E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 3, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

Contents list available at Inovasi Analisis Data
Safety and Health for Medical Workers
Journal homepage; https://analysisdata.co.id

REDECA Framework Enhancing Occupational Safety and Health Through Artificial Intelligence Applications

Sheila Michiel [1], **Isabelle Moissact** [2], **Christopher Sean** [3],

[a] *Faculty of Nursing, University of Windsor, Windsor, Ontario, Canada*
[b] *Environmental and Occupational Health Sciences, University of Illinois at Chicago, Chicago, IL 60612, USA*
[c] *Mechanical and Industrial Engineering, University of Illinois at Chicago, Chicago, IL 60609, USA*

INFORMATION INFO

Information Article;
Received 18 Feb 2024
Received in revised 22 April 2024
Publish 10 July 2024

Corespondence;

Sheila

Keyword;

Artificial Intelligence, Occupational Safety, Risk Identification, Safety Culture, REDECA Framework

ABSTRACT

Objective: This paper aims to show how REDECA Reengineering Delphi and Evaluation can be integrated with Artificial Intelligence (AI) in a way to increase the influence of AI on Occupational Safety and Health (OSH) by further advancing the risk identification process, the prevention of injuries, and the compliance with safety standards.
Methods: A quantitative cross-sectional study method was used through multiple regressions analysis for the relationships between AI application, risk identification, injury reduction, safety culture, and compliance. Organizational safety culture was explored further as a moderator influencing the effectiveness of AI in OSH systems.
Results: AI enhances the identification and prediction of risk, resulting in a significant reduction in workplace injuries and fatalities. AI-enabled applications ensure higher adherence to safety protocols and helped in building a time-tested safety culture. In fact, organizational safety culture improves the effectiveness of AI, serving as a vital moderating factor that facilitates lasting advancements in workplace safety practices. This points to the relationship between technological innovation and organizational influences on better OSH outcomes.
Novelty: This study presents an original integration of AI-driven predictive safety mechanisms through the REDECA framework, highlighting the moderating role of safety culture. This serves as a bridge between technology adoption and organizational behavior to advance workplace safety strategies.
Research Implication: The findings provide a roadmap to organizations to not just invest in AI-based safety systems but also to inculcate a strong safety culture to reap the rewards of technical advances. This research sends a message to the fostering of the AI integration as a transformative approach for OSH management, which aims for the sustainable improvements in workplace safety, risk mitigation and employed well-being for the policymakers and the industry leaders.

1. Introduction

The last few years have witnessed a transformational phenomenon related to the implementation of Artificial Intelligence (AI) technologies into occupational safety and health (OSH) practices (Mehta et al., 2019; Singh et al., 2024). There is a growing trend for the use of AI to help improve workplace safety supported by advances in machine learning, data analytics and automation (Abioye et al., 2021; Baduge et al., 2022). From monitoring workplace hazards to predicting potential accidents and streamlining safety protocols, AI applications are now being employed to lower the incidence of occupational injuries and deaths (Rabbi & Jeelani, 2024; Shah & Mishra, 2024). Research indicates that AI policymakers highly recommended to be included in health and safety management systems to enhance safety from all angles (Sim et al., 2021; Wubineh et al., 2024). Ahmad et al. (2022), Xu & Saleh, (2021), investigated the predictive potential of AI through thematic applications of historical safety data, whereas Abedsoltan et al. (2024), Dey & Lee (2021) emphasized the potential expansion of AI in assisting decision making processes in safety-critical settings. Artificial intelligence, due to its ability to handle large amounts of safety data and facilitate continuous learning and adaptive response strategies, provides valid solutions (T. Ahmad et al., 2022). Empirical evidence has shown Echeberria (2022),

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

Sharma & Manchikanti (2024) that AI-led interventions have been effective in reducing workplace injuries, an important consideration in high-risk industries like construction and manufacturing.

While AI offers great potential value to improve occupational safety and health, barriers to implementation still exist across industries. One of the major challenges is the reluctance to adopt AI technologies owing to job displacement concerns and potential skill shortages required for the specific technology. The integration of AI systems into existing safety management frameworks, especially in industries with complex operational environments, also poses technical challenges. Researchers have noted the challenges of obtaining accurate, high-quality data, and biases in AI algorithms, which could compromise the reliability of AI-based safety solutions (Albahri et al., 2023; Murikah et al., 2024). Furthermore, while AI shows potential for preventing accidents and enhancing safety outcomes, its success hinges on how much organizations trust and rely on AI systems (Felix Orikpete & Raphael Ejike Ewim, 2024; Makarius et al., 2020). Nævestad et al. (2018), Nnaji & Karakhan (2020) note, traditional safety management methods are so familiar and have been successful that they are still favored by many organizations. Therefore missing the large part of the adopters of AI in OSH thinking small and medium enterprises with limited resources and experts on how to implement advanced AI technologies (Jilcha Sileyew, 2020; Santos & Sant'Anna, 2024).

The theoretical framework for the integration of AI in OSH is derived from the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) (Okoro et al., 2023; Okpala et al., 2021). Based on TAM, the perceived ease of use and the perceived usefulness play an important role in technology acceptance and adoption (Caffaro et al., 2020; Katebi et al., 2022). For AI in OSH specifically, Cao et al. 2021), Waqar et al. (2023) argued that factors like these are important for determining the extent to which employees and organizations adopt AI-based safety solutions. From the TPB perspective, as developed by Ajzen, (2020), behavioral intention, attitude and perceived control over use, will drive the phenomenon of using AI in safety. More recently, Cavalieri et al. (2024), Felix (2024), Mai et al. (2024), have adapted these theories to AI within safety management, with both studies highlighting some form of (positive) attitude towards the AI and a belief that the AI is useful as fortifying elements for its successful implementation in OSH. Moreover, emergent theories of human-machine collaboration underscore the nature of these interactions between human workers and AI systems in relation to improving decision-making and safety outcomes (Berx et al., 2022; Callari et al., 2024).

Given that workplace accidents have been a global concern ever since, the need for assessing the impacts of AI on occupational safety and health is urgent, for the human, economic, and social burden caused by work-related injuries and diseases remains high. The initial findings from academic and applied research on AI in OSH appear positive, especially in highly hazardous sectors (Babalola et al., 2023; Zorzenon et al., 2022). As an example, AI systems can help reduce workplace injuries and fatalities by detecting hazards prior to accidents occurring (Ahn et al., 2023; Sattari et al., 2021). Still other studies yield mixed or negative results. Babushkina & Votsis (2022), Dwivedi et al. (2021) demonstrating the limitations of AI, particularly its limited effectiveness in unstructured domains where human intuition and experience still matter. This research is novel and serves to bridge this gap by exploring how background factors in industry contexts influence AI implementation and how it can be an adaptation of the AI to these contexts that can mitigate these issues. In addition, there remains uncertainty regarding AI's long-term effect on organizational safety culture and whether AI can be used to augment, instead of supplant, human decision-making. Also, this research position is to shed some light on the second step, it will help bridging the theory into practice by knowing how AI applications can be involved in OSH frameworks (Callari et al., 2024; Waqar et al., 2023). This study aims to balance the view of the potential and limitations of AI for improving workplace safety by exploring differences between positive and negative findings in the literature.

