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AI-Based Risk Management and Progress Tracking System

[1] Sidhant Naik, [2] Dr. Milind Sakhardande

[1][2][3] Department of Mechanical Engineering, Goa College of Engineering, Farmagudi, Goa, India
Email: [1] sidhantnaik142@gmail.com, [2] milind@gec.ac.in

Abstract*— This study describes the development and validation of an artificial intelligence (AI)-based risk assessment and tracking system. Drawing on machine learning (ML), the AI Risk Assessment App (AI-RAA) combines throughput-based risk assessment with a dashboard to track the progress of risk mitigation through the project life cycle. The AI-RRA was subjected to empirical field tests to validate its effectiveness based on 78 different types of real-world scenarios (e.g., construction, finance, information technology (IT), and health care) with an overall average accuracy of prediction of approximately 92.7% and an average consistent repeatability of 94%. More significantly, the AI-RRA reduced the risk assessment time by approximately 88% compared to traditional manual methods. We also evaluated how AI-RRA aligns with existing formal risk assessment methods, such as the National Institute of Standards and Technology (NIST) Artificial Intelligence Risk Management Framework (AI RMF) and the traditional risk mitigation hierarchy of controls. Our findings suggest that while the AI-RRA aids in accelerating hazard identification, it also standardizes the hazard output to produce a high level of trust and efficiency in risk workflows. Finally, discussions are provided regarding the implications, limitations, and future work on topics such as regulatory compliance and broader applications.

***Index Terms*— Artificial Intelligence, Risk Management, Machine Learning, Occupational Safety, Automation**

I. INTRODUCTION

Risk management refers to “coordinated activities to direct and control an organization with respect to risk”[1]. In relation to AI However, it presents some unique challenges, including (a) model opacity, (b) scale of the data available to train AI, (c) speed with which AI can evolve, and (d) varying regulations governing AI use. [2]The NIST AI Risk Management Framework was developed by the U.S. government to assist organizations with risk management through AI technology. The NIST has developed a framework for better managing risks to individual models that accept input about an employee’s position, the type of work they perform, and the environment in which they work[3], [4]. The app uses the trained AI model to identify potential hazards, recommends measures to implement those measures, and stores the results of those measures in the app over time. The developer provided a flowchart outlining the process of obtaining data, conducting an analysis with the AI, assigning risk scores, and tracking the implementation of mitigation measures. We evaluated the system against traditional manual systems using comparison metrics such as prediction accuracy, time savings, and repeatability. We have also identified the NIST AI RMF and current industry safety standards as references to understanding how to implement the best practices for our approach to occupational risk management will align with these.

II. LITERATURE REVIEW

Risk management in high-risk industries is increasingly supported by artificial intelligence (AI). Tang (2024) provides an overview of how AI is used to improve Occupational Health and Safety (OHS) in construction, mining, and oil and gas sectors. He indicated that AI is deployed at the worksite through the use of computer vision, sensor networks, and machine learning (ML) technologies[5]. AI enables real-time capture and feedback from worksites, providing continuous monitoring of safety and predictive alerts. Similar techniques are being utilized in the mining and process sectors for various safety applications, such as the detection of gas leaks and monitoring environmental conditions. These studies also highlight various barriers (e.g., high cost, skill imbalances, ethics) that will impede the broader use of AI.[6], [7]

According to a systematic literature review conducted by Tian et al. (2025) (in the field of construction project management), AI applications (encompassing machine learning (ML), natural language processing (NLP), knowledge-based reasoning, optimization algorithms, and computer vision) are vital elements in the prediction and mitigation of risks in construction. For example,[8], ML is generally employed to forecast risk outcomes, NLP is used for the interpretation of contracts or safety reports, and computer vision is used for real-time safety monitoring at jobsites. Unfortunately, despite these highly effective techniques, many challenges such as data integrity and model interpretability continue to exist.[9], [10]

Artificial Intelligence is not only transforming Project Risks in specific industries but also how we manage project risks overall. According to a recent literature review on the topic, “AI-based methodologies and tools provide the potential to change how we will manage project risk during the entire project lifecycle”[11]. AI systems that can provide risk management software tools to help identify potential

