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OPPORTUNITIES AND ADOPTION CHALLENGES OF ARTIFICIAL INTELLIGENCE IN THE CONSTRUCTION INDUSTRY

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Abstract: Over the past decade, while artificial intelligence (AI) has rapidly transformed numerous industries, the construction sector has been slow to adopt these advancements. However, the rise of sophisticated large language models (LLMs) such as OpenAI's GPT, Google's PaLM, and Meta's Llama has demonstrated significant potential, sparking widespread global interest. Despite this surge, there remains a lack of research specifically examining the opportunities and challenges of integrating Generative AI (GenAI) within the construction industry, resulting in a crucial knowledge gap for both researchers and practitioners. Addressing this gap is essential to effectively leveraging GenAI during its early adoption phase in construction. Given GenAI's remarkable ability to generate human-like content by learning from existing data, this study explores two key questions: What does the future hold for GenAI in the construction industry? What are the potential opportunities and challenges associated with its implementation? To answer these questions, the study conducts a literature review, assesses industry perspectives using programming-based word cloud and frequency analysis, and incorporates the authors' insights. Additionally, the paper proposes a conceptual framework for GenAI implementation, offers practical recommendations, highlights future research directions, and establishes a foundational knowledge base to support further exploration of GenAI in construction, architecture, and engineering disciplines.

Keywords: generative AI; implementation framework; construction; AEC; GPT; LLM; PaLM; Llama; fine-tuning.

Introduction

Over the past four decades, machine learning (ML), particularly deep learning based on artificial neural networks, has advanced significantly, driving transformations across various industries. Within the construction sector—an industry often lagging in efficiency and productivity—ML has been instrumental in automating processes. However, widespread adoption faces challenges, including issues related to data quality management and the lack of clear guidelines for integrating domain expertise with data-driven insights. These challenges manifest in three key areas: (1) the disparity between a feature-rich dataset and a limited number of samples, (2) the trade-off between model accuracy and broad applicability, and (3) the difficulty of aligning machine learning outputs with industry-specific knowledge.

For example, a construction company may possess extensive data on project features but only a limited number of actual projects, making it difficult to develop a precise cost prediction model. Similarly, an organization seeking to forecast project completion times must balance model accuracy with its ability to generalize across diverse projects. Additionally, a safety manager using ML to predict fall risks may find that traditional models fail to account for human factors and unforeseen conditions. These limitations highlight the

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constraints of conventional machine learning in addressing complex construction industry challenges. The rapid evolution of artificial intelligence (AI)—which enables machines to replicate human-like reasoning and decision-making—has led to the emergence of advanced large language models (LLMs) such as OpenAI's GPT, Google's PaLM, and Meta's Llama. Generative AI (GenAI), a subset of deep learning, utilizes neural networks and various learning methods (supervised, unsupervised, and semi-supervised) to generate new content, including text, images, and audio. LLMs train on extensive datasets, developing statistical models that allow them to generate coherent outputs based on input prompts. At their core, transformer-based architectures power GenAI models, processing inputs through encoders and generating outputs via decoders. GenAI can be classified into four major types: text-to-text, text-to-image, text-to-video/3D, and text-to-task. Text-to-text models generate text-based outputs, while text-to-image models create visuals from textual descriptions, often utilizing diffusion techniques. Text-to-video and text-to-3D models extend these capabilities to multimedia generation. Meanwhile, text-to-task models perform functions such as answering questions, retrieving information, making predictions, and executing complex tasks. Large-scale, pre-trained GenAI models like GPT are designed for adaptability and can be fine-tuned for various applications, including sentiment analysis, object recognition, instruction following, and more. In recent decades, AI and ML research in construction has explored applications such as safety management, cost prediction, schedule optimization, progress monitoring, quality control, supply chain and logistics management, risk mitigation, dispute resolution, waste management, sustainability assessment, visualization, and infrastructure inspection. Furthermore, integrating AI with Building Information Modeling (BIM) has enhanced information extraction, workflow efficiency, and project management. The incorporation of robotics and AI has also led to improvements in construction quality, safety, and project timelines, while mitigating labor shortages. Despite these advancements, research on the specific applications, opportunities, and adoption barriers of GenAI in construction remains limited. This gap is likely due to the technology's recent emergence, resulting in a slower pace of adoption compared to other industries that have already begun leveraging its benefits. Given this context, this study aims to answer two key research questions: (1) What are the current perspectives, evidence, and challenges surrounding GenAI adoption in construction? and (2) What are the most critical research directions for future investigations into GenAI's role in construction? The paper is structured as follows: Section 2 outlines the research methodology. Section 3 explores different GenAI models and their relevance to construction. Section 4 synthesizes existing insights, identifies potential application areas, and presents a conceptual implementation framework. Section 5 discusses challenges, ranging from technical limitations to industry-specific barriers. Section 6 offers implementation recommendations and highlights priority research questions. Finally, concludes with key findings and future considerations for advancing GenAI in construction.