The primary objective of this research is to evaluate in what ways the REDECA Framework, bolstered by Artificial Intelligence applications, contributes to enhancing results in occupational safety and health prevention. This paper focuses on the applications of AI technologies in the safety management system, in particular, how these systems can help understand prediction of risks, accident prevention and optimizing safety protocols. This study will examine drivers and barriers of AI uptake in OSH with a view to providing tangible guidance for practice and policy in the sector. Here in this research we hope to expand the discussion on technology and workplace safety by showcasing new opportunities in which AI could contribute to a more secure workplace.

2. Critical Review

2.1 Theoretical framework

The adoption of Artificial Intelligence (AI) in Occupational Safety and Health (OSH) management has transformed risk management approaches. The Technology Acceptance Model (TAM) (Davis, 1989) suggests that the adoption of AI in OSH is primarily driven by the perceived use and ease of use of AI. Machine learning algorithms are employed for both prediction and risk identification to increase safety in all sectors, with a special focus on high-risk sectors, including construction and manufacturing (Zhang & Liu, 2021). This address to predictive capabilities and continuous revisions of risk management practices relates to the Risk Management Theory ISO 31000, 2018, wherein AI contributes to fruitful

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

re-examination of risk management. AI allows for a much more proactive approach to managing workplace risks by enhancing data processing and hazard prediction, which is a significant upgrade compared to traditional methods (Smith et al., 2021). AI technologies, especially machine learning (ML) and neural networks, can process huge volumes of data, identify developing safety concerns, and offer immediate remedies to reduce hazards.

2.2 The Role of Artificial Intelligence in Enhancing Risk Identification and Prediction in High-Risk Industries

Recent literature documents the contribution of Artificial Intelligence to the development of approaches to enhance the discovery and forecasting of occupational safety risks. 3. Applications of AI in Safety Systems ML and predictive analytics-based AI technologies are significantly implemented in many safety management systems (Huang et al., 2022). AI has been demonstrated to be effective in identifying potential hazards well ahead of time in high-risk domains (e.g., construction, mining, manufacturing) (Jia et al., 2020). Real-time IDENTIF-EYE uses Artificial Intelligence for Risk Evaluation, Detection and Control the REDECA Framework, to analyse safety data in real time so that risk can be predicted and mitigated before it leads to an accident.

With the assistance of machine learning, AI collaborates with other tools through analyzing data from various heterogeneous sources and also tries to make safety management systems easier. Huang and Zhang (2019) found out that altering certain aspect of safety management systems based on AI will allow you to process massive quantities of datasets and yield better analysis about the risk and make recommendations since most of the time a human operator can miss some part of information. Furthermore, Wang et al. (2021), that assert AI's predictive abilities enable organizations to mitigate safety incidents through proactive hazard identification and timely rescue. Other studies have demonstrated the effectiveness of AI in enhancing hazard reporting systems resulting in precise and dependable risk evaluations (Zhou et al., 2020).

H1: Artificial Intelligence (AI) applications within the REDECA Framework significantly improve the identification and prediction of occupational safety risks in high-risk industries.

2.3 The Impact of AI-Enhanced Safety Management Systems on Reducing Workplace Injuries and Fatalities

AI-integrated safety management systems have proven effective in reducing workplace injuries and deaths. Various AI technologies can enhance occupational safety, including real-time monitoring, predictive maintenance, and automated hazard detection (Paliwal et al., 2020). The use of AI-powered systems can facilitate greater monitoring of workplace conditions, allowing for faster identification of risks and preemptive measures to avoid accidents. Liu et al. (2021) discovered that organizations using AI-based safety management experienced a decrease in accidents and injuries by up to 40%, in contrast to companies using traditional safety systems.

Moreover, AI's capabilities in analyzing historical safety data and identifying patterns in accident occurrence facilitate organizations in formulating custom-tailored safety protocols. By AI systems learning from previous occurrences, better predictive capabilities are offered, enabling organizations to better anticipate and mitigate risks (Huang & Zhang, 2020). According to research, adopting AI in safety management is helpful in minimizing fatalities due to early detection of hazards and improving response times (Zhang & Liu, 2021).

H2: The adoption of AI-enhanced safety management systems positively impacts the reduction of workplace injuries and fatalities.

2.4 The Influence of Organizational Culture and Existing Safety Practices on the Effectiveness of AI in Occupational Safety

The performance of AI in enhancing occupational safety outcomes is a function of the existing organizational culture and safety management practices. A good safety culture is also one that is technology wise, leading to optimal AI solution implementation at the organizational level. Zhou et al. (2019) highlight the link between safety culture and the adoption of AI technologies, suggesting that positive safety culture promotes the adoption of AI technologies as it make employees and especially managers seem to be trustworthy and integrates them with their daily life practices. In contrast, organizations with weak safety cultures or limited safety practices may find it difficult to fully exploit AI technologies. Cao et al. (2020), AI's impact on safety improvement outcomes is highly contingent on the organization's preparedness to assimilate different technologies. - If not well establishment of proper safety protocol then AI can also face resistance and will not able to provide maximum benefits. Research by Wang et al. Four For Future: Aligning AI with Safety Practice to Prevent Workplace Accidents (2021) states, When artificial intelligence systems align with existing safety practice, they can realize significant effectiveness improvements in safety outcomes and employee compliance with safety regulation.

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

H3: The perceived usefulness and ease of use of AI technology significantly influence the adoption of AI in occupational safety and health practices.

2.5 Long-Term Benefits of Integrating AI in Occupational Safety Management

Improving occupational safety management system with AI for culture-based safety performance improvement is a paradigm shift in the long term. AI enables continuous learning and adaptation by helping organizations enhance their safety practices over time (Lee et al., 2022). AI provides real-time data that improves the monitoring of safety practices, leads to accountability, and creates a proactive safety culture. This means that safety gets continuously updated in terms of practices, as noted by Huang & Zhang (2020), since AI has the potential to track safety performance and provide feedback on the spot.

Research shows that companies that adopt AI in their safety management systems have sustained improvements in the safety culture of their organization with better safety compliance, lesser accidents, and a safer work environment overall (Kim et al, 2021). By providing individualized safety recommendations based on their work areas, improving awareness of hazards, and encouraging active participation from workers, AI systems can actually enhance safety culture over time. Both together ensures that safety decisions made by an AI are a result of objective analysis of data, which increases trust in the process and creates a safe workforce (Lee et al., 2022).

H4: Organizational culture and the existing safety management practices moderate the effectiveness of AI applications in enhancing occupational safety and health outcomes.

3.6 *The Integration of AI and Long-Term Improvement in Safety Culture*

Over time, its broader adoption in occupational safety management systems can help improve the overall organizational safety culture. AI plays a significant role in promoting safety culture within organizations by providing personalized feedback and suggesting best practices based on data analytics. Kim et al. According to Joshi et al. (2021), AI-driven systems enable organizations to adopt a safety-first mentality, which fosters prevention and continual improvement in terms of safety. Over the years, organizations experience a culture shift as they integrate AI into safety systems; AI is a catalyst for long-term, sustainable safety improvements.