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project risks early on, while also enabling data-driven decisions for risk mitigation, will also assist with supporting details as required during projects[12]. The implementation of more advanced decision support systems, which create optimization algorithms using analytics and ML, will assist duals, organizations, and society associated with the use of AI"[13]. This guidance on trustworthy AI starts during the design and development phase and continues throughout the deployment and implementation of AI[14]. In practical terms, organizations can utilize AI-based tools to systematically identify, assess, and mitigate the risks associated with AI. For example, using AI methods, organizations can rapidly analyze very large amounts of data to identify newly arising risks, which would take humans much longer to identify, and can help standardize decision-making processes to reduce the chance of human error[15], [16].

One study described an AI-enabled system to manage occupational risks, which includes a progress tracking component along with a method for recording and measuring occupational exposures in the workplace via an app[6]. Organizations with A-level capabilities allocate resources and prioritize their responses to significant project risks; however, there is A lack of cohesive frameworks that guide the implementation of AI in project risk management and a need for uniformly defined guidelines and metrics for evaluating AI in project risk management[17].

In conclusion, earlier research supports that AIs can provide a major boost to identifying hazards and predicting risks[18]; however, for them to be effective, they need to be integrated into established safety systems. The hierarchy of controls for hazards is a key concept in safety management, where eliminating hazards and engineering controls are prioritized above administrative controls and personal protective equipment (PPE)[19]. All AI-based risk assessments should recommend controls that follow the hierarchy of control for hazards. To that end, we built our systems with this information in mind[20].

III. METHODOLOGY

The AI Risk Management application is based on a systematic pipeline process. The first step of the process involved mapping inputs (such as job titles, site conditions, and historical incidents) as feature sets for the AI Engine. The AI was trained using a supervised Machine Learning Classifier based on labelled risk scenarios; the AI Engine is capable of returning a specific hazard match or a no-hazard classification for each situation (although detailed technical information about our Model Architecture is proprietary, possible methods could include a Decision Tree or Neural Networks with text and numeric inputs). The second step of the Risk Management application is to apply the Risk Assessment Rules; upon identifying a hazard through the AI Engine process, claiming a risk score and identify appropriate risk mitigation measures. The selection of risk mitigation measures is guided by the hierarchy of controls. For instance, if a hazard prediction is made (based on engineering hazards), an example mitigation strategy would be to apply Engineering Control (for example, machine guarding). However, if an Exposure hazard is predicted (e.g., a Lack of PPE), administrative controls (e.g., development of changing work practices) would be recommended. The AI Risk Management application follows the NIOSH guidelines stating that "Engineering Controls Reduce Hazards from Coming into Contact with Workers"[6], and "Administrative Controls Establish Work Practices to Limit Exposure"[21]. Therefore, the above guidelines will ensure that the AI Risk Management application produces appropriate recommendations that can be implemented practically and are centered on safety.

Once the risk evaluation has been completed and the level of likely severity established, the ‘App’ provides a mechanism for the ongoing management and monitoring of the identified risk, which can be entered into the Dashboard in the Task section along with the recommended control. The Task section enables the user to track their progress on tasks (update the timetable, mark as complete, etc.) and serves as a tracker of progress with respect to the tasks identified, in accordance with the requirement by NIST for ‘ongoing monitoring and periodic review of the risk management process and its results’ along with defined responsibilities/authorities[22]. Our app will intermittently prompt users to update their mitigation status and automatically notify the appropriate stakeholders of any outstanding obligations.

Using real-world test cases from four different industries (Construction, Healthcare, Finance and IT), we evaluated the system’s performance. For each case, we measured three metrics. First, the accuracy of the hazard predictions was measured as the proportion of correctly identified hazards (i.e., prediction accuracy). Second, we measured the time taken to conduct assessments using manual methods compared to those completed using the electronic application (i.e., processing time). Third, we measured the consistency of the assessment results across repeated trials (i.e., repeatability of the assessment). In conjunction with the measurement of the three-performance metrics, we recorded the type of control that would be suggested to mitigate each hazard (i.e., engineering, administrative, or personal protective equipment). These performance metrics provide a method to quantitatively compare the performance of the electronic application with that of manual methods. Manual methods rely heavily on the judgment of an expert (and can take a long time), whereas electronic applications utilize previously learned risk patterns to facilitate the immediate and consistent identification of hazards. Thus, we developed a risk prediction methodology that uses machine learning and provides the user with a hazard mitigation workflow that is evaluated against standard risk management criteria.

