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LEVERAGING LARGE LANGUAGE MODELS TO ENHANCE SAFETY AWARENESS AND ACCESSIBILITY OF OSHA REGULATIONS FOR CONSTRUCTION WORKERS

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Abstract

Traditional methods for reviewing construction safety regulations are typically manual, time-consuming, and susceptible to inconsistencies. This study explores the use of Large Language Models (LLMs) to simplify complex regulatory language, thereby enhancing employers' and workers' understanding of OSHA policies and regulations. By processing images and textual reports from construction sites and regulations, LLMs can identify hazards, match them to relevant regulations, and provide actionable recommendations. This real-time, context-specific approach bridges the gap between regulations and practical application, fostering a safer, more informed workforce. Additionally, LLMs improve accessibility and comprehension of OSHA standards, aligning safety practices with regulatory requirements more effectively.

Introduction

The construction industry is one of the most hazardous sectors worldwide, facing significant challenges in ensuring worker safety and regulatory compliance. Effective management of construction policy and regulatory documents is critical for mitigating risks, maintaining safety standards, and adhering to legal requirements. However, traditional methods for reviewing these documents are often manual, time-consuming, and prone to inconsistencies (Han et al., 2018). Manual analysis suffers from several limitations, including scalability issues, inconsistencies, biases, poor data integration, and limited adoption of automation (Biddle et al., 2017; Chowdhury, 2010; Gupta et al., 2020). The growing volume and complexity of regulatory documents further exacerbate these challenges, highlighting the need for innovative solutions to improve efficiency and accuracy in policy review processes.

Recent advancements in automation, Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) offer transformative opportunities to streamline document review. Large Language Models (LLMs), such as OpenAI's Generative Pre-trained Transformer (GPT) series, have demonstrated exceptional capabilities in processing, analyzing, and synthesizing vast amounts of text, enabling the automation of complex and repetitive tasks (Brown et al., 2020). These technologies have the potential to revolutionize the construction industry by automating the review of policy and regulatory documents, extracting actionable insights, and providing stakeholders with data-driven recommendations.

This study explores a novel approach to leveraging LLMs to enhance access to construction policy and regulatory documents. The approach will aid in improving construction site safety by utilizing LLMs trained on OSHA regulations to process images and textual reports, enabling them to (i) identify safety hazards, (ii) map them to relevant OSHA regulations, and (iii) generate actionable mitigation recommendations. By integrating AI-driven tools to analyze multimodal construction safety information—including text, images, and reports—this research contributes to the growing body of literature on digital transformation in construction safety and management. Furthermore, it underscores the value of AI applications in addressing regulatory challenges and advancing workplace safety practices.

Literature review

The construction industry consistently experiences high rates of occupational injuries and fatalities, making it one of the most hazardous sectors globally (BLS, 2023). The Occupational Safety and Health Administration (OSHA) plays a crucial role in establishing safety standards to mitigate risks on U.S. construction sites. However, the complexity of OSHA regulations presents significant challenges for both workers and employers, leading to gaps in understanding and compliance.

Due to the technical language and dense documentation in OSHA regulations, many construction workers - especially those with limited formal education or language barriers - struggle to comprehend safety requirements. Research indicates that a lack of understanding of safety protocols is a major contributing factor to workplace accidents (Haslam et al., 2005). Additionally, studies show that workers often fail to retain information delivered through conventional training methods (Robson et al., 2012). The increasing diversity of the construction workforce, including non-native English speakers, demands more accessible and inclusive solutions to enhance regulatory awareness among workers and employers (Hislop, 1999). OSHA offers OSHA 10 and OSHA 30 training for general construction personnel. These training programs focus on hazard recognition rather than in-depth OSHA regulations, which are thoroughly covered only in advanced training, such as OSHA 502 and OSHA 500.