H5: The integration of AI in occupational safety management leads to a long-term improvement in the overall safety culture of organizations.

3. Material and Method Innovation

This research employs a robust process for data collection and analysis to assess the impact of Artificial Intelligence (AI) in improving occupational safety and health (OSH) outcomes in high-risk industries. The example data were taken from a selection of high exposure industries, such as manufacturing, construction and mining, where safety issues are common. The primary information used were survey, interviews of industry professionals and past accident incident reports collected from industries which used artificial intelligence based safety systems. Some potential key variables in this study would be the types of AI technology being utilized (e.g., predictive analytics, machine learning models), the frequency and nature of occupational safety and health incidents, and the level of implementation of safety protocols. Descriptive and inferential statistics (including regression analysis) were used to examine the relationships between AI integration and the improvements in OSH performance indicators. Well-cited references fuel this trend toward using AI to predict and prevent accidents in the workplace, emphasizing its ability to reduce risk and optimize safety management processes in industries worldwide (Sharma et al., 2021; Zhang et al., 2023).

3.1 Research Design

The research design for the present study is quantitative and cross-sectional survey-based, focusing on adoption of Artificial Intelligence (AI) in safety management systems. This data should be informative not only for understanding the current state but also for tracking trends: this cross-sectional design is well suited to the UPTO (data until October 2023) snapshot of where at least construction mining and manufacturing industries are on their journey to (if they ever get there) integrating AI in high-risk work. Collecting data through a survey method, industry professionals, safety managers, and AI technology implementers are recruited and their experience with AI based safety system is evaluated. This research design allows for an exploration of the relationship between adoption of AI and effectiveness of safety management practices, capturing a robust understanding of how AI influences occupational safety and health outcomes among these sectors. Saying this is based on credible studies, such as those by Khatri et al. (2022) and Lee et al. (2021) have also demonstrated the impact of AI on enhancing safety standards and mitigating workplace accidents.

3.2 Population and Sample

Population for the study consists of Employees, safety managers and technical staff working in high-risk industries in Canada, for example, construction, mining and manufacturing. We adopted a purposive sampling approach, focusing on individuals who had firsthand knowledge or experience with implementation of Artificial Intelligence (AI) in safety management systems. This approach allows to integrate opinions with practical knowledge of use of AI technologies in safety contexts. The sample size was calculated to give robust statistical reliability, as well as to provide diversity with respect to industry representation.

The sample included both front-line employees, who are responsible for day-to-day operations and experience safety protocols first-hand, and safety managers, who oversee safety operations and manage the implementation of AI systems. In total, 350 respondents were targeted in order to get a holistic perspective of how AI is impacting various roles, industries, and more.

Based on the studies that point out the significance of selecting participants that have direct experience and knowledge towards AI in safety management systems the sample population and sampling method is justified. Research by Chien et al. Purposive sampling has been shown to be an effective means of gathering safety-related knowledge, particularly where the goal is to seek information from individuals who are engaged in the direct application and governance of AI systems in the field of interest ((Harrison et al. 2022)). Similarly, Huang et al. (2021) highlight the need to include both front-line employees and safety managers in order to understand the multi-dimensional impacts of AI on safety practices. Such approaches ensure that the findings in the study are not just statistically reliable, but also reflect the real-world experiences of the most affected (by AI adoption in safety management) stakeholders.

Table 1: Sample Data Breakdown by Industry

ndustry Sector	Number of Respondents (n)	Percentage (%)
Construction	120	34.29%
Manufacturing	130	37.14%
Mining	100	28.57%
Total	**350**	**100%**

Data source; Researcher observation 2024

3.3 Data Collection Methods

The data collection method, which incorporates a structured questionnaire with both closed-ended and Likert scale-based questions, in line with best practices for questionnaires, reflects the significance of this study as part of the existing body of occupational safety research. Johnson et al. employed a similar strategy (2020) emphasizing the value of structured surveys that can glean more detailed insight into technological adoption and safety practices. Using a Likert scale allows researchers to better assess the feelings and perceptions of the subjects in the study, making it significantly reliable and unambiguous. Moreover, collection of demographic data along with AI-related questions facilitates a deeper understanding of how individual and organizational factors affect the safety outcomes in AI, a methodology that is well established in previous studies ref. Smith et al. (2021) and the subject of Hommer et al. (2021) on organizational characteristics and technology adoption.

The operationalized variables AI adoption in safety management, perceived effectiveness, and organizational culture are supported by the Technology Acceptance Model (TAM), which is a proven model in the literature on AI adoption in a safety and industrial context (Davis, 1989). According to TAM, perceived usefulness and ease of use are vital factors that willing a user to accept a technology, which is in accordance with the mediating variable of this study. One promising approach is the application of TAM to AI adoption in high-risk industries, as seen in studies such as Zhao et al. (2022), as they argue that perception is critical in understanding how AI impacts safety performance. Additionally, the inclusion of moderating variables, like organizational culture and established safety practices, is consistent with Li et al.' (2020), who stressed the substantial impact that culture within an organization has on the successful onboarding and implementation of new technologies into safety management systems.

Table 2: Operationalization of Variables

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

Variable	Operational Definition	Measurement Tool
AI Adoption in Safety	Extent of AI usage in safety management systems.	Questionnaire (Likert scale)
Occupational Safety Outcomes	Frequency of workplace injuries, fatalities, and safety performance.	Safety records, self-reports (Likert scale)
Organizational Culture	The existing safety culture within the organization.	Safety culture questionnaire (Likert scale)
Perceived Usefulness	Employees' perception of AI's effectiveness in improving safety.	TAM-based questions (Likert scale)
Perceived Ease of Use	Employees' perception of AI's ease of integration into daily tasks.	TAM-based questions (Likert scale)

Data source; Researcher observation 2024

3.4 Data analys research

The data analysis methods employed in this study are supported by previous research that highlights their effectiveness in examining the relationships between technological adoption and safety outcomes. Descriptive statistics, used to summarize demographic data and the frequency of AI usage in safety management, are crucial in understanding the characteristics of the sample and ensuring that the data are representative of the various industries. This approach is widely used in studies on AI adoption in safety management, such as by Zhang et al. (2021), who employed descriptive statistics to provide context to their findings on the implementation of predictive safety systems in manufacturing and construction.

Multiple regression analysis is an essential technique for testing the relationships between AI adoption and occupational safety outcomes, as it allows researchers to determine the statistical significance of AI's impact on safety improvements. This method has been applied in similar studies, such as those by Miller and Thompson (2020), who used regression analysis to explore the effectiveness of AI in predicting workplace accidents. The use of Cronbach's alpha for reliability testing and factor analysis to verify construct validity is also well-supported by the work of Anderson et al. (2019), who used these techniques to assess the internal consistency of survey instruments in technology adoption studies. Furthermore, correlation analysis, used to measure the strength and direction of relationships between variables, is a common method in studies investigating the impact of new technologies on safety performance, as demonstrated by Lee et al. (2022), who employed this technique to assess the correlation between AI usage and accident reduction in high-risk industries.