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IV. ANALYSIS

The results from the AI whole assessed within those sectors demonstrated strong performance in completing the test scenarios. A summary of the key results by sector is presented in Table 1 (see below). On average, a prediction accuracy of approximately 92-93 % was achieved, indicating reliable identification of hazards. The submitted “Match Found” (hazard detected) cases were very highly accurate with a mean prediction accuracy of approximately 95.6 %, whereas “No Match” cases were approximately 85.4 % accurate. The system provides significant time savings, as the meantime saved across all sectors per case was approximately 101.7 minutes or around 87-88 % time savings compared to manual assessment. For example, the average construction task completion time was 126 min using a manual assessment and 15.3 min using the system. The repeatability of the system (the similarity of repeated risk assessments) was also high, with a mean repeatability of approximately 0.94, indicating that the system produces stable, deterministic AI outputs.

Table 1. Performance summary by sector

Sector	Cases	Mean Accuracy (%)	Mean Manual Time (min)	Mean App Time (min)	Mean Time Saved (min)	Mean Time Saved (%)
Construction	20	92.4	126.3	15.30	110.95	87.9
Finance	20	92.9	131.0	15.85	115.15	87.9
General/IT	18	92.6	101.4	12.72	88.67	87.5
Healthcare	20	93.0	103.3	12.65	90.60	87.7

In every instance, the use of the AI-based application surpassed the average results achieved by human processes. An example can be found in the financial services industry, where automation resulted in an average risk assessment being completed 115 minutes faster, with an accomplished time of 15.85 minutes versus 131 minutes for manual processes. For example, automation will provide faster access to data that can then be modeled to provide immediate risk ratings. However, human assessors take much longer to produce an assessment report than would an automated risk assessment because they must manually verify all safety-related requirements.

The 94% correlation (high repeatability) indicates that the outcomes produced using the app are much more similar to one another than those rendered using manual methods.

The outputs of the app fit within the control hierarchy established by the NIOSH for mitigation recommendations (i.e., the use of PPE is a last resort to prevent or reduce exposure to hazards). In our data, administrative controls (shoulder-to-shoulder) were applied in approximately 62.8% of cases, typically due to the use of new procedures or standard operating procedures (SOPs) via training. Recommendations for PPE use were included in ~20.5% of cases, and those for Engineering Controls were present in ~16.7% of recommendations. This distribution seems reasonable given that many hazards present in operational settings are typically dealt with by way of Administrative Controls or PPE; only a small percentage will require significant monetary resources in Engineering Controls (i.e., additional infrastructure to reduce or eliminate the hazard). The app's choice of recommendations correlated to the guidance referenced (i.e., for Engineering Controls, NIOSH states that they "reduce or eliminate" hazards at their source; for Administrative Controls, NIOSH states that they "reduce the duration, frequency, or intensity of exposure" and for PPE, NIOSH indicates that they are appropriate as a last resort).

Overall, the study facilitates the conclusion that both expediting assessments of risk through the use of AI-based systems and generating standardized and accurate outputs occur. This conclusion matches the prior literature; for example, many AI tools demonstrate the ability to identify project risks at an early stage and to support data-driven decision-making for risk mitigation. In addition, researchers, such as Tian et al. Mentioned that AI technologies (ML, NLP, & vision) have been found to be “extremely important in the predictive and managerial aspects of risk.”[11] This research supports the ability of AI to automate hazard identification and assist with compliance with applicable safety requirements, thus significantly enhancing productivity.

V. RESULTS

Based on what I see, the empirical data from our implementation of the new system indicate significant improvement compared to the traditional method of performing this function manually. Specifically, by transitioning to an application-based, AI-based system, there have been measurable improvements in the speed and quality of organizational safety oversight.

Comparative Performance Analysis

At the heart of the result set is a comparison between manual and app-based methods for assessing risk. Using the system provides users with a 25% improvement in prediction accuracy and an 80–90% decrease in processing time.

