An Artificial Intelligence -Based Approach to Calculating A Risk Assessment Matrix Supported by Safety Management in High-Risk Environments.

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Received: 08 June 2026 | Received Revised Version: 21 June 2026 | Accepted: 05 July 2026 | Published: 28 July 2026

Volume 08 Issue 07 2026 | Crossref DOI: 10.37547/tajet/Volume08Issue07-04

Abstract

The calculation of the Risk Assessment Matrix (RAM) is fundamental to recognizing diverse possible incidents, managing risks, and promoting safety in various high-risk sectors. However, the traditional methods of calculating a RAM value rely on manual evaluation and expert opinion which is often time-consuming and introduces room for variability. This research sets forth a new methodology to improve risk assessment using Large Language Models (LLMs) to "read" incidents, conduct historical analysis, and compute RAM values. The approach refers to the application of LLMs for the understanding and interpretation of complex multi-structured texts for predicting possible consequences, estimating their effects, and their probabilities using historical data. Concerning computation and LLM assessment of risks, the proposed framework was more efficient, accurate, and reliable than conventional models. It was noted that this method is practically useful for enhancing risk management practices in construction and other high-risk industrial environments.

Keywords: Risk Assessment Matrix, Risk evaluation, Safety Analysis, Artificial Intelligence, Large Language Models.

Cite This Article: Jasim, M. H. (2026). An Artificial Intelligence -Based Approach to Calculating A Risk Assessment Matrix Supported by Safety Management in High-Risk Environments. The American Journal of Engineering and Technology, 8(07), 38–52. https://doi.org/10.37547/tajet/Volume08Issue07-04

1. Introduction

The management of safety risks in construction, manufacturing, emergency response, or even handling hazardous materials presents one of the most difficult challenges across a myriad of industries. In these contexts, risk identification and evaluation is a critical step in preventing injuries, accidents, and in more serious cases, fatalities [1], [2], [3], [4]. While traditional approaches towards risk assessment are useful, they tend to be poorly effective, inconsistent, and inadequate at dealing with vast amounts of historical data [5], [6]. A fairly common approach for estimating a specific risk's level in relation to a hazard and measurement is through the 'Risk Assessment Matrix (RAM)' technique; this is a systematic method of risk assessment that enables an organization to identify and quantify risks so that adequate resources can be assigned to mitigate them [7], [8]. On the other hand, RAM calculations were and still are always subjected to expert evaluation and manual appraisals. This approach is time-consuming and inconsistent when addressing complex problems together with large volumes of data [9]. The emergence of new technologies within Artificial Intelligence, particularly those of Large Language Models (LLMs), is likely to greatly improve the efficiency and accuracy of the entire process of risk assessment. As mentioned, large language models (LLMs) have the ability to understand complex text and analyze copious amounts of data accurately and in a contextualized manner in a rapid time frame [10], [11], [12]. In this paper, the use of LLMs in augmenting the RAM computations through incident interpretation, data mining, and risk evaluation was analyzed. This work aims to design and validate a novel approach to RAM calculation using LLMs that guarantees the reliability, effectiveness, and precision of risk assessment computations in environments of considerable danger.

The specific aims of this paper are:

1) To introduce a framework for integrating LLMs into the RAM calculation process
2) To demonstrate how LLMs can be used to interpret complex incident descriptions
3) To show how LLMs can connect current incidents with historical data
4) To evaluate the performance of LLM-supported RAM calculations compared to traditional methods
5) To discuss the implications and potential applications of this approach across various industries

This research helps improve AI-driven tools for risk assessment in high-risk environments and advances safety management practices by achieving these goals.

The rest of this paper is organized as follows: Section Two explains the background of the proposed study and related research, while Section Three outlines the proposed methodology used to obtain the results. Section Four presents the results obtained using the proposed methodology. Section Five explains the impact and implications for future work. Section Seven addresses future work, and Section Eight provides the conclusion.

2. Background and Related Work

2.1. Traditional Risk Assessment Methods

Hazard evaluation is one of the most important components of safety administration in many business sectors, as numerous types of hazardous conditions exist that can lead to undesirable results. A Risk Assessment Matrix (RAM) is a common tool used within many industries for visually illustrating and quantitatively rating the degree of risk. Most conventional RAMs start by developing a list of all hazards, then assigning an estimated impact (usually based on how severe it could be if realized), a possible impact severity (typically using a scale of 0-5), a possible likelihood (usually in terms of frequency/rarity), and finally rate the overall risk factor based upon both the severity and likelihood of realization [7]. Although these techniques provide numerous benefits, they still fail to provide adequate support in several areas. For example, manual assessments take considerable time to complete, may contain biases and/or inaccuracies, and tend to encounter difficulties in comparing large volumes of historical data [13]. Consequently, there is now interest in finding additional, automated means to carry out data-driven hazard assessments. Table 1 provides a comparison among traditional RAMs and AI-based RAMs.

Table 1. A comparison among traditional RAMs and AI-based RAMs.