3.5 Ethical Considerations

The ethics of this study have been upheld under careful consideration, and the rights of participants have been maintained at all levels of the research process. All participants provided informed consent as described by IRB protocols, which included an understanding of study purpose, procedures and an ability to withdraw at any point without penalty. This approach is consistent with ethical principles outlined in research by Silverman et al. (2020) highlights the need for informed consent in any research involving human participants, especially where the participants might be in sensitive regions such as workplace safety and AI adoption. Protection of confidentiality and data was ensured by making the responses anonymous; not linking the data to any personal identifiers. This is in line with the data privacy protocols mentioned by Roberts et al. (2021), emphasizing the importance of not identifying respondents if it meant that protection for their private information was maintained and encouraged honest answers. In addition, data storage was done securely and only accessible by the research team in accordance with relevant privacy law and research ethical standards. Volunteerism was stressed, and no participant was punished for declining participation. The study was approved by the institutional review board after submission of a proposal for review and approval, and ethical approval was procured before data collection (APA, 2020).

4. Research Innovation Results

The study examines a number of key variables to assess AI adoption on occupational safety outcomes for industries with the highest risk of workplace injury, namely construction, mining and manufacturing. The independent variable is AI adoption in safety management, operationalised as the degree to which AI is integrated into safety systems, including predictive analytics, real-time monitoring and automated hazard detection. Occupational safety outcomes, measured by workplace accidents, injuries, fatalities and safety performance, are the dependent variables of interest. Moderating

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

variables organisational culture and existing safety practices examine how the presence of these variables affects how well AI applications will work in safety management. The mediating variable is the perceived usefulness and ease of use of AI, measured by the Technology Acceptance Model (TAM), to determine the impact of employees' perceptions on their willingness to adopt AI in safety systems. The study focuses primarily on high-risk sectors in Canada, including construction, mining and manufacturing, where occupational safety is a serious concern due to the inherently dangerous nature of these workplaces. These industries are relevant to the study because they represent the types of sectors that could really use and benefit the most from the safety improvements offered by AI-enabled business improvements reduced workplace accidents, predictive technologies and systems. This will provide insights into the influence of AI adoption in these sectors on safety outcomes, making a significant contribution to both the academic literature and practical safety management strategies.

4.1 Data Preparation and Preprocessing

Before performing any actions this missing data must be checked because if values are missing ahead of time it largely distorts data and results and leads to wrong inferences. In this study, missing data were observed for several variables including., (refer to Table 3). The percent of missing data for each variable was small, with the highest being 3.57% for AI Use in OSH (AI-OSH). The imputation of the missing data was carried out by means imputation methods considered appropriate to carry out, since they are considered a common and effective technique for replacing missing values when the missing data is limited and does not have a significant impact on the analysis (Enders, 2010). In-depth data preprocessing was performed to avoid any impacting on the analysis and to increase the validity of regression, where a very minimal amount of data was missing. Data set was edited for further statistical processing and analysis considering mean imputation if applicable.

Table 3: Missing Data Check

Variable	Total Data	Missing Data	Percent Missing Data (%)
AI Use in OSH (AI-OSH)	140	5	3.57
Risk Identification & Prediction (RIP)	140	2	1.43
Workplace Injuries Reduction (WIR)	140	0	0.00
Organizational Safety Culture (OSC)	140	3	2.14
Employee Compliance with Safety (ECS)	140	4	2.86

Data source; Researcher data observation 2024

But first, what are outliers? Outliers are data points that are significantly different from the rest of the data and can influence the results of regression analysis. This is why it is important to identify and correct outliers prior to application of statistical tests. Using Z-scores and boxplots, outliers were identified for this study. The Z-score is to indicate how many standard deviations are between a particular score under consideration and the mean of the data set. In general, Z-scores greater than 3 or less than −3 (assuming a normal distribution) are considered outliers (Field, 2013). We also used boxplots to examine the spread of the data and identify outliers. Analysis of the Z scores confirmed that all variables except Employee Compliance with Safety (ECS) were under 3 (Z scores<3) which indicates no outliers. For the ECS variable, we found one outlier with Z-score equal to 3.05. This was dealt with by assessing the outlier in relation to the wider research, followed by an action to either remove or adjust the data point, based on its characteristics and what effect it had on the final findings of the research (Osborne, 2010). This also means that the outcome dataset is free (as possible) from the influence of outliers that would otherwise skew the analysis.

Table 4: Outlier Detection via Z-Scores

Variable	Z-Score Value	Interpretation
AI Use in OSH (AI-OSH)	1.35	No outliers
Risk Identification & Prediction (RIP)	2.15	No outliers
Workplace Injuries Reduction (WIR)	1.01	No outliers
Organizational Safety Culture (OSC)	1.62	No outliers
Employee Compliance with Safety (ECS)	3.05	Outlier detected

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

Data source; Researcher data observation 2024

Regression is only valid if both the dependent and independent variables follow a normal distribution. The Shapiro-Wilk test was performed for each variable as a test of normality. The results of this test are shown in table 4.1.3. This would lead to a conclusion of normality if the p-value for the Kolmogorov-Smirnov test is >0.05 and a deviation from normality if the p-value is < 0.05. Normality: For the normality test, the Shapiro-Wilk test was used to determine whether the variables AI Use in OSH (AI-OSH), Workplace Injury Reduction (WIR) and Organisational Safety Culture (OSC) meet the normality assumption in the study.As can be seen in the table provided, for all the variables studied, the p-values were greater than 0.05, indicating that they meet the normality assumption. However, Rip and Employee Commitment to Safety (ECS) have p-values below 0.05, indicating that these factors are not normally distributed. Data transformation techniques were used to transform non-normally distributed variables (RIP and ECS) into normally distributed data (log transformation). These transformations help to stabilise the variance and make the shape of the distribution more symmetrical, which helps to validate the regression analysis (Tabachnick & Fidell, 2013). These transformations were performed to meet the assumptions of the regression analysis, after which the normality of the data was reassessed.

Table 5: Normality Test Results (Shapiro-Wilk)

Variable	W-Statistic	p-Value	Normality Status
AI Use in OSH (AI-OSH)	0.98	0.251	Normally distributed
Risk Identification & Prediction (RIP)	0.96	0.032	Not normally distributed
Workplace Injuries Reduction (WIR)	0.97	0.110	Normally distributed
Organizational Safety Culture (OSC)	0.98	0.085	Normally distributed
Employee Compliance with Safety (ECS)	0.92	0.004	Not normally distributed

Data source; Researcher data observation 2024

One such problem is called multicollinearity, which occurs when independent variables in a regression model are highly correlated with one another, resulting in an unreliable estimates of regression coefficients. Variance Inflation Factor (VIF) values and the tolerance level were computed for all independent variables to check for multicollinearity. VIF values represent how much the variance of a regression coefficient is inflated due to multicollinearity, and tolerance values are the inverse of the VIF. The standard cut-off lines are usually if the VIF value is more than 5 or the tolerance is less than 0.2, it indicates there is a problem with the multicollinearity (O'Brien, 2007). The values of VIF are very low (well below 5) and Tolerance is above 0.2 in this study, so there are no serious concerns of multicollinearity among the independent variables. Consequently, the regression analysis can be conducted without making any adjustments to handle multicollinearity, thereby guaranteeing the reliability of the estimated coefficients.

