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GENERATIVE AI IN LEAN CONSTRUCTION: A SCOPING REVIEW

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ABSTRACT

Generative Artificial Intelligence (AI), specifically Large Language Models (LLMs), has the potential to reshape construction management practices. These novel solutions can transform lean construction by enabling real-time data analysis, streamlined communication, and automated decision-making across project teams. They can facilitate enhanced collaboration by generating insights from vast construction data sets, improving workflow efficiency, and reducing waste. Additionally, LLMs can support predictive modeling, proactive risk management, and knowledge sharing, aligning with lean principles of maximizing value and minimizing inefficiencies. Given the recent advancements in generative AI, it is critical to systematically shape future research directions by building on the existing body of knowledge and addressing key knowledge gaps. The first step toward identifying knowledge gaps and uncovering critical areas that remain underexplored is to systematically analyze the existing body of knowledge. Therefore, this study conducts a scoping review to synthesize the extent, range, and nature of existing studies that have proposed novel solutions using generative AI and LLMs for various aspects of construction management. The outcomes of this systematic scoping review will help identify potential research directions for future studies in this domain.

KEYWORDS

Generative AI, LLMs, Construction, Scoping Review.

INTRODUCTION

The unprecedented potential and rapid advancement of generative AI and LLMs are reshaping the landscape of many industries, including the construction sector. These technologies may introduce new possibilities for enhancing efficiency, precision, and adaptability across various phases of a construction project. Their ability to process and interpret vast volumes of multimodal data enables innovative approaches to problem-solving and decision-making. By fostering more streamlined workflows and deeper insights, generative AI and LLM unlock opportunities for better project outcomes. They also promote new ways of approaching challenges, driving innovation and continuous improvement within the construction sector. In the context of Lean Construction, generative AI and LLMs provide opportunities to enhance efficiency and value creation by aligning with core Lean principles. These technologies can optimize processes to reduce variability and improve flow by enabling more effective resource utilization and waste reduction. They facilitate better communication and collaboration among stakeholders to ensure alignment with project objectives. Generative AI and LLMs support pull planning by providing deeper insights and predictive capabilities that refine workflows and

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improve decision-making. Their ability to analyze complex systems and offer tailored solutions fosters continuous improvement and drives Lean principles in construction projects.

Despite the growing number of studies in this domain, research on developing novel solutions for Lean Construction methods remains in its early stages. While these technologies show immense promise, their application in Lean Construction is not yet fully explored or understood. It is essential to systematically identify potential research directions to guide future studies and address existing knowledge gaps. A structured approach to exploring these technologies will help uncover opportunities for innovation, ensure alignment with Lean principles, and maximize their transformative potential within the construction industry. The first step in identifying knowledge gaps and systematically determining potential research directions for future studies is to analyze and synthesize the scope of existing research through a systematic literature review.

OBJECTIVE

The primary objective of this study is to conduct a systematic scoping literature review to analyze and synthesize the extent, range, and nature of the existing body of knowledge on the applications of generative AI and LLMs in various aspects of construction management, with a focus on their potential contributions to Lean Construction. Based on the outcomes of the literature review, knowledge gaps in the current research landscape are identified to provide a clearer understanding of areas that require further investigation. These findings are then used to systematically determine potential directions for future research to ensure that subsequent studies address critical challenges and opportunities for advancing the integration of generative AI and LLMs within the framework of Lean Construction.

METHOD

A scoping review is a relatively new method for synthesizing evidence through a comprehensive and structured examination of the literature. Unlike systematic literature reviews, which focus on answering specific, well-defined research questions, scoping reviews aim to explore the breadth of available literature and address broader inquiries. This approach is particularly suitable for assessing the extent, range, and nature of research activities in emerging fields and identifying gaps in existing knowledge. Given that generative AI and LLMs in the construction industry represent a rapidly evolving area of study, a scoping review offers an effective systematic framework for summarizing current knowledge. Its outcomes can serve as a foundation for identifying key directions for future research.

SEARCH AND SYNTHESIS PROCESS

The search and synthesis process follows the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) principles and includes six main steps presented in Figure 1 (Tricco et al., 2018).

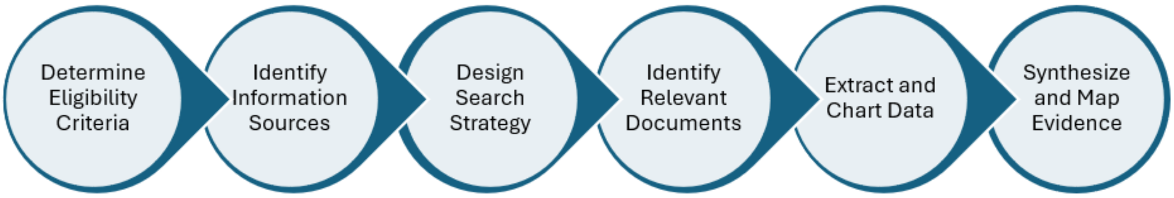

Figure 1: Search and synthesis process

Determining Eligibility Criteria

Any technical publication, including peer-reviewed journal articles, conference proceedings, and book chapters that investigated potential applications of AI and LLMs in any aspect of construction engineering and management is included in the review if it is written in English. Given the recent nature of the topic, we did not apply any date restrictions.

