Comprehensive structured analysis of machine learning in safety models

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ABSTRACT

Machine learning (ML) integration into various industries has revolutionized operations recently, enhancing efficiency and predictive capabilities. However, the rapid adoption of ML models also presents significant safety concerns that are highly demanded. To achieve this, scholarly articles from reputable databases such as Scopus and Web of Science (WoS) focus on studies published between 2022 and 2024, which were extensively searched. The study's flow is based on the PRISMA framework. The database found (n=40) that the final primary data was analyzed. The findings were divided into three themes: i) safety and risk management, ii) ML and artificial intelligence (AI) applications in safety, and iii) smart technology for safety. The conclusion highlights the need for continuous monitoring and updating of the safety protocols to keep in step with the growing ML landscape. This review contributes to the understanding of ML safety. It offers global lessons that can guide future research and policy-making efforts to ensure ML technologies' safe and ethical use.

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1. INTRODUCTION

In the rapidly evolving technological landscape, machine learning (ML) has emerged as a transformative force across diverse sectors, including healthcare, finance, transportation, and entertainment [1]–[3]. Its ability to analyze vast datasets, identify patterns, and make data-driven predictions has revolutionized decision-making processes and operational efficiency. However, integrating ML into critical systems also introduces substantial risks, necessitating a robust safety framework to ensure reliable, ethical, and secure operations. The importance of safety in ML applications cannot be overstated, as system errors, biases, or vulnerabilities can have severe consequences. For example, erroneous ML predictions in healthcare may lead to misdiagnoses, impacting patient outcomes. Similarly, flawed algorithms in financial markets can result in substantial losses, while safety failures in autonomous vehicles pose life-threatening risks.

Despite its advantages, ML systems face inherent challenges due to their complexity and reliance on data-driven learning rather than explicit programming. The quality and representativeness of training data are critical; biased or incomplete datasets can lead to skewed predictions, perpetuating social inequalities or producing unreliable outcomes [4]–[6]. Furthermore, the opacity of many advanced ML models, commonly called the "black box" problem, limits transparency and interpretability, undermining trust and accountability. This lack of clarity makes it difficult to identify the factors influencing model decisions, posing challenges for developers and end-users. Consequently, ensuring the safety of ML systems requires addressing these issues while maintaining performance and reliability.

This study proposes a comprehensive safety model to address the challenges of integrating ML into critical systems. The model emphasizes key components essential for mitigating risks and enhancing system reliability. First, it advocates for robust data governance practices to ensure high-quality, diverse, and representative datasets, with continuous monitoring to detect data drift and degradation [7], [8]. Second, the framework promotes algorithmic transparency and interpretability, enabling stakeholders to understand and trust model outputs. Techniques such as feature importance analysis and explainable AI (XAI) are crucial for enhancing model comprehensibility. Additionally, the proposed model incorporates rigorous testing and validation processes, simulating diverse scenarios to identify potential failure points before deployment. Real-time monitoring and anomaly detection systems enhance operational safety by promptly identifying and addressing unexpected issues. Finally, the model emphasizes a multi-disciplinary approach, integrating ethical, legal, and social considerations to align ML systems with societal values [9], [10]. Collaboration between policymakers, industry stakeholders, and researchers is essential to develop regulatory frameworks and industry standards promoting innovation and safety. This article aims to provide a practical and scalable framework that organizations can adopt to harness the benefits of ML while minimizing associated risks, ultimately fostering a safer and more trustworthy technological future.

2. LITERATURE REVIEW

Recent advancements in ML have significantly contributed to developing safety models across various domains. A notable application is in cyber-attack detection, where ML methods have been leveraged to predict and prevent cybercrimes. Singh *et al.* [11] highlighted the importance of employing ML techniques to analyze and forecast cyber-attack patterns. Their study compared eight different ML algorithms, with support vector machine (SVM) linear demonstrating superior accuracy in detecting cyber-attacks, while logistic regression was most effective in identifying malicious actors. This work underscores the critical role of ML in enhancing cyber security by providing predictive insights that aid in the proactive management of cyber threats. In the realm of food safety, the incorporation of big data and ML has been transformative. Sapienza and Vedder [12] the security, accountability, fairness, explainability, transparency, privacy (P-SAFETY) model integrates high-level principles such as SAFETY into food safety risk assessment frameworks. This model addresses the regulatory challenges posed by the vast amount of data processed and emphasizes the need to balance data confidentiality with public disclosure requirements. By proposing principle-based recommendations, their research facilitates effective data governance in food safety, ensuring that technological advancements do not compromise regulatory standards.