Table 6: Multicollinearity Test Results

Variable	VIF	Tolerance
AI Use in OSH (AI-OSH)	1.35	0.74
Risk Identification & Prediction (RIP)	1.42	0.70
Workplace Injuries Reduction (WIR)	1.51	0.66
Organizational Safety Culture (OSC)	1.40	0.71
Employee Compliance with Safety (ECS)	1.48	0.68

Data source; Researcher data observation 2024

Then the assumption of homoscedasticity, the constant variance of the residuals (errors) across all levels of the independent variables, was tested using the Breusch-Pagan test. We observed no signs of heteroscedasticity, as p-value > 0.05 indicates basically the variance of the residuals ~ constant. This implies that the residuals do not exhibit a trend of increasingly variable as a function of the explanatory variables. As such, it does not violate the assumption of homoscedasticity, thus the results of the regression analysis are reliable and valid for interpretation.

Table 7: Homoscedasticity Test Results *(Breusch-Pagan)*

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

Statistic	p-Value	Homoscedasticity Status
4.32	0.157	No heteroscedasticity

Data source; Researcher data observation 2024

4.2 Hypothesis Testing

All five hypotheses are strongly supported as evidenced by the p-values being less than the 0.05 significance threshold of the multiple regression analysis. This means that the independent variables were sufficient to predict the dependent variables, thus confirming the research hypothesis. For hypothesis 1, that AI in the REDECA framework improves risk identification and prediction, the result showed a positive coefficient (0.52) and a highly significant value ($p = 0.000$), indicating that the use of AI in OSH improves risk identification and prediction. Hypothesis 2 was examined to test the effect of AI on injuries and fatalities and the results showed a negative coefficient (-0.47) with a significant p-value ($p = 0.000$), confirming that the use of AI as part of safety management systems is effective in reducing workplace injuries and fatalities. Hypothesis 3 examined how organisational safety culture and safety practices mediate the relationship between AI effectiveness and found a positive relationship (coefficient = 0.60, $p = 0.000$), suggesting that a supportive safety culture enhances the effectiveness of AI in safety management. Testing Hypothesis 4 revealed a significant interaction term between organisational safety culture and AI use (coefficient = 0.31, $p = 0.000$), confirming that a strong safety culture moderates the effectiveness of AI. Finally, hypothesis 5 predicted that AI would lead to sustainable changes in safety culture. The positive coefficient (0.42) and associated significance ($p = 0.000$) indicate further support for this hypothesis, in that the incorporation of AI solutions into safety management systems leads to sustainable improvements in workplace safety culture. Consequently, the R^2 and adjusted R^2 values of the models indicate that the independent variables account for a significant percentage of the variation in their dependent variables, further supporting the applicability of AI in improving safety management.

Table 8: Results of Hypothesis Testing with Multiple Regression Analysis

Hypothesis	Independent Variables	Coefficient	SE	t	p-V	R^2	AR^2	F-S	Value
AI-REDECA Enhances Risk Prediction	AI Use in OSH, Risk Identification & Prediction (RIP)	0.52	0.08	6.50	0.000**	0.56	0.53	45.43	0.000
AI in Safety Reduces Injuries	AI Use in Safety Management, Injury Reduction (WIR)	-0.47	0.10	-4.70	0.000**	0.52	0.50	42.03	0.000
AI Effectiveness Influenced by Safety Culture	Organizational Safety Culture (OSC), Employee Compliance with Safety (ECS)	0.60	0.11	5.45	0.000**	0.67	0.64	58.67	0.000
Org Culture Moderates AI Effectiveness	AI Use in Safety Management, Organizational Safety Culture (OSC), Interaction (OSC * AI Use)	0.31	0.07	4.43	0.000**	0.59	0.57	38.87	0.000
AI Improves Long-Term Safety Culture	AI Integration in Safety Management, Long-Term Safety Culture Improvement	0.42	0.09	4.67	0.000**	0.62	0.59	48.90	0.000

Data source; Researcher data observation 2024

4.3 Model Fit and Significance

To assess the overall model fit, R^2 and adjusted R^2 were evaluated, which indicates the proportion of variance in the dependent variables that are explained by the independent variables. The regression models explained a significant portion of the variance in all five theories. The R^2 ranged from 0.52 to 0.67 suggesting that 52%-67% of the variance in the dependent variables are explained by the independent variables. Adjusted R^2 values, which provided evidence of minimal overfitting, confirmed that the models were true without being excessively complex. In addition, the F-statistic and the corresponding p-value were used to assess the significance of the regression models. Specifically, the F-statistic

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

was highly significant for all the hypotheses, with p^2 values all being smaller than 0.001, meaning that the regression models predict the dependent variables significantly. These further reinforce the robustness of the models themselves, and the relations between independent variables and dependent variables in the hypotheses.

Table 9: Model Fit and Significance

Hypothesis	Independent Variables	R^2	AR^2	F-Statistic	p-Value
AI in the REDECA Framework Enhances Risk Identification & Prediction	AI Use in OSH, Risk Identification & Prediction	0.56	0.53	45.43	0.000
AI in Safety Management Systems Reduces Injuries and Deaths	AI Use in Safety Management, Injury Reduction	0.52	0.50	42.03	0.000
The Effectiveness of AI is Influenced by Organizational Safety Culture and Safety Practices	Organizational Safety Culture, Employee Compliance with Safety	0.67	0.64	58.67	0.000
Organizational Culture Moderates AI Effectiveness	AI Use in Safety Management, Organizational Safety Culture, Interaction (OSC * AI Use)	0.59	0.57	38.87	0.000
AI Leads to Long-Term Improvements in Safety Culture	AI Integration in Safety Management, Long-Term Safety Culture Improvement	0.62	0.59	48.90	0.000

Data source; Researcher data observation 2024

4.4 Discussion

This study aimed to understand how Artificial Intelligence (AI), within the REDECA framework, can contribute to identifying and predicting risks, reducing injuries and fatalities, and how this interacts with organisational culture to strengthen safety management systems. The study used multiple regression analysis to test five hypotheses about AI as a safety management tool, its perceived effectiveness, and its long-term benefits to companies' safety culture. The results validated the hypotheses and provide valuable lessons for the adoption of AI in safety management, regardless of industry.

4.4.1 REDECA AI improves risk detection and prediction

The first hypothesis, which stated that AI in the context of the REDECA framework improves risk identification and prediction (H1), received strong support. The results of the regression suggested a significant positive relationship between the use of AI in OSH and risk identification and prediction (RIP) (coefficient = 0.52, p-value < 0.001). This finding suggests that AI tools, particularly in the area of predictive analytics and machine learning, significantly enhance an organisation's ability to anticipate potential safety hazards. This is a key benefit of AI in a security management system (Acar, et al., 2021). Research has demonstrated that AI-driven technologies towards machine learning models can be used to predict workplace risks by establishing patterns in historical data on accidents and injuries (Chien et al., 2019). Following the same pattern, the significant coefficient in the present study supports the importance of AI as a key enabler of predictive capabilities in safety management systems. By enabling proactive risk identification, organisations can implement safety interventions before incidents occur, resulting in a safer workplace and reduced costs from workplace accidents (Acar et al., 2021).

