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Review

Techniques and Models for Addressing Occupational Risk Using Fuzzy Logic, Neural Networks, Machine Learning, and Genetic Algorithms: A Review and Meta-Analysis

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Abstract: This article aims to present a structured literature review that utilizes computational intelligence techniques, specifically fuzzy logic, neural networks, genetic algorithms, and machine learning, to assist in the assessment of workplace risk from human factors. The general aim is to highlight the existing literature on the subject, while the specific goal of the research is to attempt to answer research questions that emerge after the review and classification of the literature, which are aspects that have not previously been addressed. The methodology for retrieving relevant articles involved a keyword search in the Scopus database. The results from the search were filtered based on the selected criteria. The research spans a 40-year period, from 1984 to 2024. After filtering, 296 articles relevant to the topic were identified. Statistical analysis highlights fuzzy systems as the technique with the highest representation (163 articles), followed by neural networks (81 articles), with machine learning and genetic algorithms ranking next (25 and 20 articles, respectively). The main conclusions indicate that the primary sectors utilizing these techniques are industry, transportation, construction, and cross-sectoral models and techniques that are applicable to multiple occupational fields. An additional finding is the reasoning behind researchers' preference for fuzzy systems over neural networks, primarily due to the availability or lack of accident databases. The review also highlighted gaps in the literature requiring further research. The assessment of occupational risk continues to present numerous challenges, and the future trend suggests that fuzzy systems and machine learning may be prominent.

Keywords: risk assessment techniques; human factor analysis; safety management systems; machine learning; computational intelligence in safety; occupational hazard evaluation; risk analysis

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1. Introduction

The first steps towards occupational health and safety appeared in 1911 in the United States, where a legislative intervention was undertaken to establish workers' compensation by employers. Two years later, in 1913, the National Safety Council for Workplace Accidents was founded. Due to the world wars, it took several years until the 1950s for these rights to be fully enforced. In Europe, the first laws began to be passed in the mid-1970s. In 1974, the United Kingdom enacted the Health and Safety at Work Act, placing responsibility for workplace safety on employers. In 1976, the European Community adopted Directive 76/464/EEC on pollution, indirectly contributing to workplace safety.

In 1989, the European Union approved Framework Directive 89/391/EEC, providing comprehensive safety standards to its member states. In 1992, it further emphasized safety for workers in high-risk industries. The International Labour Organization (ILO) introduced global guidelines for workplace safety management systems in 2001. In 2011, the United Nations' Global Plan of Action on Workers' Health advocated for strengthening occupational health and safety systems worldwide. Additionally, in 2018, the European Union enhanced its strategic framework to address digital risks in the workplace. Recently, in 2022, the ILO declared the fundamental right of workers to a safe and healthy working environment. It took another decade for the scientific community to intensively address these issues. The greatest challenge faced by businesses and companies in this regard is the risk that employees face while performing various tasks. In the literature, risk is defined as any negative factor that causes or may cause an obstacle to achieving the strategic and economic goals of the enterprise. Additionally, it is commonly noted that risk is a factor that prevents stability. To avoid any dangerous consequences, there are two main categories of technical risk analysis: preventive techniques and reactive techniques. The former describe the risk treatment measures that should be taken before a risk arises, while the latter investigate the factors that have caused the risk to prevent future occurrences.

Approximately 100 million workdays are lost each year due to disability [1,2], and an estimated 2.3 million people die annually worldwide on account of occupational accidents [3]. The total cost amounts to USD 11 billion in the United Kingdom and USD 50 billion annually in the United States [1,4–6]. Additionally, according to the International Labour Organization (2023), there are 395 million occupational accidents and 185 million work-related diseases annually worldwide, resulting in more than 2.93 million deaths globally each year.

This study sheds light on the field of contemporary research on safety through the lens of computational intelligence. Specifically, it seeks articles that focus on the prevention and management of occupational risks and the analysis/assessment of risk using computational intelligence methods, particularly (1) fuzzy logic, (2) neural networks, (3) genetic algorithms, and (4) machine learning. The aim of risk control is to reduce the likelihood of accident occurrences, their consequences, exposure, as well as to detect the degree of risk involved.

The necessity of this research lies in the existing research gap in providing a holistic approach to computational intelligence techniques. The existing literature reviews that aim to achieve this goal focus solely on the collection and management of data, methods, articles, and similar aspects. A similar approach is followed in this study but through a different lens, emphasizing the criteria outlined in the Section 3 (Methodology). The specific aim of this article is addressed by employing research questions. The literature review of recent years from bibliographic reviews has shown that it is not common practice for authors to utilize research questions regarding this topic. The most recent bibliographies, analyzed in the second part of this study, consist of works published in reputable scientific journals, and the number of citations for these articles is very high. However, none of the authors use the scientific tool of research questions in their reviews in the form of questions and answers.

Taking the above into account, as well as the literature gaps, the following research questions were formulated, which are attempted to be answered in this article:

1. Which of the four techniques has been used the most by researchers, for what reason, and how are the articles distributed?
2. Into which subcategories can the four techniques be divided, and what problems do they solve in risk assessment?
3. What application fields do the four techniques address in risk analysis?

4. Which countries are most involved with the four techniques in relation to their workforce?
5. What are the topics of the top five most published articles, and why were they chosen by other researchers?
6. What is the future trend?

The results analyzed in the Section 5 (Research Questions) provide an assessment of the current state and trends on the topic. Additionally, they assist in understanding and interpreting the subject matter, thereby helping to focus the research data.

There are several articles that approach the subject from different perspectives or by using only one technique [7–12]. Specifically, they highlight problems and methods of solving them in a particular sector using a specific technique, such as safety in transportation or issues in the industrial sector, among others. Moreover, they often analyze only one technique and rarely mention a second one. Additionally, the progress of technology and the rapid rate of development in these intelligence techniques do not allow for complacency and necessitate continuous evolution, with the ultimate goal of optimizing safety-related issues. Each of these technologies offers unique strengths, and their integration and collaboration can solve complex problems that are often non-linear and dynamic, where traditional algorithms fail to provide clear solutions [7].

At this point, it is deemed appropriate to specifically reference risk management in the workplace. Risk management and workplace safety involve a set of systematic practices aiming to identify, evaluate, and manage risks in the workplace in order to ensure the minimization of accidents as much as possible. The primary goal is to decrease the probability and severity of injuries and accidents in the workplace. This is achieved by identifying the risk, which may be physical or caused by human intervention [13]. Then, the risk is assessed and the severity of the damage it causes is prioritized.

Appropriate measures must then be implemented to mitigate or eliminate the risk. Risk management is an ongoing process, so regular monitoring and reviewing of both the measures and methods used are essential to ensure the effectiveness of workplace safety.

The contribution that ChatGPT will make in the coming years is worth noting since it has been influencing and changing the way we think about workplace safety. According to Rabbi and Jeelani (2024), artificial intelligence is categorized into three main forms. Artificial Narrow Intelligence (ANI) specializes in specific tasks, such as language translation or weather prediction. Artificial General Intelligence (AGI) mirrors human intelligence, enabling machines to handle various tasks autonomously. Natural Language Processing (NLP) renders machines capable of comprehending and generating human language. NLP facilitates tasks such as sentiment analysis, machine translation, and text generation, making human–computer interactions more intuitive. These models can create safety guidelines, evaluate employee feedback, and generate safety updates tailored to specific construction scenarios [14]. It would be prudent not to rely exclusively on computational intelligence. Any analysis of a safety-related issue should consider two fundamental types of references. The first is a review of the literature, and the second is guidance through legal or technical references. Moreover, the information provided should adhere to criteria of exclusion and eligibility [15].

Additionally, artificial intelligence and AI systems have the capability to analyze large datasets and predict potential risks and accidents that may occur, which is particularly beneficial in industrial environments. Automated monitoring further aids in detecting anomalies of all kinds and alerts people to the existence of preventive measures. All of the above assist in the analysis and processing of data to identify patterns that humans might not detect, thus helping to create safety protocols and risk management strategies [16–18].

Moreover, ChatGPT could provide people with real-time guidance through conversation, support organizations, and therefore help them to make safer decisions [14].

On the other hand, the automation of hazardous tasks with the aim of reducing human exposure to dangerous work may lead to job displacement. Workers may need to be retrained. Additionally, there is a decreased level of vigilance among workers as they rely on these systems, which are not infallible and may even provide incorrect information. It should be noted that there may be cybersecurity threats. These threats could come from a hacker who, by breaching these systems, is able to manipulate safety systems or, on an even larger scale, affect many professional sectors, such as the safety of the banking system and the security of air transport, the most recent example being the disruptions caused by the Microsoft blackout in July 2024.

Considering all of the above, the purpose of this study is to examine the developments in scientific knowledge in the field of computational intelligence techniques, mainly focusing on risk and evaluation in the workplace due to human factors. The first part of the document provides an extensive discussion of occupational risk and the four specific techniques—neural networks, fuzzy logic, genetic algorithms, and machine learning. The second part includes a literature review of similar articles, as well as the results from literature reviews over the past decade. The third part outlines the method used to search for the articles and how they were classified in a table. Additionally, the criteria set for the article search are defined. The fourth part presents the statistical analysis and the results of the articles under review that meet the topic's criteria. Beyond the traditional statistical analysis with numbers and bar charts, other methods of presenting the results are also provided. These include Choropleth maps and word clouds. The fifth part of this study focuses on research questions that address the research gap regarding the topic under investigation, as well as some questions that arise with new data. Finally, an extensive discussion of the conclusions drawn from the results of the research questions is provided, along with some directions for future research.

1.1. Occupational Risk

Occupational risk refers to the probability and potential severity of harm or adverse effects on workers' health, safety, and well-being arising from their activities, duties, or exposure to hazards in the workplace. These risks may include a wide range of factors, including physical, chemical, biological, ergonomic, and psychosocial hazards.

The term "occupational risk" refers to any source of potential harm or adverse health effects on people, property, or the environment. There are numerous sources of occupational risks. They may arise from exposure to hazardous substances, poor working conditions (e.g., loud noises, vibrations, and unguarded machinery), and harsh physical environments (e.g., airborne particles and adverse weather conditions).

Occupational risk management involves the systematic identification of potential hazards in the workplace. After identifying the risks, the next step involves their assessment and evaluation. Risk management methodologies include determining the probability and severity of potential incidents. This process helps to prioritize risks and allocate resources effectively to address the most critical safety concerns [19]. Workers must be informed about potential hazards, safe working practices, and the proper use of protective measures. Well-informed employees are more likely to actively contribute to a safe work environment. The use of data for risk assessment and decision-making is a key element of effective occupational risk management. Analyzing incident reports, near-miss accidents, and other relevant data sources enables organizations to identify trends, assess the effectiveness of control measures, and make informed decisions to improve workplace safety [15,20]. The goal of this comprehensive approach is to create a safer work environment, protect workers

from harm, and ensure compliance with regulatory requirements. This is achieved through qualitative and quantitative methods for assessing potential risks associated with different occupational activities [21].

The first stage involves risk identification, meaning that all the potential hazards that could cause harm must be identified. The second stage concerns risk analysis. At this stage, the probability and impact of each risk are assessed. Such steps are necessary to proceed with the adoption of appropriate risk mitigation measures. For this reason, they must be carefully defined based on the specific goals set or established by each professional sector or business [22]. Such goals involve the elimination of risk. This includes identifying and attempting to completely remove the hazard, meaning that replacing hazardous materials could provide an initial safer solution if feasible. Next comes risk control, which involves implementing measures to reduce either the likelihood or severity of the risk. Such measures could include redesigning equipment, optimizing personal protective measures, or even providing training to improve workplace safety. Additionally, part of this step is risk acceptance. Such a decision requires careful evaluation to ensure that the level of risk present aligns with the expectations for a safer work environment [10]. The third stage involves risk evaluation, where the identified risks are compared to the risk criteria to determine their significance. The fourth stage involves implementing measures that will help to reduce and eliminate risk. Finally, the last stage is monitoring and reviewing the measures that have been implemented. The effectiveness of these measures is regularly assessed and subject to improvements.

In any case, when selecting measures to address risk—beyond the human factor examined in this article—other aspects must be considered, such as the nature of the hazard, its potential consequences, the available resources, and the feasibility of implementation. Only once the most appropriate risk mitigation measures have been approved should organizations and businesses proceed with the planning of review, communication, and consultation [23]. By integrating this structured approach, the risk management process becomes more adaptable and contributes to best practices in the field of occupational safety.

Both qualitative and quantitative methods of occupational risk assessment rely on specific tools that have now evolved into methodologies. As mentioned earlier, risk management involves a systematic process of identifying, assessing, and addressing risks, continuously improving workplace conditions in line with business objectives. Beyond qualitative and quantitative methods, another classification occurs, which involves risk analysis, risk evaluation, and risk treatment [24,25].

For example, popular methods include FMEA (Failure Mode and Effects Analysis), which identifies the potential failure modes in a system and is mainly used for preventive maintenance and reliability enhancement. Another preventive measure for risk management is the Bowtie method, which incorporates FTA (Fault Tree Analysis) [26] and ETA (Event Tree Analysis) [27] processes with the ultimate goal of visually mapping risk scenarios. Additionally, the Monte Carlo method provides stochastic approaches for risk assessment, simulating potential scenarios and distributing probabilities [20,28–32].

Regarding the process of occupational risk assessment based on the four techniques discussed in this article, these offer advanced tools for modeling complex relationships, managing uncertainty, and learning from data, which traditional methods may not effectively detect.

1.2. Fuzzy Logic in Occupational Safety

Fuzzy logic is a mathematical framework that deals with decision-making and the imprecision and uncertainty that are entailed. Not resembling classical logic, which operates with binary true/false values, fuzzy logic enables degrees of truth, expressed as values

between 0 and 1. It is particularly useful in situations where the boundaries between categories are not well defined and where linguistic terminology, such as "high" or "low", is used to describe variables. In 1965, Zadeh developed the theory of fuzzy sets, which introduced a membership function providing an effective tool for addressing ambiguity and uncertainty. Today, fuzzy logic has expanded into many scientific fields with particularly beneficial outcomes. One such field is occupational safety [33].

With regard to occupational safety, fuzzy logic can be used to address the complexity and uncertainty associated with factors affecting job stability. Fuzzy logic enables the integration of subjective and qualitative assessments into occupational safety evaluations. Instead of relying solely on precise numerical data, fuzzy logic enables the use of linguistic terms and expert opinions to evaluate factors such as job stability, economic conditions, and industry trends. Occupational safety is influenced by various factors, including job performance, economic conditions, human factors, and industry stability [34–36]. Fuzzy logic can handle multiple criteria simultaneously and assign degrees of importance to each factor, which accommodates a more thorough and nuanced assessment of job safety. It is suitable for situations where the boundaries between categories are unclear, or where data are imprecise. In the context of job safety, factors such as job performance or human errors may not have clear distinctions. Fuzzy logic enables the representation of these uncertainties in a more realistic way [37]. Fuzzy logic systems can adapt to these changes by updating rules and parameters based on new information, making them more resilient in addressing evolving job safety scenarios. Fuzzy logic can be used in employee performance evaluation systems based on a combination of quantitative and qualitative factors [38]. By considering a range of performance indicators and providing feedback in linguistic terms, it can contribute to a more holistic and fair assessment of job safety [39]. These systems can take into account the specific criteria and relevant factors related to job safety, offering personalized insights to decision-makers [40]. By incorporating linguistic terms and handling inaccurate data, fuzzy logic systems contribute to more nuanced decision-making processes, ultimately enhancing job safety management in dynamic and complex environments.

1.3. Neural Networks in Job Safety

Neural networks are a type of machine learning model whose structure and function are inspired by those of the human brain. They are composed of interconnected nodes, or artificial neurons, which are layered. These layers typically include an input layer, one or more hidden layers, and an output layer.

Neural networks are trained on data so as to learn patterns, relationships, and representations, enabling them to make predictions or decisions without explicit programming. In the context of workplace safety, neural networks can be used to enhance various aspects of safety management and accident prevention. Neural networks can analyze historical data on workplace accidents, incidents, and near misses. By learning from patterns and correlations in these data, they can predict potential risks and identify areas with a higher likelihood of accidents. This enables proactive measures to prevent incidents and improve overall safety. Neural networks can be trained to adapt to the particular needs and demands of different industries and workplaces. By tailoring the models to the unique characteristics of a given environment, they can provide more accurate and relevant insights into potential safety risks [41–43].

Neural networks excel at detecting anomalies or deviations from normal behavior. In a workplace safety context, after being trained accordingly, they are able to recognize abnormal patterns in sensor data, worker behavior, or equipment operation. This enables quick identification of potential safety risks or malfunctions, facilitating timely interventions [16].

By analyzing data from sensors in machinery or equipment, these models can recognize patterns that are indicative of potential malfunctions. Preventive maintenance can then be scheduled to avoid accidents caused by equipment failure. Neural networks play a crucial role in workplace safety by leveraging their ability to examine and interpret complex data, recognize patterns, and make predictions [44]. They can enhance risk management, prevent accidents, and contribute to creating safer and more productive work environments.

1.4. Genetic Algorithms in Workplace Safety

Genetic algorithms are heuristic optimization and search methods inspired by the process of natural selection and genetics. They are a type of evolutionary algorithm used to procure nearly accurate solutions to optimization and search problems. The term "genetic" stems from the fact that these algorithms simulate the process of natural selection, during which the individuals who are the fittest are more likely to pass on their traits to the next generation. They work by developing a population of potential solutions to a problem that spans successive generations, using processes such as selection, crossover (recombination), and mutation to create new potential solutions [45,46].

Workplace safety often involves dynamic and evolving risks. Genetic algorithms can adaptively assess and respond to changing risk factors by developing solutions that take into account a series of variables, such as equipment conditions, environmental factors, and worker behaviors. Developing effective safety training programs is critical to preventing accidents. Genetic algorithms can be used to optimize training programs by generating content, delivery methods, and evaluation criteria to enhance the effectiveness of workplace safety training [47–49].

Genetic algorithms can optimize maintenance schedules by considering equipment usage patterns, performance history data, and maintenance costs to maximize equipment reliability and minimize the risk of failure [50]. Genetic algorithms provide a robust optimization framework that can be applied to improve various aspects of workplace safety. By simulating the evolutionary process and adapting solutions over time, these algorithms are conducive to the development of more efficacious safety practices, protocols, and risk management strategies in complex and dynamic work environments.

1.5. Machine Learning in Workplace Safety

Machine learning (ML) is a subset of artificial intelligence (AI) that involves developing algorithms [50,51] and models that render computers able to learn and make predictions or decisions without being explicitly programmed. It leverages statistical techniques to enable systems to improve their performance in a specific task over time as they are exposed to more data. Machine learning plays a crucial role in analyzing and interpreting complex data to improve safety practices, identify potential risks, and contribute to accident prevention. Machine learning algorithms can analyze historical data on workplace incidents, near misses, and identify patterns and correlations [17,52].

This enables the prediction of potential safety risks, allowing organizations to take preventive measures to avoid accidents and improve overall safety. ML models can be taught to identify abnormal patterns in data, such as equipment malfunctions, deviations from standard operating procedures, or unusual worker behavior. Anomaly detection helps in the timely identification of potential safety issues, enabling early intervention before accidents occur [53,54]. ML models can provide a dynamic real-time assessment of risk levels, enabling businesses to prioritize safety measures and allocate resources effectively. Additionally, they analyze human behavior in the workplace to identify unsafe practices or deviations from safety protocols. By recognizing patterns in behavioral data, organizations can proactively address unsafe actions and implement targeted safety interventions. They

can also be used to direct the correct use of Personal Protective Equipment (PPE). Cameras and sensors can detect whether employees are wearing the required PPE, ensuring that safety guidelines are being followed.

Using modern enhanced models, ML can assist in managing worker fatigue and optimizing shift schedules. By analyzing data on working hours, breaks, and sleep patterns, these models can provide recommendations for scheduling practices that minimize fatigue-related risks and enhance overall worker well-being. Machine learning facilitates the development of customized safety solutions designed to meet the specific needs and challenges of different industries and workplaces. By adapting models to the unique characteristics of a given environment, organizations can implement more effective and targeted safety measures [10,55].

Machine learning continues to revolutionize the approach to workplace safety by harnessing the power of data analysis, pattern recognition, and predictive modeling. Its adaptability, scalability, and ability to handle diverse data sources make it a valuable tool for organizations and businesses aiming to create and maintain safe work environments.

2. Literature Review

Due to the large volume of data, the complexity of the topic, and the broad scope covered by the four techniques, conducting a traditional literature review would be inappropriate as many categories and findings would be overlooked, focusing only on the most frequently occurring ones. The analysis of the 296 articles is carried out through statistical research in the Section 3 and primarily by answering the research questions presented in the Section 5, particularly the first three. Therefore, an additional search was conducted based on the eligibility and exclusion criteria presented in the Section 3 (Methodology), not for articles but for reviews on this subject. The results from Scopus yielded 25 reviews. After applying the eligibility and exclusion criteria, 13 reviews closely related to the topic under examination were selected. The remaining were excluded as they either addressed risk factors unrelated to human safety or applied risk factors to other sectors. Below is a bibliographic review of the 13 selected literature reviews.

The literature review by Mooren and colleagues [56] highlighted the issues and gaps in the field of occupational health and safety concerning road safety during heavy vehicle transportation. The initial study consisted of 124 articles, of which only 42 had significant relevance to occupational risk and safety, and only 17 out of the 42 provided basic techniques for addressing and preventing risks in transportation. The authors evaluated the safety management practices, safety culture, and risk utilization across all sectors of transportation.

One of their key findings was that there were 86 injuries per 1000 workers in the transportation sector compared to 69 injuries per 1000 workers in the industrial sector. This lack of data has been generally noted in the field of occupational safety [47,53,57], as well as in the broad category of professional driving [58]. For the heavy vehicle road transport industry, this raises particular concerns due to the high risk of collision and injury associated with the work of heavy vehicle drivers. Another significant finding is that the job of a heavy vehicle driver is considered to be a remote work environment, without supervision, which means that drivers may engage in irregularities or omissions in their work without these being easily detected by the employer [59,60]. Overall, the literature highlights a lack of data in the field of occupational safety for professional drivers. This creates particular challenges in the industrial sector of heavy vehicle road transport, where there is a high risk of collisions and injuries related to the job [56].

In their literature review, Villa and her colleagues [61] analyzed the progress achieved in risk assessment over the past decade under a general approach to Quantitative Risk

Assessment (QRA). Specifically, they argued that QRA has remained unchanged in its basic principles since the early 1980s but has continuously evolved and is now being integrated into various industries that did not exist at that time. Risk assessment techniques significantly influence the design of a system. However, this particular literature review focused on chemical substances, which may cause accidents in industry, either accidentally or deliberately, primarily related to the loss or leakage of such substances. The authors argued that similar literature reviews were conducted in the past but examined the topic from a different perspective. Nevertheless, they all converge on the fundamental value of risk assessment and the dissemination of information [61].

Another literature review [9] sought models that were popular and repeatable among researchers under the umbrella of health and safety risk assessment. By consolidating these methods and models, they categorized them into seven groups. Six out of the seven categories refer to models that are also employed by other researchers. One category, which focuses on artificial intelligence, is examined from a different perspective. It primarily examines the issue using criteria based on the riskiness of the work, drawing more from classical techniques such as VIKOR, TOPSIS, and AHP [62]. However, the review emphasizes the value of fuzzy models in occupational risk, as highlighted in eleven of the eighty-eight total research articles. Additionally, one of these eleven articles uses neural networks with fuzzy inference systems, mainly focusing on construction activities [63]. The others are based on specific systems and rules, such as Pythagorean fuzzy AHP and Takagi–Sugeno fuzzy systems, evaluating their use in factories [8,11,12,64].

In 2021, prompted by the rapid urbanization of the global population and the need for the fast development of many megacities [65], and, by extension, the construction of underground rail transportation systems, Lin and colleagues [65] acknowledged the need for a literature review concerning underground construction. Focusing on underground construction and safety, they drew from a literature review between 2010 and 2020, gathering one-thousand-six-hundred-twenty-one articles related to safety and accidents in underground construction. Despite the vast volume of articles, only eleven were found to use fuzzy logic theories, and seven articles used machine learning methods, employing some ANN and BN methods in the background [63,66].

Neto and colleagues [67] conducted a comprehensive literature review on the topic of safety related to artificial intelligence (AI) in industries. They managed a volume of over 5000 articles that had at least one reference to safety through artificial intelligence, of which a subset of 329 successfully secured AI safety using modern techniques.

Additionally, one of the key findings of the research, which set its article search to start from 1994, is that, until 2016, the number of published articles remained in the single digits (one or two). There has been a surge in this topic from 2019 onward, where the numbers have reached double digits and are approaching a three-digit number of articles. Moreover, particular attention is being paid to Artificial Neural Networks (ANNs). Security systems in the industry using artificial intelligence have increasingly implemented ANNs, from 32% in 2018 to nearly 70% in 2022 [67].

The authors in [10] carried out a literature review of 124 articles on algorithmic machine learning techniques in the field of risk assessment. This particular literature review studied occupational risks across various sectors. One of the most noteworthy observations of the research is that the automotive industries are adopting techniques that involve machine learning to assess their risks. Furthermore, they argued that Artificial Neural Networks [68,69] combined with machine learning comprise a method that helps to better assess risk. From the analysis, it emerges that ANNs are used more frequently for risk assessment compared to other methods. This is due to the use of non-linear mathematical equations that the ANN technique essentially develops [70]. Additionally, Support Vector

Machines (SVMs) play an important role in machine learning for safety evaluation. Another important finding is that only 20% of the articles use real data to create machine learning models, while over 70% use historical data and derive theoretical conclusions [10].

Waqar and colleagues [71] conducted a literature review on safety in oil refineries. Oil refining possibly has the highest number of fatal accidents in absolute terms relative to the workforce compared to other industrial sectors. They examined safety risks from a different perspective, primarily focusing on accidents caused by mechanical failure, electrocution, chemical exposure, scaffold failure, and oil spills.

The research collected 30 articles dealing with accidents in both floating and land-based oil refining structures. Interestingly, the review found that only one study used the concept of fuzzy logic to quantify risk [72]. It is therefore observed that, in such a sensitive sector, the necessary steps towards artificial intelligence have not yet been taken. Nevertheless, the authors claimed that the existing techniques help to reduce accidents, but further actions are needed for the results to be noticeable for workers [73].