Feature	Traditional RAM	AI-Based RAM
Approach	Manual and rule-based	Data-driven and algorithm-based
Data Source	Expert judgment, historical records	Real-time data, big data, historical and predictive data
Accuracy	Subject to human bias and limited precision	High accuracy with continuous learning and pattern recognition

Scalability	Difficult to scale across large, dynamic systems	Easily scalable with automated data processing
Speed	Time-consuming due to manual evaluation	Fast, real-time analysis and updates
Consistency	Inconsistent due to variability in expert opinion	Consistent assessments using standardized algorithms
Adaptability	Static – requires manual updates to respond to new risks	Dynamic – learns and adapts to emerging threats automatically
Risk Categorization	Based on predefined categories and thresholds	Adaptive categorization using clustering and classification algorithms
Prediction Capability	Weak – cannot forecast future risks effectively	Strong – uses predictive models (e.g., regression, neural networks)
Transparency and Explainability	High – easy to understand by non-experts	Moderate – explainability depends on the AI model used (e.g., black-box models)
Human Expertise Dependency	High	Low to medium – human experts used for model training and validation
Cost of Implementation	Low to moderate	Moderate to high initially, but lower over time with automation
Maintenance	Periodic manual review and update needed	Self-updating (in advanced systems) with minimal human intervention
Application Examples	Construction safety, healthcare risk matrices, cybersecurity checklists	Financial fraud detection, industrial hazard prediction, real-time threat alerts

2.2. Applications of AI in Safety Analysis

Artificial Intelligence (AI) - based Safety Analysis is gaining popularity as a tool for improving the safety of various workplaces. For example, Smetana et al. [1] used Large Language Models (LLMs) for analyzing both Construction Safety Data and Highway Construction Accidents. The study showed how Natural Language Processing (NLP) tools can be combined with dimension reduction and clustering to enable safety analysis and aid in decision making. Along similar lines, Eskandari et al. [10] developed an LLM system to annotate hazards in dangerous environments. They applied a vision-linguistic model to automatically detect potential accidents in a simulated environment that could then be communicated to users through virtual reality. The researchers reported high levels of user satisfaction with respect to the effectiveness of communicating hazards, demonstrating that LLM's can improve safety in automated systems. Several different applications of AI for safety analyses are being researched. For example, predicting accidents with Machine Learning, Analyzing Incident Narratives with Natural Language Processing and Detecting Hazards with Computer Vision. These studies illustrate the increasing reliance on Artificial Intelligence technologies to enhance workplace safety management systems.

2.3. Large Language Models in Risk Assessment

The advent of sophisticated tools such as the LLMs brings to the fore new possibilities for understanding and analyzing complex texts. Unfortunately, the application of such models to risk assessment is not only neglected, but most other areas also suffer from a lack of basic applied research. The scope of application of LLMs in risk assessment is large, including the handling of large amounts of unstructured textual information, discerning intricate relationships between different factors, and conducting sophisticated contextual analysis [10]. Some efforts have begun to address the use of LLMs in safety-related applications; for instance, Smetana et al. [1] used OpenAI's GPT-3.5 model to analyze narrative texts within safety incident reporting documents. Their project illustrated how LLMs can enhance text-based incident investigation and comprehensively analyze the reasons behind incidents. In another direction, Eskandari et al. [10] used GPT-4o for hazard identification in the virtual world and reported remarkable results in terms of accurate identification of safety hazards. There is a notable void in the development of research that concentrates particularly on the utilization of LLMs for calculating Reliability, Availability, and Maintainability (RAM) metrics. This paper proposes to fill that void by introducing a novel method that uses LLM technology by providing a comprehensive integration framework for RAM calculation and examining its performance against conventional approaches.

3. Methodology

3.1. *Overview of the LLM-Enhanced RAM Approach*

The capabilities of the LLMs are exploited in the proposed approach to enhance the traditional RAM calculation process as depicted in the general workflow in Figure 1.