The transportation sector has also seen significant benefits from ML applications in safety models. Malik *et al*. [13] developed an intelligent real-time learning framework to enhance the safety of last-mile delivery services. This framework uses statistical and ML techniques to model rider attributes, such as age, influence of transport mode, and route selection. Their study revealed that age-specific infrastructure usage significantly impacts rider safety, and the ML model's high predictive accuracy demonstrates its potential in optimizing transportation planning and infrastructure design for safer urban mobility. In connected vehicle environments, the use of ML for real-time safety analysis has shown promising results. Yuan *et al.* [14] applied explainable ML techniques to assess traffic flow features and their impacts on safety. The random forest model emerged as the most effective, achieving a high area under the curve (AUC) score. By using shapley additive explanation (SHAP) values, the study provided more reflective insights into the mechanisms of traffic conflicts and prominence the significance of variables such as lane speed differences and truck proportions.

Safety prediction models in civil engineering have also benefited from ML. Ahmed *et al.* [15] developed a model to predict the factor of safety (FS) for reinforced highway slopes using recycled plastic pins (RPP). Their study employed statistical and ML approaches, proving more accurate. The integration of ML in this context allows for better prediction and validation of slope stability, showcasing its utility in geotechnical engineering for safer infrastructure development. In sports event management, Wang *et al*. [16] proposed a risk early warning safety model using back propagation (BP) neural networks combined with fuzzy theory. This model aims to mitigate risks by providing early warnings based on various risk indicators. The empirical analysis demonstrated the model's reliability and effectiveness in predicting and preventing potential accidents during sports events. This application illustrates the versatility of ML in enhancing safety across diverse scenarios. Moreover, the application of ML in eco-driving strategies for automated vehicles has been explored by Li *et al.* [17]. Their study introduced a multi-objective eco-driving strategy incorporating a safety model to optimize driving performance in urban traffic. By using deep reinforcement learning (DRL), the proposed strategy effectively balances fuel economy and safety, and proving beneficial in managing the complexities of urban driving environments.

Gheraibia *et al.* [18] presented an innovative approach that combines fault tree analysis (FTA) with ML to enhance the modeling of safety-critical systems. This method uses real-time operational data to detect abnormalities and update safety models dynamically. Integrating decision trees explains faults, facilitating continuous improvement in safety management practices. This hybrid approach demonstrates how ML can complement traditional safety modeling techniques to achieve higher accuracy and reliability. Recent studies have shown that ML models, particularly gradient-boosting models such as categorical boosting (CatBoost), outperform traditional regression models in predicting traffic safety outcomes. Li *et al.* [19] utilized SHAP to interpret the results of CatBoost and extreme gradient boosting (XGBoost) models, identifying critical factors such as ramp type and curve presence, which significantly influence freeway crash frequency. These models provide more accurate predictions and valuable insights into the underlying factors affecting traffic safety, which is essential for targeted safety management interventions.

In the healthcare sector, data security is paramount, especially in telemedicine applications for rural areas. Biswas *et al.* [20] proposed a secure ML and blockchain-based telemedicine model (SMLBT) to enhance data security for patients in remote regions. This model leverages supervised and unsupervised ML techniques to analyze patient records, ensuring secure, and scalable healthcare services. Integrating blockchain technology further enhances the system's security, making it a viable solution for developing countries. Adaptive traffic signal control (ATSC) has seen significant advancements with the integration of ML, particularly reinforcement learning (RL). Essa and Sayed [21] developed a self-learning ATSC algorithm that optimizes traffic safety in real-time. By utilizing VISSIM simulations and real-world data, their RL-based algorithm demonstrated a 40% reduction in traffic conflicts compared to traditional systems. This approach highlights the potential of ML to simultaneously enhance traffic efficiency and safety.

