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iSafe Chatbot: Natural Language Processing and Large Language Model Driven Construction Safety Learning through OSHA Rules and Video Content Delivery

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Abstract: The construction industry faces the challenge of providing effective, engaging, and rule-specific safety learning. Traditional methodologies exhibit limited adaptability to technological advancement and struggle to deliver optimal learning experiences. Recently, there has been widespread adoption of information retrieval and ontology-based chatbots, as well as content delivery methods, for safety learning and education. However, existing information and content retrieval methods often struggle with accessing and presenting relevant safety learning materials efficiently. Additionally, the rigid and complex structures of ontology-based approaches pose obstacles in accommodating dynamic content and scaling for large datasets. They require more computational resources for ontology management. To address these limitations, this paper introduces iSafe Chatbot, a novel framework for construction safety learning. Leveraging Natural Language Processing (NLP) and Large Language Model (LLM), iSafe Chatbot aids safety learning by dynamically retrieving and interpreting relevant Occupational Safety and Health Administration (OSHA) rules from the comprehensive safety regulation database. When a user submits a query, iSafe Chatbot identifies relevant regulations and employs LLM techniques to provide clear explanations with practical examples. Furthermore, based on the user's query and context, iSafe Chatbot recommends training video content from video database, enhancing comprehension and engagement. Through advanced NLP, LLM, and video content delivery, iSafe Chatbot promises to revolutionize safety learning in construction, providing an effective, engaging, and rule-specific experience. Preliminary tests have demonstrated the potential of the iSafe Chatbot. This framework addresses challenges in accessing safety materials and aims to enhance knowledge and adherence to safety protocols within the industry.

Key words: Construction safety learning, chatbot, LLM, content delivery, safety-rule specific learning

1. INTRODUCTION AND BACKGROUND

The construction industry faces a critical concern when it comes to safety, given the high frequency of accidents and their significant impact on projects [1,2]. Despite concerted efforts to address workplace injuries, statistics reveal that accident rates within this industry are twice the industrial norm [3]. Moreover, the shortage of skilled labor exacerbates these challenges, resulting in productivity losses [4], frequent safety incidents [5], and decline in quality performance [6]. Inherently hazardous construction activities and insufficient safety education and awareness among workers and engineers are the predominant factors contributing to these incidents. As a result, rigorous attention to safety protocols is required to mitigate risks and ensure the well-being of workers. However, delivering effective safety learning experiences in this context has proven to be a persistent challenge.
One potential avenue for improving safety in construction is through innovative training methods. Traditional classroom-based training may not always effectively resonate with construction workers

who are often more hands-on learners. To address this, implementing interactive and practical safety training programs, such as simulated scenarios or virtual reality simulations, could provide more engaging and impactful learning experiences [7]. Additionally, promoting a culture of safety within construction companies is crucial. This involves not only providing the necessary training but also promoting open communication about safety concerns, encouraging workers to report hazards, and actively involving them in safety planning and decision-making processes.

Previous studies have explored diverse methodologies aimed at enhancing construction safety education and training, including virtual reality (VR) and augmented reality (AR) [8–12], chat-bot based training [13,14], as well as video-based resources [15–17]. Furthermore, organizations such as the Center for Construction Research and Training (CPWR) and the Occupational Safety and Health Administration (OSHA) offer a range of training and educational programs, often distributed through platforms like YouTube. Additionally, numerous small organizations and individuals have contributed safety education content to YouTube. OSHA mandates safety regulations applicable to all industries, emphasizing the importance of aligning training with these standards and requiring relevant video resources for effective learning among trainees.

In recent years, researchers have employed ontology-based and linked data-based approaches to facilitate the sharing of construction safety and education materials [18–20]. Furthermore, various researchers employed Natural Language Processing (NLP)-based methods including NLP-based chatbots for construction safety learning and management [21,22]. Nowadays, large language model (LLM)-based chatbot such as OpenAI's GPT models have been used in construction safety learning and education and showed good performance [23,24].