With the application of AI, especially LLMs, it is possible to process and contextualize complex information, making it suitable for addressing those challenges associated with policies and regulations, including OSHA regulations. LLMs can make OSHA guidelines more accessible to construction workers by translating dense regulatory language into plain and easily understandable terms. They can generate tailored summaries of OSHA regulations specific to job roles, allowing workers to focus on the most relevant information while reducing the time spent reviewing extensive regulatory documents. Additionally, LLMs can provide real-time, context-specific assistance by answering workers' queries about OSHA regulations and specific safety procedures based on situations of construction sites, all in their preferred languages.

Despite the potential of LLMs, research on their application in the construction industry remains limited. Many studies related to LLMs applications have been conducted in other sectors, such as finance, government administration (especially in e-government), legal, and business (Han et al., 2018). In e-government, LLMs have improved service delivery, automated processes, and enhanced citizen engagement (Han et al., 2018). With their innovative applications in transforming natural language queries into precise data retrieval systems, LLMs have shown potential in addressing challenges in public administration by streamlining processes across various areas. Papageorgiou et al. (2024) proposed a framework for improving e-government services through the integration of LLMs and AI.

In business, AI technologies like generative models are revolutionizing customer engagement and marketing by automating personalized content creation based on persuasive marketing theories (Brown et al., 2020). Similarly, AI-driven chatbots and educational tools support interactive learning and bridge gaps in remote education. Legal and regulatory domains also benefit from LLM integration. By converting complex legal texts into machine-executable formats, LLMs enhance transparency and automate compliance processes. Frameworks for AI governance emphasize transparency, accountability, and ethical standards, ensuring the responsible deployment of these technologies in both public and private sectors (Han et al., 2018).

Recently, a few studies have been conducted on the application of LLMs in the construction industry. Pu et al. (2024) proposed a multimodal large language model framework to automate the generation of construction inspection reports, meeting regulatory standards and reducing resource waste. Smetana et al. (2024) presented a highway construction safety analysis approach using LLMs to enhance text-based incident analysis by reviewing OSHA's Severe Injury Reports (SIR) database. Tran et al. (2023) proposed an LLM-based approach to extract information from construction safety documents and answer real-time safety regulatory questions. Their approach includes three key components: the construction safety investigation module, the safety condition identification module, and the safety information delivery system.

Lee et al. (2024) explored how LLMs can enhance Building Information Modeling (BIM) workflows, focusing on a speech-to-BIM system within their proposed generalized LLM-augmented BIM framework. Traditional BIM processes are complex and require expertise in data querying, modeling, compliance checks, and design tasks, creating significant cognitive demands. Recent advancements in LLMs enable users to interact with BIM systems through natural language interfaces, simplifying processes and increasing productivity. The study outlines a six-step framework for integrating LLMs into BIM applications: interpretation, gap-filling, matching, structuring, execution, and validation. This methodology is exemplified by NADIA-S, a speech-to-BIM tool designed for exterior wall detailing. NADIA-S demonstrates the potential of LLMs to streamline tasks, reduce cognitive load, and make BIM workflows more efficient. The research underscores how natural language interfaces can transform BIM by replacing traditional graphical interfaces with more conversational, user-friendly interactions, aligning with trends in AI-driven automation and digital transformation.

Chantal et al. (2024) investigated the impact of integrating real-time feedback systems with LLMs on workplace safety. These technologies are reshaping safety practices by enhancing the analysis of incidents, improving compliance, and reducing risks. LLMs excel at processing unstructured safety-related data, such as incident reports and training materials, identifying patterns and hazards that might go unnoticed. They enable a proactive safety approach by synthesizing data and offering insights for targeted preventive measures. Real-time feedback systems complement LLMs by using wearable devices, smart sensor technology, and advanced algorithms to continuously monitor workplace conditions. These systems provide immediate safety alerts, empowering workers and supervisors to address risks promptly. The synergy between LLMs and real-time feedback enhances the precision of safety initiatives. For instance, LLMs analyze data from feedback systems to inform policies and training programs, ensuring measures are data-driven and adaptable. The study highlights that real-time feedback not only improves immediate safety outcomes but also fosters a culture of continuous improvement by reinforcing safe behaviors. This dual strategy combines immediate intervention with data analysis, creating a robust framework for reducing risks and enhancing safety. Additionally, LLMs streamline processes like documentation, audits, and compliance with OSHA standards, enabling organizations to focus on strategic initiatives. The integration of LLMs and real-time feedback systems bridges digital insights with practical implementation, advancing workplace safety through AI and digital transformation.