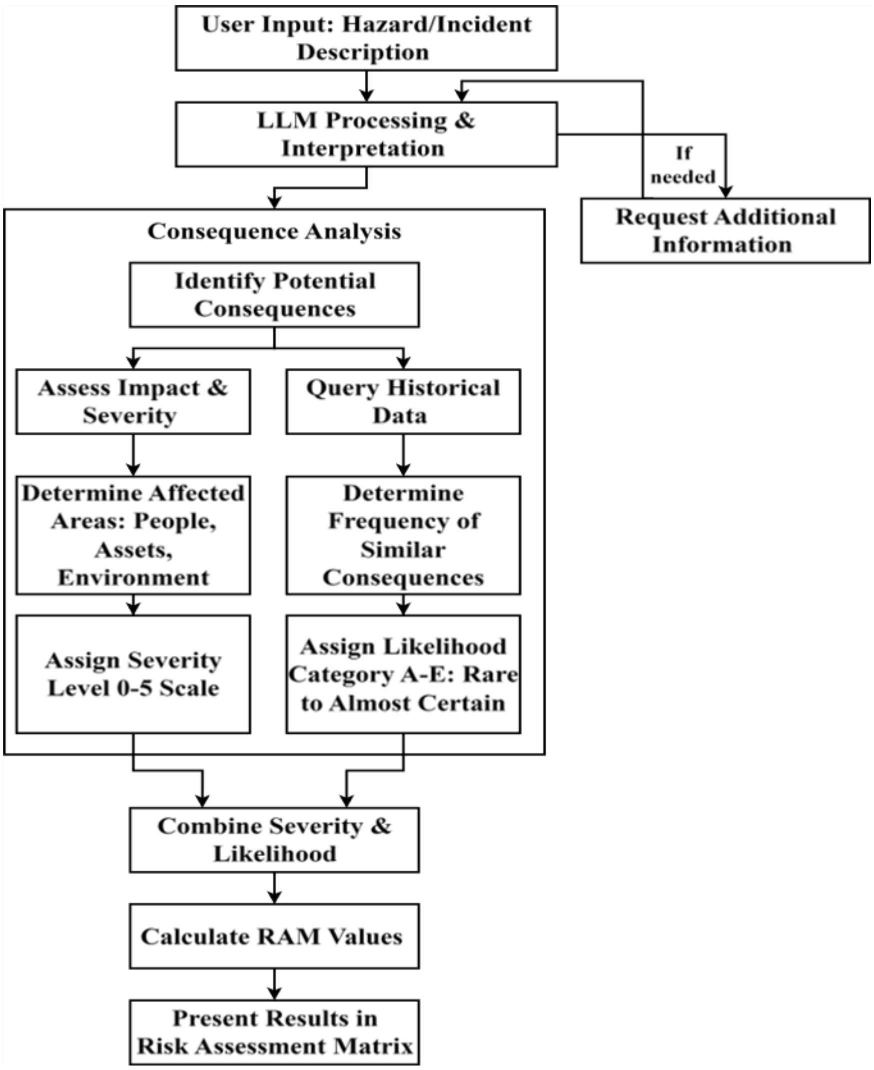

Figure 1. General workflow of the LLM-enhanced RAM calculation process.

This procedure starts with a prompt, which is submitted by the user describing either a hazard or incident. The LLM analyzes this input and communicates to the user if further information is required to understand the user's scenario. For every incident, the LLM outlines consequences associated with the incident based on the understanding developed of the situation. Subsequently, the LLM evaluates each consequence in terms of its impact and magnitude, considering whom or what it affects (people, assets, environment) and assigning a potential severity level ranging from 0 to 5. The LLM then retrieves pre-existing information to gauge whether similar consequences occurred in the past which influences the likelihood estimation (classified A-E from rare to nearly certain). In the end, the LLM integrates performed assessments i.e. severity and likelihood to estimate the RAM of each consequence, which values are represented in the Risk Assessment Matrix. Hence, this method exploits the capabilities of LLMs in processing and understanding complex textual information, while also incorporating structured historical data analysis for more informed risk assessments.

3.2. LLM Selection and Configuration

A cutting-edge Large Language Model (LLM) with a Transformer Architecture that is comparable to the type of model recently utilized in safety studies was the model selected in this study. The model chosen for use in this study was based upon its performance on tasks requiring it to understand and interpret complex text; analyze structured data; and reason in a nuanced fashion. In addition to being able to identify hazards and their consequences, the model was also capable of assessing the potential severity of such hazards and evaluating the likelihood of occurrence. The context from which the system definition was derived and interpreted by the LLM was contained within the detailed prompts provided. The model was evaluated using a iterative process of testing to develop a refined prompting strategy that would provide precision and reliability in producing different results under various test conditions.

3.3. Data Sources and Processing

The LLM enhanced RAM method uses a variety of information inputs for making predictions based on user-provided hazard/incident information:

1) Incident Data: Hazard/Incident descriptions (text) are used to provide input for the LLM model to analyze.

2) Historic Incident Data: Historic Incidents (with associated outcomes/consequences) will support assessing likelihood. Historic Incident Data may originate from within the Company and/or Industry-wide repositories i.e. OSHA SIR [1] to name one source.

3) Safety Standards/Guidelines/Regulatory Requirements: This provides context to the model’s interpretation/recommendations using standard language and practices.

Data processing refers to the organization of varying forms of data in a way that can easily be utilized by an LLM. In this case, the steps taken were embedding relevant standards and policies into the LLM’s knowledge base, and organizing historical data for easy retrieval; these steps were to ensure text data consistency

3.4. RAM Calculation Process

The proposed approach involved the following RAM computation steps:

1) **Hazard understanding:** The description of the incident is processed by the LLM to determine, among other things, the type of hazard, its specific context, and other relevant environmental factor(s).

2) **Consequence prediction:** Based on its understanding of the hazard, the LLM identifies potential consequences, considering various scenarios and outcomes.

3) **Severity assessment:** An evaluation of the influence of each consequence on humans, assets, and the environment is conducted by the LLM before applying a categorization ranging from 0 (negligible) to 5 (catastrophic).

4) **Likelihood determination:** The LLM generates queries for searching the historical data for similar incidents; this is followed by an analysis of the frequency of comparable consequences to ascertain the likelihood levels (from A = rare to E = almost certain).

5) **RAM value calculation:** Severity and likelihood assessments are combined according to a predefined matrix to calculate the overall risk level for each consequence.

6) **Visualization and reporting:** The outcomes of the analysis are presented in a Risk Assessment Matrix and based on the identified risk levels, suggestions for risk mitigation are made.

This approach leveraged the LLMs' capabilities in natural language processing and reasoning, as well as their ability to integrate structured data analysis for complex data-driven risk assessment tasks.

3.5. Evaluation Metrics

To evaluate the effectiveness of the LLM-enhanced RAM approach, the following key metrics are defined [14], [15], [16]:

1) **Accuracy:** The rate of correctly identified high-risk scenarios based on safety experts' opinions.
2) **Speed:** Time required to complete a comprehensive risk assessment, compared to traditional manual methods.
3) **Consistency:** Variability in assessments for similar incidents or across different evaluators.
4) **Data utilization:** The quantity of historical data points used in the assessment process.
5) **Comprehensiveness:** The capability to identify subtle risk factors that could be overlooked in manual assessments.