Identifying Information Sources

We conducted a search for relevant studies in two major bibliographic databases: Scopus and Web of Science. These databases cover a broad range of publications, including leading journals and conferences pertinent to the construction sector.

Designing Search Strategy

Our search strategy relies on a search query which examines the existence of different combinations of phrases linked to generative AI, LLMs, and the construction industry in the title, abstract, or keywords of a document. The query is *TITLE-ABS-KEY (("Large Language Model" OR "LLM" OR "Generative AI") AND ("aec" OR "construction" OR "civil eng*" OR "Building Information Modeling" OR "BIM" OR "Built Environment"))*

Identifying Relevant Documents

The search yielded 611 studies from Scopus and 201 studies from the Web of Science, with 154 duplicates identified between the two databases. After removing the duplicates, the total number of potentially relevant studies was reduced to 658. A review of the abstracts revealed that 73 studies were relevant to the topic of this study. Many of the excluded studies used the term "construction" in contexts unrelated to the construction industry. For instance, they referred to concepts like "algorithm construction" in their abstracts or titles. Furthermore, using a snowballing process to review the abstracts of the references cited in the identified relevant studies, we found eight additional relevant studies. This increased the total number of shortlisted documents to 79.

Extracting and Charting Data

In this step, we reviewed the full text of the identified and shortlisted documents to extract data that described their scope. During this process, we collected two sets of data from each publication. The first set includes basic attributes such as the publication year, publication type, and publishing organizations. The second set of data concentrated on the contents of the articles to describe their technical contributions to the body of knowledge. The oldest study was published in 2021, and, as shown in Figure 2, there has been a significant surge in the number of publications since 2022. In terms of the publication type, 51 studies are peer-reviewed journal articles, followed by 27 conference papers, and one book chapter. Reviewing the full text of the identified documents revealed that the level of contribution in 19 articles is limited to general discussions. These papers did not center primarily on generative AI or LLMs in construction but instead provided broad and general insights into the potential applications of these emerging technologies in construction projects. While these articles help raise awareness about possible future solutions based on generative AI, they do not directly advance the scientific or technical body of knowledge. As a result, our analysis in the final step of the scoping review, which involves synthesizing and mapping the extracted data, focuses on the remaining 60 studies. These studies make direct contributions to the body of knowledge in this domain through the solutions they propose.

Synthesizing and Mapping the Evidence

In this step, we synthesize and analyze the scope of the 60 studies that proposed solutions using generative AI and LLMs based on the following dimensions: 1) the application of the proposed solution in the construction industry, 2) the architecture of the proposed generative AI and LLM solution, 3) the fine-tuning techniques employed, 4) the prompt engineering techniques used, and 5) the potential challenges in implementing the proposed solutions. The outcomes of this step form the primary results of the scoping review.

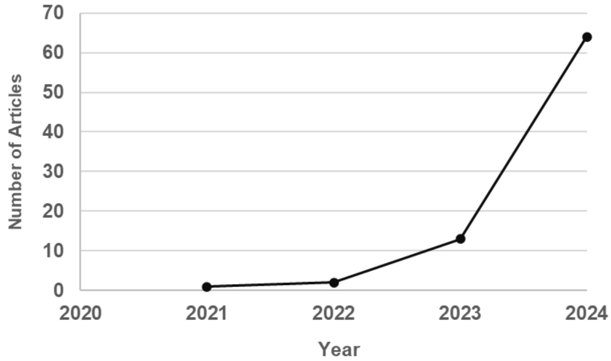

Figure 2: Number of publications in each year

RESULTS

In terms of the applications of the proposed solutions in the construction industry, the proposed solutions can be categorized into 14 areas of applications, including design, safety management, asset management, scheduling, and risk management. Table 1 shows the papers in each category.

Regarding the architecture of the proposed generative AI solution, reviewing the manuscripts indicated that 53 studies used LLMs. LLMs can be categorized into six groups based on their architecture (Shao et al., 2024). The first group covers autoregressive models, such as Generative Pre-trained Transformers (GPT), that predict the next element in a sequence (e.g., a word in a sentence) based on the chain of previous elements. The second group includes autoencoding models, such as Bidirectional Encoder Representations from Transformers (BERT), that concentrate on comprehending input by reconstructing masked or corrupted segments of text. The third group consists of sequence-to-sequence models, such as GLMs, that convert input sequences into latent representations and decode them into output sequences. The fourth group encompasses multimodal models, such as Gemini, that integrate text with other modalities (e.g., image). The fifth category contains retrieval-augmented models, like RETRO, that improve language models by incorporating external retrieval mechanisms. Finally, the sixth category includes hybrid models that combine characteristics from various model types for a specific application. Table 2 shows the studies in each category, indicating that most of the studies (i.e., 37 out of 53) use autoregressive models. This is mainly due to widespread applications of GPT models. The other studies that did not use LLMs, employed Generative Adversarial Networks (GANs) (Jiang et al., 2024; Liu et al., 2024) and Stable Diffusion models (Davari et al., 2024; Jo et al., 2024; Lee et al., 2024; Saovana & Khosakitchalert, 2024; He et al., 2025).

