

Review Article

Towards Automation and Elimination of Subjectivity in Industrial Risk Management Based on Artificial Intelligence

Kawtar Benderouach^{1*}, Idriss Bennis¹, Abdelouahad Bellat², Khalifa Mansouri¹

¹Laboratory of Modelling and Simulation of Intelligent Industrial Systems (M2S2I), ENSET of Mohammedia, Hassan II University of Casablanca, Morocco.

²PCMT Research Laboratory, Mohammed V University of Rabat, Avenue de l'Armée Royale, 10100 Rabat, Morocco.

^{1*}Corresponding Author : kawtar.benderouach@gmail.com

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Abstract - Risk management is one of the fundamental components of a company's success, whatever its sector of activity. This paper reviews the work done in the field of risk management, both traditionally and by integrating Artificial Intelligence. It highlights the way in which risk management was solved in the traditional way, discussing methods and approaches and citing the limitations of traditional risk management. It also outlines research into the integration of Artificial Intelligence into risk management in the various phases of the risk management process. Based on the open literature published in the various journals in the field of risk management, the stages of the risk management process are the result of human judgment, which may identify risks or, for psychological or/and social reasons, may not, so human subjectivity influences the risk identification phase and all phases of the risk management process. To reduce this subjectivity and to reduce human contact in this phase, our article proposes a model based on Artificial Intelligence that attempts to identify risks and treat them in order to reduce or eliminate existing risks.

Keywords - Risk management, Artificial Intelligence, Machine Learning, Natural Language Processing, Subjectivity.

1. Introduction

Industrial risk management plays a fundamental role in ensuring the safety, reliability, and continuity of operations in complex industrial systems. In high-risk environments, risks may arise from equipment failures, human errors, or environmental incidents. For example, equipment failures significantly affect system reliability [1], while human errors remain one of the main causes of industrial accidents [2]. Environmental risks also contribute to major incidents in industrial settings [3]. Effective risk management is therefore essential to prevent major accidents, reduce operational disruptions and minimize financial losses associated with system failures and unexpected events [4]. In addition, it contributes to extending infrastructure lifespan, improving maintenance planning and ensuring compliance with regulatory requirements [5]. Moreover, risk management plays a key role in improving product quality and reducing non-conformities in manufacturing processes [6] as well as in optimizing industrial operations and reducing maintenance costs [7]. To confront these problems, a number of risk assessment methods have been developed and widely adopted within industries.

The primary purpose of most of the strategies, Failure Mode and Effects Analysis (FMEA), is to locate potential failures by their critical importance and prioritize them accordingly [8]. Fault Tree Analysis (FTA) also gives a graphic representation on the source of failures in systems [9]. Hazard and Operability (HAZOP) analyze deviations from typical work conditions with particular emphasis on high-risk sectors such as chemical production [10].

Quantitative Risk Assessment (QRA) methods rely on merging probability and consequence analysis to estimate the level of risk [11] and are frequently referenced in oil and gas sectors [12, 13]. In parallel, simpler approaches such as Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis and the risk matrix [14], enable risks to be classified and prioritized at different levels. In addition, methods such as Monte Carlo simulation and scenario analysis are used to assess uncertainty in complex systems [15]. Although these methods provide important information, they are often integrated to develop a risk management strategy. Although traditional risk management methods are used in the industrial sector, they face a variety of challenges.



These methods rely on individual expertise, which introduces elements of subjectivity and inconsistency into risk assessment. Furthermore, they tend to be reactive, as they focus on assessing incidents after the fact rather than promoting proactive risk mitigation measures. The effectiveness of these systems is also compromised by their inability to handle large amounts of unstructured data and to adapt to changing industrial conditions. Furthermore, the lack of real-time data integration combined with the complexity of implementation can hinder rapid and effective decision-making.

The subjectivity inherent in industrial risk management highlights the inconsistencies in human judgment when assessing and classifying risks. This variability often stems from differences in expertise, experience and interpretations of accident reports. Consequently, similar events may be judged differently by various experts, leading to discrepancies in the decision-making process. The emergence of Artificial Intelligence (AI) and Machine Learning (ML) has recently been seen as a major breakthrough in addressing these challenges. AI enables automated analysis of large amounts of data, anomaly detection [16], predictive maintenance [17] and accident prediction [18]. In particular, Natural Language Processing (NLP) is attracting growing interest due to its ability to extract meaningful information from unstructured textual data such as incident reports.

However, despite these advances, the current literature has several shortcomings. On the one hand, most current research focuses on optimizing predictive performance without addressing the fundamental issue of the subjectivity of risk perception. On the other hand, little attention has been paid to the comparative evaluation of the effectiveness and robustness of various text feature extraction algorithms, such as Bag-of-Words, TF-IDF, and contextual representations.

Third, previous works are usually based on single-output classification and overlook the task of producing multiple perspectives of risk information simultaneously regarding the type of accident, which may affect a decision-making pattern, causes, consequences, and the degree of severity of that threat situation. Lastly, there are still more areas, such as interpretability, human supervision, and deployment in tangible industrial settings, that have yet to be addressed. To overcome these limitations, an artificial intelligence framework for industrial risk management is introduced to minimize subjective judgment and improve consistency in risk assessment.

The proposed method uses NLP methods and machine learning systems to achieve automatic risk extraction and classification from text-level accident reports. Unlike traditional frameworks, the framework uses a multi-output architecture and is able to predict the classification of accidents, their causes, effects, and severity at the same time.

The primary contributions of this article are:

- The discovery and standardization of subjectivity-based drawbacks in classical risk management procedures;
- Development of a multi-output AI-based approach for automated identification and classification of risk in unstructured textual data;
- Comparison amongst several textual feature extraction techniques such as Bag-of-Words, TF-IDF, Word2Vec, and BERT;
- Testing of diverse ML models; and implementation of SMOTE for robustness to imbalanced datasets;
- The approach addressing the aspects of interpretability, Human-in-the-Loop validation, and industrial deployment difficulties.

