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# Large Language Model Integration in Construction Safety: A Literature Review

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The construction industry continues to face persistently high rates of injuries and fatalities despite decades of safety initiatives, underscoring the need for innovative, data-driven approaches. Recent advances in artificial intelligence, particularly Large Language Models (LLMs), have opened new avenues for enhancing safety through automation, hazard recognition, and intelligent decision support. This study presents a comprehensive scientometric and thematic analysis of 60 peer-reviewed journal papers published between 2020 and 2025 that explore the intersection of LLMs and construction safety. The bibliometric results reveal a sharp growth in publications beginning in 2024, coinciding with the rise of generative AI technologies. Thematic analysis identifies five major research domains: text-based safety analytics, multimodal sensing and real-time monitoring, knowledge-enhanced reasoning, generative AI for data augmentation, and human-AI interaction for safety training and decision support. Key challenges include data scarcity, limited domain-specific reliability, and practical barriers to implementation. Overall, this study maps the intellectual landscape of LLM applications in construction safety, highlighting both current progress and future opportunities for leveraging language-based AI to achieve safer, more resilient construction environments.

Keywords: LLMs, Construction Safety, AI, Multimodal Safety System, Construction

## Introduction

### *Background: The Construction Safety Challenge*

Worker fatalities and non-fatal injuries are disproportionately prevalent in the construction sector worldwide (Hämäläinen et al., 2006). Despite ongoing improvements in site management and safety protocols, construction remains one of the most hazardous industries worldwide. In 2023, it recorded 1,075 fatalities, the highest since 2011 with 39.2% caused by falls, slips, and trips, and 22.3% by transportation-related incidents (BLS, 2024). Key challenges in construction safety include incomplete analysis of contributing risk factors, insufficient training in recognizing hazards, and evolving environments that complicate effective monitoring and incident prevention (Jeelani & Gheisari, 2022; K. Liu et al., 2025). Preventing accidents by approaches like robust safety management system is essential for the well-being of workers, to minimize financial losses and project delays associated with adverse events and support sustainable advancement of construction (Ikpe et al., 2011; Yoon et al., 2013). Recent trends emphasize integrating advanced technologies and comprehensive research strategies to address systemic safety issues in construction (Xu et al., 2024;

Yap et al., 2024). Despite ongoing efforts to improve job site safety, traditional methods like paper-based Job Hazard Analysis (JHA) still fall short of achieving zero incidents. These approaches rely on lagging indicators and are often criticized for being reactive, addressing risks only after incidents occur (Rafindadi et al., 2023; Zhou et al., 2015). As a result, there is a growing consensus that the industry may have reached saturation with respect to traditional injury prevention strategies, signaling a critical need for innovation (Esmaeili & Hallowell, 2011).

### *The Rise of AI and Large Language Models in Construction*

Artificial Intelligence (AI), specifically Large Language Models (LLMs) such as those in the GPT family, are deep learning models trained on vast quantities of text data, enabling them to understand, process, and generate nuanced, human-like text The AEC industry is data-rich but often data-poor, with vital safety and operational information trapped in unstructured sources such as daily logs, inspection forms, safety manuals, and accident reports. (Li et al., 2023; Ohene et al., 2024). LLMs possess the unique ability to process this complex unstructured data for tasks such as contract analysis, compliance checking, and risk assessment (Zhang et al., 2025). Various researchers in the construction field have acknowledged the potential of large language models to support construction safety tasks. Uddin et al. (2023) showed that incorporating ChatGPT can enhance hazard recognition for both students and construction workers by using it to identify hazards in site images. LLMs are being explored to analyze textual narratives from accident reports to identify latent risk patterns and major accident causes (Smetana et al., 2024). The studies have been done to explore the ability of multimodal LLMs to identify potential safety hazards from real-world construction images through a comparative evaluation (Chaudhary, Uddin, Albert, et al., 2025; Chaudhary, Uddin, Chandra, et al., 2025). State-of-the-art research demonstrates how LLMs are being leveraged for regulatory compliance automation, intelligent safety training, and integration into visual monitoring systems for enhanced site safety compliance (Getuli et al., 2024; Guo et al., 2025).