Choo and colleagues [7], in their literature review, explored the connection between machine learning, risk analysis, as well as the Fourth Industrial Revolution (Industry 4.0). They highlighted the adoption of preventive safety measures implemented by Malaysian industries to improve safety management. They emphasized that Singapore is a leader in artificial intelligence, which can assist in predicting events, improving processes, and simulating safety scenarios. The classification of machine learning in their review is divided into supervised, unsupervised, semi-supervised, and reinforcement learning. They stressed [74] that, in the era of globalization, it is difficult to avoid risk. The most common techniques for Quantitative Risk Assessment [75] include hazard and operability studies (HAZOPs) [76] Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Event Tree Analysis (ETA), the analytical hierarchy process (AHP), Bowtie, Bayesian Networks (BNs), formal safety assessment (FSA), and Dynamic Bayesian Networks (DBNs) [77–88]. Efforts are underway to search for articles focusing on the aforementioned techniques combined with a machine learning model. Finally, they highlighted the fact that there is no access to a database, which in turn would open up several opportunities in the field of safety and consequently in the development of machine learning algorithms for safety [7].

Other authors, in their literature review on the construction and management of hydroelectric power plants, covered the full spectrum of potential risks associated with them. Therefore, in addition to safety assessments, articles that deal with project management safety were also examined, such as climate change, delays in schedules, environmental and ecological assessments, and natural hazards like floods. Thus, a holistic approach to safety management for hydroelectric power plants was undertaken. Nevertheless, the value of neural networks for managing worker safety was highlighted [73,89,90].

In one more literature review [91], the validity of Bayesian Networks (BNs) in various industrial sectors was examined, with particular emphasis on the preventive measures BNs can provide against industrial accidents. It was noted that BNs can consider subjective failure analysis while adhering to the principles of rational consensus [91,92].

3. Method

In this section, a thorough presentation of the method by which the relevant literature on this topic was retrieved is provided. Each step followed is analyzed, explaining how the literature was classified into various categories.

3.1. Literature Search Process

The objective of this subsection is to present the methodology followed to substantiate the findings and conclusions of this study. The structure of this subsection is designed

to ensure that the literature review method is both valid and aligned with the research objectives of this work.

The methodology was executed through the following activities: (Section 3.1.1) defining search keywords, (Section 3.1.2) selecting the search engine to be used, (Section 3.1.3) analyzing the search results, and (Section 3.1.4) applying exclusion and eligibility criteria. This process is detailed in the flow diagram shown in Figure 1.

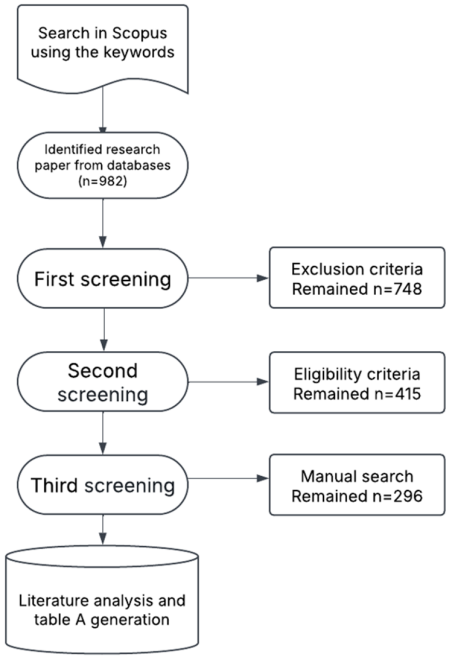


Figure 1. Literature retrieval process (flow diagram).

3.1.1. Definition of Search Keywords

The subjectivity and selection of these keywords, as well as the representativeness of the keywords, are ensured by taking into account the following:

(a) terms that appear more frequently in the article;
(b) avoidance of excessively broad terms that could lead to ambiguities;
(c) targeted words that reflect the core of the study;
(d) discussion and peer review.

Logical expressions guiding the search process were established at this stage to retrieve publications relevant to professional risk management and associated technical methodologies. Broad terms were avoided unless combined with others using operators like AND or OR to ensure specificity.

The finalized keywords for this study include “fuzzy logic”, “fuzzy system”, “risk analysis”, “industry”, “neural network”, “safety”, “genetic algorithms”, “computational intelligence”, “machine learning”, “risk assessment”, “occupational”, and “occupational risk analysis”.

While these keywords are commonly associated with safety and risk management, they are also frequently used in other fields, such as healthcare and economics. Consequently, logical operators were applied to refine the scope of the research to the domain under investigation. The way these keywords were combined is shown in Table 1.

Table 1. List of search keywords used in Scopus.

No.	TITLE-ABS-KEY	Papers
1	"fuzzy logic" OR "fuzzy system" AND "risk analysis" AND "Industry"	84
2	"fuzzy logic" OR "fuzzy system" AND "risk analysis"	589
3	"neural network" AND "risk analysis" AND "safety"	67
4	"genetic algorithms" AND "risk analysis" AND "safety"	37
5	"Computational Intelligence" AND "risk analysis" AND "safety"	3
6	"machine learning" AND "risk analysis" AND "safety"	20
7	"fuzzy logic" AND "risk assessment"AND "occupational" and "risk analysis"	29
8	"machine learning " AND "risk assessment" AND "occupational risk analysis"	85
9	"genetic algorithms" AND "risk assessment" AND "occupational risk analysis"	15
10	" neural network " AND "risk assessment" AND "occupational risk analysis"	53

The first column of Table 1 shows the numbering of the keyword combinations. In the second column, the combination of the keywords is shown, specifically only using the operator "and". The third column shows the number of articles provided by the search engine.

3.1.2. Search Engine Selection

The study did not directly utilize individual databases from major publishers, such as SpringerLink, ScienceDirect, IEEE, MDPI, or Taylor & Francis. Instead, Scopus was selected as the sole search engine due to its comprehensive coverage, which already includes the aforementioned publishers. This decision was also influenced by the high number of duplicate entries observed in other engines and their relatively smaller number of unique articles compared to Scopus.

3.1.3. Results Overview

The search conducted via Scopus yielded a total of n = 982 articles by November 2024.

3.1.4. Exclusion and Eligibility Criteria

Due to the large number of articles retrieved from the Scopus database based on the selected keywords, the scope of the search results was narrowed using a process that evaluated the results based on eligibility and exclusion criteria. For the initial screening (first screening), exclusion criteria were applied, as shown in Table 2. The purpose of the exclusion criteria was to reject articles that were irrelevant to the topic from the outset.

Table 2. Exclusion criteria (first screening).

No.	Criteria Table
C1	Articles not written in English are rejected.
C2	Articles from national conferences are rejected.
C3	Duplicates are rejected.
C4	Articles related to healthcare or economics, despite using the four techniques under examination.

The exclusion criteria included the elimination of non-English articles, articles from national conferences, articles related to medical or general health risks, and articles focused on economic risk or general financial risks. Criterion C4 was the one that rejected the largest number of articles. This approach resulted in the rejection of a significant number of articles (234) containing information not related to the subject under examination. The number of remaining articles was $n = 748$.

Subsequently, eligibility criteria were applied for a second filtering (second screening), as shown in Table 3. The ultimate goal of the eligibility criteria was to establish targeted filters to narrow the search results specifically to the topic of the literature review. Specifically, the following were retained: (a) articles that addressed at least one of the four techniques under examination (fuzzy logic, neural networks, genetic algorithms, and machine learning), (b) articles focused on workplace safety with an emphasis on humans, and (c) articles that referred to risk analysis related to human factors, excluding external factors such as material failure or wear.

Table 3. Eligibility criteria (second screening).

No.	Criteria Table
C5	The articles must apply one of the four techniques under examination, i.e., fuzzy logic, neural networks, genetic algorithms, and machine learning.
C6	The articles must focus on workplace safety, with humans being the focal point.
C7	The articles must refer to risk analysis from human factors and not from external factors.

After this second screening, the number of articles was significantly reduced, leaving $n = 415$.

The third and final stage of screening (third screening) was conducted manually. Beyond the keywords, the abstract of each article was reviewed. This process identified potential inaccuracies from the criteria used in the earlier screenings, such as articles that mainly addressed material-related risk or workplace safety intertwined with health concerns, which were essentially health-oriented. Such studies were excluded, and only those directly relevant to the subject under examination were retained.

After the final screening, the remaining articles totaled $n = 296$. Information from these articles was utilized to address the research questions and to compile Table A1 in Appendix A.

These final articles formed the basis for answering the research questions and constructing Table A1 in Appendix A.

3.2. Classification of Articles

The classification of the articles was completed by extracting valuable information and assembling it into a table, from which data analysis and processing would later be derived. In addition to the title and authors of the article, information was collected regarding the techniques the article follows, the types of data used, the sectors in which they are applied or can be applied, the year, the name of the journal, the publisher, the total number of citations of the article, and the country of origin of the first author (Table A1).

3.3. Method of Classification in the Table

As mentioned earlier, each article was studied based on the three criteria, and information was gathered regarding the article's details. For example, Arunraj et al. [93] developed a technique for understanding uncertainty in risk assessment using fuzzy sets for industrial

use. To complete this, they used fuzzy set theory through mathematical models. Therefore, it is classified under fuzzy logic. Since it is a fuzzy mathematical model, it is categorized under mathematical models as the type of data. Additionally, since the model is intended for industry, the term "industry" is placed in the column indicating the sector of application. The number of citations is 100, and the country of origin of the article is India. This method was used to classify all the articles in the final table. It should be noted that the number of citations was last updated and processed in October 2024.

4. Statistical Analysis and Results

For the analysis of the article content and to extract data that would help to answer the research questions, statistical analysis of the results was conducted using IMB SPSS Statistics Version 25.

As previously mentioned, the data were placed in a table (Table A1), which became the source for extracting the data and results. The main focus was the separation of articles based on the techniques analyzed in the present research. Specifically, the research identified one-hundred-sixty-three articles based on fuzzy logic, eighty-one articles that used neural networks, twenty-five articles that used machine learning, twenty articles that used genetic algorithms, and seven articles that used a hybrid approach, meaning a combination of two of the four techniques under study to achieve a result or reach a conclusion (Figure 2).

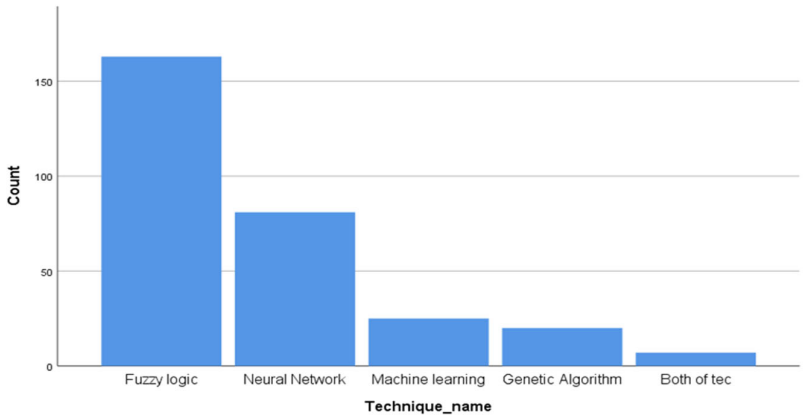


Figure 2. Total number of articles per technique.

It is clear that fuzzy logic has significant potential for development among researchers concerning worker safety. Neural networks also have a substantial number of articles addressing safety-related issues. The numbers for machine learning and genetic algorithms are smaller. Lastly, satisfactory efforts have been undertaken by some research groups to present techniques for solving worker safety issues using two techniques combined.

Figure 3 illustrates the publication distribution of articles published in scientific journals annually, with the focus being on the use of the four methods for risk assessment over the past forty years. There is an upward trend, including some milestone years. The first milestone year is 2005, when the number of articles increased from single to double digits, and, in many years, these numbers more than doubled. Additionally, 2013 was the peak year, with 21 articles. Another milestone year is 2017. The period between 2015 and 2017 was particularly productive for this topic, with a large volume of articles but also significant annual fluctuations.

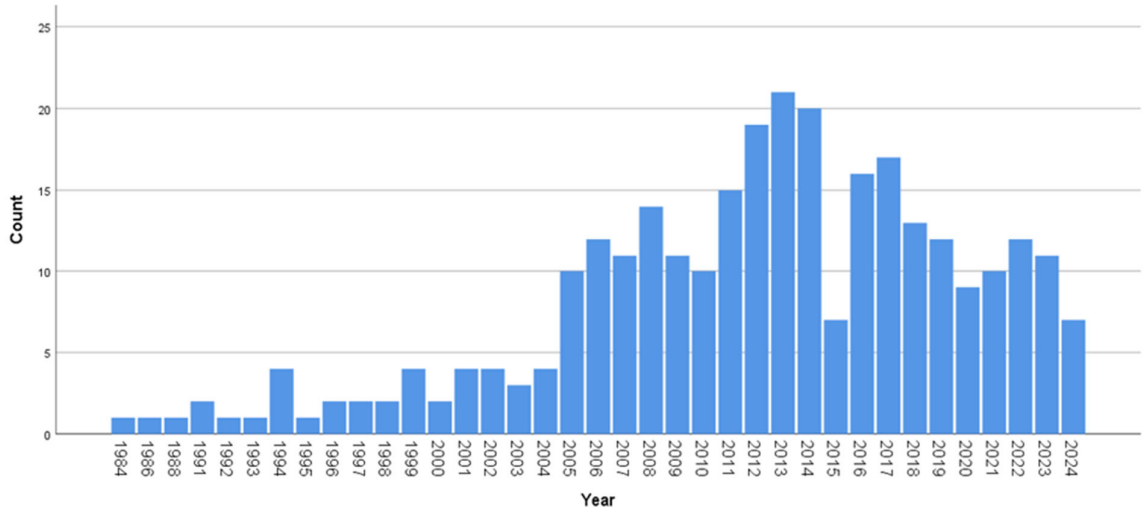


Figure 3. Annual distribution of published articles.

From 2018 to the present, there has been stability in the subject under study, with a range of 10 to 12 articles annually until today (last search conducted in October 2024).

It should be noted that, in the early period of research, from 1984 to 2014, efforts were employed to establish the four techniques under examination in the field of safety evaluation.

The reason for the stability since 2018 lies in the shift among authors from the two dominant methods—fuzzy logic and neural networks—towards the promising future technique of machine learning. This is depicted in Figure 4 below.

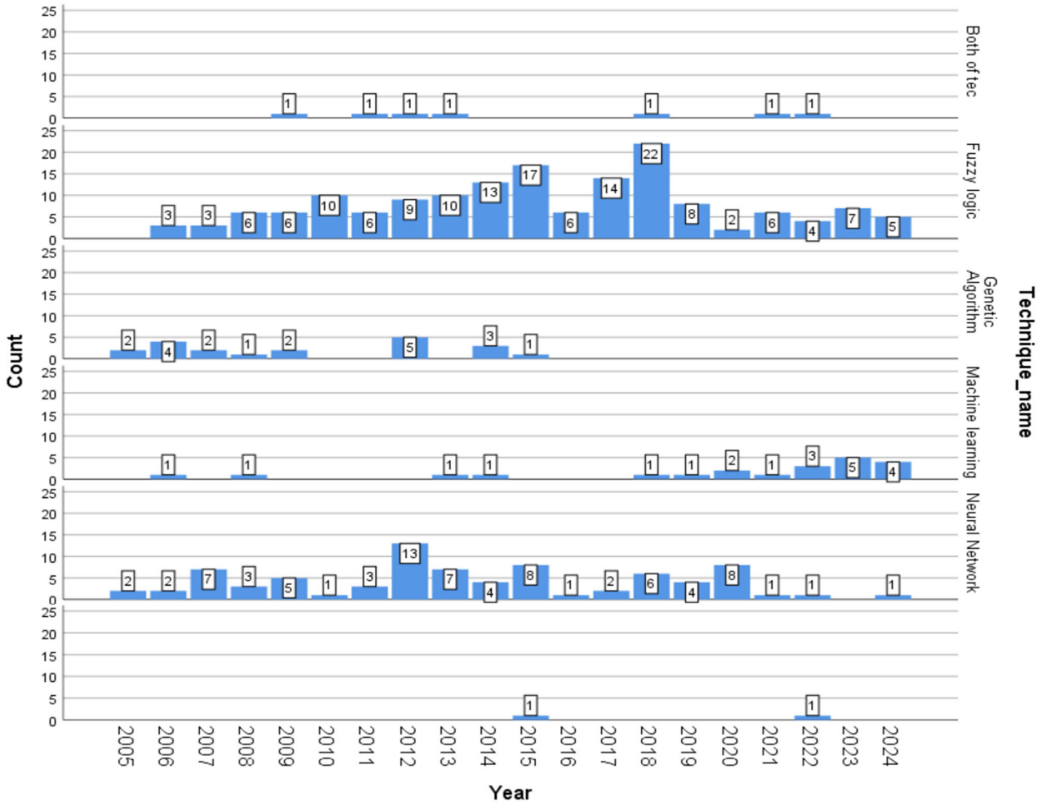


Figure 4. Annual distribution of published articles by technique.

In Figure 4, the number of articles under review per year is presented, categorized by technique. In Figure 4, only the last 20 years are presented. The first 20 years, which are

not displayed, show a sparse and scattered representation of articles that do not warrant significant study. This extensive dispersion characterizes them as the early period during which the development of such techniques was initially attempted. It is observed that fuzzy logic and neural networks follow the same trend as presented in Figure 3, representing the total number of articles per year. In contrast, in the last three years, there has been a decrease in the use of neural networks and an increase in the use of the machine learning technique.

A preliminary explanation for this is that machine learning incorporates elements and rules of neural networks. Furthermore, genetic algorithms first appeared in 2001, and their last mention was in 2014, after which their usage has significantly decreased over the last decade. A major reason for this decline is the progress in machine learning (ML) and neural networks. The rapid development of ML and artificial intelligence (AI) techniques has provided more efficient and alternative solutions. Additionally, genetic algorithms require enormous computational resources, whereas newer techniques are easier to use, implement, and develop compared to GAs.

Overall, the decline in the use of genetic algorithms in the subject matter under review is primarily due to the rise of more powerful, efficient, and user-friendly AI techniques that offer better performance and flexibility [94].

In Figure 5, the fields in which the articles under review are applied are presented. The results showed that the overwhelming majority (117 articles) apply these techniques in the industrial sector. The literature review also found that 65 articles outline a general framework for workplace safety, which can be applied across various work environments. A significant number of articles (56) deal with occupational risk in transportation.

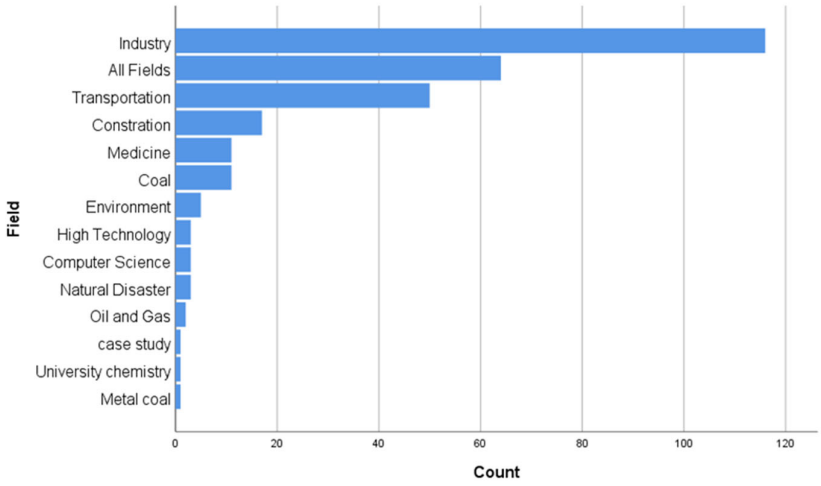


Figure 5. Distribution of risk assessment articles by sector.

Moreover, the literature review revealed that 17 articles explore the application of these techniques in the construction sector. Additionally, the same absolute number of articles (11) apply risk assessment techniques to mining—whether underground or surface mining—or in healthcare environments.

Table 4 highlights the top 10 most prominent sub-techniques used in the 289 articles based on both quantitative and qualitative data analysis. Researchers in workplace risk assessment utilize one of the four main techniques, often combining them with classical risk assessment methods. About 13.2% of the articles present mathematical models that, when combined with other techniques, create methods with unique characteristics. Moreover, 7.6% of the articles (twenty-two papers) refer to case studies, primarily focusing on how these cases could be solved using neural networks and fuzzy logic. Additionally, nine

papers provide theoretical analysis of specific techniques. The number of papers using various models decreases significantly but still incorporates well-known techniques in workplace safety and risk assessment. These techniques evolve into dynamic methods when combined with neural networks, fuzzy logic, and genetic algorithms.

Table 4. Distribution of risk assessment articles by sector.

Technique	Number of Articles	Percentage
Mathematical Model	38	13.2%
Case Study	22	7.6%
Theoretical analysis	9	3.1%
ANN model	8	2.8%
FMEA	8	2.8%
Theoretical models	7	2.4%
FTA	5	1.7%
AHP	4	1.4%
Bayesian Networks	4	1.4%
Theoretical foundations	4	1.4%
Mathematical Model	38	13.2%

The main quantitative or qualitative techniques used are FTA, ANN, BN, LOPA, ANFIS, AHP, QRA, TOPSIS, CREAM, and HAZOP.

Data extracted from the database yielded 150 subcategories. Therefore, to facilitate the results in Table A1, it was deemed necessary to display the largest of these subcategories in absolute numbers, totaling 16 (Figure 6). The top five subcategories manage data and mathematical models widely used in the field of risk, while the remaining methods are well-known in workplace risk assessment.

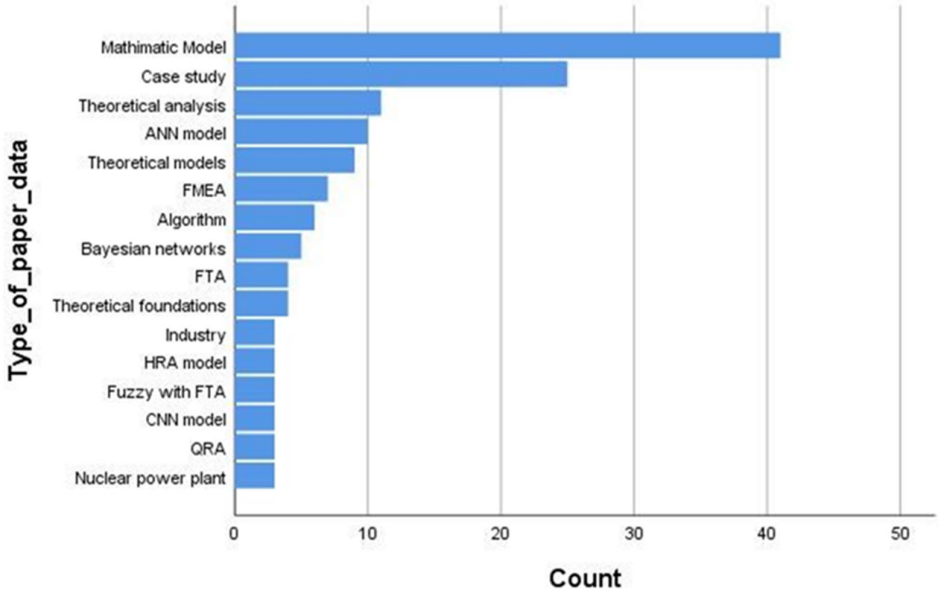


Figure 6. Distribution of articles by modeling.

Table 5 shows the 10 most frequently cited international journals out of 63 covered in the research. The literature review indicated that, in recent years, the dominance of classical journals in workplace risk assessment has shifted. Nevertheless, 10 journals, mostly focused on workplace safety, cover two-thirds of the articles in the study. The journal with the most frequent application of the examined techniques is JLPPI, with 39 articles.

Table 5. Absolute numbers and percentages of journals in the study.

Name	Frequency	Percent
JLPPI	39	12.1%
RESS	36	11.1%
SS	28	8.7%
AAP	27	8.4%
RA	19	5.9%
HM	16	5.0%
FSS	15	4.6%
SR	12	3.7%
NH	6	1.9%
EAAI	5	1.5%
Remaining 53	120	37.1%

Figure 7 displays the distribution of articles in the top 10 journals by publication frequency. Data from the database revealed that the journal with the most references in this field is JLPPI, with 39 articles. Following closely behind is RESS, with 36 articles, and in third and fourth place are AAP and SS, with 27 articles each. All other journals have fewer than 20 articles.

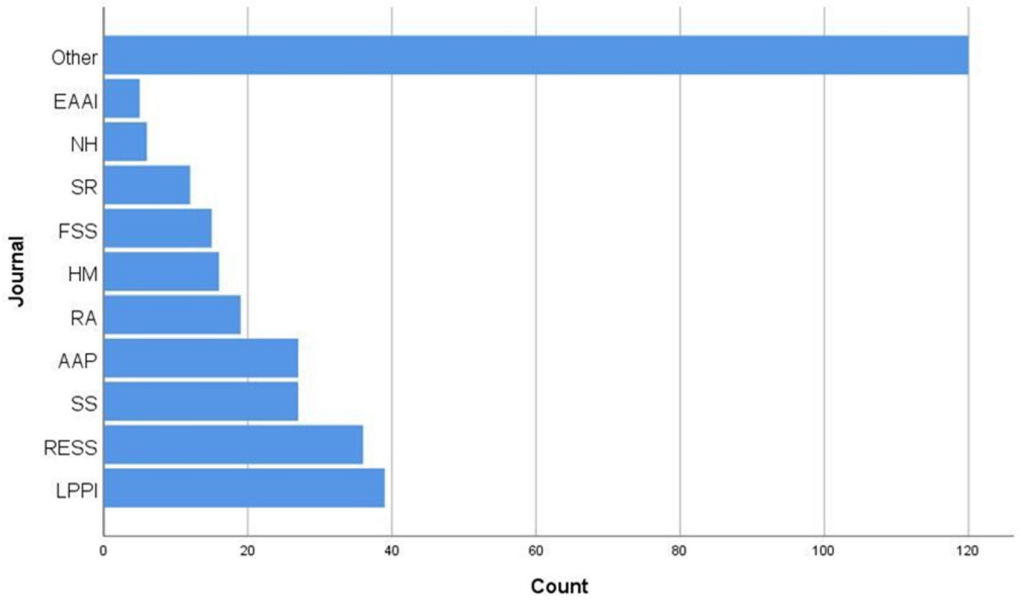


Figure 7. Distribution of selected articles among the top 10 journal sources.

Figure 8 presents a Choropleth map showing the number of published articles by country from the selected literature. The top five results show that China has the highest contribution, with 48 articles. The second through fifth positions are held by the United States, Turkey, Italy, and Iran, with 27, 25, 23, and 22 articles, respectively.

Since workplace risk analysis primarily concerns the workforce, it was deemed appropriate to create a map reflecting the number of published articles per country's workforce (Figure 9). The top five results show that Taiwan has the highest number of published articles relative to its workforce. Italy, Slovenia, Finland, and Switzerland rank second to fifth, respectively.