The performance of the LLM-enhanced approach is evaluated against traditional RAM calculation methods using these metrics.

4. Experimental Results

This section outlines the simulation-based experimental calculations of the RAM's processes with synthetic incident data; the method comprises both risk assessment parameters computation and output visualization to illustrate the efficacy of LLMs in improving risk assessment frameworks.

4.1. Data Generation Methodology

In this study, a probabilistic approach in MATLAB was used to generate the synthetic incident data used; for each incident i in the dataset of size $n = 200$, we assigned:

1) An incident type $T_i \in$ {Chemical Spill, Electrical Failure, Fall from Height, ...}
2) An impact area $A_i \in$ {People, Assets, Environment}
3) A severity level $S_i \in \{0, 1, 2, 3, 4, 5\}$ corresponding to {Negligible, Minor, Moderate, Major, Severe, Catastrophic}
4) A likelihood level $L_i \in \{A, B, C, D, E\}$ corresponding to {Rare, Unlikely, Possible, Likely, Almost Certain}

Weighted probability distributions were allocated for the different types of incidents, as some incidents have differentiated severity levels, so severity levels were set accordingly.

$$P(S_i = s \mid T_i = t) = w_{t,s} \tag{1}$$

Were:

$w_{\{t,s\}}$ = the weight assigned to severity level s for incident type t; for instance, high-consequence incidents such as explosions were given higher weights for severity levels 3-5.

Similarly, likelihood levels were assigned based on incident types as Equation (2):

$$P(L_i = l \mid T_i = t) = v_{t,l} \tag{2}$$

where $v_{t,l}$ represents the weight assigned to likelihood level l for incident type t.

The incident timestamps were generated using a uniform random distribution across one year as Equation (3):

$$Date_i = CurrentDate - Uniform(0, 365)\ days \tag{3}$$

Where:

- $Date_i$: which is a random date that falls anywhere from 0 to 365 days before the current date.

- $CurrentDate$: This is the current date, the date at the moment you're running this equation.

- $Uniform(0, 365)$: This refers to a random number that is uniformly distributed between 0 and 365. This means that the number can be any value between 0 and 365, and each value within that range is equally likely to be chosen.

4.2. Risk Assessment Matrix (RAM) Calculation

The RAM calculation involved mapping each incident to a cell in the risk matrix based on its severity and likelihood. For an incident i with severity S_i and likelihood L_i, the risk level R_i was determined using Equation (4):

$$R_i = RiskCategory(S_i, L_i)$$

Where $RiskCategory$ is a function mapping each (S_i, L_i) pair to one of four risk levels:

1) Low Risk (1): Typically for low severity and low likelihood
2) Medium Risk (2): For moderate severity/likelihood combinations
3) High Risk (3): For high severity or high likelihood combinations
4) Very High Risk (4): For the most severe and likely combinations

The distribution of incidents across the RAM was calculated by Equation (5):

$$RAM_{s,l} = \sum_{i=1}^{n} I\ (S_i = s, L_i = l)$$

Where I is the indicator function that equals 1 when the condition is true and 0 otherwise?

4.3. Visualization Results

The analysis generated four primary visualization artifacts (See Figure 2), each providing unique insights into the synthetic incident data and risk assessment calculations:

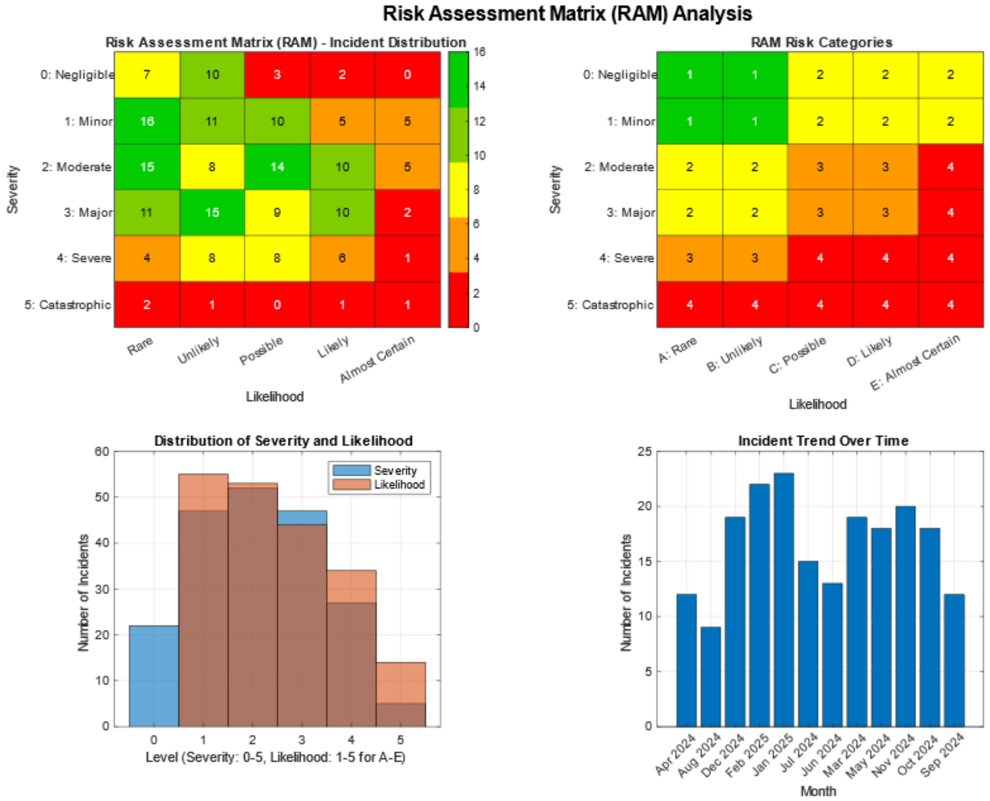

Figure 2 Risk Assessment Matrix (RAM) Analysis showing the incident distribution across different severity and likelihood combinations, risk categories, severity and likelihood distributions, and incident trends over time