The proposed framework is intended to facilitate the seamless process of creating and managing risk assessments in the real world, where text is commonly used for decision-making and decision-making. The rest of this paper is structured as follows. The research methodology for the literature review and study selection process is outlined in Section 2. In Section 3, some traditional risk management methods are critiqued and their limitations within industrial scenarios. Artificial Intelligence (AI), Machine Learning (ML) and Natural Language Processing (NLP) in risk management systems are presented in Section 4. Section 5 presents the proposed framework and the experimental methods in this study. Section 6 reports findings from the analysis and their potential effects on industrial risk management. This work finally ends with Section 7, which further describes future research directions.

2. Research Methodology

This study adopts a structured literature review methodology to analyse traditional and AI-based approaches in industrial risk management (see Figure 1).

The objective is to highlight recent advances, research areas, challenges and future prospects regarding the integration of Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) into industrial risk management frameworks. An in-depth literature review was conducted using various scientific databases, including Scopus, ScienceDirect, and Google Scholar, to identify relevant research articles. This study relied on key terms such as “industrial risk management”, “machine learning”, “natural language processing”, “accident prediction”, “risk assessment” and “AI-based safety systems.”

To ensure the quality and relevance of the selected publications, several inclusion and exclusion criteria were established. This study focused on articles written in English, published in scientific journals or presented at conferences, and directly addressing industrial risk management or traditional and artificial intelligence-based approaches applied

to safety analysis. Conversely, studies unrelated to industrial systems, redundant studies, and publications that did not provide sufficient methodological details were excluded. The selected studies were then classified into several categories, including traditional risk management approaches, machine

learning-based risk assessment methods and Natural Language Processing (NLP) applications for accident analysis. A comparative analysis was then conducted to identify methodological limitations, research gaps and emerging trends in this field [19].

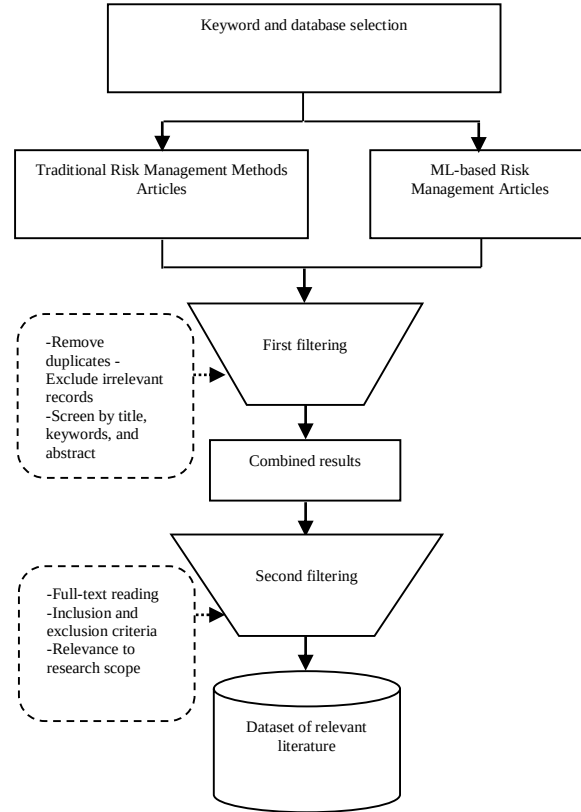


Fig. 1 Literature retrieval process

3. Traditional Risk Management

Risk management is a discipline whose aim is to identify, analyze, assess and deal with risks. These risks may be financial, strategic, legal, environmental, IT (Information Technology), technical or operational. Our literature review focuses on technical and operational risks in the fields of safety and maintenance (failures). The risk management process proposed by the Australian Risk Management Standard is illustrated in Figure 2 [20]. It consists of seven iterative sub-processes: risk context setting, risk identification, risk analysis, risk assessment, stakeholder communication and consultation, and risk event monitoring and control. Risk management is the application of the risk management process, which consists of:

- Risk identification - Finding every risk that could affect the project's goals is the major responsibility of this subprocess. Following identification, the associated impacts and probability need to be measured. Techniques like "checklists," "brainstorming," or "pondering" are quite helpful for this subprocess.

- Risk Analysis - The second subprocess helps quantify the likelihoods and effects of each element (risks); several techniques, such as Var at Risk, Delphi, Monte Carlo Simulation, etc., can be applied to this. Although risk analysis should be quantitative, it can only be qualitative. Stochastic models, for instance, can be used to help in quantitative risk analysis.
- Risk evaluation - The management of the potential outcomes happens after the implications and probability have been quantified and determined. The typical response tactics include mitigating, transferring, and avoiding. In order to aid in the implementation of the strategies and to support the project manager in providing an update on the risk's status, risk owners are also allocated to each risk.
- Risk treatment - The last subprocess relates to the particular steps a business takes in its risk management process to control and manage the risks that are identified.

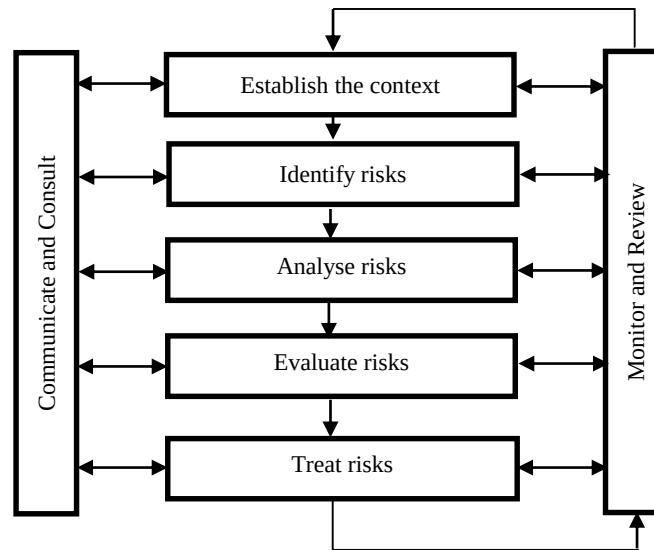


Fig. 2 Representation of the risk management process [20]

3.1. Related Works

The literature review by [21] presents the progress made in the development of risk management methods. These methods fall into four categories: qualitative, semi-quantitative, quantitative and hybrid. The study also outlines the historical evolution of this field of risk management, from statistical or traditional assessment to dynamic risk assessment and management. Based on this literature review, many studies have been carried out on risk management in general, and those applied to industrial environments are quite old, covering a multitude of methodologies and approaches to dealing with the problem. In particular, [22] established methodology for risk analysis and risk-based maintenance, as well as identified and examined elements influencing the caliber of risk analysis. The study showed that there is no single method for carrying out risk analysis and risk-based maintenance. Other works report the use of probabilistic and deterministic approaches and methods, and others combine the two. [23] listed 62 risk analysis methodologies. These methods have been classified into three different phases (identification, evaluation and prioritization). This classification has helped to detail the risk analysis method. According to this study, there are three categories of risk analysis methodologies and techniques: deterministic, probabilistic, and combinations of deterministic and probabilistic approaches.