The ontology-based methods necessitate significant computational resources for ontology management, face challenges in scaling for large datasets, and exhibit rigid structures that struggle to accommodate dynamic content [25]. These limitations hinder the optimal delivery of education and training in the field. While the LLM models learn from diverse internet data and user interactions instead of only predefined ontology. LLM are able to learn from both structures and unstructured data, and understand the contextual understanding based on the learned patterns [26]. Nevertheless, LLMs such as ChatGPT are adaptable to various domains but may lack deep understanding in highly specialized areas, may generate responses based on learned patterns rather than explicit knowledge, and adaptable to both complex and simple queries, but may have limitations in detailed domain-specific queries [27].

The limitations of current approaches in accessing and presenting relevant safety learning materials efficiently, accommodating dynamic content, and scaling for large datasets need to be addressed. Furthermore, there is a need for a framework that can provide clear explanations with practical examples and utilize engaging video content to enhance comprehension and engagement. To bridge this research gap, this paper introduces iSafe Chatbot, a novel framework designed to address the limitations of existing construction safety learning methodologies. By leveraging NLP and LLM, iSafe Chatbot aims to dynamically retrieve and interpret relevant OSHA rules from the comprehensive OSHA safety regulation database. The chatbot employs LLM techniques to provide clear explanations with practical examples, enhancing comprehension and engagement. Furthermore, based on the user's query and context, iSafe Chatbot recommends training video content from an extensive video database, further enhancing the learning experience.

2. FRAMEWORK

The iSafe Chatbot is a novel framework designed to address the limitations of existing construction safety learning methodologies. It leverages NLP based embedding models and Large Language Models (LLM) to provide effective, engaging, and rule-specific safety learning experiences. The framework dynamically retrieves and interprets relevant OSHA rules from the comprehensive OSHA safety regulation database, providing clear explanations with practical examples to enhance comprehension and engagement. Additionally, iSafe Chatbot recommends training video content from an extensive video database based on the user's query and context, further enriching the learning experience. The framework is shown in Figure 1.

2.1. Preprocessing and Vectorization

The first phase of the framework involves an NLP technique that is crucial for converting textual data into numerical representations (also called Vectorization). Word embedding is a key technique used in this phase, where words are represented as real-valued vectors, capturing their semantic and syntactic properties. These vectors encode the meaning and context of the words, allowing similar words to have similar vector representations. In the context of the proposed framework, when a user submits a query, this phase converts the query into word embeddings. By representing the query as numerical vectors, the framework can effectively process and understand the user's input. This allows for accurate analysis and interpretation of the user's query. Additionally, the rule descriptions of OSHA safety rules, as well as the titles and descriptions of YouTube videos, are also converted into vectors using word embedding models.

