UTILIZING GENERATIVE AI FOR HAZARD IDENTIFICATION

By David Stumbo

There is little guidance on the practical application of generative artificial intelligence (GenAI) for hazard identification. With the widespread adoption of artificial-intelligence-powered platforms and embedded applications, safety professionals may face a substantial learning curve.

The urgency of the situation cannot be ignored. Authorities warn: "Despite high stakes for workers, we are not prepared for the potential risk and opportunities that generative AI is poised to bring" (Kinder et al., 2024). Unfortunately, safety professionals may find many publications overly technical or focused only on device-based applications such as wearable sensors (Karakhan et al., 2021). This article provides guidance to safety practitioners, trainers and educators on how to use GenAI within a repeatable how-to framework for the essential skill of hazard identification.

GenAI can be a helpful tool to quickly provide detailed information on potential hazards. Effective application of GenAI is dependent on understanding basic operational elements of the model employed and utilizing best practices for structuring prompts. However, GenAI output must be used responsibly. This includes reviewing the output for errors, using outputs only within one's expertise, and protecting data privacy.

Hazard Identification: Foundational to Safety

Spotting hazards is an essential skill in safety, such as recognizing poorly constructed scaffolding and unguarded machinery. Its importance has been highlighted in Manuele's (2020) guide for the development of hazard analysis and risk assessment. It is also central to job hazard analysis (Islam, 2021) and controlling hazards (Roughton & Mercurio, 2002). Formal standards reinforce this emphasis. For example, ANSI/ASSP Z10.0-2019 calls on organizations to "establish, implement and maintain a process(es) for hazard identification" (Section 8.2.1). ISO 45001, Occupational Health and Safety Management Systems: Requirements With Guidance for Use (ISO, 2018), carries similar provisions in Annex 6.1.2.1.

Artificial Intelligence: Technology for Safety

Artificial intelligence systems are primarily used to analyze data and make predictions (WIPO, 2024). Early safety applications include expert safety systems (Winn et al., 2002), neural networks to describe the relationship between safety interventions and incidence rates (Al-Mutairi & Haight, 2009), video analytics to improve construction safety (Ng, 2024), and the implementation of smart PPE technology (El-Helaly, 2024).

The generative portion of GenAI means that the application generates new, original content (Investopedia, 2025). Current GenAI models can utilize "a combination of image, text, code, video, and audio generation alongside machine learning algorithms to produce solutions to a problem" (Chan & Colloton, 2024). This is a substantial improvement over internet searches that a safety professional might have previously conducted on web browsers using keywords. The world of GenAI is varied, with both free and paid models available. State-of-the-art models include Gemini, Claude and ChatGPT-4 (Yuan et al., 2025), with ChatGPT considered the most popular (Belkina et al., 2025). Several web browsers now embed GenAI tools that can be activated with a click to provide more in-depth results.

A large language model (LLM) is an algorithm trained on large datasets to provide the knowledge base for AI applications. LLMs go beyond advanced search engines because they can also perform complex operations such as making predictions and performing automated tasks. A key strength of LLMs is their ability to understand natural language inputs, meaning that the user can enter questions or prompts in a conversational style (OpenAI Academy, n.d.). For example, the user may prompt an LLM with a simple text-based prompt such as: "Provide OSHA's top 10 most cited standards."

Prompts are the inputs that formulate questions or commands given to GenAI models, and they are the key to effectively using GenAI (Wilkinson, 2024). The adage, "garbage in, garbage out," applies. Prompts must be well-structured to help the model produce more useful results. More details on effective prompting are in the following sections. Having discussed the technical basics, the following case study shows how GenAI can be integrated into instruction and practice.

Instructional Example

The following instructional example, drawn from the author's teaching experience, illustrates how GenAI can be integrated into instruction and practice. Students were enrolled in a course in hazard recognition and control required for a bachelor of science degree in Occupational Safety at Eastern Kentucky University. The three-credit-hour course met twice weekly in person over the semester and included lectures, labs and field trips.