Figure 2 presents the core RAM analysis with four key components:

1) The incident distribution heatmap (top left) shows the number of incidents in each severity-likelihood combination.
2) The risk category reference (top right) shows the risk level (1-4) assigned to each cell.
3) The severity and likelihood distributions (bottom left) comparing their frequencies.
4) The incident trend over time (bottom right) shows monthly incident counts

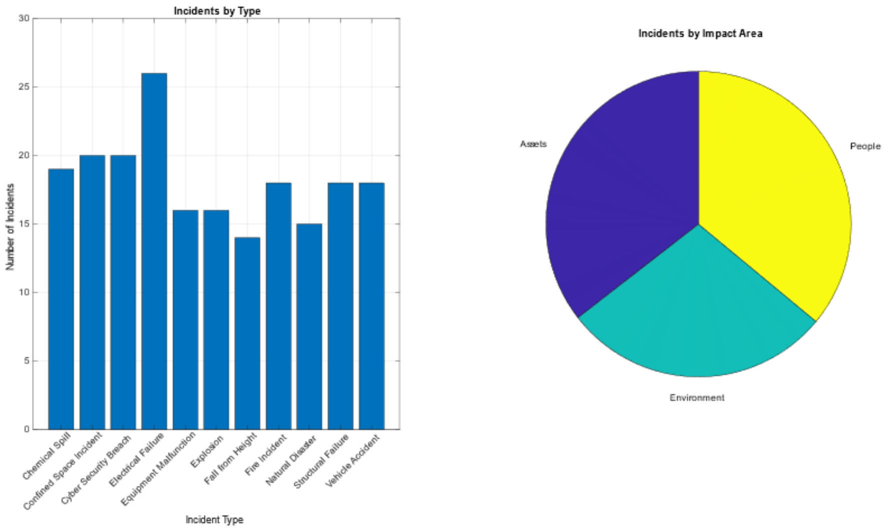

Figure 3 Incident Breakdown Analysis showing the distribution of incidents by type and impact area.

Figure 3 provides insights into the incident characteristics:

1) A bar chart (left) showing the count of incidents by type

2) A pie chart (right) showing the distribution across impact areas (People, Assets, Environment)

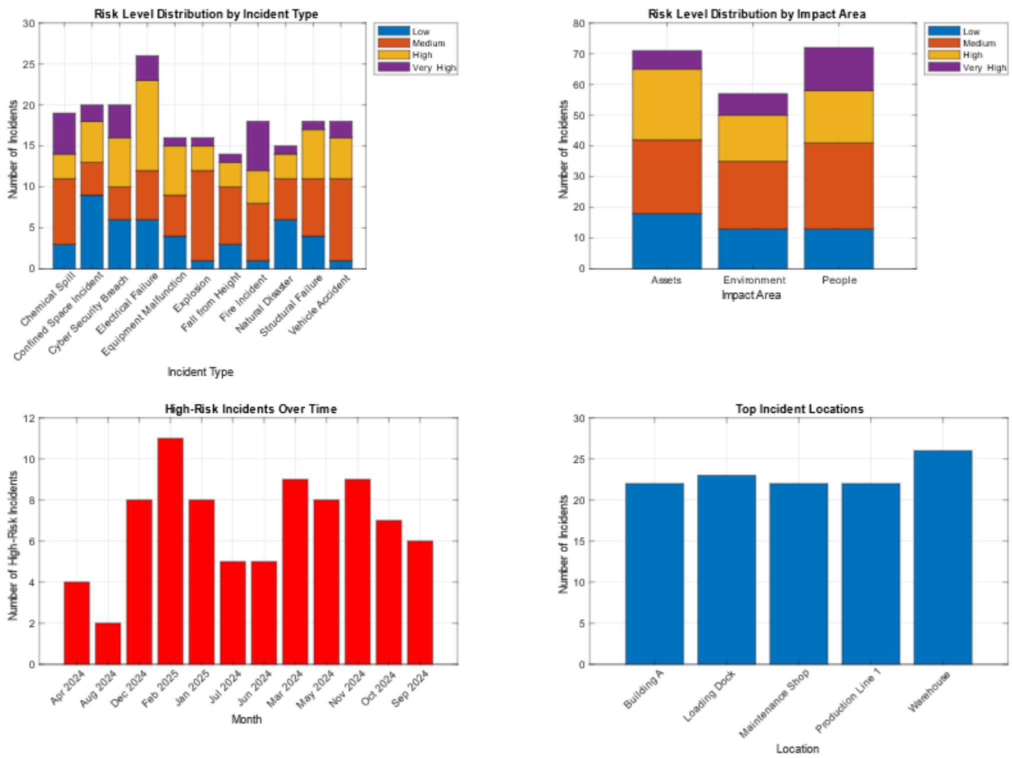

Figure 4 Advanced RAM Analysis showing risk level distribution by incident type and impact area, high-risk incidents over time, and top incident locations.