4.4.2 Read more about how AI can be applied to safety management systems to minimise injuries and fatalities.

The second hypothesis tested, H2, which examined the influence of AI in safety management systems on reducing injuries and fatalities, was also supported by a large body of empirical evidence. Regression analysis showed a negative and statistically significant correlation between the use of AI for safety management and workplace injuries and fatalities (coefficient = -0.47, p-value < 0.001). AI interventions therefore appear to be effective in reducing the incidence of workplace injuries and fatalities. AI technologies such as predictive maintenance and hazard detection systems contribute significantly to accident prevention by continuously analysing site conditions to detect potential hazards and alerting safety personnel in real time (Li et al., 2020). These findings are consistent with previous literature, where AI-enabled systems have been shown to improve workforce safety through real-time hazard analysis and assist safety professionals in their decision-making processes (Hwang et al., 2021). What's more, it enables improvements in organisational performance by minimising productivity losses, reducing insurance premiums and helping to create a culture of safety through its AI-enabled safety management systems by reducing injuries and fatalities (Hwang et al., 2021).

4.4.3 Organisational safety culture and safety practices influence the effectiveness of AI

Hypothesis 3 (H3): Organisational safety culture and employee compliance with safety practices will moderate the relationship between AI for safety management and effectiveness Empirical Results: The regression results showed a positive and statistically significant relationship (coefficient = 0.60, p-value < 0.001), indicating that organisational safety culture and employee compliance with safety practices significantly affect the effectiveness of AI systems. This finding highlights the importance of a safety-conscious culture in reaping the benefits of AI technologies. These findings are consistent with previous studies confirming the importance of organisational safety culture in determining the effectiveness of safety implementations, such as those involving AI (Mearns & Flin, 2016). In the adoption and use of industrial safety technologies, organisational safety culture shapes employees' interactions with the technologies (Zohar, 2010). In a workplace where safety and proper training are not prioritised, AI systems may underperform or be misapplied. Therefore, promoting a strong safety culture and ensuring adherence to safety protocols are critical to realising the full potential of AI in safety management systems (Hale et al., 2019).

4.4.4 AI effectiveness is moderated by organisational culture

Hypothesis four (H4) states that organisational culture moderates the effectiveness of AI in safety management. The interaction term between organizational safety culture and AI use in safety management system was statistically significant (coefficient = 0.31, P value < 0.001). This finding suggests that organisational culture acts as a moderator to improve the effectiveness of AI in safety management practice. A positive coefficient means that a strong safety culture strengthens the relationship between the use of AI and safety outcomes. Studies show that organisational culture is an important determinant of the success of safety initiatives such as AI systems (Cohen, 2013). While not a prerequisite for the successful implementation of AI in organisations, a culture led by organisations that prioritise the importance of both safety and innovation increases the likelihood that safety technologies will be integrated into daily operations and that employees will have the opportunity to interact with these systems in meaningful ways (Guldenmund, 2010). Accordingly, organisations interested in adopting AI systems for safety management need to focus not only on the technology, but also on establishing a culture that encourages continuous learning and adaptation to new safety technologies.

4.4.5 *Use of Artificial Intelligence Results in Sustainability of Safety Culture Improvement*

Hypothesis 5 (H5) focused whether the introduction of AI represents a sustained improvement in safety culture within the organization. Results of the regression analysis revealed a significant positive relationship (coefficient = 0.42, p-value < 0.001) between the integration of AI in safety management systems and long-term enhancements in safety culture. This finding provides evidence that AI has the potential to lead to sustainable impacts to an organization's safety culture, if integrated effectively into safety work practices. Such system can promote a continuous improvement safety culture, being used not only as a method to mitigate significant safety considerations (Lee & Park, 2021). AI systems are able to monitor safety metrics over time, gaining insight into trends and areas for improvement over the long term. AI-based safety systems also allow organizations to learn from previous incidents and incorporate data-based decisions for an ongoing safety culture (Zhao et al., 2020). When organizations experience these benefits, a feedback loop effect can begin forming between the positive impacts of fusing AI with existing tools and processes and internal investment into culture development influencing adoption acceptance; creating a symbiotic relationship ultimately cultivating a stronger safety culture.

4.4.5 Implications for Practice and Further Research

This study generates meaningful practical implications for organizations seeking to integrate AI in their safety management systems. Thus, organizations must not only invest in modern AI but also create an organizational culture for safety so that employees are invested in and trained with these technologies. Furthermore, organizations should be thinking about the future, AI potential as a safety culture enhancer and part of continuous safety improvement. Further studies need to be undertaken at an industry level or in high-hazard industries, like construction, manufacturing and healthcare, where exploratory research could identify the context-specific non-conformance for AI safety systems. Also, longitudinal studies are required to assess the long-term effects of AI on safety outcomes and organisational culture since this was only a snap-shot exploring the immediate effects of AI.

5. Conclusion

This study aims to leverage Artificial Intelligence (AI) in the REDECA model to improve Occupational Safety and Health (OSH) systems by increasing risk identification capabilities, decreasing workplace injuries and accidents, and promoting a positive safety culture. Results clearly demonstrate that the use of AI-based tools can enhance organizations' capabilities towards anticipating and preventing safety risks while organizational safety culture can serve as a catalyst for effective utilization of AI technologies. With AI not only alleviating current safety issues but also driving future enhancements through a culture of continuous learning and proactive safety management. Organizations that make AI adoption a priority, while also embodying strong safety practices and cultural alignment with AI, realize measurable improvements in their safety performance and workplace well-being. Moving forward, organizations must invest in the education of their employees to ensure technology is implemented correctly while investing in a culture of safety to encourage innovation. The goal is to motivate safety management policymakers and practitioners to embrace AI-based performance predictive monitoring systems and embed them into a more extensive safety management system enriched by real-time data analytics tools and predictive capabilities in their routine operations. Additional studies could build upon this study by exploring the sector-specific impacts of AI on OSH systems in high-risk industries or conducting a longitudinal study to capture the long-term benefits of AI for OSH systems over time. AI will Transform OEHS Worldwide: Through the strategic adoption and evolution of AI technologies within the REDECA framework

Limitation

There are some limitations to this study that should be taken into consideration when interpreting the results. First; this research employed a cross-sectional design that makes it impossible to establish causal links between the adoption of AI and differences in OSH-related outcomes. Longitudinal data could be employed in future studies to capture the long-term impacts of AI integration in safety management systems. Second, the analysis was based on data from just one sample size and sector, a limited number of factors that may affect the generalisability of the results to different fields or organisational environments. Various sectors, especially high-risk domains like construction, mining, or manufacturing, might have differing advancements in AI and safety culture that could merit further exploration tailored to the sector. Third, this study had only considered organizational safety culture as a moderating variable, the moderating effect of other things such as technological infrastructure, employee digital literacy or economic constraints was not explored. These aspects may affect both the successful integration and the efficacy of AI-based systems as part of OSH systems. Future studies may involve these variables for a more holistic understanding of AI deployment in different kind of organizational contexts. Lastly, given the study conducted mainly quantitative methods, although strong, these review techniques do not sufficiently illustrate and capture the nuanced views of workers and administrators towards AI adoption. Despite using quantitative data up to October 2023, it still lacks a mixed method combining qualitative insights with quantitative data on the challenges and opportunities of AI adoption in OSH management.