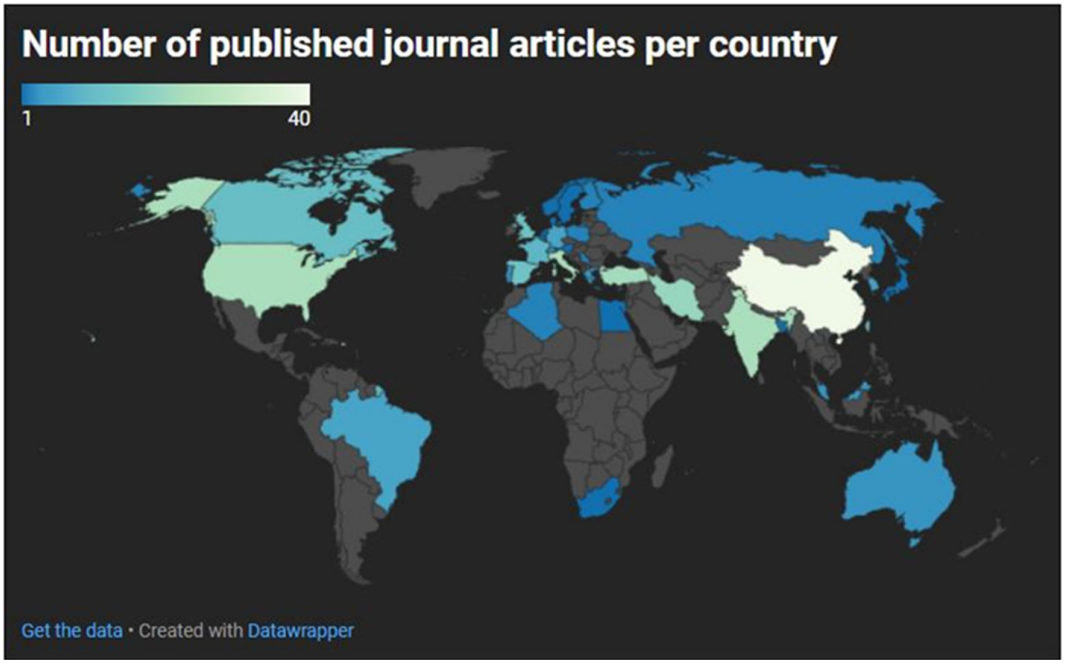


Figure 8. Number of publications by country.



Figure 9. Number of publications by country based on workforce.

Figure 10 shows the number of articles by publisher. The literature review revealed that 65.6% of the articles were published by the Elsevier publishing house, with a significant variation existing between it and other publishers. Wiley follows with 7.3%, IEEE and Springer with 6.25%, and Taylor and Francis at 4.86%. The remaining publishers share the remaining 8%.

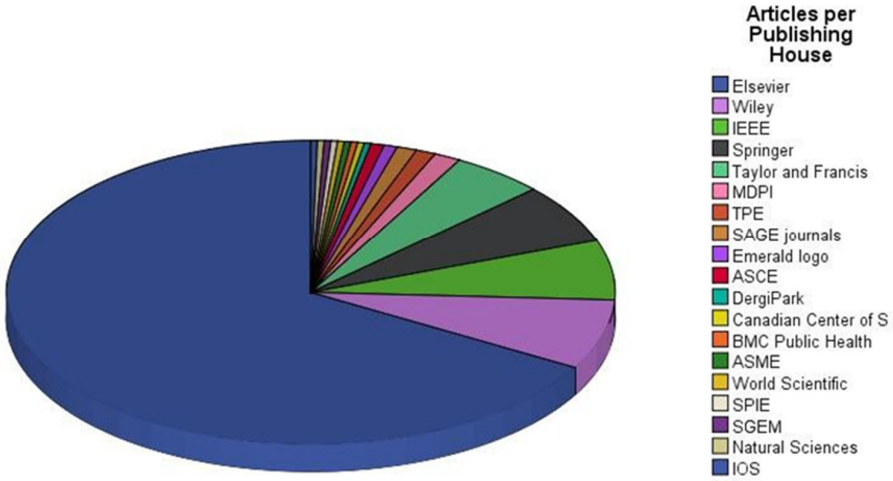


Figure 10. Publishers of the articles under review.

The distribution of contributing authors in this field was extracted by processing the citation database. Figure 11 illustrates all authors from the 289 articles in a word cloud, where authors with the most publications have their names displayed in larger font sizes. The research identified that the authors with the most papers on the subject are Wang J. (eleven articles), Liu (nine), and Zio (nine).



Figure 11. Word cloud of authors in risk assessment.

Out of 634 authors, only 10 have published more than five papers each. The next 127 authors have published two to five papers, while the rest only have one paper. The top 10 authors in terms of absolute number of articles, along with their percentage of the total database, are shown in Table 6.

Table 6. Top 10 researchers applying techniques for risk assessment.

No.	Author	Number of Articles	Percentage
1	Wang J.	11	3.82%
2	Liu	9	3.13%
3	Zio	9	3.31%
4	Yu	6	2.08%
5	Markowski	6	2.08%
6	Mannan	6	2.08%
7	Maiti	5	1.74%
8	Zhang Y.	5	1.74%
9	Xu	5	1.74%
10	Wang Y.	5	1.74%

5. Research Questions

The literature review of recent years from bibliographic reviews between 2014 and 2023 demonstrated that the use of research questions is minimal. The only ones who outline key questions in their introduction, which they attempt to answer throughout their work, are Liu [9] and Hegde [10].

Liu and colleagues [9] attempt to approach the evaluation of occupational health and safety risk assessments (OHSRAs) proposed in the literature. Additionally, they seek to identify the risk criteria considered in addressing OHSRAs, as well as weighting methods for determining risk criteria and the theories and uncertainty methods used to handle risk assessment information. On the other hand, Hegde and colleagues [10] attempt to answer questions related to machine learning methods: which sectors adopt them, how machine learning is applied alongside risk assessment, and which phase of risk assessment can be supported using machine learning. Furthermore, they explore trends in publications related to the subject under review.

Below, the research questions outlined in the introduction are answered and analyzed. The results provide a very good estimation and approach to the current trends regarding the focused points of the questions in the global risk assessment in the workplace based on the four techniques.

1. Which of the four techniques has been used more by researchers, why, and how are the articles distributed?

The answer to the first sub-question, i.e., which technique is most analyzed by authors, it is fuzzy logic. This is clearly deduced from the statistical analysis of the literature database as the number of articles using fuzzy logic in risk assessment in workplaces is double compared to the next most common technique, which is neural networks. Specifically, in the present study, 160 out of 289 articles were found to be using the fuzzy logic technique to address problems related to workplace safety and risk more broadly. Neural networks follow next with a total of 79 articles that employ this technique. Next are genetic algorithms and machine learning techniques with 20 and 22 articles, respectively, out of the total 289. It becomes clear that fuzzy logic is overwhelmingly the most sought-after technique, far outpacing the others.

To address the second part of the research question—why researchers favor fuzzy logic over other techniques—an analysis of the key characteristics of each technique's application to the specific topic is required.

Fuzzy logic has been widely used in the assessment of occupational risks due to its ability to handle uncertainty and ambiguity in decision-making. Fuzzy logic enables researchers to model and represent vague or subjective information, making it suitable for certain aspects of risk assessment where precise measurements may be challenging, difficult, or overly expensive [95–97]. Fuzzy logic enables the representation of imprecise or subjective information, which is common in occupational health and safety [98]. Furthermore, fuzzy logic is particularly suitable for modeling complex systems where there may be a lack of precise data [99–101].

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of the human brain. They excel at learning patterns from data, making them powerful tools for performing tasks such as classification, regression, and pattern recognition. Additionally, by leveraging their ability to learn complex patterns from data, ANNs can be taught, using historical data, to recognize and predict patterns related to occupational risks, making them valuable for risk assessment and prediction tasks [18]. The ability of neural networks to generalize using training data in order to make predictions about new, "unseen", or future data contributes to their popularity [102].

Genetic algorithms have been applied to optimize parameters and decision-making processes related to occupational risk assessment. They are often used to optimize complex models or to search a large solution space for the best parameters that minimize risks or improve safety conditions. As the research shows, genetic algorithms can be beneficial in scenarios where finding an optimal solution involves exploring a vast solution space [34,103]. They are especially useful when searching for the best combination of parameters or features that contribute to risk levels [103,104].

Machine learning techniques have gained significant popularity across various fields in recent years, including occupational risk assessment. Machine learning enables complex pattern recognition and can effectively handle large datasets. Neural networks, as a subset of machine learning, have been used for tasks such as risk prediction, risk recognition, and safety assessment in occupational environments [85,105]. Machine learning, in general, includes various techniques, including the aforementioned neural networks, such as HRA models, K-nearest, BN, Stacked ML, and even fuzzy risks, among others [106–117]. Researchers often use machine learning algorithms for classification, prediction, and pattern recognition in occupational risk data. Supervised learning methods, such as decision trees, Support Vector Machines, and ensemble methods, are commonly applied to predict and assess risks based on labeled training data. Unsupervised learning techniques, such as clustering, can help to identify hidden patterns in occupational risk datasets [114].

From the above, it becomes clear that, for techniques like neural networks, genetic algorithms, and machine learning to function, a significant, if not large, volume of data is required. Typically, such datasets and data volumes either do not exist or are not easily accessible to researchers due to concerns about publishing such data or the lengthy and time-consuming process of acquiring it [67,114,115]. Moreover, the nature of work in various sectors is never the same, so it is not easy to borrow data and patterns from one industry sector (e.g., the industrial sector) for another, such as transportation [116], or vice versa, for instance the construction sector to borrow data from the industrial sector. The same applies within a sector, such as mining, where a mine [103,117,118] may be above ground or underground, resulting in different characteristics that must be studied each time. This is also true for sectors with a large volume of articles, such as industry. For example, data from the food industry cannot be used to ensure worker safety in the metallurgy industry. Another example is the transportation sector, where, even if we choose the same vehicle, such as a truck or a ship [119], the literature shows that, depending on the cargo being transported, there are specific characteristics that affect risk assessment and the nature of the work.

In contrast, fuzzy logic enables the setting of parameters and obtaining approximate results that can solve safety issues in workplaces without always relying on a data reservoir. This helps authors to academically address problems that would otherwise be challenging due to the lack of data [120]. As shown in the literature database, many researchers propose solutions for various issues related to safety and occupational risk without having prior data from the sector [121,122].

Problem-solving is conducted either through a mathematical model or by fuzzifying traditional techniques for addressing safety issues, such as FTA, Bowtie, QRA, FMEA, AHP, etc. [123]. In summary, the main reason researchers are turning more and more to fuzzy logic compared to other techniques is primarily the result of insufficient data, the ease of clarifying specific parameters, and the fact that constructing a fuzzy model for risk management and problem-solving in occupational safety is easier than building and modeling a neural network, genetic algorithm, or machine learning system [124].

To better understand why researchers have been focusing more on fuzzy logic, we can present a table of method distribution. This table (Table 7) can help readers to more easily search and match authors with their respective problem-solving models.

Table 7. Model solutions by various authors across professional fields.

Field	Subcategory	Publication
Industry	AHP	[125,126]
	FTA	[127–129]
	Bowtie	[32]
	AFRA	[124]
	FMEA	[130–132]
	Monte Carlo	[30,133]
	LOPA	[134]
	FAP	[21]
	FCE	[135]
	FCM	[120]
	FHWI	[136]
	QRA	[96,137,138]
	PRAT	[139]
Transportation	AHP	[118,122]
	CART	[19]
	CREAM	[75]
	FTA	[140]
	FMEA	[141–143],
	FFTA	[123,144]
	FBN	[145]
	IVIS	[146]
Construction	AHP	[147]
	DEMATEL	[148]
	LSRA	[149]
	QRA	[150]
	ORCA	[151]
Mines	AHP	[100]
	FRA	[152]
	SPA	[103]
	IVFN	[153]
Medicine	AHP-TOPSIS	[64]
	MCDM	[154]
Environment	AHP	[155]
	ECI	[40]
Oil and gas	FMEA	[79]
All fields	BN	[156]
	CREAM	[39,75,78,157]
	FMEA	[141,158]
	FMECA	[159]
	FTA	[88,158,160]
	TOPSIS	[161,162]
	HRA	[163]
	LOPA	[106,164]
	MCDM	[165]
	QFD	[37]
University Chemistry	FMEA	[166]

From the table, it becomes clear that certain fuzzy logic methods are encountered in all or most fields of risk assessment applications. One such method is the AHP. The Analytic Hierarchy Process (AHP) is a popular decision-making tool that helps to prioritize and select alternatives based on multiple criteria. When combined with fuzzy logic, it becomes particularly useful in risk assessment by addressing the inherent uncertainty and ambiguity in human judgment. Another method that appears in most fields is FTA. Fault

Tree Analysis (FTA) is a widely used technique for analyzing the causes of system failures and assessing risk in various fields. When combined with fuzzy logic, FTA can effectively handle uncertainty and ambiguity in risk assessment, making it a powerful tool for complex decision-making processes. The same applies to other methods that appear in most fields, such as QRA, FMEA, and TOPSIS [167].

2. Into what subcategories can the four techniques be divided, and what problems do they solve in risk assessment?

As shown in the table from the previous research question, it is not the use of the technique itself but a subcategory of it that is usually referred to by the authors as a model or protocol. In this research question, the goal is to not only present the subcategory but also explain what it solves in risk assessment.

Specifically, the AHP model, when combined with fuzzy logic [168], can be used for emergency planning in the industry [169] and to prevent risks throughout the life cycle of a renewable energy source, specifically a wind turbine [170]. Furthermore, the model identifies the primary cause of accidents in mining environments and can assess risk in construction projects [125].

Additionally, the subcategory of the FTA method is also important, which, when combined with fuzzy logic and neural networks, provides significant results in risk assessment and safety assurance. Specifically, it prevents unwanted events that cause catastrophic accidents in gas facilities [171], is applied in oil storage tank zones [127], and prevents fires during production in oil tanks [128]. Moreover, it prevents accidents at intersections caused by human error [134], supports decision-making on highways, and ensures risk avoidance in marine transport by identifying qualitative and quantitative uncertainties [102].

Another method commonly combined with fuzzy logic is FMEA. FMEA has been applied to evaluate failure of conveyor belts due to human error in coal mines [172–175] and has been proposed for risk assessment in the maritime industry [131,176–178].

In addition, it aims to reduce workplace accidents in the construction sector [129] and is applied in chemical laboratories of universities, but it can also be applied in engineering and physics labs by weighing the severity index [166]. FMEA can assist in decision-making in earthwork operations and is used in textile manufacturing [131]. It was developed for application in the chemical industry and is considered to be a suitable method in unstable and uncertain environments [9,179,180]. Finally, it has been shown to help with more accurate risk assessment in technical safety management systems [181] and facilitates safety in the aviation sector as a tool for risk analysis.

MCDM is another subcategory that, when combined with neural networks, helps to ensure industrial safety and enriches regulations by using the Taiwanese government regulations [131]. It is also applied by hospital managers to keep safety risk levels low [68].

LOPA is another subcategory of fuzzy logic that finds application in industries using LNG [134] but has also been used for protection against heaters in combination with fuzzy logic [113]. QRA is a subcategory of fuzzy logic that helps to assess uncertainty in real time in chemical plants [137,139] and improves uncertainty in oil, gas, and chemical industries [138]. Similarly, the PRAT method ensures worker safety and is applied in textile companies that produce towels and bathrobes [139].

Another important subcategory that is applied in both neural networks and fuzzy logic is the TOPSIS method. The TOPSIS method is applied with the help of neural networks in industrial safety and workplace accidents, while also improving Pareto models [3]. When combined with fuzzy logic, TOPSIS helps in the field of engineering, for example, scaffolding, excavators, and trucks [161].

The HRA method is applied in combination with fuzzy logic and machine learning. It has been proposed as a method for assessing human errors in nuclear power plants [182,183]

and for managing human errors in industries combined with fuzzy logic [161]. On the other hand, it enhances machine learning, addressing occupational risk in processing industries [184].

A notable subcategory of fuzzy logic is DEMATEL, which is applied in the construction industry [148], but, in combination with methods such as AHP, MCDM, and TOPSIS, it determines the causality of risk in various occupational sectors [185].

The Monte Carlo method is combined with fuzzy logic to aid in uncertainty analysis in accident probability at nuclear power plants [186,187] and has been applied in decision-making support for wind energy projects [132].

Two well-known subcategories of neural networks, whose methods are used for facility safety, are the ANFIS and ANNs. The ANFIS has been applied to scaffolding in the construction sector [188]. ANNs help managers to make decisions in natural gas refineries [189]; they have been identified as reducing fatal accidents in the construction sector [18], they improve accidents related to musculoskeletal issues in the construction industry [190], and they have been applied for the safety and utilization of workers in transportation, such as in railways [191]. Additionally, ANNs have been used to assess deep mine risks [192], manage safety in construction work [193], and classify risks in manual loading problems [194].

One of the most significant subcategories of neural networks that aid in safety and risk assessment is Bayesian Networks (BNs) [149,195–197]. BNs have been applied in transportation, focusing on the safety of people and organizations [198,199], help to assess the severity of injury in traffic accidents [173], and are used in human and organizational evaluation systems to reduce accidents [200–202]. Additionally, they have been applied to the European railway bridge network for safety and maintenance [203], assist in accident risk assessment in nuclear facilities [204,205], and have been implemented in the construction industry for worker safety training [108]. They have also been used for risk analysis and reducing failure probability in complex work systems [206].

Other methods that can be considered subcategories of neural networks for workplace safety and risk assessment include HAZOP, which has been applied in the petrochemical industry and improves safety, RNA, which identifies risks in aerospace engineering [207], and FNN, which determines damage in engineering analysis models [208].

The PSA method, combined with neural networks, is more effective and efficient in safety and risk management in nuclear power plants [209,210]. It has been applied to reactor safety concerning human error [211] and enhances safety in nuclear plants with aging equipment [212].

3. What application fields are addressed by the four risk analysis techniques?

According to the literature review and the database created, the main fields where the four techniques are applied are the industrial sector with 134 articles, the transportation sector with 53 articles, the construction sector with 19 articles, and the mining sector with 14 articles.

Additionally, a large category called “all fields”, containing 71 articles, includes models from the four techniques, with authors claiming that the analyzed model can be applied across all professional sectors in matters of safety and risk. There are also seven other sectors (health, natural disasters, computers, fuels, high technology, environment, and chemistry) with one to five articles each.

It should be clarified that the 71 articles categorized as “all fields” are not unclassified articles but mostly mathematical models proposed for occupational health and safety. Authors claim that some existing techniques, with minor modifications, have broad applicability. Additionally, case studies are included, whose resolution, with minor adjustments, renders them usable in other sectors, as the authors highlight.

To better answer this research question, each sector with the most bibliographic references should be examined individually.

5.1. Industry

The assessment of occupational risks is a critical aspect of ensuring workplace safety, and various industries utilize techniques like fuzzy logic, neural networks, genetic algorithms, and machine learning to address this issue [213]. Industries are increasingly recognizing the importance of leveraging advanced technologies to enhance occupational risk assessments and ensure the safety of their workforce. Integrating these technologies and techniques can lead to more proactive and effective risk management strategies. This approach improves risk assessment in addition to contributing to the overall safety culture within organizations [214,215].

The classification of industrial occupational risks is usually divided into low-risk and high-risk categories. Using neural networks, valuable insights can be gained for diagnosing and preventing accidents. In this way, lower healthcare costs, fewer absences from work, and reduced disability rates can be achieved. Simultaneously, worker safety is improved [216–218].

Additionally, in many industries, fuzzy rules are used due to the ability to combine multiple parameters for risk assessment. However, researchers in this field point out that this also requires the evaluation of descriptive linguistic terms involved in risk, which is considered to be a disadvantage [20,218].

Moon-Hyun and Kwang place particular emphasis on fuzzy set theories and combine them with event trees and probabilistic risk assessment, aiming to create a safety protocol for nuclear power plants. This philosophy is also adopted by other authors dealing with nuclear power plants. Specifically, Santosh and his colleagues [219] (highlight the complexity of a nuclear plant and present a study based on Artificial Neural Networks (ANNs) aimed at assisting in quick decision-making and corrective actions on safety issues [204].

Additionally, for many years, probability safety assessment (PSA) techniques and data have been used in nuclear industries. Their combination with neural networks aims to improve the reliability of safety in these environments [151,214].

Many traditional techniques are transformed into estimation techniques with the help of intelligent systems, which can fortify the industry in safety matters. An example of this is the fuzzy-proportional risk assessment technique (PRAT), which, combined with fuzzy-PRAT, overcomes the disadvantages of the classic method. Probability, frequency, and severity are fuzzified, effectively enhancing the method. This new method provides highly detailed risk analysis results, enabling immediate interpretation of the findings [138,220–222].

Moreover, a major problem that the nuclear industry [223] had in the past was the lack of quantitative historical data, and access to such data was often limited. Most assessments were conducted by experts, leading to uncertain outcomes. This gap is being filled through fuzzy models that generate basic probabilities of event failures and enhance the experience of scientists in workplace accidents [224]. The study by Vinod and colleagues [51], being in the same vein, aims to develop a support system based on Artificial Neural Networks that help the operator to detect Initiating Events (IEs) in their early stages, before an accident occurs [28,225].

Similarly, Wang et. al [158], used a traditional method, the Risk Assessment Matrix (RAM), and machine learning techniques to better capture risk. The authors claim that the research results are comparable to other methods such as KNN and Naive Bayes.

The need for using neural networks and fuzzy logic in modeling accident prevention has existed for a long time [226–228]. Moreover, the first attempt to connect fuzzy logic with

decision trees is undertaken, demonstrating the combination of methods using imprecise and uncertain input data [130,229–231].

The same concerns are highlighted in processing plants, chemical factories [232,233], and storage tanks for energy products such as oil and natural gas [130,234,235]. In these cases, beyond increased safety measures, techniques like Process Safety Analysis (PSA) are used [236], enabling making decisions regarding selection. In combination with Fault Tree Analysis (FTA), they predict risk safety (PHA, QRA, LOPA, etc.), and, through a fuzzy evaluation grid of multiple factors, an integrated fuzzy risk assessment function is established for risk control [229,237–239].

5.2. Transport Industry

To reduce accidents in industry, coastal transportation, and transportation in general, neural models are helpful, particularly Bayesian Networks (BNs), which specialize in creating causal relationship models [173,215].

5.3. Large Transport Vehicles

The transport sector can benefit significantly from the integration of advanced technologies for the assessment and management of occupational risks. These technologies provide the opportunity for a more proactive, data-driven, and adaptive approach to ensure worker safety in various roles related to transportation [240]. In the transport sector, several authors emphasize that workers, especially drivers and captains, should apply these techniques to avoid accidents and other hazards [241,242].

According to Busacca [225], research shows that 75% to 96% of accidents in the maritime sector are due, either entirely or to a large extent, to human errors. He claims that accidents do not result from a single mistake or failure but from a series of consecutive or chain errors [243].

In 2011, due to the complexity of Bayesian Networks (BNs), a new BN model was proposed to reduce the degree of complexity by lowering the number of variables used during modeling without compromising the severity of injuries [244] or reducing model performance [173]. Researchers claim that the model, with the reduction in the number of variables, works well in accident analysis during transportation and has a positive impact on industrial applications [245,246].

Road accident analysis has always been necessary and will remain so. However, there are three key axes: the human factor, the vehicle, and the road, which affect the overall outcome of the accident. Using Artificial Neural Networks (ANNs), accidents can be modeled, and safe conclusions can be drawn, impacting results in unpredictable ways [247–252].

Beyond road and maritime transportation, rail transport is also significant. Zhan and colleagues [184] point out that high-speed trains can achieve, along with time savings and low energy levels, transportation cost reductions. In response to this, Wang and his colleagues [204] highlight the large number of rail accidents caused by human error. To improve these accidents, they propose a method called HEART, which consists of three key techniques: RARA, FANP, and fuzzy algorithms. This trio manages to minimize the likelihood of human error in high-speed trains [203]. That same year, it was emphasized that, for industries to benefit from high-speed trains without accidents, intensive work must be conducted because, in Europe, 35% of railway bridges are over 100 years old and operate at the limit. Moreover, it is noted that this factor has not been taken into account by any existing models [20,253]].

Accidents are not only encountered in land transport but also in air transport. To address dangerous accidents caused by pilots, a combination of two complex tools is

proposed. One tool is based on empirical data and pilots' perceptions, while the other conducts multi-criteria analysis and classifies risks using fuzzy logic. This combination is suggested as a counterbalance for the lack of data [204,254–259].

5.4. Small Transport Vehicles

In the field of road transport accidents, and especially in prediction, researchers currently propose only models related to neural networks. For the prediction of both theoretical and mathematical models, it is clear that ANNs offer greater flexibility compared to other techniques like fuzzy logic, genetic algorithms, and machine learning. Specifically, Delen [260] argues that factors affecting the increased risk of passenger injury in road accidents include demographic or behavioral characteristics, environmental factors, road conditions at the time of the accident, and the technical characteristics of the vehicle, among others. Thus, they conduct sensitivity analysis on trained neural network models to determine the priority of factors related to collisions as applied to different levels of injury severity. Their results provide insights into the changing importance of collision factors and confirm previous studies [261].

On the other hand, for maritime accidents, a combination of multiple regression analysis, combinatorial analysis, structural equation analysis, and factor analysis is examined through a purely mathematical model based on data from 6,007 maritime accidents. The results of this model contradict existing statistics on the subject [261–263].

In 2014, Deka and Quddus [264] developed a machine learning approach for robust accident mapping. The model is based on an ANN for machine learning. It has been used on UK highways and produces 14.7% more accurate matches compared to other models.

That same year in Australia, backpropagation neural network modeling (BPNN) was used for bus accidents. The findings showed significant benefits in road safety [265].

5.5. Construction Sector

The construction industry is increasingly adopting these technologies to improve safety practices, although the degree of implementation can vary. Some researchers have developed specific tools and systems tailored to the construction environment. It is worth noting that the application of these technologies may differ across regions, companies, and projects within the construction industry [266]. The effectiveness of these approaches also depends on factors such as data quality, integration with existing safety protocols, and the willingness of stakeholders to adopt innovative solutions [265,267].

Fuzzy logic deals with uncertainty and imprecision and is an effective tool for solving problems where knowledge uncertainty may arise [73]. The five levels of Bayesian Networks (BNs) include (i) the root causes level, (ii) the triggering events level, (iii) the events level, (iv) the accident level, and (v) the consequences level. To analyze and model the defined safety of an offshore installation, a BN model was created following the proposed five-level framework 82 [164,268–272].

Data collection and recording of accidents are minimal and inadequate, especially in construction. Estimating the severity of potential consequences of work-related accidents is a crucial step in any occupational risk assessment process. For this reason, the severity of work accidents in construction is a highly arbitrary process and not a systematic and rigorous evaluation [268]. Pinto et al. [269] also propose a fuzzy approach to assessing the severity level of work accidents in the construction sector.