Fine-tuning plays a crucial role in adapting LLMs for specialized applications. LLMs first undergo general training on a large dataset to develop broad knowledge. Fine-tuning then customizes the pre-trained model for specific tasks or domain needs. This process trains the model on a smaller dataset that matches the target application while retaining general knowledge from initial training. Adjusting the model's parameters enhances performance on specialized tasks to improve accuracy and relevance. Many fields use fine-tuning for domain expertise, including construction management, to ensure more precise and context-aware outputs. In total, 12 studies explicitly conducted fine-tuning. Eight studies employed supervised learning. This approach trains the model on a labeled dataset where each input is paired with the corresponding expected output. This process refines the pre-trained model's parameters to improve its performance on specific tasks. For example, fine-tuning for text summarization involves providing the model with example texts (inputs) and their summaries (outputs). The model learns to map inputs to desired outputs, aligning its behavior with task-specific objectives.

This method enables the model to leverage its general pre-trained knowledge while becoming highly specialized for targeted applications.

Table 1: Applications of Generative AI and LLMs in Construction Management

LLMs Application	Articles	No.
Design and Architecture	Zheng and Fischer (2023), Jang et al. (2024b), Forth and Borrmann (2024), He et al. (2025), Wang et al. (2024b), Jang and Lee (2022), Saka et al. (2024), Jo et al. (2024), Lee et al. (2024a), Davari et al. (2024), Saovana and Khosakitchalert (2024), Zhang et al. (2024b), Vaidhyanathan et al. (2023), Hartanto et al. (2024), Furtado et al. (2024)	15
Safety Management	Uddin et al. (2023), Yoo et al. (2024), Smetana et al. (2024), Dou (2024), Mohamed Hassan et al. (2022), Ray et al. (2024)	6
Urban Planning and Infrastructure Management	Chen et al. (2024b), Hao et al. (2024), Liu et al. (2024), Jang and Kim (2024), Jang et al. (2024a), Andres et al. (2023)	6
Scheduling and Planning	Prieto et al. (2023), Nunez-Morales et al. (2024), Al-Sinan et al. (2024), Amer et al. (2021), Jiang et al. (2024)	5
Education and Training	Uddin et al. (2023), Castelblanco et al. (2024), Ballen et al. (2024), Abril et al. (2024)	4
Regulatory Compliance	Chen et al. (2024a), Jang et al. (2024b), Li et al. (2024)	3
Maintenance and Inspection	Zhang et al. (2024a), Pu et al. (2024b), Pu et al. (2024a), Mateev (2023)	4
Knowledge Management and Documentation	Lee et al. (2024b), Yi et al. (2024), Zhong and Goodfellow (2024), He et al. (2024)	4
Contract Risk Identification	Zheng et al. (2024), Wong et al. (2024), Florence et al. (2024), Moon et al. (2022)	4
Robotic Control	You et al. (2023), Luo et al. (2024), Wang et al. (2024c)	3
Stakeholder Communication and Collaboration	Dortheimer et al. (2024), Lee et al. (2024a), Han et al. (2024)	3
Sustainability	Maceika et al. (2024), Turhan (2023), Płoszaj-Mazurek and Ryńska (2024)	3
Literature Review Automation	Ito et al. (2024), Jeong et al. (2024)	2
Privacy and Security Management	Wang et al. (2024a)	1

Two studies used Low-Rank Adaptation (LoRA) for fine-tuning. This method aims to make fine-tuning more efficient and cost-effective by significantly reducing the number of trainable parameters. Instead of updating all the parameters of the pre-trained model, LoRA introduces small, trainable matrices (rank decomposition matrices) into the model's architecture. These matrices are added to the layers of the model, and during fine-tuning, only these newly introduced parameters are trained, leaving the original model weights untouched. LoRA enables fine-tuning with fewer computational resources and smaller datasets while maintaining or even improving performance on specific tasks. This makes it a practical approach for adapting large-scale models to specialized domains or applications.

Two studies employed the Quantized Low-Rank Adaptation (QLoRA) method for fine-tuning. This method is an advanced process designed to make adapting LLMs even more resource-efficient. It combines quantization with LoRA to reduce memory usage and computational requirements without sacrificing performance. In this method, the pre-trained LLM is quantized, often using techniques like 4-bit quantization, which compresses the model’s parameters to a lower precision. This significantly reduces the memory footprint while preserving most of the model's accuracy. Table 3 describes the language model, application, and fine-tuning methods of the 12 studies that employed fine-tuning.

Prompt engineering serves as a key element in optimizing LLMs for specific tasks. This process focuses on designing input prompts that guide the model to produce accurate and relevant outputs. It shapes instructions, examples, or context to enhance performance without modifying the model’s architecture or applying fine-tuning. Prompt engineering can include strategies such as using few-shot learning, where a few task examples are embedded in the prompt, or zero-shot learning, where the task is described explicitly without examples. The quality of the prompt plays a critical role in achieving desired results, making it a powerful tool for maximizing the capabilities of LLMs across a wide range of applications.