In the European context, Elsler and Anyfantis (2024) analyzed the role of Vision Zero within the EU strategic framework on health and safety at work (2021–2027) and its alignment with the Sustainable Development Goals (SDGs). Vision Zero represents a commitment to eliminating workplace fatalities through collaborative, data-driven, and awareness-focused efforts. The framework prioritizes improving the quality of data on workplace accidents and occupational diseases, enabling consistent, timely, and reliable comparisons across EU Member States. This data serves as a foundation for evidence-based Occupational Safety and Health (OSH) policies. Additionally, the framework highlights the importance of enforcement, knowledge sharing, and enhanced training for labor inspectors. EU-OSHA significantly contributes to Vision Zero by promoting tools, such as the OSH barometer, a visualization platform for monitoring workplace health and safety data. The strategy also integrates OSH considerations into corporate supply chain codes and procurement practices, reflecting a systemic approach to workplace safety. Moreover, initiatives like the healthy workplace's campaigns encourage collaboration among member states and foster the exchange of best practices. Globally, Vision Zero supports the SDGs, particularly "Decent Work and Economic Growth" (SDG 8) and "Good Health and Well-Being" (SDG 3), by addressing global supply chain challenges and promoting safer workplaces worldwide.

Methodology

The approach involves training a custom GPT on existing OSHA regulations for the construction industry. Such a system is expected to improve construction site safety by leveraging LLMs trained on OSHA regulations to process images and textual reports from construction sites to (i) identify safety hazards, (ii) map them to relevant OSHA regulations and (iii) generate actionable recommendations for mitigation. Empowering site supervisors and even ground workers with such a system will alleviate the steep learning curve associated with understanding and applying OSHA regulations and enabling workers to quickly identify hazards and implement compliance measures without extensive regulatory training. It will also aid in performing Job Hazard Analysis (JHA) on site. The proposed methodology consists of the following steps:

LLM training and fine-tuning

An LLM is trained on the following data, and domain-adaptive fine-tuning is performed to enhance the accuracy of the results. The training data includes:

a. OSHA regulations: It includes the full text of OSHA regulations applicable to the construction industry, such as 29 CFR 1926 in the US (OSHA 2025).
b. Organizational safety guidelines and best practices: OSHA provides the minimum safety measures for construction sites, but companies can have their own standards that are tailored to specific projects and are often more stringent than regulatory requirements.
c. Annotated safety reports: These contain historical construction accident reports related to the organization and expert-labeled safety violations.

Hazard identification

The input can come in different modalities. In this study, the authors prioritize images and text inputs, as these are the most common forms of data generated in real-time on-site by general construction personnel. Images supplied to the system will be analyzed using the custom LLM, which will then generate a textual hazard description based on the image. Textual input and textual hazard descriptions are generated from images using underlying NLP techniques, including keyword extraction, entity recognition, and semantic analysis. The identified hazards are classified into predefined OSHA safety categories.

OSHA regulation mapping

For each identified safety hazard, the model will query its knowledge base and retrieve the most relevant OSHA standard. This step will consist of the following components:

a. Semantic similarity matching: The system will utilize transformer-based embeddings and compare hazard descriptions against existing OSHA regulations to determine the best match.
b. Extraction of appropriate regulation number: The regulation number will be extracted to (i) maintain consistency and formalize the hazard classification process, and (ii) enable the generation of text for the next step.
c. Plain-text explanation: A concise summary of the regulation will be generated in the context of the hazard to enhance worker comprehension.