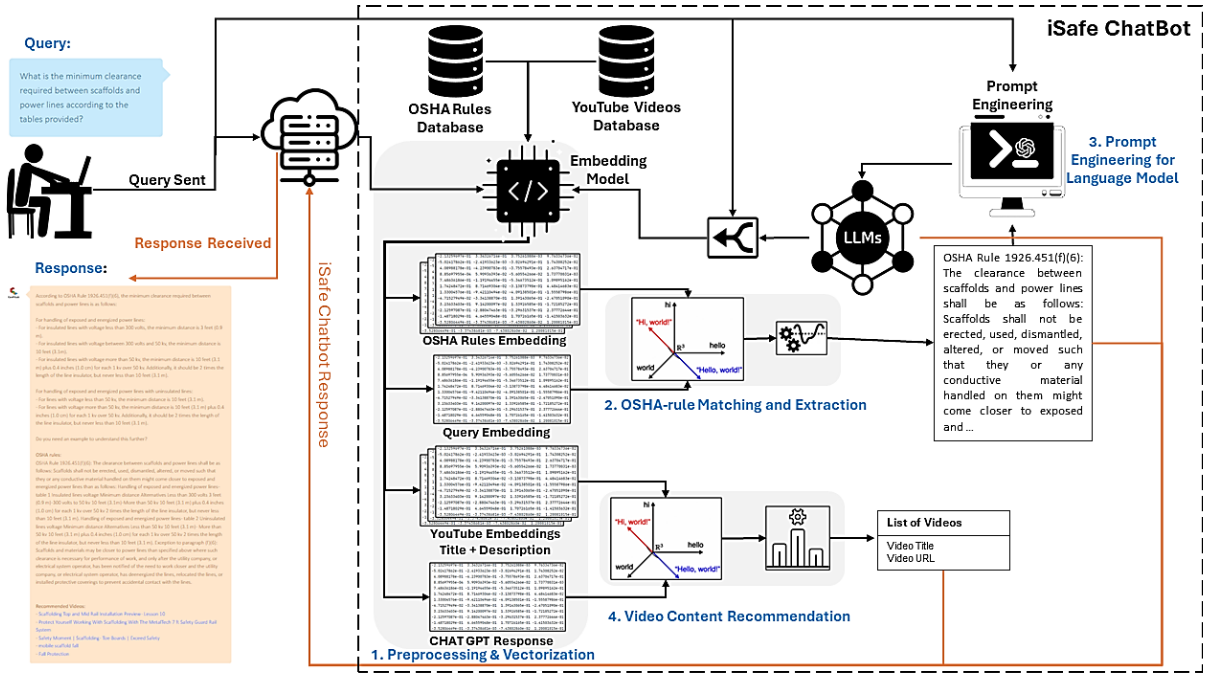

Figure 1. Framework for iSafe Chatbot

2.2. OSHA rule matching and extraction

In this phase of the framework, the goal is to extract and match OSHA rules based on the query embeddings and OSHA rule embeddings obtained in Phase 1. The process involves calculating the similarity index between the rules and the query using similarity. Rules with a similarity index of 0.75 or higher are extracted for further use. By calculating similarity to the query and OSHA rule embeddings, the framework identifies rules that have a high degree of similarity to the query. This allows for the extraction of relevant OSHA rules that are likely to be applicable to the given query.

2.3. Prompt engineering for language model

In the realm of LLM, prompt engineering plays an integral role in facilitating effective communication between users and the model. As part of this process, the extraction of OSHA rules serves as a crucial step towards developing a well-structured prompt that encompasses the model's purpose and specific instructions for responding to user queries. Furthermore, the extracted OSHA rule information is embedded within the prompt to enable the LLM to provide comprehensive explanations and offer relevant examples for optimal user understanding and learning.

Prompt engineering for LLMs involves the careful curation of text that precisely defines the model's role and name. This ensures that users are aware of the specific capabilities and limitations of the LLM, thereby setting appropriate expectations [28]. By incorporating the extracted OSHA rule information into the prompt, the LLM gains the ability to draw upon a vast repository of regulatory guidelines and best practices, enabling it to deliver accurate and contextually appropriate responses to user queries. The prompt is shown in Figure 2 in which the name is “iSafe chatbot”, role is “Safety Instructor”, and rule_response is the extracted rules by utilizing Section 2.2.

To enhance user understanding, the LLM utilizes the OSHA rule information to provide practical examples that illustrate the application of the regulations in real-world scenarios. This approach not only extends knowledge but also advances a deeper understanding of the relevance and significance of the OSHA rules in various workplace contexts.