Table 2: LLM Architectures

LLMs Architecture	Articles	No.
Autoregressive	Zheng and Fischer (2023), Uddin et al. (2023), You et al. (2023), Płoszaj-Mazurek and Ryńska (2024), Jang et al. (2024b), Pu et al. (2024a), Chen et al. (2024b), Dortheimer et al. (2024), Jeong et al. (2024), Maceika et al. (2024), Saka et al. (2024), Yoo et al. (2024), Smetana et al. (2024), Lee et al. (2024b), Luo et al. (2024), Castelblanco et al. (2024), Wang et al. (2024c), Prieto et al. (2023), Turhan (2023), Mateev (2023), Vaidhyanathan et al. (2023), Zheng et al. (2024), Pu et al. (2024b), Ballen et al. (2024), Abril et al. (2024), Wong et al. (2024), Florence et al. (2024), Al-Sinan et al. (2024), Ray et al. (2024), Han et al. (2024), Wang et al. (2024a), Ito et al. (2024), , Andres et al. (2023), Hartanto et al. (2024), Amer et al. (2021), Jang and Lee (2022)	37
Autoencoding	Chen et al. (2024a), Li et al. (2024), Forth and Borrmann (2024), Zhong and Goodfellow (2024), Nunez-Morales et al. (2024), Moon et al. (2022), Mohamed Hassan et al. (2022)	7
Multimodal	Zhang et al. (2024a), Jang and Kim (2024), Jang et al. (2024a), Zhang et al. (2024b)	4
Sequence to Sequence	Wang et al. (2024b), Hao et al. (2024)	2
Retrieval-Augmented	Yi et al. (2024)	1
Hybrid	He et al. (2024), Dou (2024)	2

Table 3: Fine-tuning Method

Articles	Language model	Fine-tuning method
Zhang et al. (2024)	GLM-4	LoRA
Li, et al., (2024)	MiniGPT4-7B	QLoRA
Jo et al. (2024)	GPT	LoRA
Lee et al. (2024)	GPT-3 and LLaMa	QLoRA
Yoo et al., (2024)	GPT-2.0 & GPT3.0	Supervised Learning
Forth and Borrmann, (2024)	BERT	Supervised Learning
Florence et al. (2024)	GPT-3	Supervised Learning
He et al. (2024)	BERT	Supervised Learning
Moon et al. (2022)	BERT	Supervised Learning
Amer et al. (2021)	GPT-2	Supervised Learning
Mohamed Hassan et al. (2022)	BERT	Supervised Learning
Zhong and Goodfellow, (2024)	BERT	Supervised Learning

Forty-five studies explicitly described their approach to prompt engineering. Eleven studies utilized template-based prompting. Nine studies adopted few-shot learning, which includes a few examples of input-output pairs within the prompt. Six studies employed zero-shot learning, where no examples are provided in the prompt. Four studies used role-based prompting, framing the model as playing a specific role to guide responses. Another four studies applied chain-of-thought prompting, involving step-by-step reasoning within the prompt to encourage logical responses. The remaining studies employed other methods, such as contextual prompting, which adds relevant background information to the prompt to enhance understanding; trigger words prompting, which uses specific keywords or phrases to activate the model's knowledge in a particular domain; and iterative prompting, involving repeated testing and refinement of the prompt to improve performance. Table 4 lists the studies which discussed their methods for prompt engineering.

Table 4: Fine-tuning Method

Prompt Engineering Technique	Articles	No.
Template-Based Prompting	You et al. (2023), Smetana et al. (2024), Li et al. (2024), Jang et al. (2024a), Wang et al. (2024c), Prieto et al. (2023), Vaidhyanathan et al. (2023), Zheng et al. (2024), Yi et al. (2024), He et al. (2024), Jang et al. (2024b)	11
Few-Shot Learning	Zheng and Fischer (2023), Chen et al. (2024a), Zhang et al. (2024a), Maceika et al. (2024), Lee et al. (2024a), Wong et al. (2024), He et al. (2024), Hao et al. (2024), Saka et al. (2024)	9
Zero-Shot Learning	Zheng and Fischer (2023), Chen et al. (2024a), Zhang et al. (2024a), Wong et al. (2024), Hao et al. (2024), Saka et al. (2024)	6
Role-based Prompting	You et al. (2023), Li et al. (2024), Vaidhyanathan et al. (2023), He et al. (2024)	4
Chain of Thought	You et al. (2023), Chen et al. (2024b), Luo et al. (2024), Dou (2024)	4
Contextual Prompting	Chen et al. (2024b), Li et al. (2024), Prieto et al. (2023)	3
Trigger Words Prompting	Jo et al. (2024), Lee et al. (2024a)	2
Iterative Prompting	Hao et al. (2024), Turhan (2023)	2

Despite rapid and significant advancements in developing novel solutions for construction project management using generative AI and LLMs, implementing such solutions remains challenging. A considerable number of studies that we reviewed in this scoping study discussed potential technical and practical challenges that need to be addressed when implementing an LLM. Table 5 lists the identified challenges and the studies that discussed them. Hallucination and lack of data are the most discussed issues.