## Objectives and Contribution

Since the integration of LLMs into construction safety is still an emerging and rapidly developing research area, there remains a limited understanding of its intellectual landscape, core themes, and progression over time. While preliminary studies, for example a study by Erfani & Mansouri (2026) highlight LLMs' significant potential, comprehensive scientometric analyses mapping research trends, collaboration networks, and thematic focus areas in this intersection are limited. In recent years, bibliometric analysis has become an important method. as it uses quantitative indicators to evaluate scientific output, track technological progress, and reveal evolving research domains for strategic insights. Scientometric analysis is a widely recognized quantitative approach, which helps visualize and assess the structure and evolution of a research field through examination of its publications, citations, and keywords. This method has been successfully applied to analyze various areas within construction research, including accident causation and worker wellbeing. Therefore, this study performs a detailed scientometric analysis focusing on how LLMs are being utilized in construction safety. Its main goals are to: (1) measure the growth and publication trends in this field; (2) determine the most influential journals publishing related papers; and (3) identify emerging themes of research, existing challenges in LLM application, and potential future directions through a content analysis. By offering a comprehensive map of this evolving research area, the study seeks to inform future investigations and assist practitioners in understanding the current landscape of LLM-driven safety innovations.

## Methodology

This study used a methodical literature review approach to find and evaluate relevant academic publications about the use of LLMs in construction safety. Initial scoping, keyword refinement, database searching, and thorough screening and selection procedure were all part of the discrete stages of the research process.

*Search Strategy, Keyword Development, and Database Search*

The research began with an exploratory scan of Google Scholar using the general query "LLM in construction." This preliminary search served as a foundation to identify key publications and commonly used terminology in the field. Rather than aiming to compile a complete dataset at this stage, the focus was on understanding the existing landscape and extracting keyword patterns. A detailed list of related terms and synonyms was created and progressively refined to develop a comprehensive search string suitable for scholarly databases and improve both the accuracy and comprehensiveness of the subsequent search process. The final search string used was:
*"construction near#3 safety" OR "construction near#3 safety training" OR "risk assessment" OR "construction hazards" OR "safety monitoring" OR "hazard identification" OR "construction site safety" OR "safety management" OR "Safety awareness" OR "construction near#3 fire safety" OR "safety hazards" OR "construction near#3 transportation safety" OR "job safety" OR "hazard recognition" OR "construction training*"
AND
*"large language models" OR "vision language models" OR "Generative AI" OR "GPT" OR "language model" OR "computer vision" OR "BERT" OR "ChatGPT" OR "Gemini" OR "LLM" OR "Claude" OR "Llama" OR "DeepSeek" OR "Mistral" OR "Qwen" OR "VLM" OR "multimodal large language model" OR "MLLM" OR "multimodal LLM"*

Following keyword refinement, a systematic literature search was conducted in the Web of Science database, as it is widely recognized for its rigorous journal indexing standards. The refined keyword set was applied with a publication year filter covering 2020–2026, reflecting the rapid advancements in LLM technologies during this period. The initial search returned 879 publication records.

*Inclusion and Exclusion Criteria*

To ensure the relevance and quality of the selected literature, the following exclusion criteria were applied:

1. *Publication type:* All articles other than peer-reviewed journal papers (e.g., conference proceedings, reviews, book chapters, theses, and reports) were excluded. Incomplete data for the year 2026 was also excluded.
2. *Domain relevance:* Papers not related to the construction industry were removed. These included studies focused solely on other domains such as healthcare, finance, education, or general AI applications without a construction context.
3. *Topical relevance*: Papers that did not involve large language models, natural language processing, or other language-based AI systems were excluded. Studies focusing only on unrelated computer vision or sensor-based systems without language components were not considered.

The inclusion criteria focused on ensuring that only high-quality and contextually relevant studies were reviewed. Peer-reviewed journal articles published in English from 2020 onward were included if they explicitly addressed the construction domain and examined safety, risk management, or hazard-related topics. Eligible studies had to apply LLMs, or other language-based AI techniques with demonstrated or potential relevance to construction safety management, training, or decision support.