In 2009, Markowski and Mannan [95] used fuzzy Layer of Protection Analysis (fLOPA) as the basis for risk assessment, applied to the transport of flammable substances through large pipelines. They claim that calculations using the LOPA methodology and fuzzy logic

systems provide protection regarding the frequency and severity of incidents and help to further demystify the overall system [268–280].

Fuzzy logic, combined with Occupational Risk Models (ORCA), which was developed as part of the Workgroup Occupational Risk Model (WORM) project, is applied at a building construction site. The site in question consists of 38 workers, including excavator operators, loaders, compaction equipment operators, and workers involved in excavation and framing phases, among others. The authors claim that their model helps to evaluate different risks, such as falls from ladders, scaffolding, roofs, falling objects, being hit by moving vehicles, and contact with moving parts [148].

Seker and colleagues [148] describe the construction industry as a dangerous sector. Their study aims to improve the Fuzzy DEMATEL approach for critical occupational risk factors using 14 criteria in the construction industry. Thanks to these advantages, DEMATEL is used to reveal better insights into the influence of cause-and-effect criteria analysis and to enhance the applicability of the model. Their findings suggest various precautions for potential occupational hazards [277]. The Fuzzy DEMATEL method is highlighted as a useful tool and is widely used across industries to tackle problems requiring group decision-making in a fuzzy environment [280].

The construction sector does not only use fuzzy logic as a risk mitigation technique but also neural networks. Chen [270] indicates that ineffective safety management and training can lead to serious work accidents. Falls are one of the most common accidents in bridge construction. Additionally, they mention that most researchers approach the issue with Fault Tree Analysis (FTA) [281] and Failure Mode Effects and Criticality Analysis (FMECA) [280,282]. The author proposes a BN network based on transforming the Fault Tree (FT). Their model was found to provide much better management capabilities for preventing falls from bridges. To address falls from heights, they also suggest a hybrid ANFIS checklist model, which has been shown to outperform other methods [187,281].

Jahangiri [187] argues that the construction industry has one of the highest rates of physical injuries. The Artificial Neural Network they propose is trained using collected data, including data from smartphones. The test results show that the trained model can predict force levels with an accuracy of over 87.5%.

According to Abduljabbar and colleagues [272], over the past several years, artificial intelligence combined with other techniques, such as Artificial Neural Networks (ANNs) [282], genetic algorithms (GAs), simulated annealing (SA), artificial immune systems (AISs), ant colony optimization (ACO), bee colony optimization (BCO), and Fuzzy Logic Models (FLMs), have been helping construction and industrial companies. In this sector, ANNs have become the foundation for building Occupational Risk Models.

5.6. All Fields

In the majority, as mentioned earlier, these are articles that deal with models and techniques related to methods that can be applied across different fields, not just one sector Each time, based on one of the four techniques under review, a mathematical or theoretical model is developed, or even a variation of existing models that have been applied in other fields, enabling wider dissemination of the specific model into other sectors and scientific disciplines [283–290]. For example, Failure Mode and Effects Analysis (FMEA) is a technique that is widely used in the safety sector [141,278], helping to eliminate knowledge of potential failures, problems, and errors. It is a significant tool used extensively in various industrial fields. To better weigh uncertainty, factors such as occurrence, severity, and detection of each failure are added. As a result, Fuzzy Risk Priority Numbers (FRPNs) are proposed to prioritize failure modes, which in turn can function across many scientific fields [152,291,292].

One of the first efforts to analyze and synthesize safety using fuzzy sets resulted in a proposed method that can be used as an alternative approach to safety analysis, particularly in situations where it is difficult or impossible to solve variations through human logic. Thus, the model helps in many industrial environments [293,294].

The development of such models for effective occupational health and safety systems has led to the integration of fuzzy logic and multi-criteria decision-making (MCDM) methods [281,282]. In the first phase, traditional risk analysis factors are positioned, and, in the second phase, preventive actions are arranged using F-TOPSIS [283–286].

In a recent study [263], a 3D ergonomic risk assessment is proposed for more effective workplace design and modifications. This can evaluate risks using integer numbers to avoid perception errors, improving movement and body posture to reduce potential risks. The model utilizes triangular and trapezoidal functions in terms of the general fuzzy coding model.

Another new model [185,295] consists of three MCDM methods: DEMATEL, AHP or ANP, and the TOPSIS methodology. DEMATEL is used to determine the causal relationships between risks, AHP or ANP to determine the risk weighting factors, and TOPSIS to prioritize risks [296–301]. The authors claim that the dynamic nature of this model can provide result analysis in many scientific fields. Another promising model for fuzzy occupational risk assessment in any type of construction site is the model proposed by Debnath and colleagues [12]. It is a dynamic Takagi–Sugeno fuzzy inference system that enables the configuration of risk factors while considering accidents and injuries as input parameters. It has been applied at various construction sites and shows progress in existing safety strategies.

In the development of the MCDM method, a hybrid structure is proposed, consisting of the Pythagorean Fuzzy Analytic Hierarchy Process (PFAHP) with cosine similarity and the Neuro-Fuzzy Analytic Hierarchy Process (NFAHP) to support handling uncertainty in the risk assessment process for production services in general [302]. As a result, critical factors that had not been identified in previous methods emerged [193,303,304].

Regarding neural networks, techniques based on ANN [193] or mathematical and algorithmic models [99,305] are proposed. Finally, regarding genetic algorithms and machine learning, there has been no significant progress in the field of safety. Techniques based solely on mathematical models or Markov functions have come to light [222,304–306].

4. Which countries engage the most with the four techniques relative to their workforce?

To answer this question, two factors must be acknowledged. These acknowledgments are necessary to minimize the complexity of the problem and to obtain quick initial insight. The first acknowledgment is how developed the country is according to the OECD, and the second acknowledgment is how much that country invests in technological development and advancement. Participation in such advanced technologies often depends on factors like the level of technological infrastructure, research funding, and the overall focus on scientific and technological advancements. Traditionally, countries with strong research institutions, advanced technology sectors, and noteworthy investments in research and development are likely to be leaders in these areas. According to OECD data, such countries include the United States, China, Japan, South Korea, Germany, Finland, Denmark, Sweden, and the United Kingdom.

However, this is not reflected in the research data presented in this article, as will be analyzed below. China ranks first, followed by the United States. The rankings drastically change for the next positions. Turkey ranks third with 25 articles, compared to 27 articles for the United States in second place. Italy is fourth with 23 articles, followed by Iran and India. Similarly, the United Kingdom ranks seventh, and Germany ranks twelfth. This shift occurs because these countries have experienced significant growth in recent

years, and the legislation regarding data and personal data access is relatively lax or non-existent [7,31,307,308].

To fully answer the research question, the number of articles must be correlated with the workforce of each country. There are several websites that report the workforce of each country. The most reliable ones, based on both the data and their use by major organizations and businesses, are "tradingeconomics.com", "theglobaleconomy.com", and "TheWorldFactbook.com". These three organizations agree on the workforce figures for each country, with any differences being fewer than a thousand, which does not affect the result of the *d*-index. More specifically, the total number of articles originating from a country should be divided by the total workforce of the respective country. The *d*-index is a frequency index. It shows the engagement of a country's scientific personnel in relation to the safety of its workforce.

$$\text{More specifically} \quad d = \frac{\sum p}{\sum e} \times 10^6 \tag{1}$$

Here, p denotes the number of articles, and e denotes the workforce of the respective country. The result of the division is multiplied by 106 because the number that results is too small to be manageable by data processing programs like Excel and SPSS. Using this formula, the resulting rankings are completely different. The country with the most engagement of its scientific personnel relative to the workforce being examined is Taiwan, according to the *d*-index. Italy ranks second, Slovenia third, Finland fourth, and Switzerland fifth. It is worth noting that the next three positions, with very little difference compared to Switzerland, are held by Serbia, Greece, and Portugal. Aside from Switzerland and Finland, which are among the top ten globally in research and development, the other countries are ranked much lower by the OECD.

Countries that lead in technology, research, and development are often at the forefront of incorporating advanced technologies like fuzzy logic, neural networks, genetic algorithms, and machine learning in various fields, including occupational risk assessment. Countries with strong academic and research institutions, as well as robust industrial sectors, are more likely to be involved in these fields. However, this research has highlighted other countries that are also pioneers in this area. This is also due to the fact that emerging economies and countries with a strong focus on technology and innovation, such as Taiwan and Italy, can indeed contribute significantly to the literature on occupational risk assessment.

5. What are the topics of the top five published articles, and why were they chosen by other researchers?

As mentioned in the introduction, due to the criteria applied, 289 articles were selected. From these articles, it becomes clear that there is a significant need within the scientific community to address and analyze occupational risks. The latest review of the reference field took place in October 2024. From this review, it was found that there are numerous articles—over two-hundred—that have between one and fifty-nine citations on the topic. Fifty articles have between sixty and one-hundred-seventeen citations, twenty articles have between one-hundred-eighteen and one-hundred-seventy-six citations, thirteen articles have between one-hundred-seventy-six and two-hundred-thirty-four citations, four articles have between two-hundred-thirty-five and two-hundred-ninety-three citations, two articles have between two-hundred-ninety-four and three-hundred-fifty-two citations, and another two articles have between four-hundred-fifty and five-hundred-twenty-seven citations. Finally, two articles have between five-hundred-twenty-eight and five-hundred-eighty-seven citations. It is important to note that there are no articles with citations between

three-hundred-fifty-two and four-hundred-seventy. The number of articles that have not yet been cited is twenty-one articles (Figure 12).

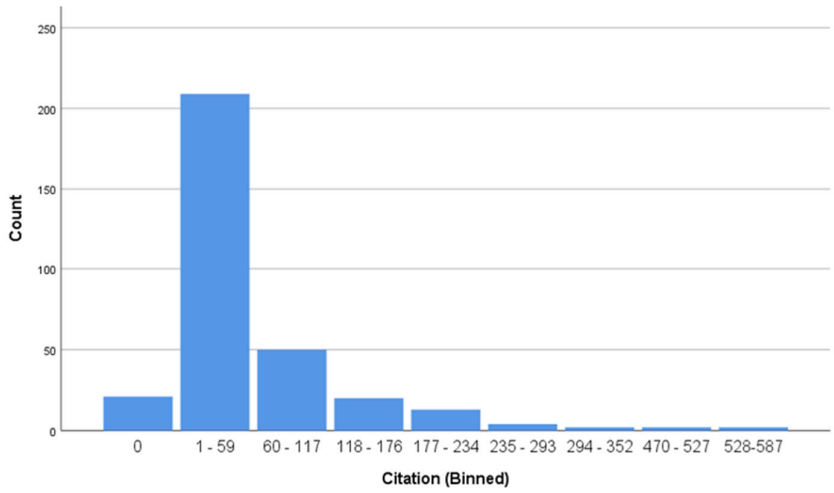


Figure 12. Citation distribution after the publication of the articles under review.

In general, it can be said that there is a clear need within the scientific community for the continuous improvement and handling of workplace safety. However, some articles gain more recognition compared to others. This research question aims to analyze why the top five articles, with the highest number of citations, managed to disproportionately increase their citations compared to the rest. The five most-cited articles are those that apply the techniques of fuzzy logic and neural networks. Additionally, three of them belong to the field of transportation, one to the industrial sector, and one to the construction sector. Generally, these are articles that take a holistic approach to their research topics. They typically combine more than two models into one technique. In Table 8 below, the top five are listed. The first column numbers the articles from one to five, the second column contains the authors' names, the third column shows the year of publication, and the last column provides the absolute number of citations. (Table 8)

Table 8. The top five researchers based on the number of citations in their work on risk assessment.

No.	Name	Reference	Year	Citations
1	Khakzad et al.	[171]	2011	587
2	Pillay & Wang	[143]	2003	492
3	Zheng et al.	[62]	2012	320
4	Delen et al.	[260]	2005	319
5	Abduljabbar et al.	[272]	2019	271

This ranking of the five articles changes if another column is added, to which column the quotient of total citations of the article per year (since its publication) is applied. Then, the ranking changes, with Abduljabbar [272] moving from fifth to first place. Khakzad [171], who held the first position, drops to second, Zheng [62] remains in third place, Pillay & Wang drop from second to fourth, and, finally, Delen [260] falls from fourth to fifth place. (Table 9)

In the following paragraphs, the content of the top five articles is analyzed, along with the reasons why other researchers chose to cite these works.

Khakzad and colleagues [171], with 587 citations, analyze safety in gas processing facilities. They argue that preventing unwanted events can avert catastrophic accidents. They emphasize that failure assessment techniques like Fault Trees (FTs) and Bayesian Networks

(BNs) are two techniques that have many similarities in various aspects. Therefore, the first part of the article analyzes the modeling aspects of both techniques and points out that they produce similar results. Although the two methods yield the same results, the BN can update its data and generate predictive values, making it more reliable for forecasting a series of events that could lead to accidents. The authors conclude that BNs have a much more flexible structure than FTs and can be used in a wider range of accident analysis and risk assessment scenarios. Moreover, this model can function and analyze accidents in real time. The number of citations confirms the success of this model. If we exclude the authors who later cited their own work (Khakzad with 66 citations, Khan with 36, and Amyotte with 10), we observe a significant number of other authors referencing this article in their work. Specifically, Reniers, G., cited it 18 times, Abbassi, R., 17 times, Yang, M., 14 times, Cozzani, V., 12 times, Zarei, E., 12 times, and Garaniya, V., 11 times. Notably, there are 151 other authors who rely on this specific article and technique in their citations.

Table 9. The top five researchers based on the number of citations in their work on risk assessment, adjusted by year.

No.	Name	Reference	Year	Citations	Citations per Year
1	Abduljabbar et al.	[272]	2019	271	61.75%
2	Khakzad et al.	[171]	2011	587	48.92%
3	Zheng et al.	[62]	2012	320	29.10%
4	Pillay & Wang	[143]	2003	492	24.60%
5	Delen et al.	[260]	2005	319	18.76%

The proposed method in [171] was analyzed in terms of the scientific fields where it is used, revealing the following: in the field of engineering with 445 citations, environmental science with 109, computer science with 96, energy-related articles with 86, decision science with 61, and mathematical modeling with 48 citations. An annual analysis of the citations shows that the article follows a linear trend in relation to the number of citations (Figure 13).

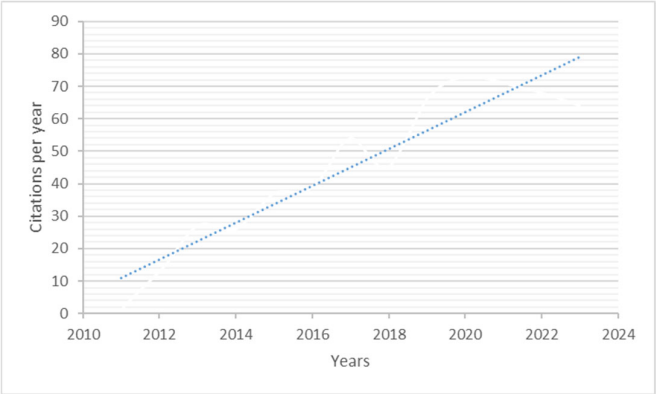


Figure 13. Citation distribution of the article by Khakzad and colleagues over the years.

Pillay & Wang [143], with 492 citations, focus on risk analysis of marine systems and accidents in the shipping industry. They use a Failure Mode and Effects Analysis (FMEA) technique, combining it with system and component failure analysis and risk assessment in the laboratory workplace. They analyze three key factors: likelihood, severity, and detectability. The new method they propose is based on fuzzy logic and gray relational theories. The authors particularly emphasize that this method can operate accurately even with unreliable or scarce data. The advantages they highlight include the ability of the model to identify weaknesses, which can then be studied and improved. Furthermore, it provides a systematic method for combining expert knowledge and experience with the

use of FMEA. To initiate the proposed approach, only a relative ranking is needed, and the system can evaluate and distinguish risks, classifying them into high-level and low-level risks.

The method proposed by Pillay & Wang [62] gained significant traction in the scientific community. Specifically, from the analysis of citations, it was observed that the main scientific fields utilizing this article include engineering with 323 citations, computer science with 184 citations, business management with 83 citations, and mathematical models with 77 citations. To a lesser extent, the work of Pillay & Wang [62] is used in other scientific disciplines as well. The annual analysis of citations showed that the article follows a polynomial model in terms of the number of citations (Figure 14). Finally, there are also authors who have referenced this article in their studies and rely on it to support their future research. Among these, the most notable are Liu, H.C. with twenty-seven citations, Tay, K.M. with fourteen citations, Lim, C.P. with twelve citations, You, J.X. with eleven citations, and Chang, K.H. & Deng, Y., each with eight citations. Furthermore, there are 115 other authors with fewer than five citations regarding the same article.

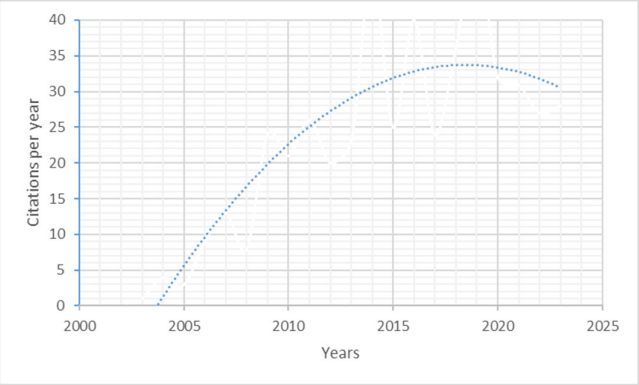


Figure 14. Distribution of citations for the article by Pillay & Wang over the years.

Zheng and colleagues [62], with 320 citations, propose a trapezoidal fuzzy AHP method for workplace safety in environments with extreme heat or cold. They emphasize that a large portion of industry employs personnel working in hot and cold environments. Additionally, they highlight the fact that temperature variations reduce productivity and create safety issues in workplaces.

Prior to applying the fuzzy Analytic Hierarchy Process (AHP), the framework for safety evaluation is defined by setting three key factors: work, environment, and workers. The authors argue that combining fuzzy AHP with trapezoidal fuzzy numbers produces results that are more logical and comprehensive for workplace environments compared to older methods. The proposed methodology for evaluating workplace safety and providing early warnings in hot and humid environments develops a system in which the degree of system safety helps in providing timely warnings, which can be strong tools for business managers and researchers. The value of their research is significant and especially beneficial for certain sectors. Specifically, from the analysis of the citations, it was observed that the main scientific fields utilizing this article include engineering with 169 citations, computer science with 112 citations, social sciences with 67 citations, environmental sciences with 66 citations, mathematical models with 54 citations, and business management articles with 39 citations. The article is also used to a lesser extent in other scientific fields. The annual analysis of citations showed that the article follows an exponential trend in the number of citations (Figure 15). Lastly, some authors rely on this research to support their future studies. These include Chen, T.C.T. with seventeen citations, Chen, T. with twelve citations,

Wang, Y.C. with eleven citations, and Karahalios, H. and Zhu, N., each with seven citations. Additionally, there are 123 other authors with fewer than five citations on the same article.

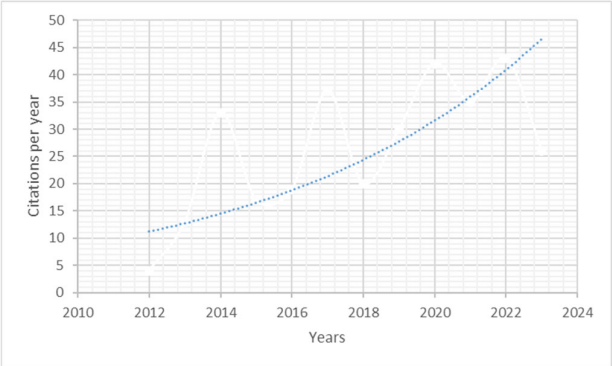


Figure 15. Distribution of citations for the article by Zheng et al. [62] over the years.

Delen and colleagues [260], with 319 citations, focus on road transportation safety. They record the overall state of road safety, how it can be improved, and under what conditions drivers and passengers are likely to suffer severe injuries in an accident, or even fatalities. They use a series of neural networks to model the level of injury severity and the factors that may cause crashes. The proposed models are sensitivity-trained neural networks using a set of binary prediction models. Furthermore, their sample consists of 30,358 police-reported accidents. They claim that such a large database helps to validate previous findings from other studies and provides new insights into the changing levels of injury severity. As a result, they developed eight neural network models with different levels of injury severity. The human factors influencing road accidents include seat belt usage, alcohol or drug consumption, age, and gender. These, combined with weather conditions and the time of the accident, do not appear to affect injury outcomes. Through this, the authors claim to achieve higher predictive results by analyzing generalized mapping techniques of neural models. This holistic model provides insights into the changing importance of collision factors in relation to severity levels and transportation safety.

This model has become the basis for producing similar models in other scientific fields beyond safety. Specifically, the article is used in various scientific fields, such as 212 citations in engineering-related articles, 129 in social science articles, 83 in computer science, 72 in pharmaceutical sciences, and 21 in mathematical models. Additionally, the authors who reference the article frequently include Asteris, P.G. with ten citations, Liu, P. with six citations, and Pradhan, B. with six citations. Moreover, 156 other authors cite the article between one and five times in their scientific studies. The article's citations over the years follow an exponential trend (Figure 16).

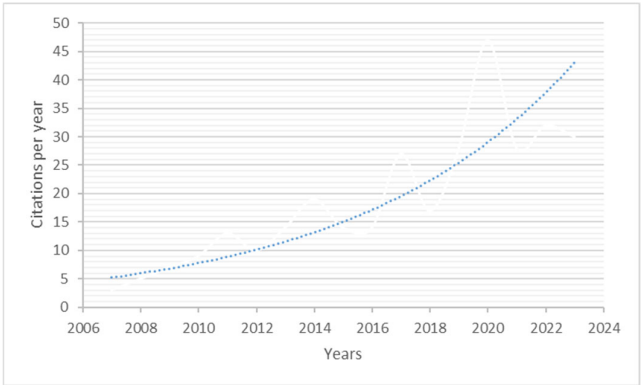


Figure 16. Distribution of citations for the article by Delen et al. [260] over the years.

Abduljabbar and colleagues [272], with 271 citations, address the applications of artificial intelligence (AI) in transportation. They approach the subject holistically, focusing on three main areas. The first involves AI in decision-making for scheduling and limiting road supply. The second aims at improving public transportation, while the third focuses on reducing accidents on highways. Through an Artificial Neural Network (ANN) model, they cover the three aforementioned areas. They claim that their model can make quick decisions in dangerous situations to avoid any road accidents, such as accidents during product transportation. For the creation of this ANN model, Probabilistic Neural Networks (PNNs) and Support Vector Machines (SVMs) were also used. Another important factor is that all these neural techniques can be used together to reduce accidents, and they should be divided into temporal and spatial patterns. The model now predicts the risk level of traffic accidents based on accident datasets and historical data. This work not only touches upon transportation risk analysis but also extends to AI more broadly. This is evident from the fact that their future research proposes further developing this model through machine learning. The model was quickly adopted by many authors, researchers, and scientists as it was cited and referenced by various scientific fields within 5 years, beyond just transportation worker safety. Specifically, the article is used in various scientific fields, with 153 citations in engineering-related articles, 71 in social sciences, 37 in energy-related articles, and 26 in business management articles. Additionally, the authors frequently referencing this study include Dia, H. with eight citations, Tsai, P.W. with three citations, and Guido, G., Vitale, A., and Astarita, V., each with three citations. Furthermore, 147 other authors cite the article between one and three times in their scientific studies. The article's citations over the years follow a linear trend (Figure 17).

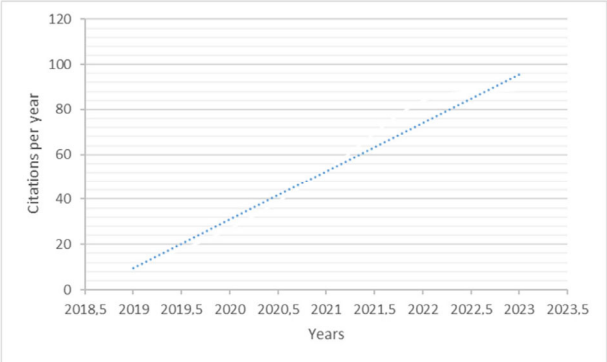


Figure 17. Distribution of citations for the article by Abduljabbar et al. [272] over the years.

The efforts undertaken through these five articles highlight the need that exists in the field of risk analysis in workplaces, as well as the attempt by the authors and researchers to model risk in technical fields. From the previous five articles, it appears that fuzzy logic was used in cases where there was insufficient data, while, when there was a large amount of data, neural networks were employed by the authors. Additionally, the creation of such models can meet the needs of other scientific fields as well as other areas of research application. Finally, it becomes clear from these five articles that, for the creation of models related to workplace safety, a single type of algorithm cannot be used. At least two or three need to be combined to provide a model with the help of a technique, whether that is neural networks or fuzzy logic. It is confirmed once again that, where variables predominantly have qualitative characteristics, they are more easily managed by fuzzy sets. In contrast, when there are data, the use of neural networks yields better results than quantitative methods, and the predictions can approach reality to a very high degree.

6. What is the future trend?

The integration of fuzzy logic, neural networks, genetic algorithms, and machine learning in the evaluation of occupational risks reflects the interdisciplinary nature of modern risk analysis in workplaces. Many researchers and scholars discuss real-time monitoring and feedback [7,10,309]. The integration of real-time data from sensors and other monitoring devices into risk assessment models enables dynamic and adaptive risk management [7]. This can enable faster responses to emerging risks and better prevention strategies. Such an approach would be easier when there is a large volume of data to be managed by techniques and models created by neural networks. As artificial intelligence evolves, with AI technologies becoming more sophisticated, there is increasing emphasis on making these systems explainable and interpretable [134,310]. Understanding the reasoning behind risk assessments generated by AI models is crucial for gaining trust and acceptance across various fields. Machine learning algorithms are able to constantly learn from new data, enabling risk assessment models to adapt to changing workplace conditions and emerging risks over time. While technology plays a critical role, there is increasing emphasis on understanding and incorporating the human element and factor in risk assessment. This includes human behavior, cognitive factors, and the influence of organizational culture on safety [35,36,311].

What emerges from several articles and authors is the need for greater collaboration and interdisciplinary research with the help of new technologies. Cloud-based platforms that facilitate collaboration between different stakeholders in risk assessment, including employers, employees, safety professionals, and regulators, may become more widespread. This enables real-time information sharing and collective risk management. The convergence of various fields, including data science, engineering, and environmental science [133,229,312,313], is likely to continue. Interdisciplinary collaborations can lead to more holistic approaches to understanding and mitigating occupational risks. This translates both to costs for employers and physical harm for employees; hence, both are oriented in the same direction, although from different starting points.