Finally [24] also presented in a state of the art the concept of risk, the risk management process, the different risk management methods and the criteria for choosing between these different methods. This state of the art has shown that global risk analysis enables the identification and evaluation of risk factors that may lead to the non-achievement of corporate goals, and that AGR (Global Risk Analysis) can be complemented by the method of global risk assessment through internal audits.

FMECA (Failure Modes, Effects and Criticality Analysis) was first used by the Department of Defense [25] and has since been tested and used in a variety of applications. The following references might be used by readers who are interested in seeing some examples of traditional applications using FMECA: [26, 27, 28]. There are many critiques of this methodology in the literature. The literature review by [29] provides an excellent overview of these criticisms. In order to improve existing methods and approaches, several proposals have been put forward; [4] proposes a method using FMECA as an operational tool that reveals areas for productivity improvement. It demonstrates that the FMECA method can be applied in a more dynamic setting that is constantly being updated by operational events. They suggest a risk-based maintenance approach based on routine, automatic updates of equipment risk analyses, which also take failure histories into account. This approach gives current knowledge on equipment risks. FMECA can be applied dynamically to manage maintenance tasks, as demonstrated by a case study. The suggested model enables identifying and estimating risks easier and more accurate.

In another work, by utilizing a technique called EZID (Energy analysis for systematic haZard Identification during Design), which aids all machine designers in the task of risk identification based on the tenet that hazards are connected to energy sources and flows, [30] propose a novel approach to risk identification. EZID detects risks by locating design characteristics connected to energy sources and flows, since hazards are connected to the presence of energy. The requirement for adding risk protection measures is therefore highlighted by the organized information it then gives designers on every potential energy exchange between the machine and its operators. [31] offer failure risk analysis techniques that are based on information obtained from a power plant that is remotely monitored.

A new risk prioritization method based on fuzzy graphs is developed, and all methods are described and compared with the aid of a few case studies. Recent studies have focused on improving traditional risk management approaches to enhance safety assessment in complex industrial environments. [32] proposed an enhanced FMEA+ method for comprehensive safety risk assessment in the steel industry, aiming to improve risk prioritization and reduce subjectivity in traditional FMEA analysis. Similarly, [33] employed the Bow-Tie method to improve occupational risk management processes by integrating hazard identification and preventive

barrier analysis. In addition, [34] introduced a hierarchical HAZOP-like framework for safety analysis in learning-enabled systems, extending traditional HAZOP techniques to intelligent and complex industrial systems. More recently, integrated FMEA–HAZOP frameworks have been proposed to combine the strengths of both approaches in order to improve industrial hazard identification, risk evaluation, and decision-making processes in safety-critical environments. Table 1 shows a summary of studies on traditional risk management.

Table 1. Traditional risk management studies

Articles	Years	Risk identification	Risk analysis	Risk evaluation	Method	Literature review	Case studies	Subjectivity
[23]	2002	X	X	X	X	X		
[26]	2004		X		X		X	
[22]	2007		X		X	X		X
[8]	2008		X		X		X	
[4]	2009		X		X		X	
[29]	2009		X		X		X	
[30]	2017	X				X	X	
[31]	2016	X					X	

3.2. Limits of Traditional Methods of Risk Management

Although traditional risk management has been the focus of researchers since the emergence of the field of risk management, it has several limitations. According to Table 1, which presents a summary of the various studies dealing with risk management of industrial systems, it can be seen that the works cited focus on just one phase of the risk management process. For example, [30, 31] deal with risk identification, while [8, 22, 29] focus on risk analysis. Works dealing with the different stages of risk management are literature review articles. The traditional methods of risk management are dealt with and analyzed in a strong manner in the period before 2016. This work focuses on human subjectivity in the risk management process.

Based on the literature presented in subsection 3.1 on risk management, it can be observed that most existing studies address risk management from a general perspective. In addition, studies applied to industrial environments are relatively old and mainly focus on various methodologies and approaches without considering other influential factors, particularly the human factor, which plays an important role throughout all stages of the risk management process. The works cited above summarize past trends in risk management. Additionally, it demonstrates that instead of static or traditional risk assessment, academics are increasingly concentrating on dynamic risk assessment and management.

Despite the automation of FMECA in the study by [24], the human factor remains present in the data collection and classification stage. At this stage, stress or fatigue can: Cause

them to forget to update their maintenance corrective actions. Or, in the classification phase, underestimate or overestimate (subjectivity) severity and probability. Still with the aim of identifying risks in an objective and comprehensive way, de [30] used the EZID method to identify risks, but this approach's sole goal is to pinpoint potential dangers without addressing the risk estimation and evaluation phases of risk analysis. In addition, the EZID method was manually implemented utilizing the current design data. Finally, this method focuses solely on energy-related risks, without taking other risks into account.

Despite the various improvements and solutions proposed to enhance the risk management approach and improve the performance and quality of the results obtained, it is easy to see that the human factor is still present and can have a negative influence on the results at the various stages of risk management. In fact, several authors have shown that subjectivity influences results. [36] shows that subjectivity is present throughout the risk management process, from risk identification to risk analysis and risk assessment. The risk analysis process involves subjective judgment at every stage, and the perception of risk differs greatly from one person to another, for psychological, social and cultural reasons.