### *Screening and Eligibility*

A multi-stage screening process following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was conducted to identify studies meeting the inclusion criteria. First, all titles were manually reviewed to remove papers that were clearly unrelated to construction or language model applications. For papers whose relevance was not evident from the title alone, abstracts were examined to determine whether the study involved LLMs or related technologies within the construction domain. When necessary, the full text of selected papers was briefly reviewed to confirm applicability and ensure alignment with the study's objectives. After screening, 60 relevant peer-reviewed papers were retained from an initial 879 using a PRISMA-based process, ensuring inclusion of only recent, construction-focused, and LLM-related studies. These 60 papers form a solid basis for analyzing language-based AI in construction safety and automation.

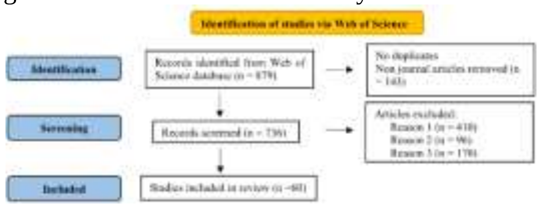


**Figure 1.** Prisma flow diagram of the literature review

## Analysis and Findings

### *Bibliometric Analysis of the Publications*

As shown in Fig 2, the publication trend from 2020 to 2026 reveals a sharp rise in research activity within the field of construction safety and LLM applications. From 2020 to 2021, the number of publications remained minimal, with only one article each year, indicating limited academic engagement during that early phase. A modest increase occurred in 2022 (6 articles), implying growing curiosity about digital transformation and automation in construction safety research. A more noticeable uptick appeared in 2023 (3 articles), but a significant surge was recorded in 2024 (17 articles) and an even more remarkable spike in 2025 (32 articles). This sharp increase aligns with the emergence and widespread adoption of ChatGPT and similar LLMs which inspired researchers to explore their potential applications in construction safety, knowledge management, and decision-making. The boom in LLM-related research across industries likely motivated the construction research community to investigate how these tools could enhance safety analysis, hazard detection, and causality understanding. Overall, this trend highlights a transformative period beginning in 2024, when there was shift from traditional safety studies toward AI-driven approaches leveraging LLMs, highlighting the growing recognition of their value in construction research and practice.

The chart in Fig 3 displays the distribution of articles published across various journals in construction-related research. Automation in Construction leads with most number articles, 16 out of 60 followed by Buildings, 9 out of 60, Advanced Engineering Informatics and Journal of Construction Engineering Management 4 out of 60, Engineering Construction and Architectural Management, Journal of Computing in Civil Engineering, and Sustainability 3 out of 60.

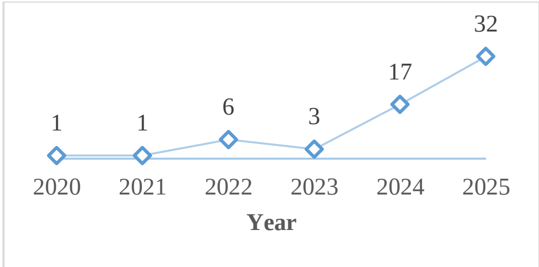


**Figure 2.** Annual Publication Trend of LLM Applications in Construction Safety (2020-2025)

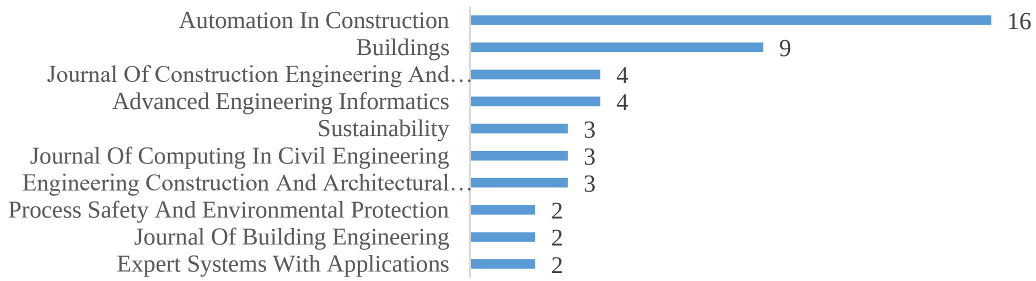


**Figure 3.** Top 10 Journals by Number of LLM-Construction Safety Publications (2020–2025)

*Thematic Analysis*

The selected literature was stratified based on research maturity and citation momentum. A significant disparity in absolute citation counts was observed: two foundational studies exceed 300 citations, while 73% of the dataset consists of recently published works (2024–2025) that have not yet reached their citation peak. To account for this, a three-tier classification system was implemented.