The increasing volume of data generated in industrial environments [58,59] can be leveraged through big data analytics. This involves analyzing large datasets to identify patterns, correlations, and trends that may not be apparent through traditional methods. Forms and protocols should be established to enable the dissemination of these data without concerns from the industries and businesses where they are generated. Industry 4.0, characterized by the integration of smart technologies into manufacturing and industrial processes, may influence risk assessment [61]. The use of smart sensors, connected devices, and data analytics in the context of Industry 4.0 can contribute to more comprehensive occupational risk management.

From the analysis of the articles, we observe that fuzzy logic follows the annual trend of the total number of articles. The same is true for the techniques analyzed by neural networks. However, this trend stops in 2019. From that point onward, the role of neural networks is replaced by articles that include machine learning. In fact, neural networks are included within machine learning since neural network techniques are, to some extent, the foundation for the creation of machine learning. We could say that neural networks are not being abolished but rather integrated under the umbrella of machine learning. Therefore, going forward, there will be fewer articles solely focusing on neural network models as they will be superseded by articles focusing on machine learning, which will include neural networks.

6. Discussion

Occupational health and safety are of vital importance for organizations and businesses. Workplace risk control not only prevents accidents, significant restoration costs,

and millions of lost work hours but also protects the most valuable asset: life itself. In this battle to reduce risks in the workplace, the scientific community responds in various ways. One approach that helps to solve such issues involves techniques based on computational intelligence. There are few contributions to the comprehensive literature review on research related to health and safety risk assessment in the workplace [9].

At this point in the discussion, it is deemed appropriate to highlight some limitations of the research. One major limitation is the potential inability of Scopus to display certain articles. There are reports from authors indicating that Scopus did not include certain articles in its database [7,56,67]. Another limitation could be the uneven distribution across various professional sectors. For example, a technique applied in one industrial sector might appear frequently in publications by different authors, while it may be underrepresented in another sector. This significantly restricts the subcategories within the study. Additionally, this research may be limited as some potentially relevant articles that did not meet the search criteria were not included in this review. Furthermore, the exclusion of non-English articles, conference papers, and studies that address hygiene-related risks could have influenced the overall perspective of the findings. For these reasons, a future study is recommended that expands the scope of the publications to identify additional scientific articles related to the subject.

This literature review highlights the contribution of four computational intelligence techniques to occupational health and safety in addressing risks and hazards in the workplace. The application of computational intelligence methods such as fuzzy logic, neural networks, genetic algorithms, and machine learning has revolutionized occupational risk assessment. These techniques provide advanced tools for managing the uncertainties and complexities associated with workplace safety [184]. The abundance of models offered by researchers cover almost the entire range of the work environment. The key areas that stand out in the research are the industrial, transportation, construction, and mining sectors. The statistical analysis indicates that the sectors with the most articles reflect the diversity of subcategories within those fields.

The statistical analysis in the Section 3 provides a record and depiction of the current state of the subject. It is a descriptive analysis conducted using SPSS. The results and visualizations of the statistical analysis preceded the formulation of the research questions. With a complete depiction of the subject, six research questions were developed.

From the analysis of the first three research questions, the broad scope and complexity of the topic become evident as there are numerous subcategories for the four techniques, which are listed in Table 7, with their acronyms provided in Appendix A. This fragmentation of each technique highlights the necessity of addressing issues on a case-by-case basis for each sector and field.

Analyzing Table 7, we observe how these sectors adopt various techniques from different authors. This variation exists because the complexity within each sector, and the enterprises and organizations they represent, differ. Additionally, each sector encompasses distinct content types.

The analysis of the articles on the specific topic of workplace risk analysis from human factors reveals relative stability in the number of published articles per year over the past five years. The research shows that most of the articles use techniques based on fuzzy logic (163 articles), while half as many articles use neural network techniques (81 articles). This difference between the two techniques is due to several factors related to the interpretability of the models, adaptability in learning, and data requirements. Fuzzy models in risk analysis are based on rules that are more easily recognizable and manageable by humans, making them more understandable compared to neural networks, where the decision-making process is harder to interpret. Regarding adaptability, fuzzy

models handle uncertainty and inadequacy by incorporating linguistic rules, while neural networks adapt and learn only from data patterns. The most important of the three factors (interpretability, adaptability, and data) is the data requirement [9,59]. Fuzzy systems can function satisfactorily with a small amount of data (or even none) and do not require extensive training, as research shows. The inherent ability of fuzzy logic to handle imprecision and uncertainty makes it particularly valuable in scenarios where data are sparse or qualitative. For example, fuzzy logic has been instrumental in scenarios where precise data are either unavailable or prohibitively expensive to obtain, such as risk assessments in mining or construction [125,130,136,314,315]. By transforming subjective expert opinions into risk models, fuzzy logic facilitates decision-making in environments characterized by high variability and complexity [107]. Its ease of application and adaptability further solidify its status as a preferred tool among researchers and practitioners.

While the ability of fuzzy logic to handle incomplete and uncertain data makes it a valuable tool for assessing professional risk, its reliance on subjective membership functions and qualitative data can limit its accuracy. This can be particularly problematic in high-risk scenarios [7,67]. In such cases, alternative methods such as machine learning or genetic algorithms, which can leverage large datasets and provide more detailed analysis, may be more suitable [61]. Additionally, the process of defining membership functions and creating rules depends heavily on expert knowledge. This subjectivity not only adds a layer of complexity but also makes the system prone to inconsistencies across different use cases or domains. Fuzzy systems also lack the ability to learn autonomously from new data, unlike machine learning algorithms, which can improve their predictions over time [48].

In contrast, neural networks require large volumes of data to function. Their training can be difficult and complex. A further significant drawback for research, as noted by researchers, is that data access is often unavailable, leading research to favor fuzzy logic. However, the application of neural networks is often constrained by the requirement for extensive datasets. Unlike fuzzy logic, which can function effectively with sparse data, neural networks rely on large volumes of well-annotated information to achieve meaningful results [56,63]. This limitation has restricted their broader adoption in industries where data collection poses a challenge. This conclusion is confirmed by other authors [7,10,311]. Therefore, public access to large databases from industries and organizations, provided by official bodies such as the Ministry of Labor, is necessary for further developing and improving risk analysis and accident models in safety. Nevertheless, neural networks excel in dynamic environments where real-time risk estimations are essential, such as equipment health monitoring or worker fatigue detection [200].

In recent years, genetic algorithms have been sidelined. According to researchers and the literature review, genetic algorithms aim to optimize models related to workplace hazards. These algorithms are particularly beneficial for addressing complex multi-variable problems, such as determining optimal maintenance schedules or designing effective safety protocols [316]. The adaptability of genetic algorithms enables them to evolve solutions over time, making them ideal for industries characterized by rapidly changing conditions. However, their computational intensity and resource demands often make them less accessible compared to other techniques. Advances in machine learning have further overshadowed genetic algorithms as newer methods offer comparable benefits with reduced complexity and greater efficiency. However, in recent years, authors have provided a multitude of models, typically specialized in a particular work sector or even a specific business. This has resulted in no significant need for the model optimization presented in the other three techniques.

Furthermore, the research indicates that machine learning and neural networks are no longer two completely separate techniques, as they were in the past. Machine learning

and neural networks do not exclude each other. In reality, neural networks are a subset of machine learning. Machine learning is a broader concept, which includes various techniques, one of which involves neural networks. This is also reflected in the research, where it is observed that, in the past few years, those techniques using purely neural networks have been declining and the use of machine learning is increasing, although neural networks are still being incorporated into these models. The scalability and ability of machine learning to handle diverse data sources position it as a critical tool for future advancements in occupational risk management. However, the limited availability of high-quality real-time data remains a significant challenge, impeding its full potential. Machine learning techniques, including neural networks, can handle complex and non-linear relationships in data. This is characteristic of accident-related data as accidents do not occur with a specific frequency and thus create complex patterns. In such cases, neural networks, as opposed to general machine learning, are recommended by researchers as the most suitable approach for addressing hazards.

Computational intelligence techniques have primarily been applied in the fields of industry, transportation, construction, and mining. The industrial sector leads in adopting these methods due to the need for enhanced safety protocols in high-risk environments. The transportation and construction sectors also demonstrate significant usage, particularly in areas such as risk detection and compliance monitoring.

A notable trend is the increasing integration of hybrid approaches, combining multiple techniques to address complex safety challenges [317]. For instance, neural networks have been combined with fuzzy logic to improve risk prediction accuracy in construction projects. Similarly, genetic algorithms have been integrated with machine learning to optimize training programs and safety protocols in the mining sector. These hybrid methodologies underscore the evolving landscape of occupational risk assessment, highlighting the need for interdisciplinary approaches to tackle emerging challenges [318].

The findings reveal a gradual shift from the traditional methods toward more advanced machine learning models. This trend reflects the developments in computational capabilities and the growing availability of big data in workplace safety. The ability of machine learning to adapt and scale with technological progress positions it as a cornerstone for future research [108]. However, the continued reliance on fuzzy logic emphasizes the importance of accessible user-friendly tools that address data limitations.

Finally, taking all the above aspects into consideration, a conceptual framework could be developed that integrates the dominant techniques to provide a unified approach for the assessment of occupational risk. The integration of fuzzy logic, neural networks, and machine learning offers a powerful hybrid approach that leverages the strengths of each method. More specifically, fuzzy logic would manage and address ambiguities in human inputs. It would also process incomplete and qualitative characteristics that have descriptive factors (e.g., high noise levels, poor lighting, high fatigue, slippery floors, etc.).

On the other hand, neural networks would be responsible for processing historical data in real time and also tasked with learning patterns. This way, neural networks could identify, for example, correlations between unsafe working hours and accident rates or predict potential accidents based on worker behavior and fatigue.

This system, combining the fuzzy logic and neural network components, would fall under the umbrella of machine learning, which can dynamically adapt to evolving risks using supervised or unsupervised learning and continuously update the model with new data. Such a combination could, for instance, predict emerging risks based on changes in working conditions and more easily categorize work into various zones of high, medium, or low risk.

This framework unifies the advantages of fuzzy logic, neural networks, and machine learning (ML) to address occupational risk in dynamic and complex workplace environments.

7. Conclusions

This 40-year literature review revealed a trend favoring the integration of fuzzy systems and machine learning. While the study highlighted significant advancements, several limitations persist. Fuzzy systems are extensively used by researchers compared to other methods. Data accessibility remains a challenge, particularly for techniques that require extensive datasets, such as neural networks and machine learning. The obstacle of limited data access is overcome with the help of computational intelligence. Additionally, neural networks require a vast amount of data to deliver satisfactory results.

For the first time, a literature review on occupational risk employed structured research questions. The analysis and answers to these questions highlighted the fragmentation and abundance of models that utilize the four techniques. Undoubtedly, it can be said that each professional field and case requires its own model or technique to reduce workplace risks significantly, if not eliminate them entirely.

As the research indicates, a significant limitation in developing more accurate models to address workplace risks is the scientific community's difficulty in accessing and collecting data. Another key finding is the increasing trend and shift toward machine learning. However, it is observed that machine learning is not used in isolation but incorporates fuzzy systems, models, and occasionally neural networks. This new hybrid approach appears to address problems in many cases and is highly promising for the future.

8. Future Research

This literature review highlights the urgent need to develop models that will tend towards a hybrid state, specifically models that will consist of fuzzy systems and learning machines, which, as mentioned, incorporate neural networks. The creation of such models will better address risk management as databases will be leveraged by the neural network part of the model, while human intervention will be more accessible in the fuzzy part of the model. Additionally, sensors could be used to collect real-time data from workplaces. Such data could continuously update the models, ensuring clarity and adaptability. In this way, large-scale datasets could be created for various industries, improving both safety and academic research.

Moreover, advanced machine learning techniques, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), could be employed to aid in risk prediction and hazard assessment in complex work environments. Such an approach could eventually lead to the development of a data-sharing platform for each sector. This would enable various scientific fields, such as industry, transportation, and others, to generate large datasets, facilitating the training of machine learning models across diverse environments and, most importantly, using very recent data. In the coming years, AI programs, such as ChatGPT, will greatly influence the evolution and improvement of the safety field in general. Additionally, they will contribute to faster advancement in safety science for the four techniques, thus revealing new horizons in addressing workplace hazards caused by human factors.

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Abbreviations

The following abbreviations are used in this manuscript for methods and techniques:

ACO	Ant Colony Optimization
AFRA	Accident Frequency Rate Analysis
AGI	Artificial General Intelligence
AHP	Analytic Hierarchy Process
AIS	Artificial Immune System
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BCO	Bee Colony Optimization
BN	Bayesian Network
BPNN	Propagation Neural Network Modeling
CART	Classification and Regression Tree
CREAM	Cognitive Reliability and Error Analysis Method
DBN	Dynamic Bayesian Network
DEMATEL	Decision-Making Trial and Evaluation Laboratory
ECI	Event Criticality Index
ETA	Event Tree Analysis
FANP	Fuzzy Analytic Network Process
FAP	Failure Analysis Process
FBN	Fuzzy Bayesian Network
FCE	Fuzzy Comprehensive Evaluation
FCM	Fuzzy Cognitive Map
FHWI	Failure Hazard Weighted Index
FIS	Fuzzy Inference System
FLM	Fuzzy Logic Model
FMEA	Failure Mode and Effects Analysis
FMECA	Failure Mode, Effects, and Criticality Analysis
FSA	Formal Safety Assessment
FTA	Fault Tree Analysis
GRA	Grey Relational Analysis
HAI	Hazard Analysis Index
HAZOP	Hazard and Operability Study
HAZOP	Hazard and Operability Study
HRA	Human Reliability Analysis
ITS	Intelligent Transportation System
IVIS	In-Vehicle Information System
JSA	Job Safety Analysis
LOPA	Layer of Protection Analysis
LSRA	Layered Safety Risk Assessment
MCDM	Multi-Criteria Decision-Making

NFAHP	Neuro-Fuzzy Analytic Hierarchy Process
NLP	Natural Language Processing
OHSRA	Occupational Health and Safety Risk Assessment
ORA	Operational Risk Assessment
PFAHP	Pythagorean Fuzzy Analytic Hierarchy Process (with cosine similarity)
PHA	Preliminary Hazard Analysis
PNN	Probabilistic Neural Network
PPE	Personal Protective Equipment
PRAT	Probabilistic Risk Assessment Technique
PSA	Probability Safety Assessment
QFD	Quality Function Deployment
QRA	Quantitative Risk Assessment
RARA	Risk And Reliability Assessment
SVM	Support Vector Machine
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
WORM	Workgroup Occupational Risk Model

The following abbreviations are used in this manuscript for journals:

AAP	Accident Analysis & Prevention
EAAI	Engineering Applications of Artificial Intelligence
ESwA	Expert Systems with Applications
FIE	Fuzzy Information and Engineering
FSS	Fuzzy Sets and Systems
NH	Natural Hazards
SR	Journal of Safety Research
RESS	Reliability Engineering & System Safety
SS	Safety Science
LPPI	Journal of Loss Prevention in the Process Industries
HM	Journal of Hazardous Materials
RA	Risk Analysis

Appendix A

Table A1. Detailed information from review of articles.

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[265]	Fuzzy logic	Case study	Transport safety	AAP	Elsevier	103	Sweden
[93]	Fuzzy logic	Mathematic Model	Industry	AAP	Elsevier	100	India
[269]	Fuzzy logic	Theoretical foundations	Construction	AAP	Elsevier	22	Portugal
[241]	Fuzzy logic	Empirical data	Transportation	AAP	Elsevier	24	USA
[263]	Fuzzy logic	Theoretical foundations	Transportation	AAP	Elsevier	62	USA
[260]	Neural Network	Theoretical models	Car Accidents	AAP	Elsevier	312	USA
[84]	Neural Network	Theoretical models	Car Accidents	AAP	Elsevier	46	Taiwan
[196]	Neural Network	Mathematic Model	Car Accidents	AAP	Elsevier	186	USA
[202]	Neural Network	Prediction Model	All Fields	AAP	Elsevier	188	USA
[243]	Neural Network	ITS	Transportation	AAP	Elsevier	97	Taiwan
[86]	Neural Network	Case study	Transportation	AAP	Elsevier	203	Spain

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[310]	Neural Network	Case study	Transportation	AAP	Elsevier	6	Singapore
[289]	Neural Network	Theoretical models	Transportation	AAP	Elsevier	214	China
[262]	Genetic Algorithm	Mathematic Model	Transportation	AAP	Elsevier	9	Taiwan
[231]	Machine learning	Mathematic Model	Transportation	AAP	Elsevier	222	Taiwan
[264]	Neural Network	Mathematic Model	Car Accidents	AAP	Elsevier	0	UK
[268]	Neural Network	Case study	Bus Accidents	AAP	Elsevier	47	Australia
[97]	Neural Network	Theoretical foundations	All Fields	AAP	Elsevier	39	France
[217]	Neural Network	Theoretical Model	Transportation	AAP	Elsevier	13	Germany
[247]	Neural Network	Case study	Transportation	AAP	Elsevier	116	Italy
[25]	Neural Network	Case study	Industry	AAP	Elsevier	39	Italy
[216]	Neural Network	Method GRA	Industry	AAP	Elsevier	19	Turkey
[175]	Neural Network	Method GRA	Industry	AAP	Elsevier	0	China
[176]	Neural Network	Case study	Industry	AAP	Elsevier	3	China
[83]	Neural Network	Prevention Model	Transportation	AAP	Elsevier	19	France
[244]	Neural Network	Diagnosis depth burns	Medicine	Burn	Elsevier	42	Spain
[68]	Neural Network	Prediction time for Excision and Grafting	Medicine	Burn	Elsevier	53	Taiwan
[222]	Fuzzy logic	Imaging method for depth of burn	Medicine	Burn	Elsevier	51	Germany
[77]	Neural Network	Computer Science and Engineering	All Fields	EAAI	Elsevier	586	France
[114]	Machine learning	Case study	Medicine	EAAI	Elsevier	41	UK
[90]	Neural Network	Case study	Industry	EAAI	Elsevier	17	Serbia
[114]	Fuzzy logic	Mathematic Model	All Fields	EAAI	Elsevier	2	India
[304]	Fuzzy logic	MULTIMOORA method	All Fields	EAAI	Elsevier	151	China
[158]	Fuzzy logic	FMEA model and Case Study	All Fields	ESwA	Elsevier	483	China
[249]	Fuzzy logic	Mathematic Model	All Fields	ESwA	Elsevier	45	China
[141]	Fuzzy logic	FMEA model and Case Study	All Fields	ESwA	Elsevier	113	India
[132]	Fuzzy logic	FMEA model in Mine	Industry	ESwA	Elsevier	84	Serbia
[230]	Fuzzy logic	AVaR Model	All Fields	FIE	Springer	5	China
[155]	Fuzzy logic	AHP Method	Environment	FIE	Springer	0	China
[208]	Fuzzy logic	LS-FSVM model	Industry	FIE	Springer	7	China
[160]	Fuzzy logic	FTA	All Fields	FSS	Elsevier	69	Japan
[226]	Fuzzy logic	Theoretical models	Industry	FSS	Elsevier	105	USA
[290]	Fuzzy logic	Theoretical models	Industry	FSS	Elsevier	198	France
[314]	Fuzzy logic	Mathematic Model	Computer Science	FSS	Elsevier	92	China
[38]	Fuzzy logic	Mathematic Model	Computer Science	FSS	Elsevier	112	China
[194]	Genetic Algorithm	Mathematic Model	Industry	FSS	Elsevier	230	China
[277]	Fuzzy logic	Case study	Natural Disaster	FSS	Elsevier	111	Germany
[47]	Genetic Algorithm	FCMs	All Fields	FSS	Elsevier	149	Canada
[50]	Neural Network	ARIMA model	All Fields	FSS	Elsevier	152	Spain
[182]	Fuzzy logic	HRA model	High Technology	FSS	Elsevier	89	Italy
[294]	Fuzzy logic	Method Comparison	Computer Science	FSS	Elsevier	257	France
[224]	Fuzzy logic	Nuclear safety assessment	Industry	FSS	Elsevier	87	International

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[69]	Fuzzy logic	Theoretical models	Industry	FSS	Elsevier	16	China
[99]	Fuzzy logic	CTDs with risk	Medicine	FSS	Elsevier	21	USA
[271]	Fuzzy logic	Algorithm	All Fields	FSS	Elsevier	112	Taiwan
[293]	Fuzzy logic	Theoretical models	Industry	NH	Springer	19	Taiwan
[41]	Fuzzy logic	Case study	Natural Disaster	NH	Springer	49	China
[20]	Fuzzy logic	Case study	Natural Disaster	NH	Springer	33	China
[275]	Neural Network	Theoretical models	Environment	NH	Springer	0	China
[276]	Fuzzy logic	Theoretical models	Environment	NH	Springer	38	China
[111]	Fuzzy logic	S-GMA	Natural Disaster	NH	Springer	119	China
[253]	Neural Network	Algorithm	Industry	SR	Elsevier	38	UK
[245]	Neural Network	Transportation Ambulance	Medicine	SR	Elsevier	41	USA
[316]	Neural Network	Case study	Medicine	SR	Elsevier	163	USA
[19]	Fuzzy logic	CART (Statistic model)	Transportation	SR	Elsevier	280	Taiwan
[199]	Neural Network	Bayesian Networks	Industry	SR	Elsevier	153	UK
[173]	Neural Network	Bayesian Networks	Transportation	SR	Elsevier	68	Spain
[249]	Neural Network	Transportation	Industry	SR	Elsevier	51	USA
[74]	Neural Network	Bayesian Networks	Medicine	SR	Elsevier	54	Spain
[229]	Machine learning	Bayesian model	Industry	SR	Elsevier	44	UK
[177]	Fuzzy logic	Logistic Regression	Industry	SR	Elsevier	70	UK
[116]	Genetic Algorithm	Accident data in Pipelines	Transportation	SR	Elsevier	67	Belgium
[147]	Fuzzy logic	AHP model	Construction Industry	SR	Elsevier	0	Turkey
[129]	Fuzzy logic	Fuzzy with FTA	Industry	RESS	Elsevier	34	South Korea
[298]	Fuzzy logic	Fuzzy Algorithm	All Fields	RESS	Elsevier	165	UK
[285]	Fuzzy logic	Theoretical analysis	All Fields	RESS	Elsevier	8	Italy
[27]	Fuzzy logic	Fuzzy with FTA	All Fields	RESS	Elsevier	8	India
[228]	Neural Network	Mathematic Model	Industry	RESS	Elsevier	2	USA
[236]	Neural Network	Algorithm	Industry	RESS	Elsevier	12	Italy
[209]	Neural Network	PSA methodologies	Industry	RESS	Elsevier	12	Italy
[302]	Neural Network	PRA	All Fields	RESS	Elsevier	221	USA
[87]	Neural Network	Nuclear waste	Industry	RESS	Elsevier	91	South Korea
[75]	Fuzzy logic	CREAM methodology	All Fields	RESS	Elsevier	204	Greece
[101]	Neural Network	HAI	Transportation	RESS	Elsevier	1	USA
[121]	Fuzzy logic	Markov with Fuzzy	High Technology	RESS	Elsevier	10	USA
[225]	Genetic Algorithm	Pareto	All Fields	RESS	Elsevier	221	Italy
[279]	Fuzzy logic	AHP Analysis	Transportation	RESS	Elsevier	79	UK
[143]	Fuzzy logic	FMEA	Transportation	RESS	Elsevier	491	UK
[297]	Genetic Algorithm	Optimization Methodology GA	Industry	RESS	Elsevier	41	Brazil
[51]	Neural Network	Nuclear power plant	Industry	RESS	Elsevier	37	India
[287]	Neural Network	An experimental railway	Transportation	RESS	Elsevier	28	France
[256]	Genetic Algorithm	Maintainability and Safety (RAMS);	Industry	RESS	Elsevier	72	Spain
[46]	Genetic Algorithm	Markov with Genetic	All Fields	RESS	Elsevier	27	India

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[205]	Genetic Algorithm	Nuclear power plant	Industry	RESS	Elsevier	109	Spain
[307]	Genetic Algorithm	Mathematic Model	All Fields	RESS	Elsevier	155	Brazil
[119]	Fuzzy logic	Mathematic Model	Transportation	RESS	Elsevier	130	China
[210]	Genetic Algorithm	PSA methodologies	Industry	RESS	Elsevier	30	India
[129]	Neural Network	Mathematic Model	Industry	RESS	Elsevier	103	India
[98]	Neural Network	Nuclear power plant	Industry	RESS	Elsevier	49	Korea
[104]	Genetic Algorithm	Mathematic Model	All Fields	RESS	Elsevier	10	Italy
[58]	Fuzzy logic	Theoretical analysis	Transportation	RESS	Elsevier	74	International
[117]	Neural Network	Predict Accidents Model	All Fields	RESS	Elsevier	85	Spain
[171]	Neural Network	FTA with BN	Transportation	RESS	Elsevier	574	Canada
[151]	Fuzzy logic	ORCA model (WORM)	Construction	RESS	Elsevier	68	Greece
[20]	Fuzzy logic	Cream Method	Transportation	RESS	Elsevier	5	China
[163]	Fuzzy logic	HRA model	All Fields	RESS	Elsevier	23	China
[145]	Fuzzy logic	FBN	Transportation	RESS	Elsevier	22	China
[211]	Neural Network	PSA	Industry	RESS	Elsevier	36	India
[32]	Genetic Algorithm	Car accident	Transportation	SS	Elsevier	43	USA
[25]	Neural Network	wood processing industry	Industry	SS	Elsevier	39	Italy
[216]	Neural Network	Grey relational analysis with NN	Industry	SS	Elsevier	19	Turkey
[292]	Fuzzy logic	Case study in Chemistry Factory	Industry	SS	Elsevier	40	Australia
[304]	Neural Network	FTA (NN future)	Transportation	SS	Elsevier	26	China
[250]	Neural Network	Accident Simulation	All Fields	SS	Elsevier	19	China
[276]	Neural Network	Bridge accident	Construction	SS	Elsevier	40	Taiwan
[175]	Both of tec	Data in coal	Industry	SS	Elsevier	16	China
[176]	Both of tec	Data in coal	Industry	SS	Elsevier	3	China
[62]	Fuzzy logic	Hot and humid environments	Industry	SS	Elsevier	315	China
[233]	Neural Network	Theoretical analysis	Industry	LPPI	Elsevier	6	Germany
[237]	Neural Network	Mathematic Model	Industry	LPPI	Elsevier	26	Italy
[232]	Neural Network	ANN model	Industry	LPPI	Elsevier	10	Turkey
[189]	Neural Network	HSEE-HSE	Industry	LPPI	Elsevier	38	International
[212]	Genetic Algorithm	PSA	Industry	LPPI	Elsevier	28	Slovenia
[118]	Genetic Algorithm	Mathematic Model	Industry	LPPI	Elsevier	20	Turkey
[284]	Fuzzy logic	Mathematic Model	Industry	LPPI	Elsevier	4	Finland
[96]	Fuzzy logic	QRA	Industry	LPPI	Elsevier	32	Australia
[179]	Fuzzy logic	Dynamic Data Exchange.	Industry	LPPI	Elsevier	12	UK
[126]	Fuzzy logic	AHP	Transportation	LPPI	Elsevier	33	China
[124]	Fuzzy logic	AFRA	Industry	LPPI	Elsevier	21	Canada
[126]	Fuzzy logic	FTA-AHP	Industry	LPPI	Elsevier	31	China
[48]	Fuzzy logic	Empirical data (FTA)	Industry	LPPI	Elsevier	165	International
[261]	Fuzzy logic	Empirical data (FTA)	Industry	LPPI	Elsevier	104	China
[21]	Fuzzy logic	FAP	Industry	LPPI	Elsevier	19	Italy
[48]	Fuzzy logic	Case study	Construction	LPPI	Elsevier	40	Poland
[317]	Fuzzy logic	Case study	Industry	LPPI	Elsevier	2	Malaysia
[89]	Fuzzy logic	Theoretical analysis	Industry	LPPI	Elsevier	67	International

