the primary design goal, recognizing its comprehensive importance.
- Model transparency hinges on inherent comprehensibility, categorized into simulation models (step-by-step emulation), decomposable models (examining components and interconnections), and algorithmically transparent models (visible internal logic and decision-making processes).

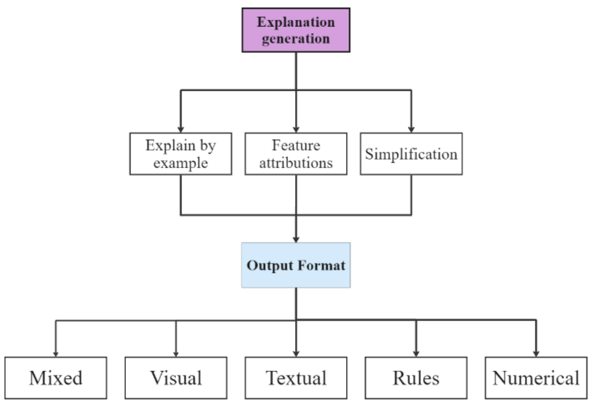

Figure 3: Various formats of XAI results (Source: Authors).

Explainable generative AI design in construction

As AI becomes increasingly integrated into applications that directly impact humans and as the ramifications of algorithmic decisions grow, the construction industry must broaden its focus beyond merely the predictive accuracy of ML and DL models to include their explainability (Love et al., 2023). Generative AI has the potential to transform data management in architecture, engineering, and construction, offering efficient processing of unstructured data through large language models (LLMs). A few examples can be found in Figure 4. Generative AI fosters seamless information exchange between tangible and digital realms in construction projects, enhancing comprehension and decision-making in project management by accessing previously inaccessible unstructured data (Ghimire et al., 2023). As the authors mention in their article, the potential of Gen AI in construction is:

1. To extract project information from construction documents such as dimensions, materials used, responsible person, point of contact, etc.
2. To generate new documents. Examples- proposals, reports, etc.
3. To classify & cluster documents based on project types, internal departments, sub-contractors, project phases, document types, materials, supply chain, etc.
4. Generating code to automate tasks.
5. Optimizing cost estimation workflow.
6. To help quality control by comparing completed tasks to project specifications to identify defects and deviations.
7. To generate an optimal schedule path.

Construction organizations have been reluctant to adopt artificial intelligence (AI) systems, not because of unwillingness, but due to the lack of explainability of autonomous decisions and actions made by AI, which undermines confidence and trust (Love et al., 2023). XAI offers significant benefits for construction, including reduced model bias, enhanced trust, actionable insights, and risk reduction. XAI elucidates the rationale behind AI decisions and capabilities (Love et al., 2023). Explanations can facilitate collaborative co-design among stakeholders, empowering them to make informed decisions about system use and appropriate timing for performance assessments (Khosravi et al., 2022). Consequently, evaluating XAI requires comprehending diverse socio-political environments of stakeholders using an interpretive approach that enables deeper understanding and generates motivation and commitment (Love et al., 2022).

As it is depicted in Figure 5, there are various approaches that can be selected for implementing XAI solutions tailored to generative design algorithms, contingent upon the differing characteristics of the models and their associated computational processes. In the following section, different types of XAI approaches that can be used to make generative design algorithms explainable are presented.

- **Local Explanations:** It focusses on explaining individual predictions or decisions made by the AI model. In the context of generative design, this could involve explaining why certain design choices were made for a specific instance. Techniques such as Local Interpretable Model-agnostic Explanations (LIME) or SHapley Additive exPlanations (SHAP) can be used to provide these local insights.
- **Global Explanations:** Unlike local explanations, global explanations aim to provide an understanding of the model's overall behavior. For generative design algorithms, this could involve explaining the general principles or rules the model uses to generate designs across different scenarios.
- **Feature Attribution Methods**: These methods explain the output of a model by attributing the prediction to the input features. For generative design, this could mean identifying which features of the input data are most influential in the design generated by the AI.
- **Visual Explanations:** Visualization techniques can be used to illustrate how the generative model is transforming input data into a design. This could include visualizing the activation of different layers in a neural network or showing intermediate steps in the design process.
- **Example-Based Explanations:** Providing examples of similar designs or design decisions made by the AI can help users understand the rationale behind the generated designs. This could include showing nearest neighbors or variations of the design that were considered by the algorithm.
- **Feature Attribution Methods**: These methods explain the output of a model by attributing the prediction to the input features. For generative design, this could mean identifying which features of the input data are most influential in the design generated by the AI.
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- **Example-Based Explanations:** Providing examples of similar designs or design decisions made by the AI can help users understand the rationale behind the generated designs. This could include showing nearest neighbors or variations of the design that were considered by the algorithm.
- **Counterfactual Explanations:** Such explanations provide insights into how the input could be changed to achieve a different outcome. In generative design, counterfactuals can help users understand how altering certain design parameters could lead to different design results.