The class demographics were:

- **Gender:** 46% were male and 54% were female.
- **Age:** student age ranged from 20 to 24 years old with a median age of 21 years old.
- **Safety experience:** 62% had no safety experience and 38% had experience as an intern.
- **GenAI familiarity:** 71% were familiar with GenAI.

A Lesson Plan for GenAI

Since the class had no knowledge of steam tunnels, instruction began from a completely uninformed perspective. The lesson was designed as a form of scaffolding. Scaffolding, as defined by Lo & Lin (2021), is an instructional technique in which the instructor determines the learners' level of knowledge (in this case, relative to the use of GenAI for hazard identification), breaks the task into a simplified process, models the skill, and then provides hints and help until the learner reaches proficiency. Thereafter, the instructor reduces directed instruction (much like scaffolding moved from a new wall) to allow for more self-directed learning. Scholars note that the application of AI in educational settings should be used to scaffold student learning rather than simply as a means to produce content to

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GETTING STARTED WITH GENERATIVE AI

- **Start with simple prompts**. Begin hazard identification by asking basic, conversational questions about the worksite or process to quickly gather foundational safety information before refining your search.
- **Refine prompts for better results.** Improve GenAI output through iteration by adding specific details such as the type of work, environment or equipment involved to generate more targeted hazard insights.
- **Verify AI-generated information.** Review all GenAI responses critically for hallucinations, outdated regulations or inaccurate details, and confirm key information using OSHA, ASSP or other authoritative sources.
- **Use visuals to improve hazard recognition.** Request photos, diagrams or equipment images through GenAI tools to better understand unfamiliar environments, processes or machinery before field work begins.
- **Create and reuse effective prompts.** Build a personal prompt library of successful questions and instructions to streamline future audits, inspections and hazard assessments.
- **Protect sensitive information.** Never upload confidential workplace data directly into GenAI tools; replace identifying details with unique placeholders to reduce privacy and security risks.

"ensure cognitive development and critical reflection" (Balart et al., 2025).

The lesson was planned to consider hazards that might be encountered on a field trip to a worksite involving renovation work to a buried steam tunnel located on the university's campus. In advance of the site visit, instruction on OSHA's (2011) Focus Four hazards—falls, caught-in/between, struck-by and electrocution—was provided by traditional lecture.

Instruction then moved to the utilization of GenAI. The instructor used direct questioning to gain an understanding of the class's experience with the tool's use. While some students had safety experience from safety internships, none had employed GenAI for hazard identification. All had used some form of GenAI for other pursuits. To ensure a basic level of familiarity, an introductory lecture on GenAI with demonstrations using the Gemini 3 Flash model was provided. These began with the basic operation of the model and then progressed to demonstrations of how prompting could be leveraged to obtain information regarding the nature of steam tunnels and potential hazards that might be encountered.

The Instructional Process

Getting Help From GenAI With a Basic Prompt

Instruction started with using a simple prompt to request information about the type of worksite (e.g., "What is a steam tunnel on a college campus?"). The GenAI model provided a substantial number of applicable details, as well as some irrelevant content. The model organized the content into a section that explained the nature of steam tunnels with typical maintenance needs. Then, it listed potential hazards such as extreme heat, asbestos and slippery surfaces.

The irrelevant information provided by the model was about legends, explained as a hazard arising out of the mysterious and cryptic nature of steam tunnels. This was an AI hallucination, which is the term for output that is inaccurate, inappropriate or nonsensical (Lin et al., 2022). The occurrence provided a substantial illustration of the need for safety professionals to critically review GenAI outputs and filter out irrelevant or inaccurate content.

Getting Visual Information

To help students better understand the basic operational and hazard information already gathered on steam tunnels, a second prompt was issued to the model: "Show me some photos of steam tunnels on college campuses." The photos provided by this prompt accurately displayed several good images of steam tunnels, but none were undergoing construction. More prompting was needed.