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[258]	Fuzzy logic	Theoretical analysis	Industry	LPPI	Elsevier	70	Greece
[82]	Fuzzy logic	Case study	Transportation	LPPI	Elsevier	246	Canada
[305]	Fuzzy logic	Mathematic Model	All Fields	LPPI	Elsevier	22	Iran
[81]	Fuzzy logic	Case study	Industry	LPPI	Elsevier	50	Italy
[259]	Neural Network	Mathematic Model	Industry	LPPI	Elsevier	28	Algeria
[113]	Fuzzy logic	Case study	Industry	LPPI	Elsevier	35	Egypt
[274]	Fuzzy logic	Mathematic Model	Transportation	LPPI	Elsevier	158	Iran
[41]	Fuzzy logic	Oil tank	Transportation	LPPI	Elsevier	142	China
[313]	Fuzzy logic	Chemical Industry	Industry	LPPI	Elsevier	109	International
[215]	Fuzzy logic	oil and gas	Industry	LPPI	Elsevier	45	Norway
[112]	Fuzzy logic	oil and gas	Industry	LPPI	Elsevier	35	Iran
[295]	Neural Network	Algorithm	All Fields	LPPI	Elsevier	0	Iran
[118]	Genetic Algorithm	Mine	Industry	LPPI	Elsevier	20	Turkey
[213]	Genetic Algorithm	Industry	Industry	LPPI	Elsevier	22	Italy
[281]	Genetic Algorithm	Industry	Industry	LPPI	Elsevier	5	France
[156]	Genetic Algorithm	Case study	Industry	LPPI	Elsevier	23	China
[233]	Neural Network	Case study	Industry	LPPI	Elsevier	6	Germany
[189]	Neural Network	ANN model	All Fields	LPPI	Elsevier	38	International
[200]	Neural Network	Bayesian Networks	All Fields	HM	Elsevier	58	China
[135]	Fuzzy logic	FCE	Industry	HM	Elsevier	17	Germany
[136]	Fuzzy logic	FHWI	Industry	HM	Elsevier	21	South Africa
[55]	Machine learning	Mathematic Model	All Fields	HM	Elsevier	21	Spain
[106]	Fuzzy logic	LOPA	All Fields	HM	Elsevier	232	International
[168]	Fuzzy logic	ECI	Environment	HM	Elsevier	36	India
[180]	Neural Network	Theoretical analysis	Industry	HM	Elsevier	28	Iran
[54]	Fuzzy logic	case study	Transportation	HM	Elsevier	47	USA
[238]	Fuzzy logic	Case study	Industry	HM	Elsevier	60	India
[239]	Fuzzy logic	Chemical Industry	Industry	HM	Elsevier	86	India
[198]	Neural Network	Maritime Traffic	Environment	HM	Elsevier	55	Finland
[252]	Fuzzy logic	Sea port	Transportation	HM	Elsevier	118	UK
[164]	Fuzzy logic	LOPA	All Fields	HM	Elsevier	18	Algeria
[127]	Fuzzy logic	FTA	Industry	HM	Elsevier	135	China
[22]	Fuzzy logic	Theoretical analysis	Transportation	HM	Elsevier	86	Italy
[273]	Fuzzy logic	Theoretical analysis	Environment	HM	Elsevier	54	USA
[223]	Fuzzy logic	Case study	Industry	RA	Wiley	11	Canada
[30]	Fuzzy logic	Monde Carlo FTA FL	Industry	RA	Wiley	106	Italy
[303]	Neural Network	Case study	Industry	RA	Wiley	99	China
[92]	Fuzzy logic	Risk Management	All Fields	RA	Wiley	28	Italy
[149]	Fuzzy logic	LSRA	Construction	RA	Wiley	18	China
[197]	Fuzzy logic	FBN	All Fields	RA	Wiley	90	UK
[26]	Fuzzy logic	Case study	All Fields	RA	Wiley	176	Canada
[111]	Fuzzy logic	Algorithm	All Fields	RA	Wiley	43	China
[308]	Fuzzy logic	Algorithm	All Fields	RA	Wiley	61	Italy
[218]	Fuzzy logic	case study	All Fields	RA	Wiley	31	Taiwan
[279]	Fuzzy logic	classification	All Fields	RA	Wiley	15	Italy
[286]	Fuzzy logic	Theoretical analysis	All Fields	RA	Wiley	26	USA
[78]	Fuzzy logic	CREAM	All Fields	RA	Wiley	75	Italy
[206]	Neural Network	WNV	Medicine	RA	Wiley	11	Canada
[220]	Neural Network	Mathematic Model	Transportation	RA	Wiley	67	France
[267]	Neural Network	Theoretical analysis	Construction	RA	Wiley	74	Netherlands

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[53]	Fuzzy logic	Mathematic Model	Construction	RA	Wiley	8	USA
[85]	Neural Network	case Study	Construction	RA	Wiley	90	USA
[254]	Neural Network	ANN model	Industry	SS	Elsevier	25	Brazil
[18]	Neural Network	ANN model	Industry	SS	Elsevier	43	Turkey
[81]	Neural Network	ANFIS	Construction	SS	Elsevier	43	Iran
[188]	Neural Network	ANN model	Construction	Proceedings—Winter Simulation Conference	IEEE	7	USA
[272]	Neural Network	ANN model	Construction	Sustainability	IEEE	247	Switzerland
[84]	Neural Network	ANN model	Transportation	Advances in Intelligent Systems and Computing	Springer	1	Russia
[44]	Neural Network	CNN model	Industry	International Conference on Vehicular Electronics and Safety	IEEE	7	Portugal
[134]	Neural Network	CNN model	Industry	Communications in Computer and Information Science	Springer	2	China
[3]	Neural Network	TOPSIS	Industry	IECON Proceedings (Industrial Electronics Conference)	IEEE	0	Italy
[235]	Neural Network	NN	Industry	International Conference on Electrical and Computer Engineering: Advancing Technology for a Better Tomorrow,	IEEE	1	Bangladesh
[252]	Neural Network	CNN model	Industry	Process Safety and Environmental Protection	Elsevier	2	China
[203]	Neural Network	Bayesian Networks	Transportation	Structural Health Monitoring	SAGE journals	89	UK
[243]	Neural Network	ANN model	Transportation	Measurement: Journal of the International Measurement Confederation	Elsevier	24	Denmark
[192]	Neural Network	ANN model	Industry	SS	Elsevier	53	China
[43]	Both of tec	NN/Fuzzy	Industry	IEEE Asia-Pacific Conference on Circuits and Systems, Proceedings, APCCAS	IEEE	5	China

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[49]	Genetic Algorithm	primary-insurance industry	All Fields	Journal of Risk Finance	Emerald logo	1	USA
[187]	Genetic Algorithm	nuclear plant	Industry	Annals of Nuclear Energy	Elsevier	13	Iran
[205]	Genetic Algorithm	SSGA	Industry	Annals of Nuclear Energy	Elsevier	65	Spain
[184]	Machine learning	HRA model	Industry	Future Generation Computer Systems	Elsevier	3	International
[306]	Machine learning	DNN	All Fields	SS	Elsevier	0	International
[80]	Machine learning	RMA	Industry	IEEE PES Innovative Smart Grid Technologies Conference - International	IEEE	4	China
[52]	Machine learning	GIS platform	Industry	Journal of Injury Control and Safety Promotion	IEEE	4	International
[140]	Fuzzy logic	FTA	Transportation	Proceedings—IEEE 16th International Conference on Industrial Informatics	Wiley	3	Brazil
[146]	Fuzzy logic	IVIS	Transportation	International Journal of Industrial Ergonomics	IEEE	0	International
[207]	Fuzzy logic	Fuzzy ANP	Transportation	Human Factors in Complex Technical Systems and Environments,	Elsevier	44	China
[183]	Fuzzy logic	ERGO	Industry	International Journal of Occupational Safety and Ergonomics	Brazil		
[234]	Fuzzy logic	fuzzy theory	Construction	Conference on Systems, Process and Control	Taylor		Iran
[266]	Fuzzy logic	Case study	Industry	Process Safety and Environmental Protection	IEEE	7	Malaysia
[112]	Fuzzy logic	Mathematic Model	Industry	Process Safety and Environmental Protection	Elsevier	78	Iran
[35]	Fuzzy logic	oil	Industry	International Conference on Industrial Engineering and Systems Management,	IEEE	19	Iran

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[120]	Fuzzy logic	Mathematic Model	All Fields	International Conference on Industrial Engineering and Systems Management,	Frank and Taylor	34	Canada
[205]	Fuzzy logic	FCM	Industry	Journal of Air Transport Management	IEEE	7	Spain
[257]	Fuzzy logic	Fuzzy with FTA	Transportation	Journal of Air Transport Management	Elsevier	14	Brazil
[79]	Fuzzy logic	Monte Carlo	Industry	Canadian Society for Civil Engineering	Elsevier	0	Canadian
[32]	Fuzzy logic	Bowtie	Industry	Process Safety and Environmental Protection	Elsevier	84	
[66]	Fuzzy logic	Construction tunnel	Construction	International Journal of Industrial Ergonomics	Elsevier	161	Turkey
[115]	Fuzzy logic	Mathematic Model	All Fields	Construction Management and Economics	Frank and Taylor	95	Iran
[137]	Fuzzy logic	Real data	Industry	SS	Elsevier	20	Spain
[315]	Fuzzy logic	Case Study	Industry	SS	Elsevier	205	Iran
[172]	Fuzzy logic	Mathematic Model	Industry	VIKOR method	Taylor	12	India
[23]	Fuzzy logic	Mathematic Model	Industry	International Journal of Injury Control and Safety Promotion	AIP	20	Iran
[245]	Neural Network	Mathematic Model	All Fields	Journal of Renewable and Sustainable Energy	Elsevier	35	Malaysia
[247]	Neural Network	Mathematic Model	Transportation	Neurocomputing	Wiley	43	China
[144]	Fuzzy logic	FFTA	Transportation	SS	Elsevier	129	Iran
[79]	Fuzzy logic	FMEA	Oil and Gas	Modern Applied Science	Canadian Center of Science and Education	13	Russia
[33]	Fuzzy logic	OSH	All Fields	ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering	ASME	3	Portugal
[12]	Fuzzy logic	Mathematic Model	All Fields	International Journal of Industrial Ergonomics	Elsevier	55	India
[105]	Fuzzy logic	Theoretical model	Computer Science	Journal of Computing in Civil Engineering	ASCE	128	Korea
[165]	Fuzzy logic	MCDM	All Fields	SS	Elsevier	6	Taiwan
[312]	Fuzzy logic	Mathematic Model	Industry	LPPI	Elsevier	131	Turkey

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[296]	Fuzzy logic	Mathematic Model	All Fields	Human Factors and Ergonomics in Manufacturing Service Industries	Wiley	12	Turkey
[161]	Fuzzy logic	TOPSIS	All Fields	Iran Occupational Health	15	Iran	
[37]	Fuzzy logic	QFD	All Fields	Uncertainty Modeling in Knowledge Engineering and Decision Making	World Scientific	0	France
[154]	Fuzzy logic	MCDM	Medicine	Applied Mathematics & Information	Natural Sciences	7	Turkey
[170]	Fuzzy logic	AHP	High Technology	Procedia Computer Science	Elsevier	5	Turkey
[240]	Fuzzy logic	Fuzzy systems	Transportation	Brodogradnja	Elsevier	15	Turkey
[251]	Fuzzy logic	RULA	Construction	Canadian Journal of Civil Engineering	49	Canada	
[178]	Fuzzy logic	Mathematic Model	All Fields	Mathematical Problems in Engineering	3	China	
[148]	Fuzzy logic	DEMATEL	Construction	Sustainability	MDPI	133	Turkey
[138]	Fuzzy logic	QRA	Industry	SS	Elsevier	61	USA
[130]	Fuzzy logic	FMEA	Industry	International Journal of Occupational Safety and Ergonomics	Taylor	18	Iran
[152]	Fuzzy logic	FRA	Coal	Safety and Health at Work	OSHRI	46	India
[137]	Fuzzy logic	QRA	Industry	SS	Elsevier	10	Spain
[153]	Fuzzy logic	Mathematic Model	Coal	International Journal of Injury Control and Safety Promotion	Taylor	24	India
[31]	Fuzzy logic	Mathematic Model	Construction	Safety and Health at Work	OSHRI	17	India
[288]	Both of tec	Mathematic Model	All Fields	SS	Elsevier	30	Italy
[166]	Fuzzy logic	FMEA	University chemistry	Human and Ecological Risk Assessment	Taylor	78	Turkey
[150]	Fuzzy logic	ORA	Construction	SS	Elsevier	24	India
[103]	Fuzzy logic	SPA	Coal	SS	Elsevier	54	China
[64]	Fuzzy logic	Delphi Technique and Fuzzy AHP-TOPSIS Method	Medicine	Journal of Environmental Health Science and Engineering	Taylor	48	Iran
[131]	Fuzzy logic	FMEA	Industry	Gazi University Journal of Science	Elsevier	20	India

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[112]	Fuzzy logic	Fuzzy logic	Oil and Gas	International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management	SGEM	0	
[162]	Fuzzy logic	F-TOPSIS	All Fields	Journal of the Faculty of Engineering and Architecture of Gazi University	Elsevier	11	Turkey
[80]	Fuzzy logic	Mathematic Model	Coal	ONE	Elsevier	10	China
[167]	Fuzzy logic	TOPSIS	case study	Work	IOS	8	Iran
[214]	Fuzzy logic	Mathematic Model	Industry	Process Safety and Environmental Protection	Elsevier	23	Poland
[288]	Neural Network	FAP	Metal coal	SS	Elsevier	30	Italy
[193]	Neural Network	ANN model	Construction	ISARC 2017	IAARC	19	South Korea
[208]	Neural Network	FNN	Coal	EURASIP Journal on Wireless Communications and Networking	Springer	2	China
[45]	Neural Network	DNN	All Fields	DNN and EM Expectation Maximization (EM)	IEEE	15	China
[194]	Neural Network	ANN model	All Fields	Benchmarking	Elsevier	2	India
[39]	Fuzzy logic	FMEA	All Fields	Journal of the Faculty of Engineering and Architecture of Gazi University	Elsevier	3	Turkey
[174]	Fuzzy logic	Fuzzy logic	Coal	International Journal on Technical and Physical Problems of Engineering	HORA	0	Turkey
[185]	Fuzzy logic	DEMATEL, AHP, and TOPSIS	All Fields	2022—4th International Congress on Human–Computer Interaction, Optimization and Robotic Applications, Proceedings	IEEE	1	Turkey

Table A1. *Cont.*

Reference to the Paper	Technique Name	Type of Model	Field	Name of Journal	Publisher	Citations	Country
[100]	Fuzzy logic	AHP and FMEA	Coal	Mining Technology: Transactions of the Institute of Mining and Metallurgy	Taylor	4	Iran
[284]	Fuzzy logic	Hybrid method (SWARA and COPRAS)	All Fields	Sustainability	MDPI	3	Switzerland
[299]	Fuzzy logic	3D fuzzy ergonomic analysis	All Fields	Automation in Construction	Elsevier	15	Canada
[168]	Fuzzy logic	Industry	Industry	Energy Sources, Part A: Recovery, Utilization and Environmental Effects	Taylor	4	
[221]	Both of tec	FTA	Coal	International Conference on Intelligent and Fuzzy Systems	Springer	3	Turkey
[300]	Fuzzy logic	PFAHP	All Fields	Human and Ecological Risk Assessment	Taylor	24	Turkey
[157]	Fuzzy logic	FMEA	All Fields	Iran Occupational Health		2	Iran
[301]	Both of tec	QFD and AHP	Coal	Advances in Intelligent Systems and Computing	Springer	2	Turkey
[133]	Fuzzy logic	Monte Carlo	Industry	Journal of Economic Theory and Practice	SAGE journals	10	USA
[278]	Fuzzy logic	DEMATEL	Transportation	Ocean Engineering	Elsevier	21	Turkey

References

1. Pistolesi, F.; Baldassini, M.; Lazzerini, B. A human-centric system combining smartwatch and LiDAR data to assess the risk of musculoskeletal disorders and improve ergonomics of Industry 5.0 manufacturing workers. *Comput. Ind.* **2023**, *155*, 104042. [CrossRef]
2. Johanning, E. Evaluation and management of occupational low back disorders. *Am. J. Ind. Med.* **2000**, *37*, 94–111. [CrossRef]
3. Lazzerini, B.; Pistolesi, F. An Integrated Optimization System for Safe Job Assignment Based on Human Factors and Behavior. *IEEE Syst. J.* **2017**, *12*, 1158–1169. [CrossRef]
4. Miller, P.; Haslam, C. Why employers spend money on employee health: Interviews with occupational health and safety professionals from British Industry. *Saf. Sci.* **2008**, *47*, 163–169. [CrossRef]
5. Maniadakis, N.; Gray, A. The economic burden of back pain in the UK. *Pain* **2000**, *84*, 95–103. [CrossRef]
6. Frymoyer, J.W. Predicting Disability From Low Back Pain. *Clin. Orthop. Relat. Res.* **1992**, *279*, 101–109. [CrossRef]
7. Choo, B.C.; Abdul, R.M.; Dayang Radiah, A.B.; Mohd, T.M.Z.; Syafiie, S. A review on supervised machine learning for accident risk analysis: Challenges in Malaysia. *Process Saf. Prog.* **2022**, *41*, 147–158. [CrossRef]
8. Durdyev, S.; Mohandes, S.R.; Mahdiyar, A.; Ismail, S. What drives clients to purchase green buildings?: The cybernetic fuzzy analytic hierarchy process approach. *Eng. Constr. Archit. Manag.* **2022**, *29*, 4015–4039. [CrossRef]
9. Liu, R.; Liu, H.C.; Shi, H.; Gu, X. Occupational health and safety risk assessment: A systematic literature review of models, methods, and applications. *Saf. Sci.* **2022**, *160*, 106050. [CrossRef]
10. Hegde, J.; Rokseth, B. Applications of machine learning methods for engineering risk assessment–A review. *Saf. Sci.* **2020**, *122*, 104492. [CrossRef]
11. Ilbahar, E.; Karaşan, A.; Cebi, S.; Kahraman, C. A novel approach to risk assessment for occupational health and safety using Pythagorean fuzzy AHP and fuzzy inference system. *Saf. Sci.* **2018**, *103*, 124–136. [CrossRef]

12. Debnath, J.; Biswas, A.; Sivan, P.; Sen, K.N.; Sahu, S. Fuzzy inference model for assessing occupational risks in construction sites. *Int. J. Ind. Ergon.* **2016**, *55*, 114–128. [CrossRef]
13. Pistolesi, F.; Teti, E. Shedding light on the relationship between ESG ratings and systematic risk. *Financ. Res. Lett.* **2023**, *60*, 104882. [CrossRef]
14. Rabbi, A.B.K.; Jeelani, I. AI integration in construction safety: Current state, challenges, and future opportunities in text, vision, and audio-based applications. *Autom. Constr.* **2024**, *164*, 105443. [CrossRef]
15. Marhavilas, P.K.; Koulouriotis, D.E. Risk-Acceptance Criteria in Occupational Health and Safety Risk-Assessment—The State-of-the-Art through a Systematic Literature Review. *Safety* **2021**, *7*, 77. [CrossRef]
16. Hosseini, S.; Ivanov, D. Bayesian networks for supply chain risk, resilience, and ripple effect analysis: A literature review. *Expert Syst. Appl.* **2020**, *161*, 113649. [CrossRef]
17. Di Noia, A.; Hasekamp, O.P.; Van Diedenhoven, B.; Zhang, Z. Retrieval of liquid water cloud properties from POLDER-3 measurements using a neural network ensemble approach. *Atmos. Meas. Tech.* **2019**, *12*, 1697–1716. [CrossRef]
18. Ayhan, B.U.; Tokdemir, O.B. Safety assessment in megaprojects using artificial intelligence. *Saf. Sci.* **2019**, *118*, 273–287. [CrossRef]
19. Chang, L.Y.; Chen, W.C. Data mining of tree-based models to analyze freeway accident frequency. *J. Saf. Res.* **2005**, *36*, 365–375. [CrossRef]
20. Sun, R.; Wang, X.; Zhou, Z.; Ao, X.; Sun, X.; Song, M. Study of the comprehensive risk analysis of dam-break flooding based on the numerical simulation of flood routing. Part I: Model development. *Nat. Hazards* **2014**, *73*, 1547–1568. [CrossRef]
21. Murè, S.; Demichela, M. Fuzzy application procedure (FAP) for the risk assessment of occupational accidents. *J. Loss Prev. Process Ind.* **2009**, *22*, 593–599. [CrossRef]
22. Bonvicini, S.; Leonelli, P.; Spadoni, G. Risk analysis of hazardous materials transportation: Evaluating uncertainty by means of fuzzy logic. *J. Hazard. Mater.* **1998**, *62*, 59–74. [CrossRef]
23. Noorollahi, E.; Fadai, D.; Ghodsipour, S.H.; Shirazi, M.A. Developing a new optimization framework for power generation expansion planning with the inclusion of renewable energy—A case study of Iran. *J. Renew. Sustain. Energy* **2017**, *9*, 015901. [CrossRef]
24. Marhavilas, P.K.; Koulouriotis, D.E. Combined Usage of Stochastic and Quantitative Risk Assessment Methodologies in the Worksites: Application on an Electric Power Provider. *Reliab. Eng. Syst. Saf.* **2012**, *97*, 36–46. [CrossRef]
25. Palamara, F.; Piglione, F.; Piccinini, N. Self-organizing map and clustering algorithms for the analysis of occupational accident databases. *Saf. Sci.* **2011**, *49*, 1215–1230. [CrossRef]
26. Ferdous, R.; Khan, F.; Sadiq, R.; Amyotte, P.; Veitch, B. Fault and event tree analyses for process systems risk analysis: Uncertainty-handling formulations. *Risk Anal.* **2010**, *31*, 86–107. [CrossRef]
27. Sharma, U.; Sudhakar, M. Use of recursive methods in fuzzy fault tree analysis: An aid to quantitative risk analysis. *Reliab. Eng. Syst. Saf.* **1993**, *41*, 231–237. [CrossRef]
28. Marhavilas, P.; Koulouriotis, D.; Mitrakas, C. Fault and event-tree techniques in occupational health-safety systems—Part I: Integrated risk-evaluation scheme. *Environ. Eng. Manag. J.* **2014**, *13*, 2097–2108. [CrossRef]
29. Marhavilas, P.K.; Koulouriotis, D.E.; Mitrakas, C.A. Fault and Event-Tree Techniques in Occupational Health-Safety Systems—Part II: Statistical Analysis. *Environ. Eng. Manag. J.* **2014**, *13*, 2371–2386. [CrossRef]
30. Baraldi, P.; Zio, E. A combined Monte Carlo and possibilistic approach to uncertainty propagation in event tree analysis. *Risk Anal.* **2008**, *28*, 1309–1326. [CrossRef]
31. Golabchi, A.; Han, S.; Fayek, A.R.; AbouRizk, S. Stochastic modeling for assessment of human perception and motion sensing errors in ergonomic analysis. *J. Comput. Civ. Eng.* **2017**, *31*, 04017010. [CrossRef]
32. Markowski, A.S.; Kotynia, A. "Bow-tie" model in layer of protection analysis. *Process Saf. Environ. Prot.* **2011**, *89*, 205–213. [CrossRef]
33. Rodrigues, M.A.; Leão, C.P.; Nunes, E.; Sousa, S.; Arezes, P. A fuzzy logic approach in the definition of risk acceptance boundaries in occupational safety and health. *ASCE-ASME J. Risk Uncertain. Eng. Syst. Part B Mech. Eng.* **2016**, *2*, 044501. [CrossRef]
34. Das, A.; Abdel-Aty, M. A combined frequency–severity approach for the analysis of rear-end crashes on urban arterials. *Saf. Sci.* **2011**, *49*, 1156–1163. [CrossRef]
35. Omidi, L.; Zakerian, S.A.; Saraji, J.N.; Hadavandi, E.; Yekaninejad, M.S. Safety performance assessment among control room operators based on feature extraction and genetic fuzzy systems in the process industry. *Process Saf. Environ. Prot.* **2018**, *116*, 590–602. [CrossRef]
36. Can, G.F.; Toktas, P. A novel fuzzy risk matrix-based risk assessment approach. *Kybernetes* **2018**, *47*, 1721–1751. [CrossRef]
37. Bas, E.; Sahin, O. A new fuzzy risk score for occupational safety and health management. In *Uncertainty Modelling in Knowledge Engineering and Decision Making: Proceedings of the 12th International FLINS Conference; World Scientific: Singapore, 2016; pp. 1063–1068.*
38. Chongfu, H. Fuzzy risk assessment of urban natural hazards. *Fuzzy Sets Syst.* **1996**, *83*, 271–282. [CrossRef]