Table 5: Challenges of Implementing LLMs

Challenges and Limitations	Articles	No.
Hallucination	Zheng and Fischer (2023), Uddin et al. (2023), Pu et al. (2024a), Dortheimer et al., (2024), Lee et al. (2024b), Jang and Kim (2024), Zheng et al. (2024), Yi et al. (2024), Dou (2024), Ray et al. (2024)	10
Data Limitations	Zheng and Fischer (2023), Płoszaj-Mazurek and Ryńska (2024), Pu et al. (2024a), Lee et al. (2024a), Yoo et al. (2024), Jang and Kim (2024), Yi et al. (2024), Hao et al. (2024), Moon et al. (2022)	9
Interpretability and Reliability	Pu et al. (2024a), Jang et al. (2024a), Saovana and Khosakitchalert (2024), Yi et al. (2024), Ballen et al. (2024), Hartanto et al. (2024)	6
Prompt Sensitivity	Zheng and Fischer (2023), You et al. (2023), Luo et al. (2024), Yi et al. (2024), Pu et al. (2024b)	5
Data Privacy and Bias	Lee et al. (2024b), Furtado et al. (2024), Castelblanco et al. (2024), He et al. (2024), Luo et al. (2024)	5
High Computational Costs	Zhang et al. (2024a), Hartanto et al. (2024), Lee et al. (2024b), Pu et al. (2024b), Luo et al. (2024)	5
Lack of Real-Time Knowledge	Maceika et al. (2024), Lee et al. (2024b), Yi et al. (2024), Saovana and Khosakitchalert (2024)	4
Inconsistency in Outputs	Uddin et al. (2023), Zhang et al. (2024a), Castelblanco et al. (2024)	3
Inability to Reflect Subjective and Semantic Perspectives	Maceika et al. (2024), Hao et al. (2024), Mohamed Hassan et al. (2022)	3
Lack of Physical Reasoning	You et al. (2023), Płoszaj-Mazurek and Ryńska (2024)	2
Limited Reasoning	Chen et al. (2024a), He et al. (2024)	2
Output Misalignment	Jang et al. (2024b), Luo et al. (2024)	2
Harmful Instructions	Uddin et al. (2023)	1
Limited Adaptability	You et al. (2023)	1
Legal Accessibility Constraints	Zhang et al. (2024a)	1
Inability to Generate 3D Models	Lee et al. (2024a)	1
Dependency on Text-Based Data	Yoo et al. (2024)	1

Hallucinations pose a significant challenge, especially in applications requiring high reliability, such as safety management, legal analysis, and technical documentation. This issue refers to the phenomenon where the model generates inaccurate or fabricated information that may appear plausible but is not based on reality or factual data. This can occur even when the model is prompted with well-defined inputs. The underlying causes include biases in the training data, limitations in the model's ability to verify facts, and the nature of LLMs generating responses based on patterns rather than verifying accuracy. Addressing hallucination issues requires ongoing research and strategies like model fine-tuning, fact-checking systems, and post-processing methods.

LLMs require large, high-quality, and domain-specific datasets to learn effectively and generate accurate outputs. However, data limitations present a significant challenge when applying LLMs to construction projects. The absence of structured and standardized data, along with the scarcity of labeled datasets for specialized tasks, limits their ability to perform optimally. Furthermore, privacy concerns and data availability from different construction projects may restrict the model's capacity to generalize across various scenarios. Overcoming these data limitations requires efforts in data collection, annotation, and integration from diverse sources within the construction industry.

DISCUSSIONS AND CONCLUSIONS

Although the reviewed studies highlight the increasing influence of generative AI and LLMs in the construction industry and lean construction, certain key areas remain insufficiently explored. Overall, future studies should focus on three main research directions. First, research should focus on expanding the applications of these technologies in lean construction by enhancing their decision-making capabilities. One example is the development of intelligent design systems. Current generative AI research primarily automates basic tasks like object search but lacks advanced decision-making. Future AI models can support lean construction by optimizing designs based on aesthetics, functionality, sustainability, and cost while also proposing innovative alternatives. Real-time safety monitoring and hazard detection with LLM-enhanced AI is another promising topic in this line of research. Despite some preliminary work listed in Table 1, future studies may focus on using generative AI to analyze past accidents, predict risks, and suggest preventive measures on a real-time basis in dynamic site settings. Second, future research should focus on enhancing existing AI solutions by integrating them with emerging technologies. Examples include LLM-based natural language interfaces for human-robot collaboration and generative AI systems combined with Augmented Reality (AR) and Virtual Reality (VR) to create dynamic, immersive design environments. Finally, future research must address the existing and emerging limitations of generative AI models, including privacy and data security, data scarcity, computational costs, hallucinations, bias, reliability, transparency, and accountability. For example, future studies could focus on designing and implementing novel methods for fact-checking mechanisms that ground AI models with real-time data sources to reduce hallucinations. Research could also explore explainability frameworks that improve transparency by clarifying how AI-generated recommendations and decisions are made. Developing enhanced model training and fine-tuning techniques with more diverse data and designing fairness-aware models that identify and neutralize biased patterns should be a target to address concerns related to ethical considerations. Additionally, multilayer decision-making procedures, such as human-in-the-loop approaches, could improve the reliability of models by evaluating outcomes from different perspectives before execution.

REFERENCES

Abril, D. E., Guerra, M. A., & Ballen, S. D. (2024). ChatGPT to Support Critical Thinking in Construction-Management Students. *Proceedings of the 2024 ASEE Annual Conference & Exposition*, Portland, Oregon.