1) *Tier 1:* Foundational Pillars (<5% of dataset) This category includes high-impact seminal works with over 300 citations. These studies established the fundamental deep learning frameworks for construction engineering prior to the widespread adoption of Large Language Models (LLMs), serving as the theoretical basis for current developments.
2) *Tier 2:* Established Methodological Validations (25% of dataset) Comprising studies with 15 to 100 citations, this tier represents the "BERT-based" era (2020–2023). These papers provide empirically validated methods for text classification and accident report analysis, representing the transition from traditional machine learning to Transformer-based natural language processing.
3) *Tier 3:* Emerging Frontiers (70% of dataset) This tier encompasses the most recent research surge from 2024 and 2025. Despite lower absolute citation counts (0–15), these papers demonstrate high citation velocity and represent the current "cutting edge" of the field. Research in this tier focuses on the integration of GPT-4, multimodal Vision-Language Models (VLMs), and Retrieval-Augmented Generation (RAG).

To get a deeper understanding of the content of the selected papers, the research team conducted a thematic analysis with a view to answering the following questions:

1. What are the primary areas of research focus in construction safety where LLMs have been applied?
2. How do specific LLM architectures and data modalities align with various construction safety tasks, and what are their current usage frequencies and implementation challenges?
3. What limitations and challenges arise when deploying LLM-based solutions for construction safety?

### *Primary Areas of Research Focus*

The analysis of the selected papers reveals five primary, interconnected themes that define the current research landscape at the intersection of LLMs and construction safety.

*Text-based analytics for safety insights:* This foundational theme focuses on applying text-mining and LLMs to the vast archives of unstructured safety documents. This includes reactive analysis of past events by mining accident reports to extract risk factors and analyze causation. It also includes proactive analysis of present rules by parsing complex safety regulations, technical standards, and contractual documents to automate compliance checking and risk identification.

*Multimodal sensing and real-time monitoring:* This theme represents the evolution from text-only analysis to the integration of vision and language. It covers the use of Vision-Language Models (VLMs) to interpret real-time site imagery, identify hazardous conditions (e.g., missing PPE, ergonomic risks), and check for regulatory compliance. This area also includes the development of structured representations of visual data, such as Scene Graphs, to bridge the semantic gap between object detection and true hazard reasoning.

*Knowledge-enhanced reasoning and grounding:* This theme directly addresses the critical limitation of general-purpose LLMs i.e., their lack of domain-specific reliability and hallucinations. Research in this area focuses on grounding LLM outputs in verifiable facts. The primary methods include constructing explicit, domain-specific Knowledge Graphs (KGs) from safety documents and using Retrieval-Augmented Generation (RAG) to connect LLMs to these external KGs or document databases, forcing them to base their answers on a retrieved source of truth.

*Generative AI for data augmentation and reporting:* This theme explores the generative capabilities of these models. This includes generating synthetic text data, such as automated daily safety and inspection reports, often by combining VLM scene analysis with LLM text generation and generating synthetic image data of rare hazardous events using text-to-image diffusion models, which solves the data scarcity problem for training more robust visual AI detectors.

*Human-AI interaction for training and decision support:* This final theme examines the direct application of LLMs as tools for human operators. This includes developing personalized and adaptive safety training modules and creating interactive question-answering chatbots for on-site decision support. This theme also includes critical usability studies that analyze the trustworthiness and limitations of these tools for practitioners.

### *LLM Architectures and Task-Modality Alignment*

The research landscape exhibits clear stratification based on model architecture, data modality, and task suitability as shown in Table 2. The most established cluster, representing 38.3% of the literature, relies on foundational Encoder-only models (e.g., BERT). These are frequently integrated with architectures like BiLSTM and CRF for specialized Named Entity Recognition (NER) and accident report classification, forming the "BERTology" backbone of text-based safety analytics. Concurrently, there is a rapid shift toward Hybrid RAG systems (31.7%) and Multimodal VLMs (11.7%). While general-purpose models like GPT-4V and LLaVA are gaining traction, high-impact "Core Literature" indicates that out-of-the-box versions often lack the domain-specific nuances required for construction site safety. Consequently, recent studies prioritize Retrieval-Augmented Generation (RAG) to ground outputs in verifiable safety standards and bridge the semantic gap between low-level object detection and high-level hazard reasoning. This mapping serves as a technical decision support tool, revealing that model selection is directly driven by specific data requirements and the inherent technical difficulty of the safety application.