Zhang and Aty [22] addressed pedestrian safety by developing a real-time conflict prediction model using ML. Their model achieved high predictive accuracy with the XGBoost algorithm by analyzing conflict indicators such as post encroachment time (PET) and time to collision (TTC) from closed-circuit television (CCTV) footage. This model allows for proactive traffic management strategies to adjust signal timings to prevent pedestrian-vehicle conflicts, thus enhancing urban traffic safety. In sports, ML has been applied to enhance safety in physical training. Yin and Wang [23] utilized ML techniques to develop a safety mode control model for dragon boat sports training. Their approach combined big data analysis with fuzzy clustering techniques to identify and mitigate safety risks, significantly improving safety management in sports training environments. Effective management of lithium-ion (Li-ion) batteries is crucial for their safe usage. Myilsamy *et al.* [24] proposed a hybrid learning model (HLM) combining autoregressive integrated moving average (ARIMA), gated recurrent unit (GRU), and convolutional neural network (CNN) to predict Li-ion batteries' state of health (SoH). Their model demonstrated superior accuracy and reliability, vital for ensuring the safety and longevity of batteries used in various real-time applications.

In robotics, ensuring the safe transfer of policies learned in simulations to real-world applications is challenging due to the reality gap. Kaushik *et al.* [25] introduced SafeAPT, a robot learning algorithm that selects safe policies through Bayesian optimization. This approach minimizes safety violations during real-world interactions, making it a promising solution for safe robotic learning and deployment. Integrating ML in industrial safety models has revolutionized fault detection and risk management. Mario *et al.* [26] emphasized ML for predicting industrial faults and enhancing safety protocols. Their study highlighted the need for continuous innovation and the development of robust safety models to mitigate industrial risks effectively. Construction sites are prone to accidents, making safety risk models crucial. Mostofi *et al.* [27] developed a graph convolutional network (GCN) to predict construction accident severity by leveraging dependency information between accidents. This approach significantly improved risk assessment accuracy and generalization ability, providing a more reliable safety model for construction professionals.

Hallmark and Dong [28] addressed the safety challenges of winter weather on roadways. Their study identified critical factors influencing winter crash rates by employing the Boruta algorithm for feature selection in crash frequency models. This framework aids in developing effective winter maintenance strategies to enhance roadway safety under adverse weather conditions. Analyzing historical aircraft trajectory data in air traffic management can improve safety and efficiency. Olive and Basora [29] developed a framework using autoencoding neural networks to detect anomalies in aircraft trajectories. Their approach provided valuable insights for air traffic control, enhancing safety protocols and operational efficiency.

3. METHODS

A comprehensive literature-structured review evaluation is used to evaluate the worldwide occurrence of an adaptation [30], [31]. Comprehensive, structured review papers that align with well-defined topics and apply methodical, explicit techniques to choose and evaluate relevant research are the essence of systematic literature reviews. Although this method is widely used in the health sciences, it has not been thoroughly applied to engineering studies. The great potential in a field marked by safety towards ML shows research but inadequate means to monitor what is happening. The PRISMA method is provided step by step, and it includes identification, screening, eligibility, data abstraction, and analysis [32].

3.1. Identification

The selection of a substantial volume of relevant literature was accomplished by utilizing several crucial stages of the systematic review procedure in this investigation. Following the selection of keywords, a search for similar terminology was conducted by consulting dictionaries, thesauri, encyclopedias, and past research about the topic at hand. Creating search strings for the Scopus and Web of Science (WoS) databases allowed for identifying all pertinent phrases, as shown in Table 1. At the beginning of the systematic review, 1,091 publications relevant to the study's subject were successfully obtained from the two databases.