For example, one person may underestimate a risk because of high confidence in their experience or competence, while another may overestimate a risk because of fear of change or uncertainty. The steps in the risk management process can be influenced by the personal opinions, past experiences and cognitive biases of those involved in the risk

management process. It is therefore important to take subjectivity into account when managing risk, using risk management techniques and methods that take account of individual differences and divergent opinions. Open and transparent communication between stakeholders can also reduce the influence of bias and improve objective decision-making. Finally, risk management training and awareness-raising can help reduce subjectivity by providing the knowledge and skills to objectively assess potential risks. Identification, assessment, and management of possible risks within an organization are all parts of risk management. However, it's important to recognize that subjectivity can be a key factor in this process.

In order to lessen the effect of the human factor and achieve high-performance diagnostics, the [37] method draws on many knowledge sources (construction and design knowledge, expert knowledge, feedback) to locate defects accurately, completely and efficiently. This method can be applied in our risk identification phase to determine all the risks associated with an industrial product in an objective way. Also, [38] propose the integration of time margins and human factors under uncertainty and its effects on multi-product manufacturing system scheduling while preserving worker productivity and well-being. [39] proposes a global approach to the feedback process, as well as a human error analysis approach to improve the feedback process for rail transport systems, involving three complementary levels (contextual, cognitive and behavioral analysis). It seems that the presence of the human factor in the risk management process itself poses a risk to the reliability of the results obtained, so it would be interesting to explore solutions to overcome the subjectivity of the human factor.

According to the literature review, most studies focus on risk management methodologies without taking into account the human factor, and more specifically, subjectivity, in the entire risk management process. This subjectivity influences the results, whether in terms of identification, analysis or risk assessment. Subjectivity, which is absent from studies of risk management, may be a key factor in this process.

4. Integration of AI in Risk Management

4.1. Related Works

Deep learning is a subset of machine learning, and machine learning is a subset of artificial intelligence, as shown in Figure 3. Data science is the application of techniques from computer science, deep learning, machine learning, and artificial intelligence.

Additionally, it is important to identify the main subfields of AI in order to comprehend the current state of AI in risk management. Machine learning, computer vision, natural language processing, knowledge-based systems, optimization, robotics, automated planning, and scheduling are just a few of

the well-known subfields of artificial intelligence that have emerged as a result of the advancements in AI applications in industry. Below is an overview of each of these subfields.

4.1.1. Integration of Machine Learning into Risk Management

The creation and application of computer programs to learn from experience or historical data in order to model, control, or predict using statistical techniques without explicit programming is known as machine learning. Among the machine learning techniques are: The study of how machines make judgments based on what they have learned from labelled datasets-that is, input and desired output pairings-is known as supervised machine learning. It falls into two categories: regression and classification [40]; (A) The goal of unsupervised machine learning is to teach computers to recognize important patterns in unlabeled datasets. It falls into two categories: (B) Reinforcement Learning (RL), which is described as "learning of a mapping from situations to actions so as to maximize a scalar reward or reinforcement signal" [41]; and (C) Clustering and dimension reduction techniques [42]. (D) Deep Learning: This is the state-of-the-art in machine learning and has been shown to produce more accurate predictions than traditional machine learning techniques. It is a computational approach that involves learning from the results of interactions with the environment [43]. Also, in the application of AI in risk management, [44] introduced SVMs (Support Vector Machine) as a new artificial intelligence tool in electrostatic risk management applications. Presentation of SVMs and their use in SCOUT (Static Control with Up-to-date Technology), a new approach to electrostatic risk management. This method focuses on the occurrences that create hazards (by inflicting a specific type of damage) and the factors that lead to these events. SVMs are a productive method for regression and classification.

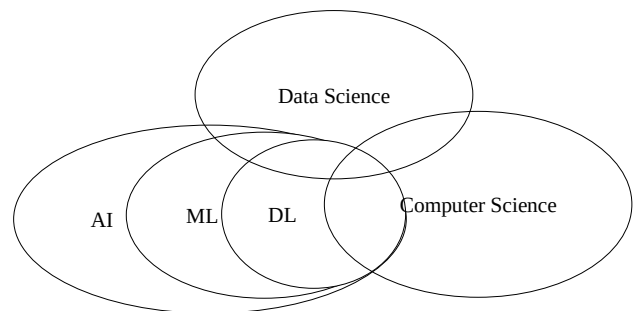


Fig. 3 Components of AI [43]

Since a decade ago, autonomous technologies, such as fully unmanned workstations and mining robots, have been included into the mining industry to maintain a safe working environment. These technologies include AI and ML (Machine Learning) models. Using AI and machine learning, [45] were able to find solutions to unidentified risks during mining. Effective risk assessment is made possible by these stand-alone technologies, which also have several economic advantages like cost savings, uninterrupted production,

decreased worker exposure to dangerous conditions, and enhanced safety. This study will be an interesting resource to explain the progress of AI in risk assessment in the mining sector. This study also closes the gaps in coal mining sector safety measures left by contemporary technology and AI advancements.

In the sphere of safety and security, risk assessment methodologies have evolved through time, moving from qualitative and semi-quantitative to quantitative procedures, via interconnection networks to Bayesian networks, and their applications in process industries are presented in [46]. The purpose of this study is to outline the advantages and disadvantages of Bayesian networks in comparison to conventional and competing approaches, and to offer recommendations for further research.

Still in the application of machine learning in risk management, [16] presented in his literature review machine learning methods for anomaly and failure detection. In the field of predictive maintenance, [47] presented a dynamic deep learning model based on incremental compensation for bearing equipment fault diagnosis. Also, [17] made a comparative study of introducing a Random Forest (RF) based prognostic method for tool wear prediction and comparing the performance of RF with that of Feed-Forward Back-Propagation neural networks (FFBP) and SVRs. (Arcos Jiménez et al., 2020) used several machine learning algorithms, namely Decision Trees, Discriminant Analysis, Quadratic Support Vector Machines, Nearest Neighbors and Ensemble Classification for wind turbine blade maintenance.

Recent advances in Machine Learning (ML) have significantly improved industrial risk management and accident prediction. Several studies have demonstrated the effectiveness of algorithms such as Support Vector Machines (SVM), Random Forest (RF), Logistic Regression (LR), and XGBoost for accident classification and severity prediction ([48, 49]). In addition, Explainable Artificial Intelligence (XAI) approaches are increasingly used to improve transparency and trust in AI-based safety systems.