Al-Sinan, M. A., Bubshait, A. A., & Aljaroudi, Z. (2024). Generation of Construction Scheduling through Machine Learning and BIM: A Blueprint. *Buildings*, *14*(4), 934. https://doi.org/10.3390/buildings14040934

Amer, F., Jung, Y., & Golparvar-Fard, M. (2021). Transformer machine learning language model for auto-alignment of long-term and short-term plans in construction. *Automation in Construction*, *132*, 103929. https://doi.org/10.1016/j.autcon.2021.103929

Andres, J., Ocampo, R., Bown, O., Hill, C., Pegram, C., Schmidt, A., Shave, J., & Wright, B. (2023). The Human-Built Environment-Natural Environment Relation - An Immersive Multisensory Exploration with System of a Sound, *28th International Conference on Intelligent User Interfaces*, 8-11. https://doi.org/10.1145/3581754.3584119

Ballen, S. D., Abril, D. E., & Guerra, M. A. (2024). Board 40: Work in Progress: Generative AI to Support Critical Thinking in Water Resources Students. *Proceedings of the 2024 ASEE Annual Conference & Exposition*, Portland, Oregon.

Castelblanco, G., Cruz-Castro, L., & Yang, Z. (2024). Performance of a Large-Language Model in scoring construction management capstone design projects. *Computer Applications in Engineering Education*, *32*(6), e22796. https://doi.org/10.1002/cae.22796

Chen, N., Lin, X., Jiang, H., & An, Y. (2024a). Automated Building Information Modeling Compliance Check through a Large Language Model Combined with Deep Learning and Ontology. *Buildings*, *14*(7), 1983. https://doi.org/10.3390/buildings14071983

Chen, Y., Zhang, S., Han, T., Du, Y., Zhang, W., & Li, J. (2024b). Chat3D: Interactive understanding 3D scene-level point clouds by chatting with foundation model for urban ecological construction. *ISPRS Journal of Photogrammetry and Remote Sensing*, *212*, 181-192. https://doi.org/10.1016/j.isprsjprs.2024.04.024

Davari, S., Tohidifar, A., & Kim, D. (2024). A Step from Virtual to Reality: Investigating the Potential of a Diffusion-Based Pipeline for Enhancing the Realism in Fully-Annotated Synthetic Construction Imagery. *Proceedings of the International Symposium on Automation and Robotics in Construction*, *41*, 683-690.

Dortheimer, J., Martelaro, N., Sprecher, A., & Schubert, G. (2024). Evaluating large-language-model chatbots to engage communities in large-scale design projects. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, *38*, e4, 1-16. https://doi.org/10.1017/S0890060424000027

Dou, W. (2024). The Application of Generative AI Technology in ESP Courses for Civil Engineering Majors. *2024 International Conference on Artificial Intelligence and Digital Technology*, 144-147. https://doi.org/10.1109/ICAIDT62617.2024.00039

Florence, G., Kikuchi, M., & Ozono, T. (2024). Delay Risk Detection in Road Construction Projects Utilizing Large Language Model. *International Conference on Intelligent Systems Design and Applications*, 106-115. https://doi.org/10.1007/978-3-031-64836-6_11

Forth, K., & Borrmann, A. (2024). Semantic enrichment for BIM-based building energy performance simulations using semantic textual similarity and fine-tuning multilingual LLM. *Journal of Building Engineering,* *95*, 110312. https://doi.org/10.1016/j.jobe.2024.110312

Furtado, L. S., Soares, J. B., & Furtado, V. (2024). A task-oriented framework for generative AI in design. *Journal of Creativity*, *34*(2), 100086. https://doi.org/10.1016/j.yjoc.2024.100086

Han, D., Zhao, W., Yin, H., Qu, M., Zhu, J., Ma, F., Ying, Y., & Pan, A. (2024). Large language models driven BIM-based DfMA method for free-form prefabricated buildings: framework and a usefulness case study. *Journal of Asian Architecture and Building Engineering*, 1-18. https://doi.org/10.1080/13467581.2024.2329351

Hao, Y., Qi, J., Ma, X., Wu, S., Liu, R., & Zhang, X. (2024). An LLM-Based Inventory Construction Framework of Urban Ground Collapse Events with Spatiotemporal Locations.

Proceedings of International Journal of Geo-Information, *13*(4), 133. https://doi.org/10.3390/ijgi13040133

Hartanto, E., Chen, A., & Koh, I. (2024). Empirical Insights into Architectural Aesthetics: A Neuroscientific Perspective. *Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia*, *3*, 69-78.

He, C., Yu, B., Liu, M., Guo, L., Tian, L., & Huang, J. (2024). Utilizing Large Language Models to Illustrate Constraints for Construction Planning. *Buildings*, *14*(8), 2511. https://doi.org/10.3390/buildings14082511

He, Z., Wang, Y.-H., & Zhang, J. (2025). Generative AIBIM: An automatic and intelligent structural design pipeline integrating BIM and generative AI. *Information Fusion*, *114*. 102654. https://doi.org/10.1016/j.inffus.2024.102654

Ito, K., Kang, Y., Zhang, Y., Zhang, F., & Biljecki, F. (2024). Understanding urban perception with visual data: A systematic review. *Cities*, *152*, 105169. https://doi.org/10.1016/j.cities.2024.105169

Jang, K. M., Chen, J., Kang, Y., Kim, J., Lee, J., Duarte, F., & Ratti, C. (2024a). Place identity: a generative AI's perspective. *Humanities and Social Sciences Communications*, *11*(1), 1-16. https://doi.org/10.1057/s41599-024-03645-7

Jang, K. M., & Kim, J. (2024). Multimodal Large Language Models as Built Environment Auditing Tools. *The Professional Geographer*, 1-7. https://doi.org/10.1080/00330124.2024.2404894