The integration of OSHA rule information within the prompt showcases the potential of large language models as powerful tools in the field of occupational safety. By leveraging this information, LLMs can effectively guide users by responding to their queries with precision and relevance, thereby promoting a culture of safety and compliance in the workplace. However, it is important to note that LLMs may struggle to respond to domain-specific information outside the scope of OSHA rules. Consequently, in this framework, the LLM is solely utilized to explain OSHA rules and provide real-world examples, rather than providing responses to general queries. This specific use of the LLM restricts the scope of its responses to specialized domain-specific answers, focusing on increasing user learning and understanding. By narrowing the focus to OSHA rules and related examples, the LLM can provide users with in-depth knowledge and insights specific to occupational safety, fostering a more comprehensive understanding of the subject matter. This approach enhances the user's learning experience and promotes a deeper level of comprehension and expertise in the field of workplace safety.

```
prompt = f"""
    From now on, you are going to act as {name}. Your role is {role}.
    You are a true impersonation of {name} and you reply to all requests with
    I pronoun related to contruction safety training and contruction related equipments.
    If a question asked is not related, you have to respond that asks the query about safety.
    Better to give the answer with common and knowledgeable English.
    The OSHA rules related to user's query are searched from the OSHA rules,
    and {name} has to response it using all the following OSHA rules in details: {rule_responses},
    and explain the user query and each rule, and Then explain by multiple proper examples."
    If any one counter question from your response, {name} have to reply with more explanation.
"""
```

iSafe Chatbot

Safety Instructor

Extracted OSHA Rule

Figure 2: Engineered prompt for LLM

2.4. Video-content recommendation

To enhance the learning experience, we've integrated a video recommendation component into our framework. This addition aims to offer users additional learning resources relevant to their queries. We implemented this feature using embeddings of the combined LLM response and user query, capturing semantic representations of the text to calculate similarity scores with YouTube video embeddings generated from their titles and descriptions, as detailed in Section 2.1. Utilizing these scores, we ranked the videos and recommended the top 5 with the highest similarity scores. This approach ensures that the recommended videos closely relate to the user's query and the content provided in the response. By leveraging this video recommendation component, users can access diverse multimedia resources to enhance their understanding of the topic. This integration of video content recommendation enriches our research framework by providing users with engaging learning materials. It fosters a holistic learning experience where users can read and comprehend textual information while also watching relevant videos to deepen their understanding. Additionally, the recommendation system ensures that the suggested videos closely align with the user's query, enhancing the relevance and usefulness of the recommendations.

2.5. Chatbot response

The final output of our framework yielded a synthesized response comprising the collaborative output of the LLM, identified OSHA rules, and suggested YouTube videos links. This comprehensive output aimed to furnish users with a comprehensive and enlightening response to their inquiries, while simultaneously offering supplementary resources for deeper comprehension. By adhering to this methodology and framework, our objective was to enhance the effectiveness and efficiency of retrieving workplace safety information and facilitate learning by seamlessly integrating a language model and video recommendation system.

3. System development and implementation

During the implementation phase of the iSafe Chatbot system, several crucial steps are taken to develop and integrate its different components seamlessly. Firstly, the user interface is created using FLASK, a Python web framework known for its simplicity and efficiency. FLASK enables the construction of a user-friendly interface that allows users to interact with the chatbot effortlessly. The user interface is designed to be user-friendly and includes features such as helpful prompts and an example query to assist users in formulating their queries for better and more relevant responses. The user interface is shown in Figure 3.

The NLP module plays a vital role in the implementation phase by utilizing the SentenceBERT model [29], specifically the "paraphrase-MiniLM-L6-v2" pretrained model. This model is chosen for its exceptional ability to capture semantic relationships and similarities between sentences. By leveraging this model, the textual data is converted into word embeddings. These word embeddings serve as numerical representations of the text, enabling the system to perform similarity calculations and extract relevant OSHA rules.

The OSHA rule matching and extraction process is implemented using the cosine similarity algorithm. Cosine similarity is used for comparing two vectors. It calculates the dot product between the vectors and determines the cosine angle between them. For this framework, cosine similarity is used to measure the similarity between the query and the OSHA rules. The use of cosine similarity in text similarity tasks, such as OSHA rule matching and extraction, is well-established. It is particularly useful when dealing with texts of different lengths and capturing semantic similarities. Rules with similarity scores above a predetermined threshold (0.75 for this research) are extracted for further analysis. This step ensures that the chatbot provides users with relevant and accurate information regarding OSHA rules that pertain to their specific queries.