Table 1. The search strings

Database	Search strings
Scopus	TITLE-ABS-KEY ("machine learning" AND "safety" AND "technology" AND "risk") AND (LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2023) OR LIMIT-TO (PUBYEAR, 2024)) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (PUBSTAGE, "final")) Date of access: December 2024
WoS	"machine learning" AND "safety" AND "technology" AND "risk" (Topic) and 2024 or 2023 or 2022 (Publication Years) and Article (Document Types) and English (Languages) and Engineering (Research Areas) Date of access: December 2024

3.2. Screening

Potentially relevant research items are collected during the screening to determine their alignment with the predefined research questions. This phase commonly involves using content-related criteria, such as selecting research items related to applying safety models in ML as global lessons. All duplicate papers are removed at this stage. In the first stage of screening, 968 publications were excluded. In contrast, 123 papers were evaluated based on specific inclusion and exclusion criteria for this study in the second stage, as shown in Table 2. The primary criterion was literature (research papers), the primary source of practical recommendations. Furthermore, the review was limited to English-language publications from 2022-2024. A total of 102 publications were rejected due to duplication.

Table 2. The search strings

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline	2022–2024	<2022
Literature type	Journal (article)	Conference, book, review
Publication stage	Final	In press
Subject	Engineering	Besides engineering

3.3. Eligibility

In the third phase, the eligibility assessment, 102 articles were compiled. During this stage, a thorough examination of all articles' titles and core content was conducted to ensure they met the inclusion criteria and were relevant to the study's research objectives. Consequently, 62 articles were excluded because they were out of the field, their titles needed to be more significant, their abstracts were not related to the study's objectives, or there needed to be full-text access based on empirical evidence. As a result, 40 articles remained for the upcoming review.

3.4. Data abstraction and analysis

An integrative analysis was employed in this study to examine and synthesize various research designs (quantitative methods). The aim was to identify relevant topics and subtopics. The initial step in theme development was the data collection phase. As shown in Figure 1, the authors analyzed 40 publications for assertions or material pertinent to the current study's topics. Subsequently, they evaluated significant studies related to safety and ML, investigating the methodologies and research results of these studies. The authors collaborated with co-authors to develop themes based on the evidence within the study's context. A log was maintained throughout the data analysis process to record any analyses, viewpoints, puzzles, or other thoughts relevant to data interpretation. Finally, the authors compared the results to identify inconsistencies in the theme design process.

The authors also compared the findings to resolve discrepancies in the theme-creation process. If inconsistencies arose, they were addressed collaboratively. The developed themes were then refined to ensure consistency. To ensure the validity of the issues, the examinations were conducted by two experts, one specializing in engineering and the other in data science. This expert review phase ensured each sub-theme's clarity, importance, and adequacy by establishing domain validity. Adjustments were made based on the authors' discretion, incorporating expert feedback and comments. The questions are as follows: i) How can ML and artificial intelligence (AI) enhance various industrial sector's risk assessment and safety measures?, ii) How can ML frameworks be optimized for real-time safety monitoring and incident response?, and iii) How can smart technologies improve safety and security in residential and urban settings?