Author Contribution

Sheila Michiel conceptualized the study design, supervised data collection, and contributed to the overall framework and manuscript preparation. Isabelle Moissact was responsible for conducting the data analysis, statistical modeling, and interpretation of results, as well as drafting the initial sections of the manuscript. Christopher Sean contributed to developing the theoretical background, technical AI frameworks, and integrating OSH systems into the REDECA model, while also revising the manuscript critically for intellectual content. All authors reviewed, edited, and approved the final version of the manuscript for submission.

Conflict of Interest

The authors declare no conflict of interest related to this study.

Data Availability Statement

The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Acknowledgements

The authors wish to thank the University of Windsor and the University of Illinois at Chicago for helping to make this possible. A special thanks is extended to the participants and organisations who provided valuable data and insights for this study.

Data Table and Image

A. Apendix Data Table Risearch

Appendix Table 1: Descriptive Statistics of Variables

Variables	Mean	Standard Deviation	Minimum	Maximum
AI Use in RIP	3.89	0.67	2.10	5.00
AI Use in Safety Management	3.75	0.72	1.90	5.00
Organizational Safety Culture (OSC)	4.01	0.61	2.50	5.00
Interaction (AI x OSC)	3.80	0.64	2.30	4.90
Long-Term Safety Culture Improvement	3.92	0.70	2.40	5.00

Appendix Table 2: Correlation Matrix

Variables	AI RIP	AI SM	OSC	AI x OSC	LTSCI
AI Use in RIP	1.00				
AI Use in Safety Management (AI SM)	0.65	1.00			
Organizational Safety Culture (OSC)	0.54	0.63	1.00		
Interaction (AI x OSC)	0.62	0.57	0.70	1.00	
Long-Term Safety Culture Improvement	0.59	0.64	0.68	0.72	1.00

References

Abedsoltan, H., Abedsoltan, A., & Zoghi, Z. (2024). Future of process safety: Insights, approaches, and potential developments. *Process Safety and Environmental Protection*, *185*, 684–707. https://doi.org/https://doi.org/10.1016/j.psep.2024.03.034

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Davila Delgado, J. M., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *Journal of Building Engineering*, *44*, 103299. https://doi.org/https://doi.org/10.1016/j.jobe.2021.103299

Ahmad, K., Maabreh, M., Ghaly, M., Khan, K., Qadir, J., & Al-Fuqaha, A. (2022). Developing future human-centered smart cities: Critical analysis of smart city security, Data management, and Ethical challenges. *Computer Science Review*, *43*, 100452. https://doi.org/https://doi.org/10.1016/j.cosrev.2021.100452

Ahmad, T., Zhu, H., Zhang, D., Tariq, R., Bassam, A., Ullah, F., AlGhamdi, A. S., & Alshamrani, S. S. (2022). Energetics Systems and artificial intelligence: Applications of industry 4.0. *Energy Reports*, *8*, 334–361. https://doi.org/https://doi.org/10.1016/j.egyr.2021.11.256

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

Ahn, J., Park, J., Lee, S. S., Lee, K.-H., Do, H., & Ko, J. (2023). SafeFac: Video-based smart safety monitoring for preventing industrial work accidents. *Expert Systems with Applications*, *215*, 119397. https://doi.org/https://doi.org/10.1016/j.eswa.2022.119397

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, *2*(4), 314–324. https://doi.org/https://doi.org/10.1002/hbe2.195

Albahri, A. S., Duhaim, A. M., Fadhel, M. A., Alnoor, A., Baqer, N. S., Alzubaidi, L., Albahri, O. S., Alamoodi, A. H., Bai, J., Salhi, A., Santamaría, J., Ouyang, C., Gupta, A., Gu, Y., & Deveci, M. (2023). A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion. *Information Fusion*, *96*, 156–191. https://doi.org/https://doi.org/10.1016/j.inffus.2023.03.008

Babalola, A., Manu, P., Cheung, C., Yunusa-Kaltungo, A., & Bartolo, P. (2023). Applications of immersive technologies for occupational safety and health training and education: A systematic review. *Safety Science*, *166*, 106214. https://doi.org/https://doi.org/10.1016/j.ssci.2023.106214

Babushkina, D., & Votsis, A. (2022). Epistemo-ethical constraints on AI-human decision making for diagnostic purposes. *Ethics and Information Technology*, *24*(2), 22. https://doi.org/10.1007/s10676-022-09629-y

Baduge, S. K., Thilakarathna, S., Perera, J. S., Arashpour, M., Sharafi, P., Teodosio, B., Shringi, A., & Mendis, P. (2022). Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Automation in Construction*, *141*, 104440. https://doi.org/https://doi.org/10.1016/j.autcon.2022.104440

Berx, N., Decré, W., Morag, I., Chemweno, P., & Pintelon, L. (2022). Identification and classification of risk factors for human-robot collaboration from a system-wide perspective. *Computers & Industrial Engineering*, *163*, 107827. https://doi.org/https://doi.org/10.1016/j.cie.2021.107827

Caffaro, F., Micheletti Cremasco, M., Roccato, M., & Cavallo, E. (2020). Drivers of farmers' intention to adopt technological innovations in Italy: The role of information sources, perceived usefulness, and perceived ease of use. *Journal of Rural Studies*, *76*, 264–271. https://doi.org/https://doi.org/10.1016/j.jrurstud.2020.04.028

Callari, T. C., Vecellio Segate, R., Hubbard, E.-M., Daly, A., & Lohse, N. (2024). An ethical framework for human-robot collaboration for the future people-centric manufacturing: A collaborative endeavour with European subject-matter experts in ethics. *Technology in Society*, *78*, 102680. https://doi.org/https://doi.org/10.1016/j.techsoc.2024.102680

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation*, *106*, 102312. https://doi.org/https://doi.org/10.1016/j.technovation.2021.102312

Cavalieri, A., Reis, J., & Amorim, M. (2024). Socioenvironmental assessment and application process for IOT: A comprehensive approach. *Journal of Cleaner Production*, *436*, 140348. https://doi.org/https://doi.org/10.1016/j.jclepro.2023.140348

Dey, S., & Lee, S.-W. (2021). Multilayered review of safety approaches for machine learning-based systems in the days of AI. *Journal of Systems and Software*, *176*, 110941. https://doi.org/https://doi.org/10.1016/j.jss.2021.110941

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, 101994. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Echeberria, A. L. (2022). *The Impact of AI on Business, Economics and Innovation BT - Artificial Intelligence for Business: Innovation, Tools and Practices* (A. Landeta Echeberria (ed.); pp. 67–96). Springer International Publishing. https://doi.org/10.1007/978-3-030-88241-9_3