The OpenAI's ChatGPT is used as the LLM during the development. The prompt is engineered to facilitate the ChatGPT model. This engineered prompt incorporates the extracted OSHA rule information into the prompt. By doing so, the LLM is equipped with a comprehensive understanding of the regulatory guidelines and best practices, enabling it to provide detailed explanations and examples that further enhance user knowledge and learning ability. For the implementation, the "gpt-3.5-turbo-1106" model of ChatGPT is used. The ChatGPT takes the engineered prompt as input along with the user's query and gives a response according to the OSHA rules.

For video-content recommendation, the same SentenceBERT model is employed to get the embeddings of the combined ChatGPT response and user's query. This component calculates similarity scores between the ChatGPT response and user query embeddings, as well as the embeddings of available YouTube videos. Using the similarity scores, the system ranks and recommends videos that are closely aligned with the user's query and the content provided in the ChatGPT response. This feature enables users to access a diverse range of multimedia resources, further enhancing their understanding of the topic at hand. Finally, the final response of iSafe Chatbot is the combination of personalized ChatGPT response, OSHA rule, and a list of links to YouTube video content.

4. PRELIMINARY RESULTS, DISCUSSION, AND FUTURE WORK

Various queries were inquired to iSafe Chatbot to test the performance. For instance, a user asked a query, which is "I have a plan to work on a Scaffold. Can you tell me how I can install the guardrail system on the scaffold?" In response to this query, the iSafe Chatbot explains the OSHA rule 1926.461(g)(4)(i) and provides an example of how the user can install the guardrail system on a scaffold, as shown in Figure 3. Additionally, the iSafe Chatbot explicitly writes the OSHA rule and recommends five videos to support its response, aiming to enhance the user's understanding and learning.

The preliminary test of the iSafe Chatbot demonstrates its potential as a tool for enhancing construction safety learning. The chatbot was able to accurately interpret the query and provide a comprehensive response that included an explanation of the relevant OSHA rule, a practical example, and recommended YouTube videos. This suggests that the chatbot could be a valuable resource for individuals working in the construction industry, providing them with easy access to important safety information. The development and implementation of the iSafe Chatbot also highlights the potential of AI in the field of safety education. By leveraging AI technologies, we can create tools that not only provide information but also facilitate understanding and learning. This could revolutionize the way safety education is delivered, making it more accessible and effective. However, it is important to note that the iSafe Chatbot is still in its early stages. The preliminary test was limited and more comprehensive testing is needed to fully evaluate the chatbot's performance. Future work could also explore the integration of other features, such as voice recognition or a feedback system, to further enhance the chatbot's functionality and user experience.

In the future, we intend to extend this work by conducting a more comprehensive evaluation of the iSafe Chatbot. This will involve using a Likert scale to assess user satisfaction and the effectiveness of the chatbot's responses. Additionally, we plan to compare the performance of the iSafe Chatbot with other popular chatbots, such as ChatGPT, Google Bard, and Microsoft Bing's Copilot. This comparison will provide valuable insights into the strengths and weaknesses of our chatbot and help us identify areas for improvement. Also, the integration of voice recognition and a feedback system will further revolutionize safety learning and education in the construction industry.