4.1.2. Integration of NLP into risk management.

Researchers have recently tried to integrate NLP into computers to address issues with document analysis and management as a result of the development and expanding use of automatic natural language processing in computing. Work on NLP began in the 1950s with the discovery of machine translation from one language to another [50]. NLP is a fairly general discipline that covers a very wide range of applications, including machine translation, sentiment analysis, marketing, automatic correction, text classification and summarization, etc....

The work of [51] offers a comparison between three NLP methods and two risk-related domains, and which may also

provide clues to other domains dealing with large volumes of textual data. The aim is therefore to offer an automatic aid for analyzing scientific literature to detect phrases indicative of the risk posed by chemical substances or bacteria. The task is approached as a categorization problem: categorizing the sentences in the texts into classes of substance-related risk. Three approaches are used and evaluated: rule-based, supervised learning and information retrieval. Better results are obtained with supervised learning and information retrieval. Depending on the approach, results show F-measurements of up to 0.8.

For example, [52] presents a method for measuring and quantifying incident risks in industrial production and operations centers, so as to identify concrete solutions for improving production processes and reducing risks. This method uses artificial intelligence and automatic language processing techniques applied to the analysis of plant incident logs. This method is embodied in a software program, Proxem Studio, developed by Proxem to enable users to analyze large volumes of textual data without any particular computer or linguistic knowledge, and can be applied to any type of textual content.

In another context of risk identification, and this time in the risks found in legal documents, [53] introduces the "risk-o-meter" framework, which employs natural language processing and machine learning to analyze and assess the risks of any legal document. This framework makes use of the Paragraph Vector template, which creates a text vector representation. In order to determine whether or not a paragraph falls within one of many predetermined risk categories, The framework subsequently feeds the vector space into a supervised classification algorithm. Thus, the framework removes paragraphs that could exist a risk. The approach will help companies to analyse risks from a large document base with relatively less human input toward long-term, risk-reduced growth.

A system for extracting risk cases is outlined in the framework provided by [54]. They also propose a method for identifying risks that integrates two natural language processing techniques: the vector space model and semantic query expansion. It introduces the concept of using Python to build out a prototype system for how the proposed approach can be supported.

[55] report the development process of the OPT (Operation Planning Tool), which aims to leverage natural language understanding for eliciting the types of equipment and tasks associated with past incidents and linking these to planned activity. They showed a solution to using the contents of the incident database and contextualize incidents by detailing the systems, operations, and tools that were in and around the incident, and the asset conditions at the time of the incident.

4.1.3. Integration Expert Systems into Risk Management

It has been determined that techniques related to artificial intelligence serve as a crucial foundation for methods that undoubtedly enhance the precision of risk evaluation. An examination of artificial intelligence algorithms utilized for risk assessment was carried out by [59]; these algorithms were primarily categorized into artificial neural networks, expert systems and hybrid intelligent systems. This study outlines each categorization system's fundamental concepts as well as how it can be used in the security industry. In addition, the fuzzy expert system, neural networks, and the neuro-fuzzy adaptive inference system were compared and contrasted in this study.

As stated by AI pioneer [60], advancements in artificial intelligence have introduced innovative techniques that enhance the procedural rationality of decision-makers, helping them navigate complexity and manage large volumes of data. Artificial neural networks, expert systems and hybrid intelligent systems are the three main categories of AI techniques that are most frequently used in literature and used to risk assessment. An AI inference technique aimed at diminishing the uncertainties associated with traditional methods of pipeline risk assessment is introduced by [59]. In addition, this study presents a case study of the Colombian oil transportation network to demonstrate the applicability of the model developed. The findings of the inference system and the conventional approach are compared in this study's uncertainty analysis for risk values. The outcomes demonstrate the inference system's superior performance because its mean error and standard deviation are smaller than those of the conventional method.

The use of artificial intelligence methods, in this case fuzzy logic, to the conventional FMEA approach in order to enhance the risk analysis method has been the subject of several scholarly studies published over the previous ten years. Failure risk analysis built on the FMEA method has been developed by [61]. The enhancement of the traditional FMEA approach by incorporating artificial intelligence methodologies-specifically, the application of fuzzy logic along with principles derived from a unique categorization of identified failures-contributes significantly to the advancement of risk assessment techniques. Thus, the impact of methodological inconsistency and other noted shortcomings of the conventional FMEA method is reduced.

The FMEA method has been improved, enabling a more accurate assessment of the risk of failure and, therefore, better prediction and minimization of undesirable events. A fuzzy logic approach to handling an FMEA is also proposed in the research paper by [62] to handle the problem of taking interdependencies between different failure modes with ambiguously obtained and imprecise information into account. The paper demonstrates the use of the fuzzy logic-based FMEA method on a diesel engine turbocharger during

the development stage. In fact, the results are more unbiased from an analytical perspective and more adaptable compared to applying failure information and assuming that there is nothing to be calculated from the actual circumstances in which turbochargers are used when failure information is seen as fuzzy variables. It further serves the purpose of exploring the interdependence of several identified failure modes and their implications in the system. [63] uses an approach similar to that proposed in [62] for the unidirectional rotary switch.

Here, the focus lies primarily on the fact that the fuzzy FMEA produced yields responses to the most complex consequences of known failures, in addition to the benefits suggested in [62]. And by integrating the knowledge and experiences of the people who applied the FMEA method into the practical application, considerable economic benefits have been gained through this method.

In order to optimize the classical FMEA approaches, [64] and [65] showcase the synergy of fuzzy logic and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) techniques, used for identifying the preference of alternatives to risk. It grants considerable flexibility when it comes to determining factor weights, making it more applicable in real-world circumstances and better suited to guide better decisions. The method's application was validated based on the study of expected failures in producing steel.