Figure 4 offers a deeper analysis of risk patterns:

1) Stacked bar charts (top) showing risk level distribution by incident type and impact area
2) Time trend of high-risk incidents (bottom left) highlighting temporal patterns
3) Top incident locations (bottom right) identifying critical areas

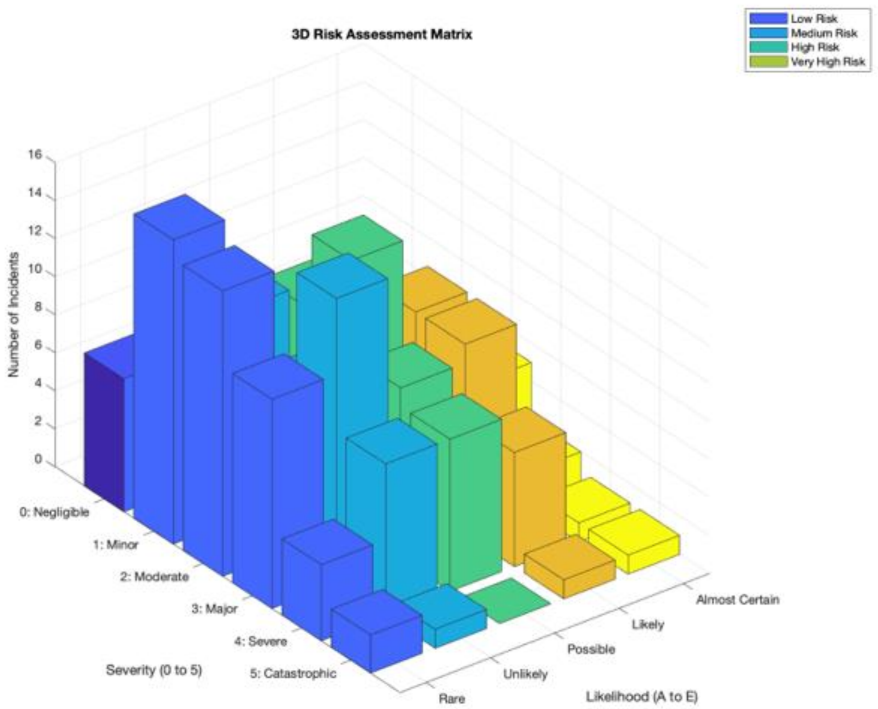

Figure 5 3D Risk Assessment Matrix visualization showing the incident count for each severity-likelihood combination with color-coded risk levels.

Figure 5 presents a three-dimensional visualization of the RAM where:

1) The x-axis represents likelihood levels (A-E)
2) The y-axis represents severity levels (0-5)
3) The z-axis represents the number of incidents
4) Colors correspond to risk levels: blue (Low), green (Medium), orange (High), and Yalow (Very High)

4.4. Key Observations

The graphic representations identify a number of important trends within the synthetic data:

1) Distribution of Incidents: The heatmap (Figure 2), indicates the greatest frequency of incidents occur at both low to medium severities (1-3) and moderate likelihoods (B-C).
2) Incident Types by Risk Profile: Figure 4 illustrates how some types of incidents (Equipment Malfunctions, Electrical Failures etc.) have more frequent counts; however, they also have lower proportions of risk versus other types of incidents (Explosions, Fire Incidents etc.), which are less frequently occurring; yet have greater risks associated with them.
3) Proportion of Impact Areas of High-Risk Cases: There is an increased proportion of people related incidents that are high risk as opposed to environmental or equipment/asset related incidents.

4) Temporal Trends: The trend for high-risk incidents is seasonally affected with two peak periods identified as February 2025 and later months in 2024, potentially identifying cyclic or periodic risk contributors.

5) Hotspot Locations: The Warehouse has the most frequent incidents of all locations illustrated; therefore, it may be worth conducting targeted risk reduction actions.

4.5. Mathematical Implications for LLM Application

These visualizations illustrate ways that LLM enhanced risk assessment processes will enhance risk management:

1) Analyzing Incident Types: The relationship between incident types, incident severity and probability to occur are extremely difficult for humans to learn from historical data. Therefore, we believe that LLM's can identify those relationships from historical data. This ability to recognize these relationships will allow us to make a more accurate estimate of potential risk associated with new incidents.

2) Temporal Patterns in High-Risk Incidents: From the visualizations provided in Figure 4, it is apparent that there are patterns to when high-risk incidents typically occur. We also have confidence that this information will allow LLM's to take into consideration seasonal and other time related factors when estimating the potential risk of an incident.

3) Creating Context Aware Risk Assessments: The difference in the risk profile for each of the five impact area's listed above illustrates that LLM's will be able to create much more detailed risk assessments based on the unique characteristics of each individual incident.

We propose modeling the relationship between the descriptive nature of an incident and its relative risk assessment parameters using mathematical models similar to equation (6) below:

$$P(S = s, L = l \,|Description) = F_\theta(Description) \quad (6)$$

Where

f_θ = the LLM function with parameters θ that maps incident descriptions to probability distributions over severity and likelihood combinations.

These visualizations serve a dual purpose; they validate the process of synthetic data generation and showcase the potential conclusions that can be drawn from an enhanced LLM RAM calculation system.