The generated report will be presented to the user. Each step detailed above will go through a validation process both individually and as a combined system. A committee will be formed, including industry experts, safety managers, OSHA personnel from the regional OSHA office, and ground workers to examine the accuracy, reliability, and acceptability of the reports' comprehension level.

Discussion and sample preliminary results

While the goal is to host an LLM locally and devise a system supported by the LLM, available to the audience through an app, the authors are in the preliminary stages of research. They have been conducting a literature review on the subject matter, interviewing industry experts, and gathering feedback on the idea. The desire for a more comprehensible way to access OSHA regulations was frequently mentioned during the interviews.

As of now, the authors have created a custom GPT on OpenAI's ChatGPT-4, using the entire 29 CFR 1926 as the knowledge base. Two of the authors were previously OSHA Authorized Trainers and have a long history in construction safety research. They are currently using their expertise to fine-tune the model and evaluate the acceptability of the results relative to the effort invested in building the GPT. The authors will soon host a local model and train the data on available safety reports, safety data shared by industry partners, and seek expert evaluation of the results.

This paper presents preliminary results of the effort. The authors are presenting four unique examples to showcase the current status of the research and to discuss the method's capabilities and limitations. Since the authors used a custom GPT, the prompt does not necessarily possess a significant importance in generating the following results. However, the prompt used for all four examples is as follows:

"Identify potential safety hazards in the picture/report, create a table with a list of hazards along with their corresponding regulation numbers and a short description for each regulation. Also, provide a few recommendations to mitigate the hazards at the end."

Example 1: Lunch atop a skyscraper

It is a famous picture (Figure 1) of eleven ironworkers sitting on a steel beam on September 20, 1932, during the construction of the Rockefeller Center in New York. This was before OSHA was established in 1971 (OSHA, 2025). Although it is easy for the human eye to realize that the workers are sitting in an unsafe area, it takes considerable reasoning for an algorithm to understand the context. This picture provides an opportunity to assess whether the current state of AI is capable enough to use reasoning to understand such context.

Table 1 shows the hazards that were recognized automatically and the corresponding OSHA regulations. The authors found that the major safety concerns were correctly identified. It is interesting to observe that although no context outside the picture was provided, other potential issues, such as overhead work (possibly inferred from the wire running from above), lack of fall hazard knowledge and hence, training (based on how the workers were sitting and how many were sitting), and proper access to the area (as both the sides lead to narrow entry/egress without any support) were identified. This shows the potential of identifying hazards not directly featured in the picture but implied by the ambience. One can rightfully argue that such inferences could lead to misleading results if left to work autonomously without a human oversight.

Figure 1: Lunch atop a skyscraper

Table 1: Safety hazards (fall hazard) scenario and related OSHA regulations

Safety Hazard	OSHA Regulation (OSHA, 2025)	Description
Lack of fall protection (e.g., no harnesses, guardrails, or nets)	29 CFR 1926.501(b)(1)	Workers on a walking/working surface with an unprotected edge above 6 feet must use fall protection systems (harnesses, guardrails, or safety nets).
Workers seated on a narrow beam with no secure footing	29 CFR 1926.451(c)(2)(iv)	Scaffolds and structural members used as work surfaces must be designed to prevent falls or instability.
No visible personal fall arrest systems (e.g., lanyards)	29 CFR 1926.502(d)(1)	Personal fall arrest systems must be used when fall hazards are present and must meet OSHA criteria.
Overhead work without protection from falling objects	29 CFR 1926.501(c)	Workers must be protected from falling objects using toe boards, screens, or canopies when working above others.
Lack of proper access to the work area (beam)	29 CFR 1926.451(e)(1)	Proper access must be provided to all working levels, such as ladders or scaffolding, to reduce the risk of falls or unsafe access.
Workers eating and relaxing on a high-elevation surface	General Duty Clause, Section 5(a)(1)	Employers must provide a workplace free from recognized hazards that are causing or likely to cause death or serious physical harm, including unsafe breaks.
No fall protection training for workers (assumed from image)	29 CFR 1926.503(a)(1)	Employers must ensure workers exposed to fall hazards are trained to recognize and minimize such hazards.