Table 2. AI tools utilized in articles

AI Tools	Articles
Machine Learning	[16, 17, 44-47, 66]
Natural Language Processing (NLP)	[51, 52, 55, 59]
Expert Systems	[61-65, 67]

4.2. Limits of Integrating Artificial Intelligence into Risk Management

The literature review of AI and NLP integration in risk management has several limitations:

According to the study conducted by [59], an optimal and accurate risk assessment can be achieved through a collaborative integration of artificial intelligence. This holds true despite the fact that the selection of a risk assessment method is influenced by the intricacy of the environment and the quality of available information. The subjectivity of defuzzification approaches and the scarcity of data for activating and training ANNs (Artificial Neural Networks) are two factors that contribute to these artificial techniques' limitations, among the limitations of integrating AI and, more specifically, fuzzy logic into the FMEA method in the contribution by [61]. It is crucial to remember that any technical system occasionally fails for unknown reasons. These breakdowns come on quickly and unexpectedly, and they cannot be prevented. Support vector machines, a new artificial intelligence tool, are intended to be introduced into electrostatic risk treatment applications in the study by [44].

There are now applications for both fuzzy expert systems and artificial neural networks. Although both approaches have advantages, fuzzy systems and neural networks vary fundamentally. A neural network can conduct binary classification, but a fuzzy system allows us to designate many output "classes" (but it can also have multiple outputs and perform regressions). A fuzzy system also handles probabilistic issues with ease. Its primary flaw is that it is not intended to carry out regression tasks, and a solid rule foundation is essential for a fuzzy expert system to operate. On the other hand, the SVM has two functions: classifier and regressor. Advanced systems can assist researchers in obtaining additional data to train and evaluate machine learning algorithms, according to a study by [45]. AI and ML can help laws requiring safety precautions to prevent accidents. Additionally, the mining sector is increasingly implementing these sophisticated solutions, particularly in the areas of automated machinery and self-driving cars.

Understanding these technologies' full potential in many mining processes, however, necessitates more time-consuming work, a sizable initial investment, and the availability of qualified labor. Artificial intelligence's lofty goal is to give computers some of the mental abilities that humans possess, such as learning, recognizing, and thinking. The foundation of AI is its capacity for both reasoning and natural language understanding. It is correct to state that the use of artificial fuzzy inference systems allows for a reduction in the uncertainty associated with conventional risk assessment methods, as demonstrated by the case study presented in the work of [67]. This study also shows that it is possible to validate risk values using real-world methods. Therefore, the following can be used to outline the drawbacks of adopting the Bayesian approach to risk assessment:

In order to effectively capture the behavior of the system while using Bayesian networks as standalone approaches, their structural creation needs to be assisted by specialists who have a thorough understanding of the system.

To generate conditional probability tables, it is necessary to fully comprehend the dependencies between the various components of a Bayesian network model.

Based on the literature related to the integration of NLP into risk management, it can be observed that:

The risks addressed are based on the history of past risks, without taking new risks into account. Hence, the need to develop a model that deals with existing risks without forgetting the new risks to be addressed.

The above-mentioned work on the application of NLP to risk management focuses solely on the first stage of the risk management process, namely risk identification, without taking into account the other stages, such as risk analysis, assessment and treatment. Furthermore, there aren't much research that address the problem of semantic similarity.

In spite of the studies dealing with risk identification using NLP, the latter, which aims to mimic the human being and reduce human intervention and consequently subjectivity, requires human supervision to track and monitor the operations carried out using NLP. Efficient and effective risk management requires risks to be identified and dealt with objectively. Table 3 shows the strengths and weaknesses of traditional risk management and risk management with AI integration.

Table 3. Strengths and weaknesses of the two types of risk management

Criteria	Traditional risk management	AI-based risk management
Data analysis	Limited	High capacity (big data)
Risk prediction	Reactive	Proactive and predictive
Automation	Low	Strong
Objectivity	Dependent on humans (subjectivity)	Dependent on ML and DL models (objective)
Complexity	Easy to understand	Sometimes difficult to explain (black box)
Cost	Less costly in the short term	Costly in terms of infrastructure and skills
Adaptability to new risks	Flexible thanks to human expertise	Less flexible, depends on historical data

5. Proposed Framework and Experimental Methodology

Risk identification is considered one of the most critical stages in the risk management process. According to [68], risk identification represents the initial step of risk management and plays a fundamental role in ensuring effective prevention and mitigation strategies. However, efficient risk management does not rely solely on risk identification, but also on risk analysis, classification, evaluation, and the implementation of corrective and preventive actions. In this study, a novel AI-

based risk management framework is proposed to improve the identification, analysis, and classification of industrial risks using Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) techniques. The framework proposed in this paper enables risk assessment to avoid the risks due to personal opinion by automatically searching textual industrial reports for relevant information and connects any detected risk to corrective actions and existing resources. The broader architecture of the proposed framework is depicted in Figure 4.