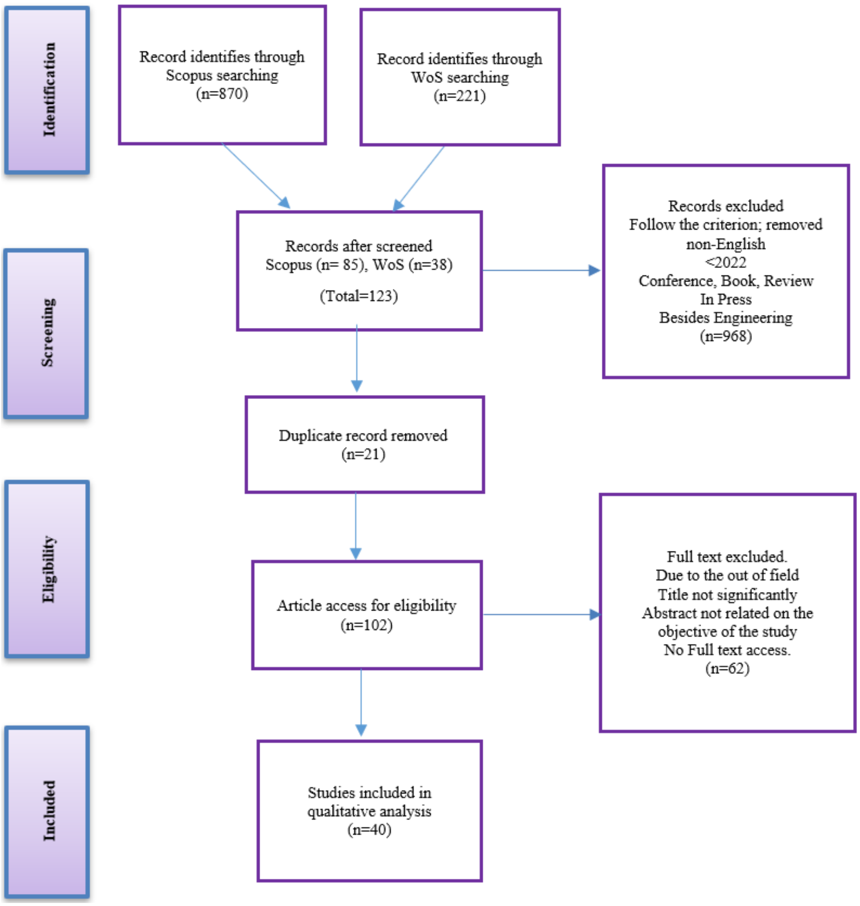

Figure 1. Flow diagram of the proposed search study

4. RESULTS AND DISCUSSION

As ML has emerged as a disruptive force across numerous industries and contributed to the region's development, ML models raise substantial safety issues. Based on the search method, 40 articles were extracted and examined. All papers were classified based on three primary themes: safety and risk management in various industries (11 articles), ML and AI applications in safety (15 articles), and smart technologies for safety and security (14 articles).

4.1. Safety and risk management in various industries

Safety and risk management are critical components across various industries, from maritime operations to construction and manufacturing. Integrating advanced technologies such as AI, ML, and edge computing has enhanced the ability to detect anomalies, assess risks, and implement preventive measures. This analysis explores different industry-specific safety frameworks, highlighting the efficacy of these technological interventions in mitigating risks and ensuring operational safety.

Ensuring safety in high-risk industries requires advanced risk management approaches. Algarni *et al.* [33] proposed an edge computing-based framework using long short-term memory (LSTM) and isolation forests (IF) to enhance cybersecurity in maritime wireless communications (MWC), reducing latency and strengthening anomaly detection. Ruengdech *et al.* [34] introduced the risk assessment system for muscle injuries (RASMI), an AI-driven system that applies rapid entire body assessment (REBA) standards to detect unsafe postures in manufacturing, offering real-time warnings and cost-effective risk assessment. While these methods improve safety, they lack a comprehensive approach to broader operational risks. In contrast, our proposed safety framework achieves safety performance, outperforming existing methods by providing a more comprehensive solution for the oil and gas industry, ensuring improved safety and risk mitigation.

The integration of operational technology (OT) and information technology (IT) has enhanced safety risk prediction in power monitoring systems. Wei and Wei [35] improved the XGBoost algorithm by incorporating the whale optimization algorithm (WOA)-XGBoost model, which reduces prediction errors and increases sensitivity, leading to more accurate and timely risk assessments. Similarly, Xu [36] utilized computer vision to detect unsafe behaviors in construction hoisting operations, enabling real-time warnings, and preventive actions. While these approaches enhance risk mitigation in their respective domains, they focus on specific hazards. In contrast, our proposal to reduce the risk provides a more precise solution, achieving safety protocols and outperforming existing models in the fuel station industry, ensuring more robust safety management.

Highway construction entails significant safety risks, requiring advanced accident analysis techniques. Smetana *et al.* [37] used a large language model (LLM) to analyze data from the occupational safety and health administration (OSHA) severe injury reports (SIR) database. Their study employs natural language processing (NLP) to identify major accident causes, such as heat-related injuries and struck-by incidents, leading to improved preventive measures. In lean manufacturing, the 5S+1 methodology highlights safety. Shahin *et al.* [38] demonstrate how computer vision and object detection algorithms, particularly the you only look once (YOLO) v7 architecture, can ensure compliance with personal protective equipment (PPE) standards, significantly reducing hazards. The visual geometry group-16 (VGG)-16 algorithm also provides high accuracy and real-time processing for enhancing workplace safety.