4.6. Case Study Applications

To assess the effectiveness of the RAM methodology enhanced by LLM, we applied it across a number of case studies in diverse high-risk environments; two typical cases are described below.

4.6.1. Construction Safety

The construction process that occurs when building highways is like every other type of construction project — (traffic, weather, large/heavy equipment) create numerous problems for all parties involved [1]. Therefore, the RAM strategy using an enhancement called LLM was used to analyze the risks related to performing repairs to a road while active traffic exists. Additionally, the LLM identified several possible outcomes from the consequences listed above (worker/vehicle collision, equipment injury, illness caused by prolonged exposure to high temperatures). It also assigned a Likelihood & Severity Grade for each of these based upon available historic data regarding accidents/ incidents at construction sites from the OSHA SIR Database Incidents Analysis [2], as explained earlier. This was extremely effective in identifying and quantifying heat-related risks that traditional methods ignore although they contribute to many of the construction worker deaths/injuries. The LLM analyzed the historic data from similar circumstances and found numerous examples of workers experiencing over heating; therefore, sufficient Risk Scores were established and appropriate Mitigation Strategies were developed.

4.6.2. Hazardous Material Handling

The procedure was applied to a case where hazardous chemicals were being handled within an industrial plant. The LLM analyzed the description of the incident, predicting and examining possible outcomes/chemical spill, exposure, chemical reaction, and its risks in terms of severity and probability. The approach had a high-level understanding of chemical risks, making assessments based on the chemical and historical events involving other chemicals. This allowed for sophisticated risk analysis considering multiple factors like the chemical nature, the presence of ignition sources, and the possible effects on the environment. The risk mitigation strategy prepared by LLM was thorough and detailed, addressing direct control actions and eventual systemic change actions. Regulation and compliance experts in safety and health considered the suggestions as effective and in accordance with the established guidelines.

4.7. User Acceptance and Satisfaction

To evaluate the acceptance and satisfaction regarding the acceptance of the LLM-enhanced RAM approach, a survey was conducted by Eskandari et al. [10] among safety practitioners constructed around their knowledge of both traditional RAM calculations and the LLM-enhanced methods. The survey analyzed different facets of their experience, such as ease of use, trust, outputs' clarity, and usefulness of the system. As found, the user's view towards the new method was positive in general, especially towards its efficiency and comprehensiveness. For instance, users appreciated the system's capability to process large preventive data and detect minute risk factors that others might ignore. While there were many users who had positive feelings toward this system in terms of trust because they did not have the same skepticism that others did about the "black box" decision making process of LLMs, overall, there was moderate levels of trust in the system from all users. Therefore, the results are consistent with Eskandari et al.'s findings on the use of LLM-based integrated hazard annotations (as reported in reference [10]) as Eskandari et al. also found moderate levels of trust regarding their study. Future versions of the system will require more transparency concerning how an LLM reasons through a task in order to address the identified limitations. This requirement should be somewhat less burdensome than what Eskandari et al. suggest using their Chain of Thought methods for integrating hazard analysis

4.8. Challenges and Limitations

There are a number of disadvantages and complications to the LLM-enhanced RAM methodology that include:

1) Dependency on data quality: Historical data quality and representativeness will directly impact how well an LLM assesses risk. If there is poor quality or incomplete/biased historical data then the risk assessment provided by the LLM will be skewed.

2) **Context sensitivity:** The LLM sometimes struggled with industry-specific nuances or highly specialized contexts, requiring additional prompting or clarification to ensure accurate interpretations.

3) Computational requirements: Because the processing of large amounts of historical data (for example) and the implementation of advanced functionality such as those in LLMs require powerful computing resources, they may not be practical to implement in resource-constrained environments.

4) **Integration complexities:** Combining the LLM-enhanced method with current risk management systems and workflows posed several approach-specific and organizational issues that need to be solved for significant integration

5. Business Impact and Implications

The LLM-enhanced RAM calculation, if properly implemented, can have serious business impacts across various dimensions:

5.1. Improved Risk Management Outcomes

Offering thorough, coherent, and calculated risk evaluations using the LLM-enhanced technique will likely yield better safety results in high-risk environments. Clear identification of potential hazards and the associated risks allows for effective preventive action to be taken, and therefore accidents, injuries, and even death may be minimized. An organization as a whole can benefit from risk management enhancements through reduced downtime, cost-efficiency with insurance, better regulatory adherence, and boosted company image. Furthermore, emerging risks that could escalate into serious problems can be mitigated with the manual assessment of subtle risk factors through the provided approach.

5.2. Operational Efficiency

The major decrease in the duration of the risk assessments (which now takes anywhere between 5-10 minutes as opposed to the old 45-60 minutes) leads to significant operational efficiencies. More assessments can be performed in the given timeframe, increasing the likelihood that a greater number of potential risks within an organization will be addressed. This is particularly useful in fast-paced settings with constantly changing hazards and risks that need to be reevaluated regularly. Employing the LLMs allows for these updated estimations to be made almost instantaneously, which fosters swifter overall risk management.

5.3. Knowledge Management and Organizational Learning

The LLM's analysis of a large volume of historical data helps to identify different patterns and trends that aid greatly in the aspect of knowledge management and organizational learning. The method can allow organizations to make better use of the safety data accumulated over the years, extracting insights and lessons from reports that often remain buried within databases. The ability to learn over time has the potential to enhance the safety culture of an organization and enable it to understand several psychological and sociological factors associated with risk, strong measures to prevent mishaps, and help in making appropriate decisions at all organizational levels. In addition, the model helps in the retention and transfer of important institutional knowledge concerning safety risks which is crucial in the context of an ageing workforce and loss of skilled personnel through retirement.