Success From a Refined Prompt

A refined prompt next asked the GenAI model to provide photos for a college steam tunnel "being renovated" to ensure that the output included construction work. The output provided several good photos of a steam tunnel undergoing renovation work. The model also hyperlinked to a website where the photos originated, at a campus located in California. The website was then reviewed and found to offer insights into that project, such as work processes and materials of construction. This served as an opportunity to demonstrate how links provided in GenAI output could be explored to discover more unsafe conditions. For example, the project involved welding, a process that could be subjected to further research and hazard identification.

From Scaffolding to Self-Directed Learning

After students demonstrated an understanding of prompting, they applied the Gemini 3 Flash GenAI model themselves. The class was directed to use the same prompt: "What occupational hazards could arise during a steam tunnel renovation on a college campus?" Discussions then considered the output, which concerned hazards such as excavations, falls, traffic and heavy equipment operation. The class was then directed to further explore the output provided by the model into areas such as the nature of excavation hazards and traffic-zone safety for self-directed learning and practice using the model.

Verification Through Application

To verify skill acquisition, students were given homework assignments in which they had to apply GenAI for hazard identification. These assignments expanded into additional subject areas (e.g., causal analysis) and confirmed that the students could apply what they had learned.

Implications of Using GenAI for Hazard Identification

This case study demonstrates that structured instruction can move learners from general familiarity to the successful application of GenAI to detecting potential hazards. As a result, they are now equipped to utilize GenAI for hazard identification in future scenarios, laying a foundation for broader use in professional practice. The case study has implications beyond the classroom, as it offers guidance to both instructors and practicing safety professionals.

Education & Training

Educators at both community college and university levels can adapt this approach to strengthen instruction on hazard identification. Safety professionals, who often provide training on workplace hazard recognition and assessment, can utilize the methodology as well. For example, a safety committee training session could provide instruction using a GenAI model accessed directly from their smartphones during the instruction. This approach makes training more interactive and modern.

Field Work

EHS professionals can also apply the methods described in this article to learn how to use GenAI effectively for their work in the field. A key benefit is that information returned is likely to be faster and more clearly presented than the traditional practices of multiple internet

TABLE 1

BEST PRACTICES FOR HAZARD IDENTIFICATION PROMPTS

Consider the following scenario. You have been assigned to conduct a safety and health audit at a poultry processing facility, an operation about which you have little previous knowledge or experience. You know the value of using audit checklists, so you would like to create one for this operation. This table offers relevant example prompts for this scenario that follow the six best practices for prompting for hazard identification. The list is not in a particular order.

Best practice	Example prompt
Set the stage by providing context and roles.	"Act as a senior safety professional with 30 years of experience in poultry processing, who must conduct a safety and health audit of a poultry processing facility."
Define the task that you want the model to perform.	"List and explain the occupational safety and health hazards that are likely to be present."
Specify the format and parameters of the response.	"Provide the hazards in a numbered checklist, with separate columns with the headings 'Hazard,' 'Yes,' 'No,' 'Location' and 'Notes.'"
Provide examples of where the task was done correctly.	"Use the attached file as an example." Use this prompt along with a file upload of the desired example.
Evaluate quality by identifying errors and rating responses.	"The checklist is good, except that the fifth and sixth items are too similar." Identify specific errors and issues. "The third sample file is preferred over the others." Provide ranking of the output.
Divide labor by breaking down a complex task into smaller, more manageable steps.	"This will be in three steps. This is the first step." Start with directions for the first step. After the model has completed one step, give directions for the next step.

queries or manually reviewing standards and guidance documents.

Additionally, GenAI models can accommodate site specifics into hazard identification. For instance, a safety professional preparing to evaluate a grain silo on a hot summer day could use their smartphone's GenAI application to summarize confined space hazards that might be encountered when entering a grain silo during the heat of the summer. The returns would consider aspects of grain silo safety and temperature-related hazards, which would have otherwise required more research time. It is worth noting that a GenAI model may also remind the practitioner of hazards that they might otherwise overlook, reinforcing comprehensive hazard recognition and reducing errors.

How to Use GenAI for Hazard Identification

Several best practices for prompting that a safety professional might employ are shown in Table 1. These have been identified as being most effective for GenAI prompting (Anthropic, 2025; Phoenix & Taylor, 2024). Keep in mind that the list is in no particular order, nor are all best practices needed for success with any given task.