Results and methodology.

To achieve our research objectives—identifying the opportunities and challenges of Generative AI (GenAI) in construction, developing a conceptual implementation framework, and outlining future research directions—we followed the research framework illustrated in Figure 1. Given the limited existing literature on GenAI in construction, we adopted a non-systematic review approach.

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Our initial literature search used keywords such as **"Generative AI AND Construction"**, **"Generative AI"**, and **"Large Language Models AND Construction"** in academic databases like Scopus and Google Scholar. To further expand our sources, we applied the snowball method, examining key articles and tracing their references and citations to uncover additional relevant studies.

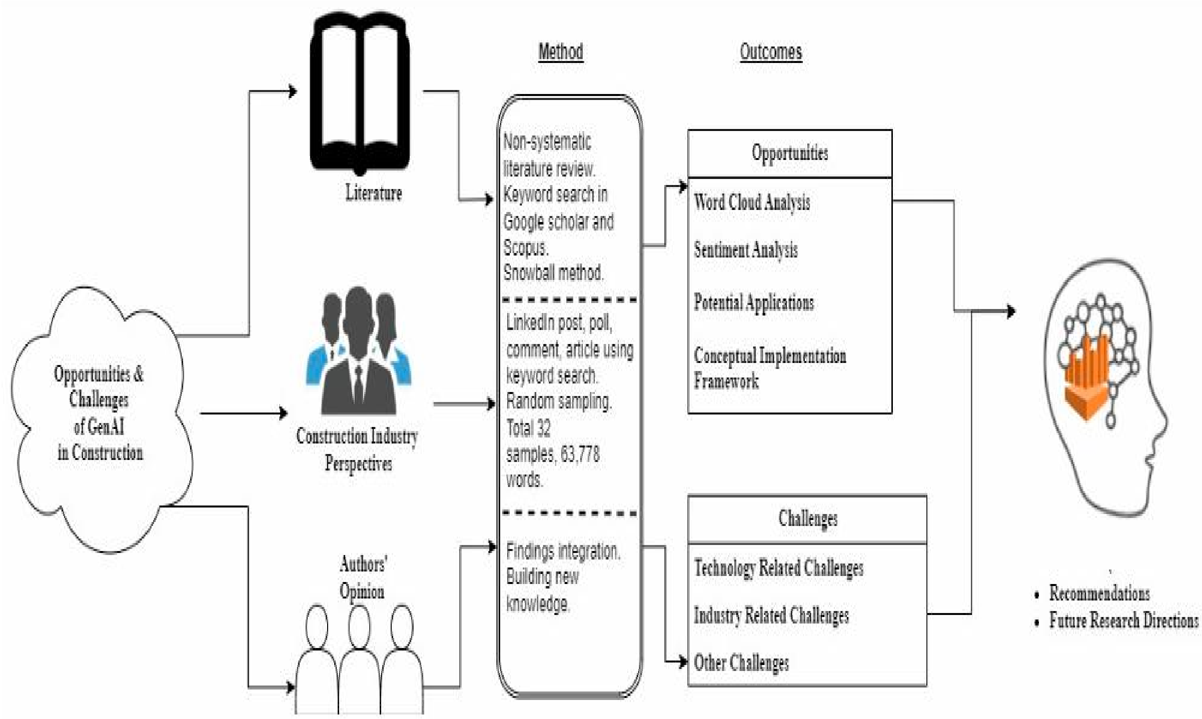

Figure 1. Research framework

In recent years, researchers have been refining generative AI (GenAI) models to address industry-specific challenges. The choice of a GenAI model depends on the task at hand, as different models excel in different applications. There are five major types of GenAI models, as shown in Figure 2, and ongoing advancements continue to shape the field. Researchers actively explore novel architectures and methodologies to enhance model capabilities.

The five major types of GenAI models include:

❖ **Generative Adversarial Networks (GANs):** Commonly used for image generation, GANs create realistic images by training a generator and discriminator in a competitive setting.

❖ **Variational Autoencoders (VAEs):** Typically applied in text generation, VAEs learn the underlying data distribution, enabling the production of grammatically coherent and meaningful text samples.

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❖ **Autoregressive Models:** These models generate text token by token, conditioning on previous tokens to ensure coherence and fluency. They are widely used in natural language processing tasks.

❖ **Diffusion Models:** Used primarily in image synthesis, these models begin with noise and gradually refine images by reversing a diffusion process, leading to high-quality outputs.

❖ **Flow-Based Models:** These models transform data into a latent representation, allowing for creative and diverse content generation in both image and text domains.

Each of these models has unique strengths and limitations. In the following subsections, we will explore their architectures, operational mechanisms, and constraints. Additionally, we will examine their relevance to the construction industry, identify existing use cases, and summarize their key advantages and disadvantages.

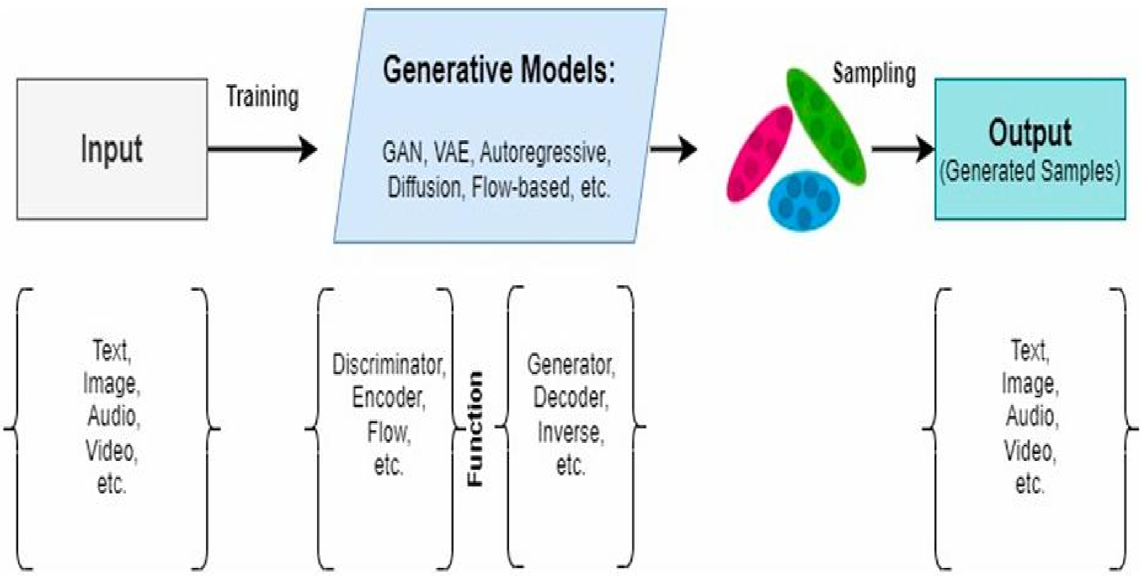

Figure 2. GenAI Models.