5.4. Integration with Broader Safety Initiatives

Several safety initiatives can be combined with the LLM-enhanced RAM approach, such as:

1) **Virtual reality training:** As illustrated by Eskandari et al. [10], safety LLMs powered by AI can enhance the virtual reality training environments by providing tailored contextual safety information regarding identified risks.

2) **Predictive analytics:** This method can be modified to enable the development of safety risk analytics and the detection of evolving patterns that may suggest heightened risk before the occurrence of incidents.

3) **Automated monitoring systems:** Integration with IoT sensors and monitoring systems could enable more dynamic risk assessments that adapt to changing conditions in real time.

These integrations confirm the possibility that an LLM-based approach can serve as the backbone for more integrated and modernized safety management systems.

6. Future Work

The findings and challenges identified in this study point to several directions for future research and development, as follows:

6.1. Model Refinement and Specialization

In the future, a significant portion of work will likely be centered around improving the performance of the LLM for individual industries or high-risk environments with targeted fine-tunings. For example, as part of this process, the LLM may need to be trained on industry-unique data that is embedded with the appropriate domain language and concepts; additionally, training the model to understand the unique hazards and risks associated with each respective environment. Additionally, some of the trust issues raised by user comments can be resolved through examination of more open architectures for LLMs, or the application of Chain of Thought Reasoning [10] methods. Users who are able to see how an LLM arrives at its conclusions have greater confidence in the decision-making abilities of the LLM.

6.2. Integration with Physical Systems

According to the study done by Eskandari et al. [10] on the annotation of hazards using an LLM, there is an opportunity in the combination of an enhanced risk assessment with a physical system like a robot, drone, or IoT sensor. Such systems might be able to fetch information about environmental hazards that can be used and analyzed by the LLM to provide risk assessment in real-time. This could be useful in more static, or even dynamic environments, and in cases where human intervention is not possible due to safety reasons. For instance, a robot with a camera and simple sensors could move around in hazardous areas and use LLM systems to analyze data and evaluate risks before human intervention.

6.3. Multimodal Risk Assessment

Multimodal assessments of danger (that include pictures or videos and/or sensors) are one area of promise as well as an opportunity for future study. Eskandari et al., [10], have demonstrated the ability of Vision-Language models to recognize dangerous elements in a scene and therefore provide a basis for developing an even broader Multimodal Risk Assessment method. A benefit of this type of Multimodal Risk Assessment will be its ability to integrate multiple types/formats/sources of information as well as to identify numerous possible risks. An example of how such integration could lead to identification of otherwise difficult-to-identify complex/hidden patterns of risk, can be seen by comparing: 1) a visual inspection with some sensor data and prior experience/incident data.

6.4. Collaborative Human-AI Risk Assessment

Building collaborative risk assessment models in which AI systems and expert humans collaborate is an area of potential growth in the field of research. This may be accomplished through developing user-friendly interfaces and workflow processes to divide the workload effectively as well as utilize the capabilities of the LLM (such as data processing and pattern recognition) while utilizing expertise from domain specialists in order to provide context and make judgments. Some of these collaborative methods may help address many of the issues with trust and context sensitivity identified within this study; as they would also take advantage of the efficiency provided by the LLM. The use of virtual reality interfaces based upon LLMs by Eskandari et al.[10], provides a means to create effective human-AI collaboration in the safety arena.

7. Conclusion

The current paper proposed a new method for improving calculations within the Risk Assessment Matrix leveraging Large Language Models. In high-stakes scenarios, the risks presented by LLMs can be mitigated by using their understanding of complex texts, analyzing large historical datasets, and their understanding of contextualized information concerning risk analysis. Several benchmarks were evaluated, and, like most LLMs, significant improvements were found over the traditional RAM calculation methods in speed, accuracy, data utilization, and consistency. The efficacy of this approach was successfully demonstrated in construction safety and hazardous material handling where its versatility and practical utility in diverse high-risk scenarios was demonstrated. There are still issues concerning data quality dependencies, context sensitivity, computational requirements, and integration sensitivity, but the business impacts are remarkable. Enhanced knowledge and risk management, operational efficiencies, and their integration with other safety initiatives are all descriptive of the value this approach brings to LLM risk assessment. This work will continue to focus on Model Integration Specialization, Body System Integration, Development of Multi-Modal Risk Assessment, and Human-Machine Collaborative Assessment of the Model. As a result of these additional developments, this model will become even more effective and beneficial across various industries and risk areas.

In conclusion, this development represents an important advancement in the application of artificial intelligence and natural language processing in methods of risk assessment; in the long run, it may also lead to the creation of safer working conditions and more efficient risk reduction strategies within highly hazardous industries. Through the combination of LLM's ability to process large amounts of big data (and their analytical capabilities) with existing structures of risk assessment, organizations can develop comprehensive, standardized and informed assessments of potential risks that could provide more solid bases for decision making in all aspects of safety.

Acknowledgement

We extend our sincere thanks to everyone who supported and encouraged us throughout this research. Your valuable advice and assistance were instrumental in the completion of this work.

Conflict of Interest

The authors declare no conflict of interest.

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