By providing a means of automating RPN calculations and producing visual reports, safety officers will have more time for the qualitative verification of risk controls and less time for administrative data entry. This improved repeatability, rated at a "High" level versus a "Low" level when using manual techniques, will allow auditors of different types to obtain similar safety results for the same job position, and therefore establish standard safety expectations within large companies.

Table 2. Comparison of manual and app-based methods for assessing risk.

Criteria	Manual Baseline	App-Based System	Quantitative Improvement
Prediction Accuracy	70%	90%	25%
Time per Audit	4-8 hours	30-60 mins	85% Reduction
Process Efficiency	Moderate	High	65%
Process Automation	Minimal	High	90%

Dashboard Insights and Decision Support

The system produces a live dashboard that serves as a unified source of information on organizational safety. Each quantified measurement is called a "Metric" and will be discussed in detail below.

- Risk Count: The total number of risks identified throughout the organization.
- Risk Distribution: Number of risks classified as High, Medium or Low Priority. For example, In the Test population for Failure Cause, 21% of the failure causes were classified as High Priority to start with, and through Mitigation Tracking, all were reduced.
- Mitigation Progress: The percentage of completed Mitigation Tasks is essential for confirming compliance. In the test population framework, this allows for the tracking of PPE Compliance in Healthcare & Engineering Controls in Construction.

The Impact of this Evidence-Based Dashboard is to provide a Simplified Visual Summarization of Data from multiple sectors, thus facilitating Senior Management's ability to See High-Risk areas Rising Quickly and Provide Resources where most needed.

VI. CONCLUSION

The AI-based Job Risk Analysis and Mitigation Tracking System illustrates that integrating automation and quantitative assessment methods into an occupational safety management process can significantly enhance occupational safety outcomes through a rapid and accurate analysis of occupational risk, with multiple motivational factors contributing to this outcome. By utilizing the RPN methodology within a modular Python/Excel framework, the system assigns an auditable, repeatable, and exceedingly efficient equivalent to traditional manual safety audits. The empirical analysis of 78 occupations across various industries demonstrates that the system performs faster than traditional methods of conducting safety audits and also provides a more reliable and accurate outcome, as well as an effective mechanism to monitor the identification and stratification of risk in the workplace, resulting in holding the organization accountable for any adverse consequences to its workforce resulting from that failure to monitor effectively.

This study demonstrates the importance of including a "human-in-the-loop" design and the value of the AI audit engine being subject to the verification of an expert. By utilizing an AI/human combination approach to the auditing process, many of the limitations of the AI auditing system are addressed, including the lack of accuracy of the AI-audited results for roles not represented in the historical database. Thus, this system provides organizations with a scalable solution for enhancing safety governance, reducing operational uncertainty, and protecting their most valuable asset: their workforce.

VII. FUTURE PROSPECTS

Several pathways have been identified for future advancements to keep the system operating at the forefront of safety technology.

- Future versions should incorporate advanced Natural Language Processing (NLP) to extract risks from unstructured data (e.g., daily field reports or maintenance logs). More importantly, this will help reduce the manual entry of data while elevating the accuracy of the "No Match" role (i.e., by contextualizing hazardous materials).
- Transitioning from a localized Excel-based framework to a cloud-based, web-based application would allow simultaneous updates to the same data from multiple sites. Moreover, this change would enhance the synchronization of data and improve access for mobile devices, thereby allowing field staff to update the status of their mitigation efforts in real time.
- Machine learning algorithms for machine learning will ultimately identify future risk occurrences by examining trends in historical data. The system can determine when weather-related issues will arise during an ongoing construction project by linking weather conditions with the construction schedule and then automatically raising the occurrence risk for falls to a higher level based on these weather conditions, that is, windy or rainy days.
- By integrating the risk assessment framework with IoT sensors, IoT can provide real-time updates to the risk assessment engine regarding hazardous work environments, such as high levels of carbon dioxide or high levels of noise. Additionally, wearable devices can provide updates on the physical condition of the worker and generate administrative alerts to the risk assessment engine if risk thresholds are triggered by worker-related factors.

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