**Table 1**. LLM Technology Selection Matrix and Data Modalities for Construction Safety

| **Application Scenario** | **Recommended Architecture** | **Primary Data Modality** | **Usage (n=60)** | **Technical Strength** | **Difficulty** |
|---|---|---|---|---|---|
| Accident Analysis & Classification | Encoder-only (e.g., BERT, Robert) | Unstructured Text (Reports, Logs) | 23 (38.3%) | High precision in semantic labeling and NER. | Low |
| Safety Q&A & Training | Decoder-only (e.g., GPT-4, Llama) | Text-to-Text (Conversational) | 11 (18.3%) | Human-like reasoning and context retention. | Medium |
| Real-time Hazard Recognition | VLM / Multimodal (e.g., LLaVA, GPT-4V) | Vision-Language (Images/Video) | 7 (11.7%) | Bridges the semantic gap between pixels and risk. | High |
| Regulatory Compliance | Hybrid / RAG (LLM + Knowledge Graph) | Structured Data & Text (Manuals) | 19 (31.7%) | Cross-references rules to eliminate hallucinations. | Medium |

### *Limitations and Challenges in Current Research*

The deployment of LLM-based solutions in the safety-critical domain of construction is not without significant challenges. The literature identifies a clear and consistent set of limitations, which current research is actively working to solve. These challenges can be grouped into four main categories.

*Data quality and scarcity:* The most frequently cited barrier to deploying high-performance models is the lack of large-scale, high-quality, and properly labeled datasets specific to construction safety. This data scarcity problem is a persistent challenge, particularly for hazardous events, which are rare. Compounding these are issues of imbalanced data, where common, low-risk events far outnumber rare, high-risk ones, and label noise from inconsistent or inaccurate manual reporting.

*Model reliability and lack of domain context:* General-purpose LLMs (e.g., GPT-4) are probabilistic and prone to hallucinations providing fluent, confident-sounding, but factually incorrect answers. This is unacceptable for safety-critical applications. Several usability studies confirm this, noting that while LLMs are intuitive, experienced professionals contend that the software lacks contextual depth and exhibits inadequate causal reasoning and insufficient contextual consideration. This creates a significant trust barrier.

*The semantic gap and technical hurdles:* A fundamental technical limitation, known as the semantic gap, exists between low-level perception (e.g., object detection) and high-level cognition (e.g., understanding risk). A simple computer vision model can detect a "person" and an "edge," but it cannot reason that a person near an edge without fall protection constitutes a hazard. This gap is also seen in text analysis, where models capture simple keywords but fail to capture contextual semantic nuances or complex syntactic dependencies. Furthermore, models struggle with heterogeneous data, such as parsing the intricate layout of complex tables in regulatory documents.

*Practical and operational hurdles:* Beyond model accuracy, several practical hurdles exist for real-world deployment. These include the high computational demands and cost of both large-scale models and advanced sensor systems. Other cited issues include integration barriers with existing company software, as well as ethical and cybersecurity concerns. Finally, many models are not fully autonomous and still require human supervision to ensure reliability.

## Conclusion

This study provides a comprehensive overview of how LLMs are transforming construction safety, revealing a rapidly expanding research domain with a marked surge in publications since 2024. While text-based analytics have reached maturity, the frontier of the field lies in the deployment of trustworthy, multimodal agents. Based on the analyzed literature, a strategic research roadmap is proposed: in the short-term (1–2 years), the widespread adoption of Retrieval-Augmented Generation (RAG) and domain-specific fine-tuning (e.g., BERTology) will become the standard for mitigating hallucinations in compliance checking; in the mid-term (3–5 years), the industry will transition toward "Construction-Foundation Models" that integrate site-specific knowledge graphs to capture complex causal reasoning; and in the long-term (5+ years), research will culminate in the development of autonomous, end-to-end multimodal systems (VLMs) capable of real-time safety interventions with minimal human supervision. Ultimately, realizing these benefits requires continued interdisciplinary collaboration and ethical implementation frameworks to ensure the creation of intelligent, data-driven, and resilient construction environments.

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