Jang, S., & Lee, G. (2022). Interactive Design by Integrating a Large Pre-Trained Language Model and Building Information Modeling. *Computing in Civil Engineering 2023*, 291-299. https://doi.org/10.1061/9780784485231.035

Jang, S., Lee, G., Oh, J., Lee, J., & Koo, B. (2024b). Automated detailing of exterior walls using NADIA: Natural-language-based architectural detailing through interaction with AI. *Advanced Engineering Informatics*, *61*, 102532. https://doi.org/10.1016/j.aei.2024.102532

Jeong, J., Gil, D., Kim, D., & Jeong, J. (2024). Current Research and Future Directions for Off-Site Construction through LangChain with a Large Language Model. *Buildings*, *14*(8), 2374. https://doi.org/10.3390/buildings14082374

Jiang, F., Ma, J., Webster, C. J., Wang, W., & Cheng, J. C. P. (2024). Automated site planning using CAIN-GAN model. *Automation in Construction*, *159*, 105286. https://doi.org/10.1016/j.autcon.2024.105286

Jo, H., Lee, J.-K., Lee, Y.-C., & Choo, S. (2024). Generative artificial intelligence and building design: early photorealistic render visualization of façades using local identity-trained models. *Journal of Computational Design and Engineering*, *11*(2), 85-105. https://doi.org/10.1093/jcde/qwae017

Lee, J.-K., Yoo, Y., & Cha, S. H. (2024a). Generative early architectural visualizations: incorporating architect's style-trained models. *Journal of Computational Design and Engineering*, *11*(5), 40-59. https://doi.org/10.1093/jcde/qwae065

Lee, J., Jung, W., & Baek, S. (2024b). In-House Knowledge Management Using a Large Language Model: Focusing on Technical Specification Documents Review. *Applied Sciences*, *14*(5), 2096. https://doi.org/10.3390/app14052096

Li, H., Yang, R., Xu, S., Xiao, Y., & Zhao, H. (2024). Intelligent Checking Method for Construction Schemes via Fusion of Knowledge Graph and Large Language Models. *Buildings*, *14*(8), 2502. https://doi.org/10.3390/buildings14082502

Liu, Z., Li, T., Ren, T., Chen, D., Li, W., & Qiu, W. (2024). Day-to-Night Street View Image Generation for 24-Hour Urban Scene Auditing Using Generative AI. *Imaging*, *10*(5), 112. https://doi.org/10.3390/jimaging10050112

Luo, H., Wu, J., Liu, J., & Antwi-Afari, M. F. (2024). Large language model-based code generation for the control of construction assembly robots: A hierarchical generation approach. *Developments in the Built Environment*, *19*, 100488. https://doi.org/10.1016/j.dibe.2024.100488

Maceika, A., Bugajev, A., & Šostak, O. R. (2024). Evaluating Modular House Construction Projects: A Delphi Method Enhanced by Conversational AI. *Buildings*, *14*(6), 1696. https://doi.org/10.3390/buildings14061696

Mateev, M. (2023). Predictive Analytics Based on Digital Twins, Generative AI, and ChatGPT *Proceedings of the 27th World Multi-Conference on Systemics, Cybernetics and Informatics*: *WMSCI 2023*, 168-174. https://doi.org/10.54808/WMSCI2023.01.168

Mohamed Hassan, H. A., Marengo, E., & Nutt, W. (2022). A BERT-Based Model for Question Answering on Construction Incident Reports. *Natural Language Processing and Information Systems*, 215-223. https://doi.org/10.1007/978-3-031-08473-7_20

Moon, S., Chi, S., & Im, S.-B. (2022). Automated detection of contractual risk clauses from construction specifications using bidirectional encoder representations from transformers (BERT). *Automation in Construction*, *142*, 104465. https://doi.org/10.1016/j.autcon.2022.104465

Nunez-Morales, J. D., Jung, Y., & Golparvar-Fard, M. (2024). Evaluation of Mapping Computer Vision Segmentation from Reality Capture to Schedule Activities for Construction Monitoring in the Absence of Detailed BIM. *Proceedings of the 41st International Symposium on Automation and Robotics in Construction*, *41*, 847-854.

Płoszaj-Mazurek, M., & Ryńska, E. (2024). Artificial Intelligence and Digital Tools for Assisting Low-Carbon Architectural Design: Merging the Use of Machine Learning, Large Language Models, and Building Information Modeling for Life Cycle Assessment Tool Development. *Energies*, *17*(12), 2997. https://doi.org/10.3390/en17122997

Prieto, S. A., Mengiste, E. T., & García de Soto, B. (2023). Investigating the Use of ChatGPT for the Scheduling of Construction Projects. *Buildings*, 13(4), 857. https://doi.org/10.3390/buildings13040857

Pu, H., Yang, X., Li, J., & Guo, R. (2024a). AutoRepo: A general framework for multimodal LLM-based automated construction reporting. *Expert Systems with Applications*, *255*, 124601. https://doi.org/10.1016/j.eswa.2024.124601

Pu, H., Yang, X., Shi, Z., & Jin, N. (2024b). Automated Inspection Report Generation Using Multimodal Large Language Models and Set-of-Mark Prompting. *Proceedings of the International Symposium on Automation and Robotics in Construction*, *41*, 1003-1009.