Recommendations:

1. Implement a fall protection system: Use personal fall arrest systems or install guardrails and safety nets.
2. Provide proper training: Ensure all workers are trained in fall protection per 29 CFR 1926.503.
3. Use stable platforms for breaks: Designate safe, secured areas for workers to take breaks.
4. Protect against falling objects: Install overhead protection if workers are exposed to falling debris.
5. Use proper access systems: Provide ladders, scaffolding, or other access methods compliant with OSHA regulations.

Example 2: A Hazard not specific to construction

Figure 2 shows a temporary light bulb, not necessarily found only in a construction environment, but also in any temporary settings, work-related or otherwise. The goal behind using this example is to test the system and see how the system will respond to a very limited set of objects to analyze. Example 1 contained people, structures in the background, activities being performed by people, and clear potentially fatal hazards in the frame. This example intends to demonstrate the system's capability to examine minute details in a specific object found in an active work area.
The resulting table (Table 2) lists hazards, which align with the authors' expectations, and the provided recommendations were found to be reasonable.

Figure 2: A makeshift lightbulb with exposed wiring

Table 2: Safety hazard (electrical hazard) scenario and related OSHA regulations

Safety Hazard	**OSHA Regulation (OSHA, 2025)**	**Description**
Exposed wiring with damaged insulation	29 CFR 1926.405(a)(2)	Electrical equipment must be installed and used in a manner that does not expose wires or create a hazard.
Temporary or makeshift light fixture installation	29 CFR 1926.403(b)(1)	Electrical installations must be safe, properly secured, and meet the manufacturer's specifications.
Lack of grounding for the light fixture	29 CFR 1926.404(f)(6)	Electrical equipment must be properly grounded to prevent electrical shock.
Use of improper connectors (alligator clips)	29 CFR 1926.405(b)(1)	Conductors must be connected with proper fittings or splices; makeshift connections are not allowed.
Improper hanging of electrical equipment	29 CFR 1926.416(e)(1)	Electrical equipment and cords must be placed to prevent damage or hazards.
Potential fire hazard from exposed electrical components	General Duty Clause, Section 5(a)(1)	Employers must provide a workplace free from recognized hazards likely to cause death or serious injury, such as fire.
No strain relief on cables	29 CFR 1926.405(g)(2)(iv)	Strain relief must be used to prevent tension on the conductors.

Recommendations:

1. Replace damaged wiring: Damaged wires should be repaired or replaced to meet safety standards.
2. Use proper light fixtures: Install light fixtures designed for the application, following manufacturer instructions.
3. Ensure proper grounding: Verify that the fixture is grounded to reduce the risk of electrical shock.
4. Avoid makeshift connections: Use approved connectors and wiring methods for all electrical work.
5. Secure electrical components properly: Attach components securely to prevent falling or contact with flammable materials.
6. Provide strain relief: Ensure strain relief mechanisms are in place to prevent wear or damage to cables.

Example 3: Typical picture from a construction site

Figure 3 shows a trench with improperly placed shores. If anyone encounters such a situation on a construction site and wants to consult the regulations corresponding to the issues, a picture from the site will generate the following Table 3 for the individual. The system was found to satisfactorily identify existing hazards in the picture and infer potential issues that might have contributed to the hazards. The recommendations are presented in simple language without the use of jargon and seem actionable. Since this is a more practical example of the real-time use of this system, it is worthwhile to discuss its merits. Access to such a system can not only raise awareness about potential hazards on site among all workers, but it will also help administrators perform Job Hazard Analysis (JHA) before work begins and, more importantly, accelerate the rate at which new workers learn how to stay safe on site. With an aging demographic in the construction industry, job readiness in the incoming batch of workers is often overlooked in an effort to keep up with time constraints and project budgets.