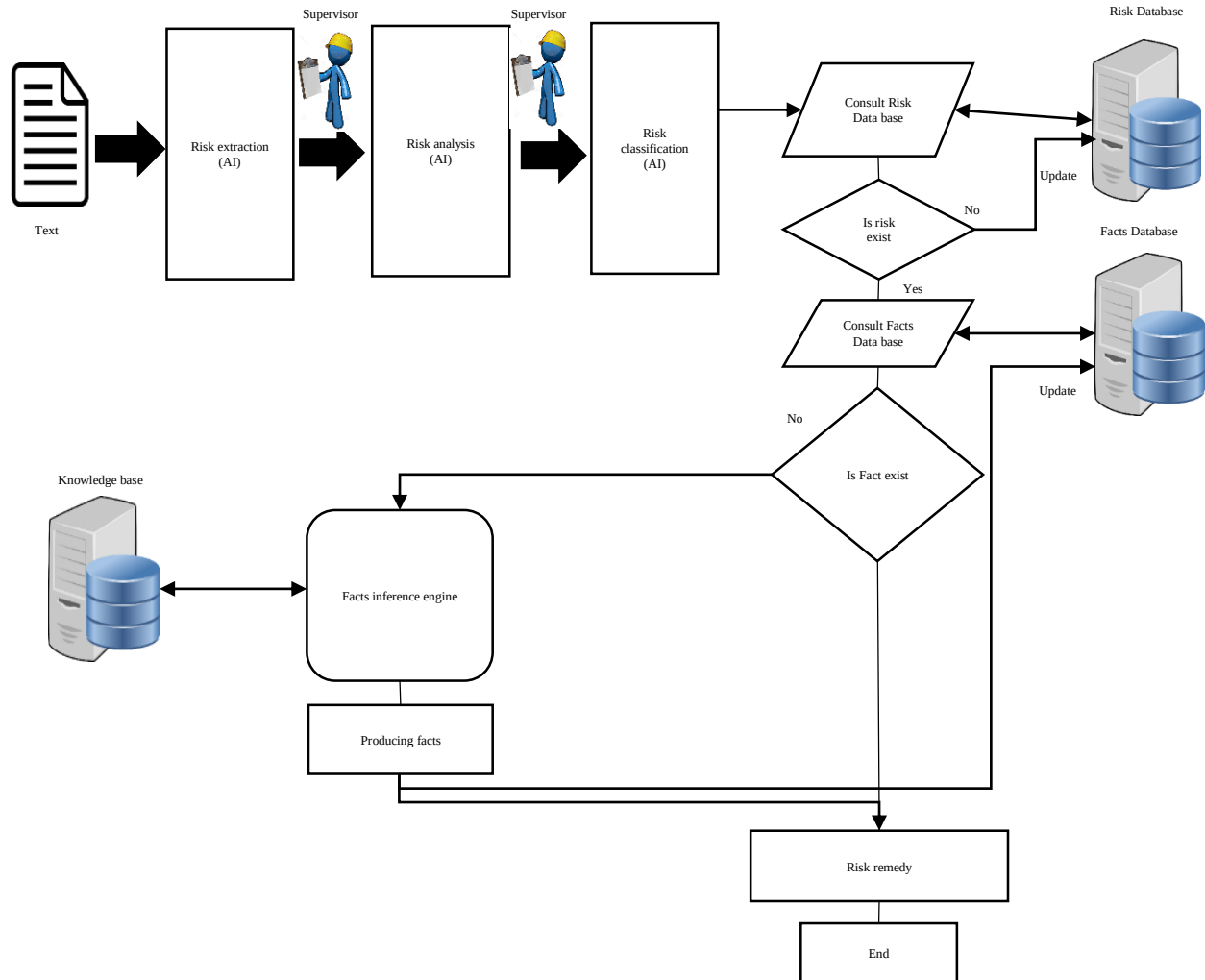


Fig. 4 Proposed risk management model

The proposed framework has six primary stages. The first phase is to collect the data: the industrial incident reports, failure reports and accident descriptions available from risk-associated databases. This includes both structured and unstructured information relating to hazardous conditions, accident factors, environmental conditions and operational malfunctions.

Step 2: Using AI and NLP techniques for risk assessment. This phase involves text preprocessing, including cleaning, tokenization, stop-word removal and normalization. Various approaches to text feature extraction can be implemented, such as Bag of Words (BoW), TF-IDF, Word2Vec or contextual representations like BERT. These methods enable the conversion of textual accident descriptions into numerical formats suitable for training machine learning models.

The third phase, which is part of a risk-based approach, involves a risk assessment. This assessment focuses on the identified risks, taking into account their potential causes,

their impacts and the factors contributing to them. Through NLP algorithms, semantic data can be extracted from textual materials in order to make sense of accident events into meaningful linguistic structures and associations between accident occurrence, human factors and environmental situations.

Stage Four addresses risk classification in this stage. In this phase, machine learning algorithms like Support Vector Machines (SVM), Logistic Regression (LR), Random Forest (RF), Naïve Bayes (NB) and XGBoost, based on multiple criteria (incident type and severity level, occurrence frequency and fatal/non-fatal), are used to classify risks. To tackle the often-seen class imbalance problem in accident datasets, SMOTE method is used in the training.

The fifth stage is the verification of the risk database. Following identification and classification, the system checks if there are risks in the risk database to see if they already exist. If there is already an underlying risk, the framework retrieves

the associated preventive and corrective actions. Otherwise, the risk previously identified is classified as a new risk, and the database is updated as a result.

The sixth stage is corrective action management and knowledge base updates. Within the facts database, the framework confirms that appropriate corrective actions or mitigation measures are already available. If appropriate actions are available, they are recommended to be taken. Otherwise, new corrective actions are generated through a fact inference engine connected to the knowledge base, and both the facts database and knowledge base are updated continuously.

To evaluate the effectiveness of the proposed framework, a comparative experimental analysis is conducted using different textual feature extraction techniques and multiple machine learning classification algorithms. The effectiveness of the models is evaluated through various assessment metrics such as accuracy, recall, precision, F1-score and ROC-AUC curves. This experimental methodology aims to identify the most effective combinations of feature extraction techniques and classification models for industrial accident risk analysis and severity prediction.

6. Discussion

From the literature review, it can be observed that only a limited number of studies have addressed the issue of human subjectivity in the risk management process. For example, (Redmill, 2002) demonstrated that human subjectivity is present throughout the different stages of risk management, including risk identification, analysis, assessment, and treatment. Despite its significant influence on decision-making, the issue of human subjectivity remains insufficiently addressed in existing risk management approaches.

On another front, the integration of artificial intelligence into risk management has been able to deal with several aspects, namely classification, prediction and monitoring, without taking into account the subjectivity aspect of risk management. The literature on the integration of artificial intelligence into risk management does not provide us with a model that diminishes human subjectivity.

The literature review of traditional risk management or risk management incorporating artificial intelligence does not provide a model that aims to eliminate or reduce human subjectivity from the entire risk management process. Our proposed model gives us automatic risk management using the tools of artificial intelligence.

Artificial intelligence plays a crucial role in risk management by reducing human subjectivity. Using algorithms and data, this tool is able to identify trends and patterns that might go unnoticed by the human eye. This

promotes more informed decision-making that is less susceptible to personal bias.

However, it is important to note that AI does not completely replace human judgment, but rather complements it by providing additional information and helping to assess risks in a more informed way.

There are multiple ways in which Artificial intelligence can lessen the subjectivity that comes with risk management processes.

Assessing objective information: Risk assessment is integrated within a great deal of information, which can be bias. Artificial intelligence in objective form can likely analyze all information in a distilled form in no time.