Recent studies leveraging Large Language Models (LLMs) to solve construction-related challenges highlight the long-term opportunities of generative AI (GenAI) in the industry. Some key developments include:BIM-GPT Integration: In 2023, Zheng and Fischer introduced a BIM-GPT framework that enables LLMs to retrieve, summarize, and answer questions from Building Information Modeling (BIM) databases. This addresses challenges in automating complex information extraction from rich BIM models. Despite BIM's growing adoption, issues like interoperability and standardization remain. Using LLMs to extract and standardize BIM data can streamline workflows.Automated Construction Scheduling: Prieto et al. (2023) tested ChatGPT for generating coherent construction schedules, improving activity sequencing and scope alignment.Safety and Risk Classification: Hasan et al. developed a BERT-based model to classify injury narratives, identifying risks and hazards in construction sites. This technique has also been used for detecting contractual risk clauses in

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construction specifications.Document Analysis and Synthesis: While construction projects generate extensive documentation (e.g., contracts, reports, and drawings), traditional systems struggle to utilize this data effectively. GenAI models like ChatGPT and Bard can synthesize construction documents, answering queries and extracting key information from these data sources.

The use of robotic systems in construction requires efficient sequence planning. Traditional mathematical and machine-learning methods have struggled to adapt to dynamic construction environments. RoboGPT, a model leveraging ChatGPT, was introduced to enhance robotic assembly sequence planning. However, challenges remain in translating human language into robot-interpretable instructions.Studies suggest that current LLMs still face limitations in numerical and physical reasoning, necessitating further improvements for fully autonomous robotic construction planning.

- **AI Policy and Regulation**:

The CREATE AI Act (2024) and the National Artificial Intelligence Research Resource (NAIRR) indicate growing governmental support for AI in construction. NAIRR aims to expand access to AI resources, fostering innovation in sectors like architecture, engineering, and construction.

LLMs are being developed under both open-source and closed-source approaches, each with distinct implications: Promote transparency by providing access to source code, training data, and model parameters.Enable collaboration, allowing researchers and developers to enhance models for specific construction applications.Require significant infrastructure and hosting costs for deployment.Closed-Source LLMs:Are proprietary models restricted to license holders, limiting external development opportunities.Offer reliable cloud-based deployment with dedicated resources, ensuring uptime and scalability.Provide better data privacy by restricting access to training data and algorithms.As GenAI adoption in construction continues to grow, balancing the trade-offs between model scale, cost, accessibility, and transparency will be critical for optimizing its impact in the industry.

Conclusion.

The construction industry, historically slow to adopt digital transformation, is now experiencing a paradigm shift with the emergence of Generative AI (GenAI). This study explored the current applications, challenges, and future opportunities of GenAI in construction, demonstrating its potential to enhance productivity, streamline processes, and improve decision-making.Key advancements, such as BIM-GPT for data extraction, AI-driven scheduling, risk classification, and robotics integration, highlight the transformative role of GenAI in addressing industry-specific challenges. However, limitations persist, including issues related to data availability, model accuracy, domain knowledge integration, and real-world adaptability. The balance between open-source and closed-source LLMs also presents strategic trade-offs for organizations seeking to optimize cost, performance, and transparency.Despite these challenges, government initiatives like the CREATE AI Act and NAIRR indicate a growing commitment to fostering AI development across sectors, including construction. To fully leverage GenAI, further research is needed to refine LLM-

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based automation, improve interoperability in BIM workflows, and enhance AI-driven decision-making frameworks. Ultimately, GenAI represents a promising frontier for the construction industry, offering solutions to long-standing inefficiencies. By addressing existing barriers and investing in innovation, the industry can harness AI's full potential, driving increased efficiency, safety, and sustainability in the built environment.

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