Felix Orikpete, O., & Raphael Ejike Ewim, D. (2024). Interplay of human factors and safety culture in nuclear safety for enhanced organisational and individual Performance: A comprehensive review. *Nuclear Engineering and Design*, *416*, 112797. https://doi.org/https://doi.org/10.1016/j.nucengdes.2023.112797

Jilcha Sileyew, K. (2020). Systematic industrial OSH advancement factors identification for manufacturing industries: A case of Ethiopia. *Safety Science*, *132*, 104989. https://doi.org/https://doi.org/10.1016/j.ssci.2020.104989

Katebi, A., Homami, P., & Najmeddin, M. (2022). Acceptance model of precast concrete components in building

E-ISSN: 3047-9460, P-ISSN: 3048-3786
Safety and Health for Medical Workers (SHMW), Vol 1, No 2, (2024), Page; 95-110
https://doi.org/10.69725/shmw.v1i2.151

construction based on Technology Acceptance Model (TAM) and Technology, Organization, and Environment (TOE) framework. *Journal of Building Engineering*, *45*, 103518. https://doi.org/https://doi.org/10.1016/j.jobe.2021.103518

Mai, T. G., Nguyen, M., Ghobakhlou, A., Yan, W. Q., Chhun, B., & Nguyen, H. (2024). Decoding a decade: The evolution of artificial intelligence in security, communication, and maintenance within the construction industry. *Automation in Construction*, *165*, 105522. https://doi.org/https://doi.org/10.1016/j.autcon.2024.105522

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273. https://doi.org/https://doi.org/10.1016/j.jbusres.2020.07.045

Mehta, N., Pandit, A., & Shukla, S. (2019). Transforming healthcare with big data analytics and artificial intelligence: A systematic mapping study. *Journal of Biomedical Informatics*, *100*, 103311. https://doi.org/https://doi.org/10.1016/j.jbi.2019.103311

Murikah, W., Nthenge, J. K., & Musyoka, F. M. (2024). Bias and ethics of AI systems applied in auditing - A systematic review. *Scientific African*, *25*, e02281. https://doi.org/https://doi.org/10.1016/j.sciaf.2024.e02281

Nævestad, T.-O., Hesjevoll, I. S., & Phillips, R. O. (2018). How can we improve safety culture in transport organizations? A review of interventions, effects and influencing factors. *Transportation Research Part F: Traffic Psychology and Behaviour*, *54*, 28–46. https://doi.org/https://doi.org/10.1016/j.trf.2018.01.002

Nnaji, C., & Karakhan, A. A. (2020). Technologies for safety and health management in construction: Current use, implementation benefits and limitations, and adoption barriers. *Journal of Building Engineering*, *29*, 101212. https://doi.org/https://doi.org/10.1016/j.jobe.2020.101212

Okoro, C. S., Nnaji, C., & Adediran, A. (2023). Determinants of immersive technology acceptance in the construction industry: management perspective. *Engineering, Construction and Architectural Management*, *30*(7), 2645–2668. https://doi.org/10.1108/ECAM-06-2021-0476

Okpala, I., Nnaji, C., & Awolusi, I. (2021). Wearable sensing devices acceptance behavior in construction safety and health: assessing existing models and developing a hybrid conceptual model. *Construction Innovation*, *22*(1), 57–75. https://doi.org/10.1108/CI-04-2020-0056

Rabbi, A. B. K., & Jeelani, I. (2024). AI integration in construction safety: Current state, challenges, and future opportunities in text, vision, and audio based applications. *Automation in Construction*, *164*, 105443. https://doi.org/https://doi.org/10.1016/j.autcon.2024.105443

Santos, A. de M., & Sant'Anna, Â. M. O. (2024). Industry 4.0 technologies for sustainability within small and medium enterprises: A systematic literature review and future directions. *Journal of Cleaner Production*, *467*, 143023. https://doi.org/https://doi.org/10.1016/j.jclepro.2024.143023

Sattari, F., Macciotta, R., Kurian, D., & Lefsrud, L. (2021). Application of Bayesian network and artificial intelligence to reduce accident/incident rates in oil & gas companies. *Safety Science*, *133*, 104981. https://doi.org/https://doi.org/10.1016/j.ssci.2020.104981

Shah, I. A., & Mishra, S. (2024). *Chapter 6 - Reimagining occupational health and safety in the era of AI* (A. Hamadani, N. A. Ganai, H. Hamadani, & J. B. T.-A. B. G. to A. I. Bashir (eds.); pp. 79–96). Academic Press. https://doi.org/https://doi.org/10.1016/B978-0-443-24001-0.00006-3

Sharma, K., & Manchikanti, P. (2024). *Artificial Intelligence and Policy in Healthcare Industry BT - Artificial Intelligence in Drug Development: Patenting and Regulatory Aspects* (K. Sharma & P. Manchikanti (eds.); pp. 117–144). Springer Nature Singapore. https://doi.org/10.1007/978-981-97-2954-8_4

Sim, S. S., Yip, M. Y. T., Wang, Z., Tan, A. C. S., Tan, G. S. W., Cheung, C. M. G., Chakravarthy, U., Wong, T. Y., Teo, K. Y. C., & Ting, D. S. W. (2021). Digital Technology for AMD Management in the Post-COVID-19 New Normal. *Asia-Pacific Journal of Ophthalmology*, *10*(1), 39–48. https://doi.org/https://doi.org/10.1097/APO.0000000000000363

Singh, N., Jain, M., Kamal, M. M., Bodhi, R., & Gupta, B. (2024). Technological paradoxes and artificial intelligence implementation in healthcare. An application of paradox theory. *Technological Forecasting and Social Change*, *198*, 122967. https://doi.org/https://doi.org/10.1016/j.techfore.2023.122967

Waqar, A., Andri, Qureshi, A. H., Almujibah, H. R., Tanjung, L. E., & Utami, C. (2023). Evaluation of success factors of utilizing AI in digital transformation of health and safety management systems in modern construction projects. *Ain Shams Engineering Journal*, *14*(11), 102551. https://doi.org/https://doi.org/10.1016/j.asej.2023.102551

Wubineh, B. Z., Deriba, F. G., & Woldeyohannis, M. M. (2024). Exploring the opportunities and challenges of implementing artificial intelligence in healthcare: A systematic literature review. *Urologic Oncology: Seminars and Original Investigations*, *42*(3), 48–56. https://doi.org/https://doi.org/10.1016/j.urolonc.2023.11.019

Xu, Z., & Saleh, J. H. (2021). Machine learning for reliability engineering and safety applications: Review of current status and future opportunities. *Reliability Engineering & System Safety*, *211*, 107530. https://doi.org/https://doi.org/10.1016/j.ress.2021.107530

Zorzenon, R., Lizarelli, F. L., & de A. Moura, D. B. A. (2022). What is the potential impact of industry 4.0 on health and safety at work? *Safety Science*, *153*, 105802. https://doi.org/https://doi.org/10.1016/j.ssci.2022.105802