Ray, U., Arteaga, C., & Park, J. (2024). Comparative Analysis of Cognitive Agreement between Human Analysts and Generative AI in Construction Safety Risk Assessment. *Proceedings of the International Symposium on Automation and Robotics in Construction*, *41*, 452-458.

Saka, A., Taiwo, R., Saka, N., Salami, B. A., Ajayi, S., Akande, K., & Kazemi, H. (2024). GPT models in construction industry: Opportunities, limitations, and a use case validation. *Developments in the Built Environment*, *17*, 100300. https://doi.org/10.1016/j.dibe.2023.100300

Saovana, N., & Khosakitchalert, C. (2024). Assessing the Viability of Generative AI-Created Construction Scaffolding for Deep Learning-Based Image Segmentation. *International Conference on Robotics, Engineering, Science, and Technology*, 38-43. https://doi.org/10.1109/RESTCON60981.2024.10463583

Smetana, M., Salles de Salles, L., Sukharev, I., & Khazanovich, L. (2024). Highway Construction Safety Analysis Using Large Language Models. *Applied Sciences*, *14*(4), 1352. https://doi.org/10.3390/app14041352

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., ... & Straus, S. E. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. *Internal Medicine*, *169*(7), 467-473. https://doi.org/10.7326/M18-0850

Turhan, G. D. (2023). Life Cycle Assessment for the Unconventional Construction Materials in Collaboration with a Large Language Model. *International Conference on Education and Research in Computer Aided Architectural Design in Europe*, 39-48.

Uddin, S. M. J., Albert, A., Ovid, A., & Alsharef, A. (2023). Leveraging ChatGPT to Aid Construction Hazard Recognition and Support Safety Education and Training. *Sustainability*, *15*(9), 7121. https://doi.org/10.3390/su15097121

Vaidhyanathan, V., Radhakrishnan, A., del, J. L. G., & López, C. y. (2023). Spacify: A Generative Framework for Spatial Comprehension, Articulation and Visualization Using Large Language Models (LLMs) and EXtended Reality (XR). *Association for Computer-aided Design in Architecture (ACADIA)*, *2*, 430-443.

Wang, B., Garcia, L. A., & Srivastava, M. (2024a). PrivacyOracle: Configuring Sensor Privacy Firewalls with Large Language Models in Smart Built Environments. *2024 IEEE Security and Privacy Workshops (SPW)*, 239-245. https://doi.org/10.1109/SPW63631.2024.00028

Wang, J., Yang, Q., & Chen, Y. (2024b). A Large Language Model–based Approach for automatically Optimizing BIM. *2024 43rd Chinese Control Conference (CCC)*, 8518-8523.

Wang, M., Li, Y., & Li, S. (2024c). Robotic Assembly of Interlocking Blocks for Construction Based on Large Language Models. *Construction Research Congress 2024*, 777-786. https://doi.org/10.1061/9780784485262.079

Wong, S., Zheng, C., Su, X., & Tang, Y. (2024). Construction contract risk identification based on knowledge-augmented language models. *Computers in Industry*, *157*, 104082. https://doi.org/10.1016/j.compind.2024.104082

Yi, M., Ceglinski, K., Ashok, P., Behounek, M., White, S., Peroyea, T., & Thetford, T. (2024). Applications of Large Language Models in Well Construction Planning and Real-Time Operation. *International Drilling Conference and Exhibition*, SPE-217700-MS. https://doi.org/10.2118/217700-MS

Yoo, B., Kim, J., Park, S., Ahn, C. R., & Oh, T. (2024). Harnessing Generative Pre-Trained Transformers for Construction Accident Prediction with Saliency Visualization. *Applied Sciences*, *14*(2), 664. https://doi.org/10.3390/app14020664

You, H., Ye, Y., Zhou, T., Zhu, Q., & Du, J. (2023). Robot-Enabled Construction Assembly with Automated Sequence Planning Based on ChatGPT: RoboGPT. *Buildings*, *13*(7), 1772. https://doi.org/10.3390/buildings13071772

Zhang, C., Lei, X., Xia, Y., & Sun, L. (2024a). Automatic bridge inspection database construction through hybrid information extraction and large language models. *Developments in the Built Environment*, *20*, 100549. https://doi.org/10.1016/j.dibe.2024.100549

Zhang, L., Tang, M., Xu, Y., & Zhang, C. (2024b). Application Research on Artificial Intelligence Generated Content in Architectural Design. *2024 International Conference on Machine Intelligence and Digital Applications*, 671-680. https://doi.org/10.1145/3662739.3673681

Zheng, C. M., Tang, Y. Q., & Su, X. (2024). A Knowledge Graph Modeling Approach for Augmenting Language Model-Based Contract Risk Identification. *EC3 Conference 2024*, Greece. http://www.doi.org/10.35490/EC3.2024.178

Zheng, J., & Fischer, M. (2023). Dynamic prompt-based virtual assistant framework for BIM information search. *Automation in Construction*, *155*, 105067. https://doi.org/10.1016/j.autcon.2023.105067

Zhong, Y., & Goodfellow, S. D. (2024). Domain-specific language models pre-trained on construction management systems corpora. *Automation in Construction*, *160*, 105316. https://doi.org/10.1016/j.autcon.2024.105316