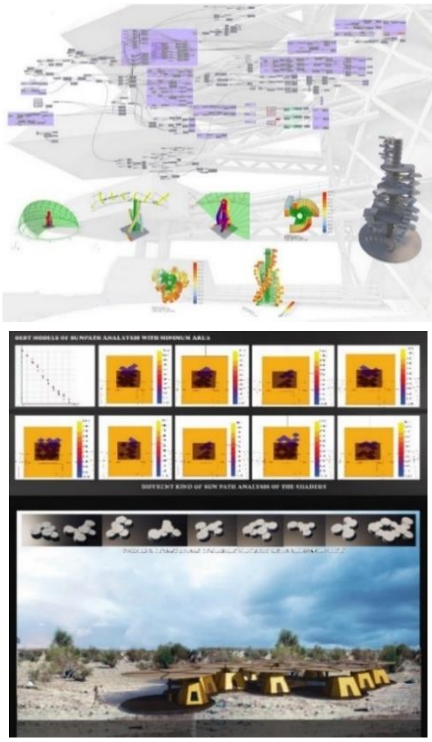

Figure 4: Examples of generative design process in the initial conceptual or scheme design (Source: Authors).

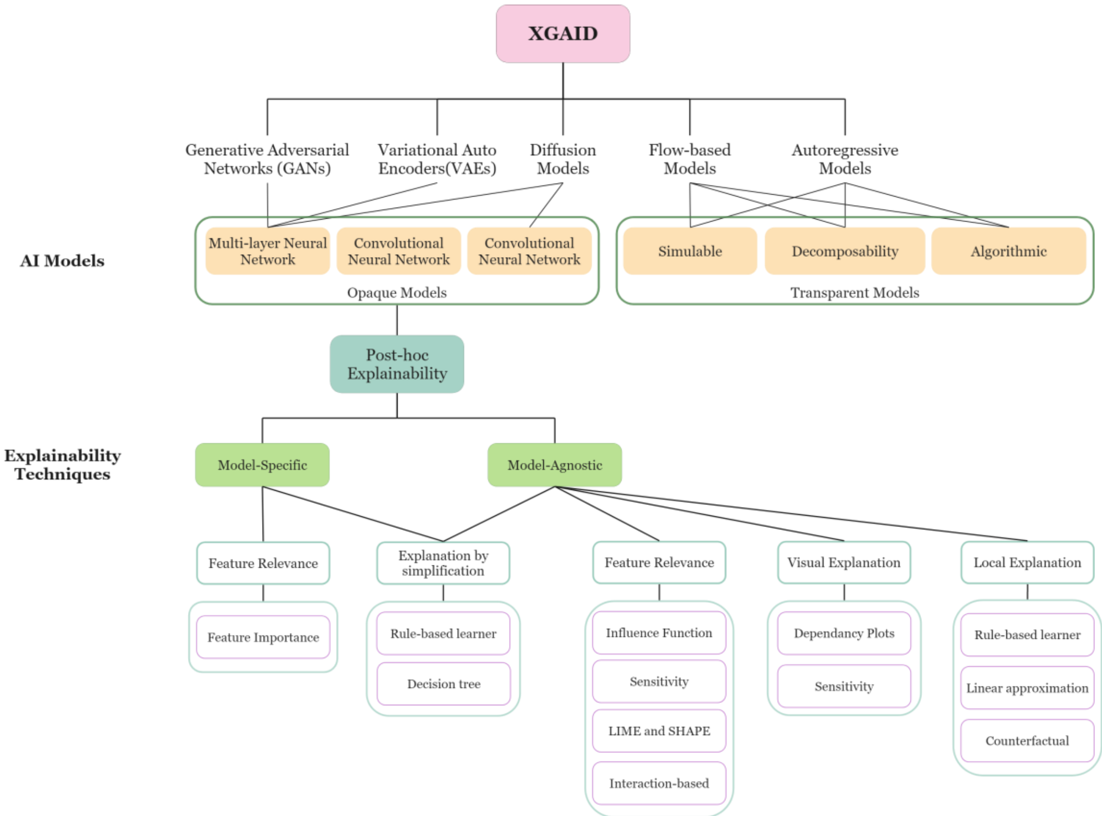

Figure 2: Proposed explainable generative AI design taxonomy (Source: Authors).