Assessing risks in a more accurate manner: Complex algorithms can AI construct that can accurately determine risks with logic that would be too complex for a human.

Recommendations based on objective evaluation: Artificial intelligence can propose risk management strategies in an objective manner, heuristically with no subjectivity applied.

Elimination of the impulsivity of a human: There are several human errors that come with risk management that AI can improve with more reliability.

Integrating these strategies can show how AI can lessen the subjectivity that comes with risk management and increase the quality of decisions being made.

6.1. Comparative Analysis: Traditional vs AI-based Risk Management

Traditional risk management methods and those based on artificial intelligence differ in their principles, capabilities and constraints. Traditional methods, such as the risk matrix and FMEA analysis, and expert-based assessments, are typically derived from historical data and human experience. While they are generally known for their transparency, compliance with standards and regulations and ease of interpretation, they will always be limited by human subjectivity, being static in terms of analysis due to their traditional algorithms or struggling to cope with the complex dynamics within industry that see constant evolution.

While the systems that adopt AI techniques offer many advantages, they are also facing various challenging problems. These are, among others, data dependency, model interpretability, algorithmic bias and high computing resources requirement. This is an issue for many machine learning models because they act like "black boxes" that cannot provide interpretable results in high-stakes

applications. Therefore, a hybrid approach that mixes traditional risk management methods with those based on artificial intelligence is likely to be one of the best solutions. Traditional methods provide reasonable interpretability and structured analysis, whereas AI enhance on predictive power, leading to less human bias towards decision making. Such systems enable more adaptive and robust industrial risk management.

6.2. Human-in-the-Loop vs Full Automation in Industrial Risk Management

The future role of artificial intelligence in industrial risk management poses important questions about the extent of automation and whether human expertise matters or not. There are basically two approaches, fully automated and Human-In-The-Loop (HITL).

In a fully automated systems, machine learning models assess risks and decisions. The advantages of these solutions include scalability, consistency, speed and less human subjectivity in how the data is processed. However, in safety-critical system areas, complete autonomy also raises issues of trust, interpretability and accountability. Most AI-based algorithms, especially deep learning ones, are black boxes in which it is difficult to understand how decisions are arrived at and hence verifying the decision-making process.

On the other hand, “human-in-the-loop” methods use human expertise to contribute to final decision-making. In these systems, the task of AI models can be described as decision-making support tools that provide predictions or recommendations that specialists examine and validate. Such a methodology improves interpretability, traceability and contextuality of the results. But human presence can certainly inject bias as well as inconsistencies.

This study proposes a semi-automated model that marries the strengths of both these techniques. Machine learning systems can autonomously make sense of workplace accident reports and help ease the burden on safety specialists. Nevertheless, it is extremely important to have human involvement in deciding on key choices and ensure reliable results.

As a result, an ideal balance between automation by AI and input from humans seems to be the best ticket for industrial risk management. These hybrid systems can offer efficiency gains, subjectivity reduction and human supervision in safety-critical environments.

6.3. Ethical, Legal, and Social Implications (ELSI)

The integration of artificial intelligence into industrial risk management raises a variety of ethical, legal, and social questions, particularly in situations where decisions are critical to ensuring safety. From an ethical standpoint,

machine learning models can introduce algorithmic biases due to the use of training data that is unbalanced or unrepresentative. These biases have the potential to lead to inaccurate or unfair risk assessments, especially when certain events are underrepresented in the datasets. Furthermore, the limited ability to explain the results produced by complex artificial intelligence and deep learning models can undermine confidence in the decisions made by these systems, particularly in industrial contexts where it is crucial for decision-makers to be able to interpret and justify the conclusions drawn.

From a legal perspective, the use of automation in risk analysis raises significant questions regarding civil liability and liability in general. When inaccurate predictions lead to risky situations, it becomes difficult to determine who is responsible, including model designers, system administrators, and decision-makers. Thus, human oversight is essential, and artificial intelligence systems must be viewed as tools to support decision-making rather than as fully autonomous entities.

Compliance with safety standards and industry regulations is also a fundamental requirement for the implementation of artificial intelligence technologies in industrial sectors. From a societal perspective, AI-driven automation could impact the role of security experts and raise concerns about job losses or excessive reliance on automated systems. Therefore, it is essential to view AI as a tool that complements and enhances human skills, rather than as a complete substitute for human capabilities. For these reasons, it is essential to adopt a balanced approach that integrates machine learning techniques, “human-in-the-loop” frameworks, explainable artificial intelligence methods, and continuous validation processes. This is crucial to ensuring the effectiveness, transparency, ethical soundness, and social acceptability of AI-based risk management systems.

7. Conclusion

This article summarizes a literature review of conventional and AI-based approaches to risk management in industrial environments, focusing on the application of Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) techniques in the fields of industrial safety and accident analysis. The research provided an overview of contemporary risk assessment techniques, from FMEA, HAZOP and Bow-Tie analysis, to AI-based tools for accident prediction, risk classification and textual risk analysis.

According with the literature review, an innovative AI-based framework was introduced as an advanced tool for industrial risk. The framework proposes to facilitate automatic recognition, statistical analysis, categorisation and management of industrial risks by NLP and machine learning

tools. Moreover, from the perspective of humans, the framework helps in mitigating human subjectivity in risk assessment through automatic extraction and analysis of information from industrial incident reports and textual safety data. In addition, the proposed approach initiates a dynamic interaction between risk databases, knowledge bases and corrective action management systems to enhance decision-making and proactive safety management. The research also emphasized multiple challenges associated with AI-based risk management systems, including data quality, class imbalance, model interpretability and the integration of explainable and human-centered AI approaches in safety-critical industrial environments. Implementation and validation of the proposed framework will be conducted on real industrial datasets in future work. Special focus will be paid to NLP-based risk

extraction approaches, contextual textual representations using transformer-based models, including BERT, and hybrid AI systems for accident severity prediction and causal analysis.

Further research will also investigate Explainable Artificial Intelligence (XAI), Human-in-the-Loop approaches and knowledge-based inference systems in order to further improve transparency, reliability and automation in industrial risk management processes.

Conflicts of Interest

“The authors declare that there is no conflict of interest regarding the publication of this paper.”

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