The effective utilization of GenAI hinges very heavily on how well the safety professional frames their prompt. Well-crafted prompts can turn GenAI into a rich resource for hazard identification. Once a prompt is given to the model, if the results are not satisfactory, the user can seek to improve the results by the process of iteration, where prompts are improved and refined through rounds of feedback and modification (Symbio6, n.d.).

Photo prompting can use GenAI that is run on a smartphone to provide details for hazard assessment while in the field. For example, when an unfamiliar piece of equipment is encountered (e.g., a front-end loader), upload a photo of it along with prompting text asking about the equipment's operation and potential hazards. GenAI can then list hazards, identify the make and model of the equipment, and likely locate the operator's manual. The audit can now proceed with equipment-specific information. The speed and level of access to safety-related information represent significant advancement in safety practice.

While general instructional videos on GenAI prompting can be found readily found on the internet, it might be easier to follow those produced by the developers of the GenAI model you employ. For example, prompt engineering videos created by Google draw on video and images that show visuals taken directly from Gemini models.

Once the user has become practiced at prompting, they may find that prompts structured in a certain way, such as with certain keywords or phrases, provide consistent returns from the specific GenAI model they use. Saving effective prompts by setting up a list, or prompt library, of helpful prompts to refer to and reuse can help with efficient GenAI operation (Louisiana Tech University & Washington State University, 2024).

Limitations

While GenAI offers clear benefits for hazard recognition, safety professionals must recognize its limitations. Dokas (2025) warns that LLMs can "exhibit significant shortcomings when more profound domain expertise, regulatory compliance, or systematic risk assessment is required." Accordingly, safety professionals using GenAI for hazard identification must employ it responsibly.

A substantial limitation is the risk of hallucinations (i.e., errors in GenAI output. Examples include revoked regulations, fictitious references or outdated exposure limits. Qualified human oversight is essential to review output for appropriateness and accuracy (Iyenghar, 2025; Office of Educational Technology, 2023). For safety professionals, one practical method beyond basic output review is to perform a check that the sources provided by the model link to the appropriate governmental sources (e.g., OSHA), professional safety resources (e.g., ASSP) or scholarly publications.

Users must be cognizant of the limitations of their own depth of understanding and capabilities. Accepting a model's output as the unquestionable truth risks violating the professional ethical standards, such as BCSP's (2022) Code of Ethics edict that safety professionals perform their duties only when appropriately "qualified by education or experience in the specific technical field(s) involved." Also, safety professionals must be cognizant that GenAI is best thought of as only one tool, not a substitute for the formal hazard identification and analysis practices required by standards such as ANSI/ASSP Z10.0-2019.

Finally, privacy is a concern since data breaches, unauthorized access and exploitation of sensitive information in the datasets leveraged by LLMs are possible (Gupta et al., 2023). The GenAI user must treat all data given to the model in prompts with care, following the same privacy practices they would with other applications and on other platforms. A practical and commonly engaged safeguard is to replace sensitive data with unique identifiers, stored separately from confidential records, and never included in prompts or files uploaded into models. By recognizing and accounting for these limitations, safety professionals can ensure that GenAI remains a supportive tool, rather than a replacement for professional judgment, regulatory compliance or ethical responsibility.

Conclusion

Safety professionals must learn to effectively use GenAI for hazard identification rather than risk being left behind while their peers reap the benefits of the powerful technology. It is likely to quickly become a core competency in the EHS field. An understanding of how to operate GenAI models can quickly provide a wealth of information on hazards. Structuring prompts effectively can be mastered by following the best practices discussed in this article. While its limitations must be addressed, safety professionals stand to benefit significantly from GenAI. It is time to integrate this remarkable technology into safety practice. PSJ

Disclaimer

During the preparation of this article, the author used Microsoft Copilot and Google Gemini 3 Flash to assist with editing. The author has reviewed and edited and takes full responsibility for the content, accuracy and originality of the final publication. Unless cited, all other content was originally created. For updated ASSP AI policy information, see **https://assp.us/AI**.

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