- **Interactive Explanations:** These tools allow users to explore and manipulate the AI model's inputs and observe the changes in the outputs. This hands-on approach can be particularly effective in helping users understand the generative process and the impact of their design choices.
- **Model Simplification:** Simplifying complex models into more interpretable forms can also serve as an XAI approach. For instance, a complex generative design model could be approximated by a simpler model that captures the main trends and patterns, making it easier to understand and explain.
- **Causal Inference:** Causal inference methods aim to understand the cause-and-effect relationships within the data that the AI model uses. In generative design, this could involve identifying which elements of the design are causing certain features or outcomes in the generated product. Techniques like causal diagrams or intervention analysis can help in providing these insights.
- **Process Tracing:** This approach involves tracing the decision-making process of the AI model step by step. For generative design, this could mean detailing the sequence of operations the model performs to arrive at a particular design, which can help users understand the generative process in a more granular way.
- **Natural Language Explanations:** Some XAI systems can generate textual descriptions that explain the AI's decisions in human-readable form. For generative design, the AI could provide annotations or descriptions of why it made certain design choices, which can be more intuitive for users without technical expertise.
- **Sensitivity Analysis:** This involves studying how changes in the input affect the output of the AI model. In generative design, sensitivity analysis can help determine which design parameters are most influential and how variations in these parameters can alter the final design.
- **Uncertainty Quantification:** Providing information about the uncertainty and confidence of the AI's decisions can be a form of explanation. In generative design, this could mean indicating the level of certainty the AI has about each aspect of the design it generates, which can help users make informed decisions about whether to accept, modify, or reject the AI's suggestions.
- **Rule Extraction:** Some XAI approaches aim to extract human-understandable rules from complex models. For generative design, this could involve distilling the AI's decision-making

process into a set of rules or guidelines that explain how different design outcomes are achieved.

Also, there is the option to make hybrid approaches by including more than one XAI algorithm at once. Hybrid approaches aim to leverage the strengths of both ante-hoc and post-hoc explainability. For example, a model may be trained with regularization techniques that promote sparsity, making it easier to identify which features are most influential, while still allowing for post-hoc analysis to explain individual predictions. Another hybrid strategy might involve training a complex model to achieve high performance and then using a simpler, inherently interpretable model to approximate the complex model's behavior in a way that is understandable to humans (Sun et al. 2022, Amershi et al.2014, Ross et al. 2021).

Discussion

While AI has been implemented across various industries, those systems cannot yet fully replace construction managers, engineers, and clients in building projects due to concerns around replacing human judgment with computational processes. However, this paper proposes a framework integrating explainable AI techniques into generative design workflows, which could improve process clarity for users. By increasing trust in AI through explainable methods, these systems may gain wider acceptance in construction. However, within current literature, evaluation frameworks for explainable AI remain underdeveloped, as the notion of explainability lacks consensus.

The proposed taxonomy aims to provide researchers and practitioners with a simple yet effective way of evaluating the XAI approaches available for the GD AI algorithm used in a systematic manner. The selection of the XAI algorithm from an effective manner has not yet been evaluated and remains a work in progress.

Nonetheless, basic tenets like interpretability and transparency are agreed upon. Although explainability has received limited focus in AI research on construction generative design, future work could employ existing post-hoc explanation methods to elucidate the functioning of machine and deep learning models. Qualitative approaches may also evaluate explanations as a precursor to developing quantifiable metrics. Moreover, while this paper presented a broad taxonomy for most generative AI models in design, more specific taxonomies for all model types require investigation. The relationship between individual mechanisms and their combination can be separately considered and presented. Additionally, balancing model performance and explainability poses challenges. More complex models like deep neural networks can generate higher quality outputs yet tend to be less interpretable, whereas simpler models may be more explainable but have limitations in producing novel optimized designs. Hence, hybrid approaches leveraging both complex and simple models warrant exploration.

Conclusion

This paper proposes a taxonomy for the integration of explainable AI (XAI) into generative design, with the aim of increasing user trust and paving the way for future AI applications in the construction industry. XAI enables transparency and accountability, building trust in AI-enabled construction solutions. The adoption of XAI is necessary to maintain a competitive edge and comply with evolving regulatory mandates. By merging XAI with generative algorithms, design quality, efficiency, and stakeholder satisfaction can be enhanced. However, realizing XAI's full potential requires investment in professional training and research refining XAI for construction-specific deployment. In conclusion, explainable AI has the potential to revolutionize construction design through human-centered generative practices and a unified commitment to its progression.

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