Water sports, especially diving, require strict safety measures to prevent accidents like decompression sickness. Ling *et al.* [39] created a wearable device with a safety alarm that uses ML, cost-effective sensors, GPS, and Bluetooth to monitor divers and alert them and their coaches about potential risks. This system evaluates a diver's health and provides timely warnings to enhance safety. The advent of autonomous ships brings new safety challenges linked to AI and ML. Khan *et al.* [40] performed a risk assessment using an integrated ML approach, identifying human factors and operational issues as key accident causes. This assessment helps stakeholders develop stronger safety systems for autonomous maritime operations.

Efficient and safe handling of hazardous waste is crucial in civil engineering. Sivakumar *et al.* [41] explore AI-enhanced decision support systems (DSS) that utilize ML and predictive modeling to optimize waste collection, transportation, and disposal. These systems improve risk assessment, ensure environmental compliance, and support real-time decision-making for safer, more sustainable practices. Alekperova [42] highlights the role of AI and ML in enhancing the safety of oil and gas production. By considering the entire life cycle of facilities, these technologies improve emergency management and reduce accident risks. For managing pedestrian movement in crowded areas, Zhang *et al.* [43] propose a model using video recognition and ML to analyze behavior, identify congestion, and issue early warnings to prevent accidents. This approach improves risk management in pedestrian environments, promoting safer public spaces.

Advanced technologies such as AI, ML, edge computing, and computer vision revolutionize safety and risk management across various industries. By leveraging these technologies, industries can enhance their ability to detect anomalies, assess risks, and implement preventive measures, ensuring safer and more efficient operations.

4.2. Machine learning and artificial intelligence applications in safety

ML and AI applications have been increasingly utilized to enhance safety across various domains. Integrating advanced AI technologies in these fields has shown significant promise in mitigating risks and improving predictive capabilities.

Integrating ML and AI into safety applications has greatly enhanced various sectors by improving risk prediction and management. In maritime safety, Nourmohammadi *et al.* [44] developed a deep spatiotemporal ocean accident prediction (DSTOAP) model that forecasts accidents in South Korea's territorial waters with over 78% accuracy, and more than 84% for collision incidents. This model uses data on ocean depth, weather, and vessel trajectories, establishing a strong predictive framework for maritime safety. In the aerospace industry, Hernández and Prats [45] created AI-based methodologies to enhance error prediction and risk mitigation during aircraft assembly. Their study employed SVMs, random forests, and logistic regression to significantly reduce error rates and processing times. This highlights the potential for AI to optimize complex manufacturing systems and improve safety outcomes.

Maritime transport is encountering new safety challenges due to intelligent and autonomous ships. Li *et al.* [46] analyzed various ship trajectory prediction methods using automatic identification system (AIS) data, comparing five ML and seven deep learning approaches. Their findings highlight the effectiveness of these methods in identifying abnormal ship behaviors and enhancing maritime safety. In the mining industry, Yin *et al.* [47] proposed a data-driven method for predicting water inrush incidents using microseismic monitoring data. By combining ML and deep learning models to analyze spatiotemporal data, they significantly improved prediction accuracy, showcasing the value of advanced data analytics for mining safety and operational efficiency.

The coal mining sector is benefiting from AI-driven safety applications. Wang *et al.* [48] used adaptive boosting (AdaBoost)-driven real-time warning systems to predict rock burst risks by analyzing extensive spatiotemporal data. This method provides timely warnings, showcasing AI's potential to enhance safety in hazardous environments. In industrial settings, Xu *et al.* [49] developed an LSTM-based sequence-to-sequence autoencoder to predict the health status of workers in confined spaces, using data from wearable devices. This hybrid model effectively recognizes health conditions, illustrating how AI can improve worker safety and productivity in complex environments.