Figure 3: Improper shoring in a trench

Table 3: Safety hazard (for shoring) scenario and related OSHA regulations

Safety Hazard	OSHA Regulation (OSHA, 2025)	Description
Lack of proper trench access and egress	29 CFR 1926.651(c)(2)	Trenches 4 feet or deeper must have a safe means of egress, such as a ladder, ramp, or steps, located within 25 feet of all workers.
Inadequate trench protection against cave-ins	29 CFR 1926.652(a)(1)	Trenches 5 feet or deeper must have protective systems (sloping, shoring, or shielding) unless the excavation is in stable rock.
Improper use of trench shoring system	29 CFR 1926.652(d)	Shoring systems must be installed and maintained according to manufacturer specifications or designs from a qualified person.
Unstable or poorly secured trench walls	29 CFR 1926.651(j)(2)	Excavated materials ("spoils") and equipment must be set back at least 2 feet from the edge of the excavation to prevent material from falling into the trench.
No visible worker fall protection near trench edges	29 CFR 1926.501(b)(7)	Workers near trench edges 6 feet or deeper must be protected from falls by guardrails, fences, or fall arrest systems.
Potentially insufficient inspection of trench	29 CFR 1926.651(k)(1)	A competent person must inspect the excavation and protective systems daily and after any event that could increase hazards (e.g., rain, vibrations).
Cross-bracing without visible safety measures	29 CFR 1926.651(h)(1)	Protective systems and supports, such as cross-braces, must not be altered or damaged, and they must be used properly to prevent collapse.

Recommendations:

1. Install proper access and egress systems: Ensure that ladders, ramps, or other means of egress are provided in the trench.
2. Implement cave-in protective systems: Use sloping, benching, shoring, or trench boxes designed and maintained per OSHA standards.
3. Set spoils at a safe distance: Move spoil piles at least 2 feet from the edge of the excavation to reduce the risk of cave-ins.
4. Provide fall protection near the trench: Use guardrails or barriers near open trench edges to protect workers from falling.
5. Conduct daily trench inspections: A competent person must inspect the trench and shoring systems to ensure safety before work begins.
6. Ensure proper use of shoring systems: Verify that cross-braces and shoring supports are installed per design and remain in good condition.

Example 4: A fatality report

The construction industry experiences the highest number of fatal workplace injuries in the United States, with 985 deaths in 2015, representing 20.4% of all work-related fatalities, despite construction workers accounting for less than 7% of the workforce (BLS, 2016; CPWR, 2017). Effective injury prevention requires thorough analysis and surveillance of contributing factors, yet data sources often lack detailed contextual information, such as safety training or equipment use (Higgins et al., 2001). To address these gaps, the National Institute for Occupational Safety and Health (NIOSH) established the Fatality Assessment and Control Evaluation (FACE) program in 1982, later expanding it with the State FACE program in 1989 (NIOSH, 2024). These programs investigate specific fatal incidents, focusing on areas, such as construction falls, machinery-related deaths, and risks among foreign-born workers. FACE reports compile detailed information, including employer safety practices, training, and use of personal protective equipment, offering valuable insights into the mechanisms of fatalities, and providing actionable recommendations for prevention.

Despite the existing studies on workplace safety and the development of advanced frameworks, such as Vision Zero and the integration of LLMs, there is a critical gap in the systematic review of fatality reports, particularly in the context of detailed, actionable insights. While initiatives like the NIOSH FACE program have provided valuable recommendations and influenced policy and legislation, existing studies largely focus on individual safety aspects or broader strategic frameworks without establishing a comprehensive methodology to critically analyze and standardize fatality reports. The lack of a robust framework to evaluate and synthesize these reports limits their potential for driving evidence-based preventive measures and safety improvements. This study addresses this gap by proposing a structure for the critical review of fatality reports, using NIOSH FACE reports as a case study to enhance their applicability and impact on occupational safety practices.