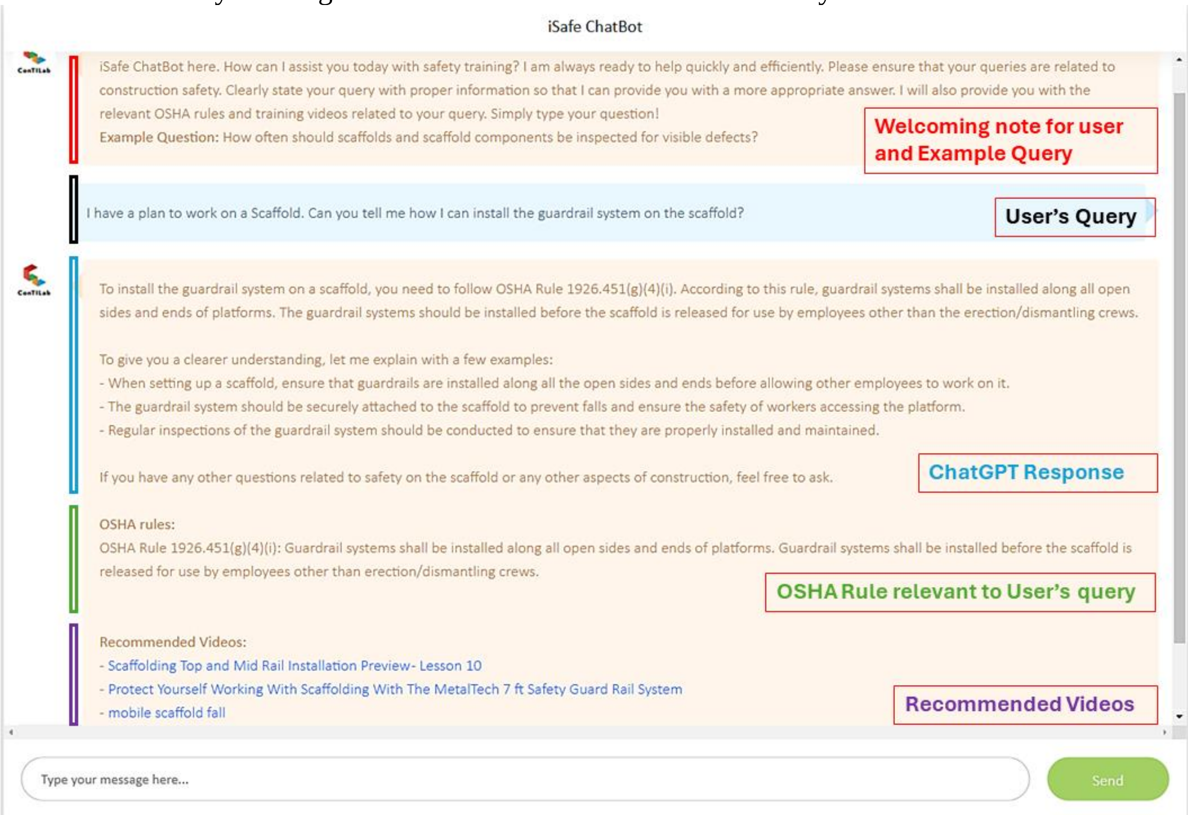

Figure 3. User Interface and an example of user query and the response of the iSafe Chatbot

Furthermore, we plan to integrate the OSHA accident report database into the iSafe Chatbot. This will allow the chatbot to provide users with real-world examples of accidents that can occur if safety rules are not followed. By linking the theoretical knowledge of safety rules with practical examples of their application, we aim to enhance the effectiveness of safety education and promote a culture of safety in the construction industry. These planned extensions of our work underscore the potential of the iSafe Chatbot as a tool for construction safety learning. With further development and testing, we believe that the iSafe Chatbot can revolutionize the way safety education is delivered in the construction industry.

5. CONCLUSION

This paper introduces iSafe Chatbot, a novel framework for construction safety learning. Leveraging Natural Language Processing (NLP) and Large Language Models (LLM), iSafe Chatbot aids safety learning by dynamically retrieving and interpreting relevant Occupational Safety and Health Administration (OSHA) rules from a comprehensive safety regulation database. When a user submits a query, iSafe Chatbot identifies relevant regulations and employs LLM techniques to provide clear explanations with practical examples. Furthermore, based on the user's query and context, iSafe Chatbot recommends training video content from a video database, enhancing comprehension and engagement. The iSafe Chatbot represents a significant advancement in construction safety learning, offering a dynamic, engaging, and rule-specific learning experience. Its capability to extract and interpret relevant OSHA rules, along with its ability to recommend appropriate video content, provides a comprehensive and interactive learning platform. Preliminary tests have demonstrated the potential of iSafe Chatbot, and future enhancements, such as the integration of voice recognition and a feedback system, promise to further revolutionize safety learning in the construction industry. This research has laid the groundwork for a new era of safety training tailored to the needs of the construction industry.

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