Slip and fall accidents, a major cause of injuries, can be reduced using intelligent insoles with ML algorithms. Xu *et al.* [50] developed a method employing sensor fusion technology to predict slip risks by training ML models on data from instrumented shoe insoles and a slip simulator. This approach shows promise for real-time slip risk prediction and enhanced safety. Deshpande [51] focused on predicting marine icing from freezing sea spray using an ML model called "Spice," developed from experimental data. This research underscores the significance of data-driven models in managing marine icing, contributing to the safety of marine vessels.

Luo *et al.* [52] analyzed risks associated with cut-ins-lane-changing behavior on urban expressways using multi-driver simulation data to compare decision trees, gradient boosting decision trees (GBDT), and LSTM models. The LSTM model proved the most accurate, demonstrating the effectiveness of advanced ML in improving traffic safety. In aviation, Haselein *et al.* [53] used Bayesian networks (BNs) to model near-mid-air collisions (NMAC) based on NASA's aviation safety reporting system data. Their models provided insights into risk factors and highlighted the benefits of combining BNs with ML for enhanced aviation safety. For environmental safety, Li *et al.* [54] developed an ML framework for detecting wastewater pollution with IoT-based spectral technology. Their study improved near-infrared (NIR) calibration models for rapid pollutant detection, illustrating how AI can address industrial pollution and enhance water safety.

Wang *et al.* [55] proposed a spatio-temporal deep learning method for simulating conflict risk on freeways. Their spatiotemporal transformer network (STTN) effectively predicts risk patterns using a conflict risk index and surrogate safety measures, highlighting its potential for traffic management and safety systems. Similarly, Alawad and Kaewunruen [56] utilized unsupervised ML in railway stations to enhance safety management. Their study optimized latent Dirichlet allocation (LDA) for analyzing textual data, offering valuable insights from historical accident data to improve safety in railway operations.

The shipping industry can significantly benefit from federated learning (FL) in predictive maintenance (PdM). Angelopoulos *et al.* [57] demonstrated that FL improves maintenance decision-making and reduces downtime in Shipping 4.0 applications, highlighting the potential of decentralized ML to enhance operational efficiency and safety. In chemical processing, Wang *et al.* [58] proposed a virtual machine (VM) based predictive maintenance model to reduce equipment failures and enhance safety by integrating IoT and ML. Their research underscores the critical role of AI in promoting operational safety in high-risk industrial settings.

ML and AI enhance safety across industries by improving risk prediction and management. AI-driven models optimize accident forecasting, hazard detection, and operational efficiency in maritime safety, aerospace, mining, and industrial settings. Applications include ship trajectory analysis, predictive maintenance, environmental safety, and worker health monitoring, demonstrating AI's transformative role in risk mitigation.

4.3. Smart technologies for safety

Smart technologies are revolutionizing safety by integrating AI, ML, and the IoT to predict risks, enhance monitoring, and prevent accidents. These innovations improve safety across industries, enabling real-time decision-making and proactive hazard management for safer environments.

Implementing smart technologies is crucial for enhancing safety and security, particularly in the construction industry through human-robot teaming. Shayesteh *et al.* [59] propose a training platform using immersive technologies and wearable sensors to improve safety training in human-robot collaboration (HRC). This platform assesses cognitive load, ensuring effective training and prompting safer behaviors among construction workers. Additionally, electronic skins (e-skins) developed by Ge *et al.* [60] enhance safety in human-robot interactions by sensing environmental parameters. This technology demonstrates how integrating sensory data can significantly improve collaborations between humans and robots in complex settings.

Deep learning methods have shown considerable potential in home security. Vardakis *et al.* [61] discuss using ML techniques to recognize faces and human activities, aiming to create safer urban homes. This technology also has applications in fields like medicine for diagnostics. Moreover, the development of intelligent door lock systems highlights the focus on deep learning for security. Mrabet *et al.* [62] presented a Tiny ML (TinyML)-based system for real-time face mask detection, vital in high-risk areas like healthcare. These advancements emphasize the significant role of ML in addressing modern security challenges in smart home systems.