This example uses the developed system to analyze one of the reports to demonstrate the case of textual data, rather than a picture. Unlike being used in real-time on site as shown in Example 3, this example is expected to be used to make sense of already existing reports, data, and guidelines by administrators. Table 4 presents an instance of such a report that contains details about the incident, including demographic information about the victim, location, scene description, incident details, the investigation report, and future recommendations. It is also presented because the NIOSH FACE report database can be used to further develop this system and test its applicability and reliability by feeding the data (without the investigation report and recommendations) into the system and generating the system's response to compare against the findings and recommendations provided by experts in these situations.

The authors found the results were satisfactory for the current stage of the system. Further improvements are expected to enhance the responses.

Table 4: Safety hazard analysis with OSHA regulation reviewing NIOSH FACE report

Safety Hazard	OSHA Regulation (OSHA, 2025)	Description
Failure to guard skylights with railings or screens	29 CFR 1926.501(b)(4)(ii)	Walking/working surfaces must be protected from tripping on or stepping through holes, including skylights.
Failure to utilize fall protection at heights	29 CFR 1926.501(b)(1)	Workers on unprotected edges or surfaces 6 feet or higher must use guardrails, safety nets, or personal fall arrest systems.
Failure to enforce fall protection	29 CFR 1926.503(a)(1)	Employers must ensure employees exposed to fall hazards are trained to recognize and minimize these risks.
Lack of job hazard analysis (JHA)	General Duty Clause, Section 5(a)(1)	Employers must assess job hazards and implement controls to prevent recognized hazards causing death or serious harm.

Recommendations from the Report:

1. Guard skylights with railings or screens to prevent falls through fragile or transparent surfaces.
2. Enforce the use of fall protection through clear policies, frequent inspections, and disciplinary actions for non-compliance.
3. Perform a job hazard analysis to identify and mitigate risks associated with specific tasks, such as working around skylights or on elevated surfaces.
4. Design out hazards (Prevention through Design) by using materials and structures that inherently reduce risk, such as impact-resistant skylights.

Conclusions and limitations

The use of LLMs offers a groundbreaking approach to improving safety awareness and access to OSHA regulations for construction workers. The complexity of legal language and the diverse backgrounds of the workforce often create challenges in effectively communicating safety guidelines through conventional methods.

The goal of this study is to enhance construction site safety by utilizing LLMs trained on OSHA regulations. These models process images and textual reports from construction sites to identify hazards, align them with relevant OSHA guidelines, and generate actionable recommendations for risk mitigation. This approach enables workers to quickly understand safety regulations, recognize potential hazards, and implement compliance measures without requiring extensive regulatory training. Additionally, it supports on-site Job Hazard Analysis (JHA).

The authors present four examples demonstrating how the approach functions and its expected outcomes. Findings indicate that LLMs have the potential to simplify complex regulatory language, provide task-specific safety guidance, and offer context-aware support. By making safety regulations more understandable and accessible, these AI-driven tools can enhance workplace safety, reduce risks, and improve compliance with OSHA standards, ultimately contributing to a safer and more efficient construction environment.

This research is susceptible to all the limitations of current LLMs, including confidentiality and privacy issues, model hallucinations (although the model is trained on OSHA regulations, it might return fictional responses when appropriate OSHA regulations are not found), and the fine-tuning necessary for specific use cases. The authors plan to fine-tune the current model to statistically validate the applicability of the approach. Statistical validation is critical because the study focuses on the safety and health of individuals, and the consequences of inaccurate responses can be life-threatening. This also highlights the need for an easy-to-use approach in this domain. With the rapid development of reasoning models, the accuracy and reliability of the model are expected to improve significantly, opening new doors for further research.

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