39. Cebi, S.; Karamustafa, M. A new fuzzy-based risk assessment approach for the analysis of occupational risks in the manufacturing sector. In *International Conference on Intelligent and Fuzzy Systems*; Springer International Publishing: Cham, Switzerland, 2022; pp. 261–270.
40. Arunraj, N.S.; Maiti, J. Development of an environmental consequence index (ECI) using fuzzy composite programming. *J. Hazard. Mater.* **2008**, *162*, 29–43. [CrossRef]
41. Wang, D.; Zhang, P.; Chen, L. Fuzzy fault tree analysis for fire and explosion of crude oil tanks. *J. Loss Prev. Process Ind.* **2013**, *26*, 1390–1398. [CrossRef]
42. Zhang, Z.; Polet, P.; Vanderhaegen, F.; Millot, P. Artificial neural network for violation analysis. *Reliab. Eng. Syst. Saf.* **2003**, *84*, 3–18. [CrossRef]
43. Niu, J.; Dartnall, J. Application of fuzzy-MRP-II in fast-moving consumer goods manufacturing industry. In Proceedings of the 2008 Winter Simulation Conference, Miami, FL, USA, 7–10 December 2008; pp. 1939–1945.
44. Melotti, G.; Premebida, C.; Bird, J.J.; Faria, D.R.; Gonçalves, N. Probabilistic object classification using CNN ML-MAP layers. *arXiv* **2020**, arXiv:2005.14565.
45. Sarkar, D.; Mishra, N.; Biswas, A. Genetic Algorithm-Based Deep Learning Models: A Design Perspective. In Proceedings of the Seventh International Conference on Mathematics and Computing; Springer: Singapore, 2022; pp. 361–372.
46. Vinod, G.; Kushwaha, H.S.; Verma, A.K.; Srividya, A. Optimisation of ISI interval using genetic algorithms for risk-informed in-service inspection. *Reliab. Eng. Syst. Saf.* **2004**, *86*, 307–316. [CrossRef]
47. Stach, W.; Kurgan, L.; Pedrycz, W.; Reformat, M. Genetic learning of fuzzy cognitive maps. *Fuzzy Sets Syst.* **2005**, *153*, 371–401. [CrossRef]
48. Markowski, A.S.; Mannan, M.S.; Bigoszewska, A. Fuzzy logic for process safety analysis. *J. Loss Prev. Process Ind.* **2009**, *22*, 695–702. [CrossRef]
49. Ha, S. Optimal insurance risk allocation with steepest ascent and genetic algorithms. *J. Risk Financ.* **2013**, *14*, 129–139. [CrossRef]
50. Valenzuela, O.; Rojas, I.; Rojas, F.; Pomares, H.; Herrera, L.; Guillen, A.; Marquez, L.; Pasadas, M. Hybridization of intelligent techniques and ARIMA models for time series prediction. *Fuzzy Sets Syst.* **2007**, *159*, 821–845. [CrossRef]
51. Vinod, S.G.; Babar, A.K.; Kushwaha, H.S.; Raj, V.V. Symptom-based diagnostic system for nuclear power plant operations using artificial neural networks. *Reliab. Eng. Syst. Saf.* **2003**, *82*, 33–40. [CrossRef]
52. Leite, J.B.; Mantovani, J.R.S.; Dokic, T.; Chen, Q.Y.P.C.; Kezunovic, M. Failure probability metric by machine learning for online risk assessment in distribution networks. In Proceedings of the 2017 IEEE PES Innovative Smart Grid Technologies Conference—Latin America (ISGT Latin America), Quito, Ecuador, 20–22 September 2017; pp. 1–6.
53. Vangay, P.; Steingrimsson, J.; Wiedmann, M.; Stasiewicz, M.J. Classification of *Listeria monocytogenes* persistence in retail delicatessen environments using expert elicitation and machine learning. *Risk Anal.* **2014**, *34*, 1830–1845. [CrossRef]
54. Qiao, Y.; Keren, N.; Mannan, M.S. Utilization of accident databases and fuzzy sets to estimate the frequency of HazMat transport accidents. *J. Hazard. Mater.* **2009**, *167*, 374–382. [CrossRef]
55. Matias, J.; Taboada, J.; Ordonez, C.; Nieto, P. Machine learning techniques applied to the determination of road suitability for the transportation of dangerous substances. *J. Hazard. Mater.* **2006**, *147*, 60–66. [CrossRef]
56. Mooren, L.; Grzebieta, R.; Williamson, A.; Olivier, J.; Friswell, R. Safety management for heavy vehicle transport: A review of the literature. *Saf. Sci.* **2014**, *62*, 79–89. [CrossRef]
57. Grayson, G.B.; Helman, S. Work-Related Road Safety: A Systematic Review of the Literature on the Effectiveness of Interventions. TRL Report for Institute of Occupational Safety and Health Research Report. 2011, Volume 11. Available online: https://api.semanticscholar.org/CorpusID:29788754 (accessed on 25 June 2024).
58. Hale, A.; Ale, B.; Goossens, L.; Heijer, T.; Bellamy, L.; Mud, M.; Roelen, A.; Baksteen, H.; Post, J.; Papazoglou, I.; et al. Modeling accidents for prioritizing prevention. *Reliab. Eng. Syst. Saf.* **2007**, *92*, 1701–1715. [CrossRef]
59. Robson, L.S.; Clarke, J.A.; Cullen, K.; Bielecky, A.; Severin, C.; Bigelow, P.L.; Irvin, E.; Culyer, A.; Mahood, Q. The effectiveness of occupational health and safety management system interventions: A systematic review. *Saf. Sci.* **2007**, *45*, 329–353. [CrossRef]
60. Mayhew, C.; Quinlan, M. Economic pressure, multi-tiered subcontracting, and occupational health and safety in Australian long-haul trucking. *Empl. Relat.* **2006**, *28*, 212–229. [CrossRef]
61. Villa, V.; Paltrinieri, N.; Khan, F.; Cozzani, V. Towards dynamic risk analysis: A review of the risk assessment approach and its limitations in the chemical process industry. *Process Saf. Environ. Prot.* **2016**, *89*, 77–93. [CrossRef]
62. Zheng, G.; Zhu, N.; Tian, Z.; Chen, Y.; Sun, B. Application of a trapezoidal fuzzy AHP method for work safety evaluation and early warning rating of hot and humid environments. *Saf. Sci.* **2012**, *50*, 228–239. [CrossRef]
63. Haqiqat, E.; Mehrjerdi, Y.Z.; Bidaki, A.Z. Fuzzy inference system-Latin hypercube simulation: An integrated hybrid model for OHS risks management. *J. Proj. Manag.* **2019**, *4*, 127–140. [CrossRef]
64. Asghari, M.; Nassiri, P.; Monazzam, M.R.; Golbabaei, F.; Arabalibeik, H.; Shamsipour, A.; Allahverdy, A. Weighting criteria and prioritizing of heat stress indices in surface mining using a Delphi technique and fuzzy AHP-TOPSIS method. *J. Environ. Health Sci. Eng.* **2017**, *15*, 1. [CrossRef]

65. Lin, S.S.; Shen, S.L.; Zhou, A.; Xu, Y.S. Risk assessment and management of excavation systems based on fuzzy set theory and machine learning methods. *Autom. Constr.* **2020**, *122*, 103490. [CrossRef]
66. Gürcanli, G.E.; Müngen, U. An occupational safety risk analysis method at construction sites using fuzzy sets. *Int. J. Ind. Ergon.* **2008**, *39*, 371–387. [CrossRef]
67. Neto, A.V.S.; Camargo, J.B.; Almeida, J.R.; Cugnasca, P.S. Safety Assurance of Artificial Intelligence-Based Systems: A Systematic Literature Review on the State of the Art and Guidelines for Future Work. *IEEE Access* **2022**, *10*, 130733–130770. [CrossRef]
68. Yeong, E.K.; Hsiao, T.C.; Chiang, H.K.; Lin, C.W. Prediction of burn healing time using artificial neural networks and reflectance spectrometer. *Burns* **2005**, *31*, 415–420. [CrossRef] [PubMed]
69. Li, L.; Lu, Z.; Cheng, L.; Wu, D. Importance analysis on the failure probability of the fuzzy and random system and its state dependent parameter solution. *Fuzzy Sets Syst.* **2014**, *250*, 69–89. [CrossRef]
70. Bevilacqua, A.; MacDonald, K.; Rangarej, A.; Widjaya, V.; Caulfield, B.; Kechadi, T. Human Activity Recognition with Convolutional Neural Networks. In *Machine Learning and Knowledge Discovery in Databases*; Lecture Notes in Computer Science; Springer: Cham, Switzerland, 2019; pp. 541–552.
71. Waqar, A.; Khan, M.B.; Othman, I.; Mansoor, M.S.; Shafiq, N. A Systematic Literature Review on Risk Analysis of Health and Safety in Oil Refinery and Onshore Pipeline Construction Projects. In Proceedings of the 2022 International Conference on Data Analytics for Business and Industry (ICDABI), Sakhir, Bahrain, 25–26 October 2022.
72. Beriha, G.S.; Patnaik, B.; Mahapatra, S.S.; Padhee, S. Assessment of safety performance in Indian industries using fuzzy approaches. *Expert Syst. Appl.* **2011**, *39*, 3311–3323. [CrossRef]
73. Shaktawat, A.; Vadhera, S. Risk management of hydropower projects for sustainable development: A review. *Environ. Dev. Sustain.* **2021**, *23*, 45–76. [CrossRef]
74. Herrero, S.G.; Saldaña, M.Á.M.; Rodriguez, J.G.; Ritzel, D.O. Influence of task demands on occupational stress: Gender differences. *J. Saf. Res.* **2012**, *43*, 365–374. [CrossRef]
75. Konstandinidou, M.; Nivolianitou, Z.; Kiranoudis, C.; Markatos, N. A fuzzy modeling application of CREAM methodology for human reliability analysis. *Reliab. Eng. Syst. Saf.* **2005**, *91*, 706–716. [CrossRef]
76. Marhavilas, P.K.; Filippidis, M.; Koulinas, G.K.; Koulouriotis, D.E. A HAZOP with MCDM-Based Risk-Assessment Approach: Focusing on the Deviations with Economic/Health/Environmental Impacts in a Process Industry. *Sustainability* **2020**, *12*, 993. [CrossRef]
77. Weber, P.; Medina-Oliva, G.; Simon, C.; Iung, B. Overview on Bayesian networks applications for dependability, risk analysis, and maintenance areas. *Eng. Appl. Artif. Intell.* **2010**, *25*, 671–682. [CrossRef]
78. Marseguerra, M.; Zio, E.; Librizzi, M. Human reliability analysis by fuzzy "CREAM". *Risk Anal.* **2007**, *27*, 137–154. [CrossRef]
79. Petrovskiy, E.A.; Buryukin, F.A.; Bukhtiyarov, V.V.; Savich, I.V.; Gagina, M.V. The FMEA-risk analysis of oil and gas process facilities with hazard assessment based on fuzzy logic. *Mod. Appl. Sci.* **2015**, *9*, 25. [CrossRef]
80. Wang, H.; Li, J.; Wang, D.; Huang, Z. A novel method of fuzzy fault tree analysis combined with VB program to identify and assess the risk of coal dust explosions. *PLoS ONE* **2017**, *12*, e0182453. [CrossRef] [PubMed]
81. Curcurù, G.; Galante, G.M.; La Fata, C.M. Epistemic uncertainty in fault tree analysis approached by the evidence theory. *J. Loss Prev. Process Ind.* **2012**, *25*, 667–676. [CrossRef]
82. Shahriar, A.; Sadiq, R.; Tesfamariam, S. Risk analysis for oil & gas pipelines: A sustainability assessment approach using fuzzy-based bow-tie analysis. *J. Loss Prev. Process Ind.* **2011**, *25*, 505–523.
83. Riviere, C.; Lauret, P.; Ramsamy, J.F.M.; Page, Y. A Bayesian neural network approach to estimating the energy equivalent speed. *Accid. Anal. Prev.* **2005**, *38*, 248–259. [CrossRef]
84. Chiou, Y.C. An artificial neural network-based expert system for the appraisal of two-car crash accidents. *Accid. Anal. Prev.* **2006**, *38*, 777–785. [CrossRef]
85. Lord, D.; Geedipally, S.R.; Guikema, S.D. Extension of the application of Conway-Maxwell-Poisson models: Analyzing traffic crash data exhibiting underdispersion. *Risk Anal.* **2010**, *30*, 1268–1276. [CrossRef]
86. De Oña, J.; Mujalli, R.O.; Calvo, F.J. Analysis of traffic accident injury severity on Spanish rural highways using Bayesian networks. *Accid. Anal. Prev.* **2010**, *43*, 402–411. [CrossRef]
87. Lee, C.J.; Lee, K.J. Application of Bayesian network to the probabilistic risk assessment of nuclear waste disposal. *Reliab. Eng. Syst. Saf.* **2005**, *91*, 515–532. [CrossRef]
88. Ventikos, N.P.; Stavrou, D.I. Estimating the safety of STS transfer operations with fuzzy FTA. In *Towards Green Marine Technology and Transport*; CRC Press: Boca Raton, FL, USA, 2015; pp. 753–760.
89. Markowski, A.S.; Mannan, M.S.; Kotynia, A.; Siuta, D. Uncertainty aspects in process safety analysis. *J. Loss Prev. Process Ind.* **2010**, *23*, 446–454. [CrossRef]
90. Lilić, N.; Obradović, I.; Cvjetić, A. An intelligent hybrid system for surface coal mine safety analysis. *Eng. Appl. Artif. Intell.* **2010**, *23*, 453–462. [CrossRef]

91. Yazdi, M.; Nedjati, A.; Zarei, E.; Abbassi, R. A novel extension of the DEMATEL approach for probabilistic safety analysis in process systems. *Saf. Sci.* **2019**, *121*, 119–136. [CrossRef]
92. Cameron, E.; Peloso, G.F. Risk management and the precautionary principle: A fuzzy logic model. *Risk Anal.* **2005**, *25*, 901–911. [CrossRef]
93. Arunraj, N.S.; Mandal, S.; Maiti, J. Modeling uncertainty in risk assessment: An integrated approach with fuzzy set theory and Monte Carlo simulation. *Accid. Anal. Prev.* **2013**, *55*, 242–255. [CrossRef]
94. Altaf, I.; Kaul, A. Vulnerable road user safety: A systematic review and mesh-networking based vehicle ad hoc system using hybrid of neuro-fuzzy and genetic algorithms. *Int. J. Commun. Syst.* **2021**, *34*, e4907. [CrossRef]
95. Markowski, A.S.; Mannan, M.S. Fuzzy logic for piping risk assessment (pfLOPA). *J. Loss Prev. Process Ind.* **2009**, *22*, 921–927. [CrossRef]
96. Quelch, J.; Cameron, I.T. Uncertainty representation and propagation in quantified risk assessment using fuzzy sets. *J. Loss Prev. Process Ind.* **1994**, *7*, 463–473. [CrossRef]
97. Abdat, F.; Leclercq, S.; Cuny, X.; Tissot, C. Extracting recurrent scenarios from narrative texts using a Bayesian network: Application to serious occupational accidents with movement disturbance. *Accid. Anal. Prev.* **2014**, *70*, 155–166. [CrossRef]
98. Lee, S.J.; Kim, M.C.; Seong, P.H. An analytical approach to quantitative effect estimation of operation advisory system based on human cognitive process using the Bayesian belief network. *Reliab. Eng. Syst. Saf.* **2007**, *93*, 567–577. [CrossRef]
99. Bell, P.M.; Wang, H. Fuzzy linear regression models for assessing risks of cumulative trauma disorders. *Fuzzy Sets Syst.* **1997**, *92*, 317–340. [CrossRef]
100. Rahimdel, J. Fuzzy approach for the safety risk assessment in dimension stone mining. *Earth Sci. Res. J.* **2023**, *27*, 37–45. [CrossRef]
101. Sullivan, N.; Schoelles, K.M. Preventing in-facility pressure ulcers as a patient safety strategy: A systematic review. *Ann. Intern. Med.* **2013**, *158*, 410–416. [CrossRef] [PubMed]
102. Ventikos, N.P.; Louzis, K.; Koimtzoglou, A.; Delikanidis, P. Enhanced Decision Making through Probabilistic Shipwreck Risk Assessment: Focusing on the Situation in Greece. *Front. Mar. Sci.* **2016**, *3*, 97. [CrossRef]
103. Chong, T.; Yi, S.; Heng, C. Application of set pair analysis method on occupational hazard of coal mining. *Saf. Sci.* **2016**, *92*, 10–16. [CrossRef]
104. Podofillini, L.; Zio, E. Designing a risk-informed balanced system by genetic algorithms: Comparison of different balancing criteria. *Reliab. Eng. Syst. Saf.* **2008**, *93*, 1842–1852. [CrossRef]
105. Kim, H.; Kim, K.; Kim, H. Vision-based object-centric safety assessment using fuzzy inference: Monitoring struck-by accidents with moving objects. *J. Comput. Civ. Eng.* **2015**, *30*, 04015075. [CrossRef]
106. Markowski, A.S.; Mannan, M.S. Fuzzy risk matrix. *J. Hazard. Mater.* **2008**, *159*, 152–157. [CrossRef]
107. Kuleshov, V.; Enam, S.Z.; Ermon, S. Audio Super Resolution using Neural Networks. *arXiv* **2017**, arXiv:1708.00853.
108. Nayak, S.; Goveas, L.C.; Selvaraj, R.; Vinayagam, R.; Manickam, S. Advances in the utilisation of carbon-neutral technologies for a sustainable tomorrow: A critical review and the path forward. *Bioresour. Technol.* **2022**, *364*, 128073. [CrossRef]
109. Rijo-Garcia, S.; Segredo, E.; Leon, C. Computational Thinking and User Interfaces: A Systematic Review. *IEEE Trans. Educ.* **2022**, *65*, 647–656. [CrossRef]
110. Kazemi, F.; Asgarkhani, N.; Jankowski, R. Optimization-based stacked machine-learning method for seismic probability and risk assessment of reinforced concrete shear walls. *Expert Syst. Appl.* **2024**, *255*, 124897. [CrossRef]
111. Huang, C.; Ruan, D. Fuzzy risks and an updating algorithm with new observations. *Risk Anal.* **2008**, *28*, 681–694. [CrossRef] [PubMed]
112. Sa'idi, E.; Anvaripour, B.; Jaderi, F.; Nabhani, N. Fuzzy risk modeling of process operations in the oil and gas refineries. *J. Loss Prev. Process Ind.* **2014**, *30*, 63–73. [CrossRef]
113. Khalil, M.; Abdou, M.A.; Mansour, F.; Farag, H.A.; Ossman, M.E. A cascaded fuzzy-LOPA risk assessment model applied in the natural gas industry. *J. Loss Prev. Process Ind.* **2012**, *25*, 877–882. [CrossRef]
114. Singh, P.; Borah, B. An efficient time series forecasting model based on fuzzy time series. *Eng. Appl. Artif. Intell.* **2013**, *26*, 2443–2457. [CrossRef]
115. Nasirzadeh, F.; Afshar, A.; Khanzadi, M.; Howick, S. Integrating system dynamics and fuzzy logic modeling for construction risk management. *Constr. Manag. Econ.* **2008**, *26*, 1197–1212. [CrossRef]
116. Van Raemdonck, K.; Macharis, C.; Mairesse, O. Risk analysis system for the transport of hazardous materials. *J. Saf. Res.* **2013**, *45*, 55–63. [CrossRef]
117. Rivas, T.; Paz, M.; Martín, J.E.; Matías, J.M.; García, J.F.; Taboada, J. Explaining and predicting workplace accidents using data-mining techniques. *Reliab. Eng. Syst. Saf.* **2011**, *96*, 739–747. [CrossRef]
118. Kumral, M. Reliability-based optimization of a mine production system using genetic algorithms. *J. Loss Prev. Process Ind.* **2005**, *18*, 186–189. [CrossRef]
119. Hu, S.; Fang, Q.; Xia, H.; Xi, Y. Formal safety assessment based on relative risks model in ship navigation. *Reliab. Eng. Syst. Saf.* **2006**, *92*, 369–377. [CrossRef]

120. Jamshidi, A.; Ait-Kadi, D.; Ruiz, A.; Rebaiaia, M.L. Dynamic risk assessment of complex systems using FCM. *Int. J. Prod. Res.* **2017**, *56*, 1070–1088. [CrossRef]
121. Leuschen, M.L.; Walker, I.D.; Cavallaro, J.R. Evaluating the reliability of prototype degradable systems. *Reliab. Eng. Syst. Saf.* **2001**, *72*, 9–20. [CrossRef]
122. Sii, H.S.; Ruxton, T.; Wang, J. A fuzzy-logic-based approach to qualitative safety modeling for marine systems. *Reliab. Eng. Syst. Saf.* **2001**, *73*, 19–34. [CrossRef]
123. Tunçel, A.L.; Beşikçi, E.B.; Akyuz, E.; Arslan, O. Safety analysis of fire and explosion (F&E) accidents risk in bulk carrier ships under fuzzy fault tree approach. *Saf. Sci.* **2023**, *158*, 105972.
124. Mohammadi, L.; Meech, J.A. AFRA—Heuristic expert system to assess the atmospheric risk of sulphide waste dumps. *J. Loss Prev. Process Ind.* **2012**, *26*, 261–271. [CrossRef]
125. Mahdinia, I.; Mohammadnazar, A.; Arvin, R.; Khattak, A.J. Integration of automated vehicles in mixed traffic: Evaluating changes in performance of following human-driven vehicles. *Accid. Anal. Prev.* **2021**, *152*, 106006. [CrossRef]
126. Chen, G.; Zhang, X. Fuzzy-based methodology for performance assessment of emergency planning and its application. *J. Loss Prev. Process Ind.* **2008**, *22*, 125–132. [CrossRef]
127. Kang, J.; Liang, W.; Zhang, L.; Lu, Z.; Liu, D.; Yin, W.; Zhang, G. A new risk evaluation method for oil storage tank zones based on the theory of two types of hazards. *J. Loss Prev. Process Ind.* **2014**, *29*, 267–276. [CrossRef]
128. Shi, L.; Shuai, J.; Xu, K. Fuzzy fault tree assessment based on improved AHP for fire and explosion accidents for steel oil storage tanks. *J. Hazard. Mater.* **2014**, *278*, 529–538. [CrossRef]
129. Chun, M.H.; Ahn, K.I. Assessment of the potential applicability of fuzzy set theory to accident progression event trees with phenomenological uncertainties. *Reliab. Eng. Syst. Saf.* **1992**, *37*, 237–252. [CrossRef]
130. Mard, H.R.S.A.; Estiri, A.; Hadadi, P.; Mard, M.S.A. Occupational risk assessment in the construction industry in Iran. *Int. J. Occup. Saf. Ergon.* **2016**, *23*, 570–577. [CrossRef] [PubMed]
131. Efe, B.; Efe, Ö.F.; Kurt, M. An integrated intuitionistic fuzzy set and mathematical programming approach for an occupational health and safety policy. *Gazi Univ. J. Sci.* **2017**, *30*, 73–95.
132. Petrović, D.V.; Tanasijević, M.; Milić, V.; Lilić, N.; Stojadinović, S.; Svrkota, I. Risk assessment model of mining equipment failure based on fuzzy logic. *Expert Syst. Appl.* **2014**, *41*, 8157–8164. [CrossRef]
133. Erfani, A.; Tavakolan, M. Risk Evaluation Model of Wind Energy Investment Projects Using Modified Fuzzy Group Decision-making and Monte Carlo Simulation. *Arthaniti-J. Econ. Theory Pract.* **2020**, *22*, 7–33. [CrossRef]
134. Darwish, S.A.; Mansour, M.S.; Farag, H.; Ezzat, K.H. Applying LOPA and fuzzy logic to identify SIL requirements for safety-critical functions in a direct reduction iron industry. *Alex. Eng. J.* **2020**, *59*, 3575–3585. [CrossRef]
135. Liu, X.; Wirtz, K.W. Consensus oriented fuzzified decision support for oil spill contingency management. *J. Hazard. Mater.* **2005**, *134*, 27–35. [CrossRef]
136. Musee, N.; Lorenzen, L.; Aldrich, C. An aggregate fuzzy hazardous index for composite wastes. *J. Hazard. Mater.* **2006**, *137*, 723–733. [CrossRef]
137. Dan, J.R.G.; Arnaldos, J.; Darbra, R.M. Introduction of the human factor in the estimation of accident frequencies through fuzzy logic. *Saf. Sci.* **2015**, *97*, 134–143.
138. Pasman, H.J.; Rogers, W.J.; Mannan, M.S. Risk assessment: What is it worth? Shall we just do away with it, or can it do a better job? *Saf. Sci.* **2017**, *99*, 140–155. [CrossRef]
139. Supciller, A.A.; Abali, N. Occupational Health and Safety Within the Scope of Risk Analysis with Fuzzy Proportional Risk Assessment Technique (Fuzzy Prat). *Qual. Reliab. Eng. Int.* **2015**, *31*, 1137–1150. [CrossRef]
140. De Mello, F.L. A fuzzy model for knowledge base IoT information security evaluation. *J. Inf. Secur. Cryptogr. (Enigma)* **2018**, *5*, 20–26. [CrossRef]
141. Mandal, S.; Maiti, J. Risk analysis using FMEA: Fuzzy similarity value and possibility theory-based approach. *Expert Syst. Appl.* **2013**, *41*, 3527–3537. [CrossRef]
142. Stanojević, D.; Ćirović, V. Contribution to the development of risk analysis methods by application of artificial intelligence techniques. *Qual. Reliab. Eng. Int.* **2020**, *36*, 2268–2284. [CrossRef]
143. Pillay, A.; Wang, J. Modified failure mode and effects analysis using approximate reasoning. *Reliab. Eng. Syst. Saf.* **2003**, *79*, 69–85. [CrossRef]
144. Ramzali, N.; Lavasani, M.R.M.; Ghodousi, J. Safety barriers analysis of offshore drilling system by employing fuzzy event tree analysis. *Saf. Sci.* **2015**, *78*, 49–59. [CrossRef]
145. Zhang, L.; Wu, X.; Skibniewski, M.J.; Zhong, J.; Lu, Y. Bayesian-network-based safety risk analysis in construction projects. *Reliab. Eng. Syst. Saf.* **2014**, *131*, 29–39. [CrossRef]
146. Aksjonov, A.; Nedoma, P.; Vodovozov, V.; Petlenkov, E.; Herrmann, M. Detection and evaluation of driver distraction using machine learning and fuzzy logic. *IEEE Trans. Intell. Transp. Syst.* **2018**, *20*, 2048–2059. [CrossRef]