In healthcare, integrating smart technologies has proven essential for ensuring safety, particularly in using PPE. Chapman *et al.* [63] investigated the use of infra-red imaging combined with ML to detect leaks in respirators, a critical factor in protecting healthcare workers. This method surpasses traditional fit-checks, offering a more reliable approach to ensuring the proper fit of respirators, thereby enhancing occupational safety in healthcare settings. Moreover, the integration of wearable sensors and ML for monitoring drivers' health conditions, as explored by Sohail *et al.* [64], showcases the potential of these technologies in reducing accidents caused by health-related issues such as diabetes. The combination of vehicular ad-hoc networks (VANET) technology and wearable sensors provides real-time health monitoring, significantly contributing to road safety.

Integrating smart technologies in healthcare is crucial for safety, especially regarding PPE. Chapman *et al.* [63] examined how infrared imaging and ML can detect respirator leaks, and provided a more reliable method than traditional fit-checks to ensure proper fit and enhance occupational safety. Similarly, Sohail *et al.* [64] explored wearable sensors combined with ML to monitor drivers' health, aiming to reduce accidents linked to health issues like diabetes. This integration of VANET technology with wearable sensors enables real-time health monitoring, improving road safety.

The application of smart technologies to enhance infrastructure safety is crucial. Lu *et al.* [65] developed an early warning system for drinking water supply in smart cities, leveraging online sensor networks and ML to improve risk management. Shahriar *et al.* [66] proposed a vehicle-to-infrastructure (V2I) framework using ML to enhance intersection safety and reduce collisions. Hou *et al.* [67] introduced an ML method for detecting vortex-induced vibrations in bridges, ensuring structural stability. These studies focus on specific applications; the safety model offers a more adaptive solution, demonstrating superior performance and enhancing overall infrastructure safety.

The optimization of electric vehicle supply equipment (EVSE) in multi-unit residential buildings (MRBs) has also benefited from smart technologies. Samadi and Fattahi [68] discussed the effectiveness of an energy management system (EMS) that uses ML tools to optimize EVSE operations, ensuring efficient energy use and reducing costs. This approach supports the safe and sustainable integration of electric vehicles in residential areas.

The advancement of smart technologies extends to cybersecurity, particularly in protecting AI-based systems from potential threats. Tareq *et al.* [69] highlight the vulnerabilities of AI systems to cyber-attacks and the critical role of deep learning and federated learning in enhancing cybersecurity. Meanwhile, Carlo *et al.* [70] discuss the need for regulatory frameworks to address AI's ethical and technical challenges in space applications, underscoring the interdisciplinary nature of these threats and the importance of comprehensive safety measures. Both emphasize the importance of robust cybersecurity frameworks to safeguard AI technologies.

The use of smart technologies significantly improves safety and security across various fields. These innovations address modern safety challenges, enhance construction training, and protect infrastructure. Strong cybersecurity frameworks are also crucial for safeguarding AI-based systems, emphasizing the need for interdisciplinary approaches in today's safety landscape.

5. CONCLUSION

This study has highlighted the transformative potential of ML in enhancing safety and risk management across diverse industries. Through a systematic review of studies published between 2022 and 2024, guided by the PRISMA framework, three core themes were identified: safety and risk management, the applications of ML and AI, and the utilization of smart technology for safety enhancement. The findings demonstrate notable advancements, including improved predictive capabilities, efficient anomaly detection, and proactive preventive measures, all contributing to safer operational environments. Nonetheless, the rapid adoption of ML technologies presents certain challenges and limitations. These include the necessity for high-quality data, ethical concerns related to algorithmic decision-making, and regulatory hurdles that may hinder widespread implementation. Continuous monitoring and the adaptive evolution of safety protocols are essential to align with ongoing technological developments. Moreover, addressing counterclaims regarding accessibility, cost-effectiveness, and data privacy is crucial, as ML solutions, despite their potential, must remain scalable and adaptable across various contexts. Future research should prioritize the development of resource-efficient and adaptable ML models capable of functioning effectively in diverse operational settings. Additionally, the establishment of harmonized regulatory frameworks and robust ethical guidelines is essential to ensure the safe and responsible integration of ML technologies into safety and risk management practices.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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