147. Aminbakhsh, S.; Gunduz, M.; Sonmez, R. Safety risk assessment using analytic hierarchy process (AHP) during planning and budgeting of construction projects. *J. Saf. Res.* **2013**, *46*, 99–105. [CrossRef]
148. Seker, S.; Zavadskas, E. Application of Fuzzy DEMATEL Method for Analyzing Occupational Risks on Construction Sites. *Sustainability* **2017**, *9*, 2083. [CrossRef]
149. Chen, T.T.; Leu, S.S. Fall risk assessment of cantilever bridge projects using Bayesian network. *Saf. Sci.* **2014**, *70*, 161–171. [CrossRef]
150. Amiri, M.; Ardeshir, A.; Zarandi, M.H. Fuzzy probabilistic expert system for occupational hazard assessment in construction. *Saf. Sci.* **2016**, *93*, 16–28. [CrossRef]
151. Aneziris, O.N.; Topali, E.; Papazoglou, I.A. Occupational risk of building construction. *Reliab. Eng. Syst. Saf.* **2011**, *105*, 36–46. [CrossRef]
152. Verma, S.; Chaudhari, S. Safety of workers in Indian mines: Study, analysis, and prediction. *Saf. Health Work* **2017**, *8*, 267–275. [CrossRef]
153. Samantra, C.; Datta, S.; Mahapatra, S.S. Analysis of occupational health hazards and associated risks in fuzzy environment: A case study in an Indian underground coal mine. *Int. J. Inj. Control Saf. Promot.* **2016**, *24*, 311–327. [CrossRef]
154. Delice, E.K.; Zegerek, S. Ranking Occupational Risk Levels of Emergency Departments Using a New Fuzzy MCDM Model: A Case Study in Turkey. *Appl. Math. Inf. Sci.* **2016**, *10*, 2345–2356. [CrossRef]
155. Zheng, Y.; Li, K. Ecological safety comprehensive evaluation on mineral-resource enterprises based on AHP. *Int. Conf. Fuzzy Inf. Eng.* **2007**, *28*, 472–480.
156. Pan, Y.; Zhang, Y.; Jiang, J.; Ding, L. Prediction of the self-accelerating decomposition temperature of organic peroxides using the quantitative structure–property relationship (QSPR) approach. *J. Loss Prev. Process Ind.* **2014**, *31*, 41–49. [CrossRef]
157. Pouyakian, M.; Farhadi, R.; Jafari, M.J.; Zarei, F. Evaluation of the explosion hazard of a 1-butene tank in a polymer complex based on consequence analysis. *J. Hum. Environ. Health Promot.* **2017**, *2*, 147–153. [CrossRef]
158. Wang, Y.M.; Chin, K.S.; Poon, G.K.K.; Yang, J.B. Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean. *Expert Syst. Appl.* **2007**, *36*, 1195–1207. [CrossRef]
159. Ahmed, S.; Gu, X.C. Accident-based FMECA study of Marine boiler for risk prioritization using fuzzy expert system. *Results Eng.* **2020**, *6*, 100123. [CrossRef]
160. Furuta, H.; Shiraishi, N. Fuzzy importance in fault tree analysis. *Fuzzy Sets Syst.* **1984**, *12*, 205–213. [CrossRef]
161. Yarahmadi, R.; Shahkohi, F.; Taheri, F.; Moridi, P. Prioritizing occupational safety and health indexes based on multi-criteria decision making in construction industries. *Iran Occup. Health J.* **2016**, *12*, 39–47.
162. Yılmaz, Z. A fuzzy AHP-TOPSIS model based case study for selecting vehicles to buy casco insurance under limited budget. *Pamukkale Univ. J. Soc. Sci. Inst.* **2017**, *2017*, 367–381. [CrossRef]
163. Su, X.; Mahadevan, S.; Xu, P.; Deng, Y. Inclusion of task dependence in human reliability analysis. *Reliab. Eng. Syst. Saf.* **2014**, *128*, 41–55. [CrossRef]
164. Ouazraoui, N.; Nait-Said, R.; Bourareche, M.; Sellami, I. Layers of protection analysis in the framework of possibility theory. *J. Hazard. Mater.* **2013**, *262*, 168–178. [CrossRef]
165. Chang, S.C.; Lin, C.F.; Wu, W.M. The features and marketability of certificates for occupational safety and health management in Taiwan. *Saf. Sci.* **2016**, *85*, 77–87. [CrossRef]
166. Ozdemir, S.; Altin, N.; Sefa, I. Fuzzy logic-based MPPT controller for high conversion ratio quadratic boost converter. *Int. J. Hydrogen Energy* **2017**, *42*, 17748–17759. [CrossRef]
167. Khandan, M.; Koohpaei, A.R.; Nili, M.; Farjami, Y. Occupational musculoskeletal disorders management using fuzzy TOPSIS assessment of repetitive tasks (ART). *Work* **2017**, *56*, 267–276. [CrossRef]
168. Badida, P.; Selvaprakash, T.; Jayaprakash, J. Risk analysis of hazardous activities using fuzzy multicriteria decision making tools: A case study in a gas turbine manufacturing plant. *Energy Sources Part A. Recovery Util. Environ. Eff.* **2021**, 1–13. [CrossRef]
169. Chen, Y.; Khan, S.; Paydar, Z. To retire or expand? A fuzzy GIS-based spatial multi-criteria evaluation framework for irrigated agriculture. *Irrig. Drain.* **2009**, *59*, 174–188. [CrossRef]
170. Adem, A.; Dağdeviren, M.; Çolak, A.; Kabak, M. Fuzzy Prioritization Approach for Risks of Wind Turbine Life Cycle. *Procedia Comput. Sci.* **2016**, *102*, 406–413. [CrossRef]
171. Khakzad, N.; Khan, F.; Amyotte, P. Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches. *Reliab. Eng. Syst. Saf.* **2011**, *96*, 925–932. [CrossRef]
172. Samantra, C.; Datta, S.; Mahapatra, S.S. A risk-based decision support framework for selection of appropriate safety measure system for underground coal mines. *Int. J. Inj. Control Saf. Promot.* **2015**, *24*, 54–68. [CrossRef]
173. Mujalli, R.O.; De Oña, J. A method for simplifying the analysis of traffic accidents injury severity on two-lane highways using Bayesian networks. *J. Saf. Res.* **2011**, *42*, 317–326. [CrossRef]
174. Zile, M. Occupational safety risk assessment analysis modeling and software for mines created based on fuzzy logic. *Int. J. Tech. Phys. Probl. Eng.* **2022**, *14*, 378–384.

175. Nian, Q.; Shi, S.; Li, R. Research and application of safety assessment method of gas explosion accident in coal mine based on GRA-ANP-FCE. *Procedia Eng.* **2012**, *45*, 106–111. [CrossRef]
176. Xiaoxu, G. Establishment and application of intrinsic coal-workman evaluation model based on wavelet neural network. *Procedia Eng.* **2012**, *45*, 225–230. [CrossRef]
177. Hassan, H.M.; Abdel-Aty, M.A. Predicting reduced visibility related crashes on freeways using real-time traffic flow data. *J. Saf. Res.* **2013**, *45*, 29–36. [CrossRef]
178. Antucheviciene, J.; Kou, G.; Maliene, V.; Vaidogas, E.R. Mathematical models for dealing with risk in engineering. *Math. Probl. Eng.* **2016**, *2016*, 1–3. [CrossRef]
179. Sebzali, Y.M.; Wang, X.Z. Joint analysis of process and operator performance in chemical process operational safety. *J. Loss Prev. Process Ind.* **2002**, *15*, 555–564. [CrossRef]
180. Keshavarz, M.H.; Zali, A.; Shokrolahi, A. A simple approach for predicting impact sensitivity of polynitroheteroarenes. *J. Hazard. Mater.* **2008**, *166*, 1115–1119. [CrossRef] [PubMed]
181. Stanojević, D.; Stanojević, P.; Jovanović, D.; Lipovac, K. Impact of riders' lifestyle on their risky behavior and road traffic accident risk. *J. Transp. Saf. Secur.* **2018**, *12*, 400–418. [CrossRef]
182. Zio, E.; Baraldi, P.; Librizzi, M.; Podofillini, L.; Dang, V.N. A fuzzy set-based approach for modeling dependence among human errors. *Fuzzy Sets Syst.* **2009**, *160*, 1947–1964. [CrossRef]
183. Krykhtine, F.; Sáfortes, L.E.N.; Cosenza, C.A.N.; Villarino, M.; Caldeira, J.; Aredes, M.; de Oliveira Reis Filho, P. Fuzzy logic for evaluating electrician maintenance teams at transmission lines' work environment. In Proceedings of the 2018 Third International Conference on Human Factors in Complex Technical Systems and Environments (ERGO), St. Petersburg, Russia, 4–7 July 2018; 2018; pp. 234–240.
184. Zhan, Y.; Tadikamalla, P.R.; Craft, J.A.; Lu, J.; Yuan, J.; Pei, Z.; Li, S. Human reliability study on the door operation from the view of Deep Machine Learning. *Future Gener. Comput. Syst.* **2019**, *99*, 143–153. [CrossRef]
185. Yakut, M.; Kaya, I.; Bozkus, E. A Two-Dimensional Fuzzy Risk Assessment Model for Occupational Health and Safety Evaluations. In Proceedings of the 2022 International Congress on Human-Computer Interaction, Optimization, and Robotic Applications (HORA), Ankara, Turkey, 9–11 June 2022.
186. Shams, A.; Roelofs, F.; Komen, E.M.J.; Baglietto, E. Quasi-direct numerical simulation of a pebble bed configuration. Part I: Flow (velocity) field analysis. *Nucl. Eng. Des.* **2012**, *263*, 473–489. [CrossRef]
187. Hadavi, S.M.H. Risk-based genetic algorithm approach to optimize outage maintenance schedule. *Ann. Nucl. Energy* **2007**, *35*, 601–609. [CrossRef]
188. Jahangiri, M.; Solukloei, H.R.J.; Kamalinia, M. A neuro-fuzzy risk prediction methodology for falling from scaffold. *Saf. Sci.* **2019**, *117*, 88–99. [CrossRef]
189. Azadeh, A.; Rouzbahman, M.; Saberi, M.; Fam, I.M. An adaptive neural network algorithm for assessment and improvement of job satisfaction with respect to HSE and ergonomics program: The case of a gas refinery. *J. Loss Prev. Process Ind.* **2011**, *24*, 361–370. [CrossRef]
190. Jahanbanifar, S.; Akhavian, R. Evaluation of wearable sensors to quantify construction workers' muscle force: An ergonomic analysis. In Proceedings of the 2018 Winter Simulation Conference (WSC), Gothenburg, Sweden, 9–12 December 2018; pp. 3921–3929.
191. Kulagin, M.; Sidorenko, V. Transport Workers Activities Analysis Using an Artificial Neural Network. In Proceedings of the Third International Scientific Conference "Intelligent Information Technologies for Industry" (IITI'18); Advances in Intelligent Systems and Computing. Springer: Cham, Switzerland, 2018; pp. 308–316.
192. He, X.; Chen, W.; Nie, B.; Zhang, M. Classification technique for danger classes of coal and gas outburst in deep coal mines. *Saf. Sci.* **2009**, *48*, 173–178. [CrossRef]
193. Seong, H.; Choi, H.; Cho, H.; Lee, S.; Son, H.; Kim, C. Vision-Based Safety Vest Detection in a Construction Scene. In Proceedings of the ISARC, Taipei, Taiwan, 28 June–1 July 2017.
194. Asjad, M.; Alam, A.; Hasan, F. A comparative study of classifier techniques for lift index data analysis. *Benchmarking Int. J.* **2018**, *25*, 632–641. [CrossRef]
195. Huang, H.Z.; Zuo, M.J.; Sun, Z.Q. Bayesian reliability analysis for fuzzy lifetime data. *Fuzzy Sets Syst.* **2005**, *157*, 1674–1686. [CrossRef]
196. Pande, A.; Abdel-Aty, M. Assessment of freeway traffic parameters leading to lane-change related collisions. *Accid. Anal. Prev.* **2006**, *38*, 936–948. [CrossRef] [PubMed]
197. Eleye-Datubo, A.G.; Wall, A.; Wang, J. Marine and offshore safety assessment by incorporative risk modeling in a fuzzy-Bayesian network of an induced mass assignment paradigm. *Risk Anal.* **2008**, *28*, 95–112. [CrossRef] [PubMed]
198. Helle, I.; Lecklin, T.; Jolma, A.; Kuikka, S. Modeling the effectiveness of oil combating from an ecological perspective—A Bayesian network for the Gulf of Finland in the Baltic Sea. *J. Hazard. Mater.* **2010**, *185*, 182–192. [CrossRef]
199. Ren, J.; Jenkinson, I.; Wang, J.; Xu, D.L.; Yang, J.B. A methodology to model causal relationships on offshore safety assessment focusing on human and organizational factors. *J. Saf. Res.* **2008**, *39*, 87–100. [CrossRef]

200. Wang, Y.F.; Roohi, S.F.; Hu, X.M.; Xie, M. Investigations of Human and Organizational Factors in hazardous vapor accidents. *J. Hazard. Mater.* **2011**, *191*, 69–82. [CrossRef]
201. Shieh, J.S.; Linkens, D.A.; Asbury, A.J. A hierarchical system of on-line advisory for monitoring and controlling the depth of anesthesia using self-organizing fuzzy logic. *Eng. Appl. Artif. Intell.* **2004**, *18*, 307–316. [CrossRef]
202. Xie, Y.; Lord, D.; Zhang, Y. Predicting motor vehicle collisions using Bayesian neural network models: An empirical analysis. *Accid. Anal. Prev.* **2007**, *39*, 922–933. [CrossRef]
203. Vagnoli, M.; Remenyte-Prescott, R.; Andrews, J. Railway bridge structural health monitoring and fault detection: State-of-the-art methods and future challenges. *Struct. Health Monit.* **2017**, *17*, 971–1007. [CrossRef]
204. Zywiec, W.J.; Mazzuchi, T.A.; Sarkani, S. Analysis of process criticality accident risk using a metamodel-driven Bayesian network. *Reliab. Eng. Syst. Saf.* **2020**, *207*, 107322. [CrossRef]
205. Martorell, S.; Sánchez, A.; Carlos, S.; Serradell, V. Simultaneous and multi-criteria optimization of TS requirements and maintenance at NPPs. *Ann. Nucl. Energy* **2002**, *29*, 147–168. [CrossRef]
206. Pan, L.; Qin, L.; Yang, S.X.; Shuai, J. A neural network-based method for risk factor analysis of West Nile Virus. *Risk Anal.* **2008**, *28*, 487–496. [CrossRef] [PubMed]
207. Wang, W.; Liu, X.; Qin, Y. A modified HEART method with FANP for human error assessment in high-speed railway dispatching tasks. *Int. J. Ind. Ergon.* **2018**, *67*, 242–258. [CrossRef]
208. Yu, J.; Li, Y. Intelligent optimization for support pressure zone algorithm based on fuzzy neural network damage identification. *EURASIP J. Wirel. Commun. Netw.* **2018**, *2018*, 139. [CrossRef]
209. Marseguerra, M.; Nutini, M.; Zio, E. Approximate physical modeling in dynamic PSA using artificial neural networks. *Reliab. Eng. Syst. Saf.* **1994**, *45*, 47–56. [CrossRef]
210. Rao, K.D.; Gopika, V.; Kushwaha, H.S.; Verma, A.K.; Srividya, A. Test interval optimization of safety systems of nuclear power plants using a fuzzy-genetic approach. *Reliab. Eng. Syst. Saf.* **2006**, *92*, 895–901.
211. Varde, P.V.; Sankar, S.; Verma, A.K. An operator support system for research reactor operations and fault diagnosis through a connectionist framework and PSA based knowledge based systems. *Reliab. Eng. Syst. Saf.* **1998**, *60*, 53–69. [CrossRef]
212. Kančev, D.; Gjorgiev, B.; Čepin, M. Optimization of test interval for ageing equipment: A multi-objective genetic algorithm approach. *J. Loss Prev. Process Ind.* **2011**, *24*, 397–404. [CrossRef]
213. Caputo, A.C.; Pelagagge, P.M.; Palumbo, M. Economic optimization of industrial safety measures using genetic algorithms. *J. Loss Prev. Process Ind.* **2011**, *24*, 541–551. [CrossRef]
214. Markowski, A.S.; Siuta, D. Selection of representative accident scenarios for major industrial accidents. *Process Saf. Environ. Prot.* **2017**, *111*, 652–662. [CrossRef]
215. Ratnayake, R.M.C. Application of a fuzzy inference system for functional failure risk rank estimation: RBM of rotating equipment and instrumentation. *J. Loss Prev. Process Ind.* **2014**, *29*, 216–224. [CrossRef]
216. Akay, D. Grey relational analysis based on instance-based learning approach for classification of risks of occupational low back disorders. *Saf. Sci.* **2011**, *49*, 1277–1282. [CrossRef]
217. Onken, R.; Feraric, J.P. Adaptation to the driver as part of a driver monitoring and warning system. *Accid. Anal. Prev.* **1997**, *29*, 507–513. [CrossRef]
218. Ung, S.; Shen, W. A Novel Human Error Probability Assessment Using Fuzzy Modeling. *Risk Anal.* **2010**, *31*, 745–757. [CrossRef]
219. Santosh, T.V.; Vinod, G.; Saraf, R.K.; Ghosh, A.K.; Kushwaha, H.S. Application of artificial neural networks to nuclear power plant transient diagnosis. *Reliab. Eng. Syst. Saf.* **2006**, *92*, 1468–1472. [CrossRef]
220. Wang, J.; Sii, H.S.; Yang, J.B.; Pillay, A.; Yu, D.; Liu, J.; Maistralis, E.; Saajedi, A. Use of advances in technology for maritime risk assessment. *Risk Anal.* **2004**, *24*, 1041–1063. [CrossRef]
221. Yaşlı, F.; Bolat, B. Evaluation of Occupational Safety Risk in Underground Mining Using Fuzzy Bayesian Network. In *Intelligent and Fuzzy Techniques: Smart and Innovative Solutions*; Advances in Intelligent Systems and Computing; Springer: Cham, Switzerland, 2020; pp. 1363–1372.
222. Eisenbeiß, W.; Marotz, J.; Schrade, J.P. Reflection-optical multispectral imaging method for objective determination of burn depth. *Burns* **1999**, *25*, 697–704. [CrossRef]
223. Rastogi, A.; Gabbar, H.A. Fuzzy-logic-based safety verification framework for nuclear power plants. *Risk Anal.* **2012**, *33*, 1128–1145. [CrossRef]
224. Purba, J.H.; Lu, J.; Zhang, G.; Pedrycz, W. A fuzzy reliability assessment of basic events of fault trees through qualitative data processing. *Fuzzy Sets Syst.* **2013**, *243*, 50–69. [CrossRef]
225. Busacca, P.G.; Marseguerra, M.; Zio, E. Multiobjective optimization by genetic algorithms: Application to safety systems. *Reliab. Eng. Syst. Saf.* **2001**, *72*, 59–74. [CrossRef]
226. Karwowski, W.; Mital, A. Potential applications of fuzzy sets in industrial safety engineering. *Fuzzy Sets Syst.* **1986**, *19*, 105–120. [CrossRef]
227. Dubois, D.; Prade, H. Epistemic entrenchment and possibilistic logic. *Artif. Intell.* **1991**, *50*, 223–239. [CrossRef]

228. Xing, L.; Okrent, D. The use of neural networks and a prototype expert system in BWR ATWS accidents diagnosis. *Reliab. Eng. Syst. Saf.* **1994**, *44*, 361–372. [CrossRef]
229. Bertke, S.J.; Meyers, A.R.; Wurzelbacher, S.J.; Bell, J.; Lampl, M.L.; Robins, D. Development and evaluation of a Naïve Bayesian model for coding causation of workers' compensation claims. *J. Saf. Res.* **2012**, *43*, 327–332. [CrossRef] [PubMed]
230. Peng, J. Credibilistic Value and Average Value at Risk in Fuzzy Risk Analysis. *Fuzzy Inf. Eng.* **2011**, *3*, 69–79. [CrossRef]
231. Yu, R.; Abdel-Aty, M. Utilizing support vector machine in real-time crash risk evaluation. *Accid. Anal. Prev.* **2012**, *51*, 252–259. [CrossRef]
232. Dağdeviren, M.; Eraslan, E.; Çelebi, F.V. An alternative work measurement method and its application to a manufacturing industry. *J. Loss Prev. Process Ind.* **2010**, *24*, 563–567. [CrossRef]
233. Neumann, J.; Deerberg, G.; Schlüter, S. Early detection and identification of dangerous states in chemical plants using neural networks. *J. Loss Prev. Process Ind.* **1999**, *12*, 451–453. [CrossRef]
234. Ibrahim, H.D.; Odedele, T.O. Prediction of toxicity effects of oil field chemicals using adaptive genetic neuro-fuzzy inference systems. In Proceedings of the SPE Western Regional Meeting, Garden Grove, CA, USA, 22–26 April 2018; p. D051S014R009.
235. Sowgath, M.T.; Ahmed, S. Fault detection of Brahmanbaria Gas Plant using neural network. In Proceedings of the 8th International Conference on Electrical and Computer Engineering, Dhaka, Bangladesh, 20–22 December 2014; pp. 733–736.
236. Marseguerra, M.; Ricotti, M.; Zio, E. Approaching system evolution in dynamic PSA by neural networks. *Reliab. Eng. Syst. Saf.* **1995**, *49*, 91–99. [CrossRef]
237. Caputo, A.C.; Pelagagge, P.M. An inverse approach for piping networks monitoring. *J. Loss Prev. Process Ind.* **2002**, *15*, 497–505. [CrossRef]
238. Bajpai, S.; Sachdeva, A.; Gupta, J.P. Security risk assessment: Applying the concepts of fuzzy logic. *J. Hazard. Mater.* **2009**, *173*, 258–264. [CrossRef] [PubMed]
239. Renjith, V.R.; GMadhu, N.; Nayagam, V.L.G.; Bhasi, A.B. Two-dimensional fuzzy fault tree analysis for chlorine release from a chlor-alkali industry using expert elicitation. *J. Hazard Mater.* **2010**, *183*, 103–110. [CrossRef] [PubMed]
240. Acuner, O.; Cebi, S. An effective risk-preventive model proposal for occupational accidents at shipyards. *Brodogr. Int. J. Nav. Archit. Ocean. Eng. Res. Dev.* **2016**, *67*, 67–84.
241. Abou, S.C. Fuzzy-logic-based network for complex systems risk assessment: Application to ship performance analysis. *Accid. Anal. Prev.* **2011**, *45*, 305–316. [CrossRef]
242. Mokhtari, K.; Ren, J.; Roberts, C.; Wang, J. Application of a generic bow-tie based risk analysis framework on risk management of sea ports and offshore terminals. *J. Hazard. Mater.* **2011**, *192*, 465–475. [CrossRef]
243. Dabrowski, D. Condition monitoring of planetary gearbox by hardware implementation of artificial neural networks. *Measurement* **2016**, *91*, 295–308. [CrossRef]
244. Serrano, C.; Acha, B.; Gómez-Cía, T.; Acha, J.I.; Roa, L.M. A computer-assisted diagnosis tool for the classification of burns by depth of injury. *Burns* **2005**, *31*, 275–281. [CrossRef]
245. Shew, C.; Pande, A.; Nuworsoo, C. Transferability and robustness of real-time freeway crash risk assessment. *J. Saf. Res.* **2013**, *46*, 83–90. [CrossRef]
246. Chang, W.L.; Pang, L.M.; Tay, K.M. Application of self-organizing map to failure modes and effects analysis methodology. *Neurocomputing* **2017**, *249*, 314–320. [CrossRef]
247. Mussone, L.; Ferrari, A.; Oneta, M. An analysis of urban collisions using an artificial intelligence model. *Accid. Anal. Prev.* **1999**, *31*, 705–718. [CrossRef]
248. Chung, S.H.; Lam, H.M.A.; Chan, H.K. Cascading delay risk of airline workforce deployments with crew pairing and schedule optimization. *Risk Anal.* **2016**, *37*, 1443–1458. [CrossRef] [PubMed]
249. Deng, Y.; Sadiq, R.; Jiang, W.; Tesfamariam, S. Risk analysis in a linguistic environment: A fuzzy evidential reasoning-based approach. *Expert Syst. Appl.* **2011**, *38*, 15438–15446. [CrossRef]
250. Zhang, Y.; Xie, Y.; Li, L. Crash frequency analysis of different types of urban roadway segments using generalized additive model. *J. Saf. Res.* **2012**, *43*, 107–114. [CrossRef]
251. Golabchi, A.; Han, S.; Fayek, A.R. A fuzzy logic approach to posture-based ergonomic analysis for field observation and assessment of construction manual operations. *Can. J. Civ. Eng.* **2016**, *43*, 294–303. [CrossRef]
252. Wu, H.; Wu, D.; Zhao, J. An intelligent fire detection approach through cameras based on computer vision methods. *Process Saf. Environ. Prot.* **2019**, *127*, 245–256. [CrossRef]
253. Ung, S.T.; Williams, V.; Bonsall, S.; Wang, J. Test case based risk predictions using artificial neural networks. *J. Saf. Res.* **2006**, *37*, 245–260. [CrossRef]
254. Nara, E.O.B.; Sordi, D.C.; Schaefer, J.L.; Schreiber, J.N.C.; Baierle, I.C.; Sellitto, M.A.; Furtado, J.C. Prioritization of OHS key performance indicators that affect business competitiveness—A demonstration based on MAUT and neural networks. *Saf. Sci.* **2019**, *118*, 826–834. [CrossRef]

255. Zhan, J.; Sun, B.; Alcantud, J.C.R. Covering-based multigranulation (I,T)-fuzzy rough set models and applications in multi-attribute group decision-making. *Inf. Sci.* **2018**, *476*, 290–318. [CrossRef]
256. Martorell, S.; Villanueva, J.; Carlos, S.; Nebot, Y.; Sánchez, A.; Pitarch, J.; Serradell, V. RAMS+C informed decision-making with application to multi-objective optimization of technical specifications and maintenance using genetic algorithms. *Reliab. Eng. Syst. Saf.* **2004**, *87*, 65–75. [CrossRef]
257. Pacheco, R.R.; Fernandes, E.; Domingos, E.M. Airport airside safety index. *J. Air Transp. Manag.* **2013**, *34*, 86–92. [CrossRef]
258. Kazantzi, V.; Kazantzis, N.; Gerogiannis, V.C. Risk-informed optimization of a hazardous material multi-periodic transportation model. *J. Loss Prev. Process Ind.* **2011**, *24*, 767–773. [CrossRef]
259. Benkouider, A.M.; Kessas, R.; Yahiaoui, A.; Buvat, J.C.; Guella, S. A hybrid approach to faults detection and diagnosis in batch and semi-batch reactors using EKF and neural network classifier. *J. Loss Prev. Process Ind.* **2012**, *25*, 694–702. [CrossRef]
260. Delen, D.; Sharda, R.; Bessonov, M. Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks. *Accid. Anal. Prev.* **2005**, *38*, 434–444. [CrossRef] [PubMed]
261. Guo, L.; Gao, J.; Yang, J.; Kang, J. Criticality evaluation of petrochemical equipment based on fuzzy comprehensive evaluation and a BP neural network. *J. Loss Prev. Process Ind.* **2009**, *22*, 469–476. [CrossRef]
262. Chiou, Y.C.; Lan, L.W.; Chen, W.P. A two-stage mining framework to explore key risk conditions on one-vehicle crash severity. *Accid. Anal. Prev.* **2012**, *50*, 405–415. [CrossRef]
263. Buddhavarapu, P.; Banerjee, A.; Prozzi, J.A. Influence of pavement condition on horizontal curve safety. *Accid. Anal. Prev.* **2013**, *52*, 9–18. [CrossRef]
264. Deka, L.; Quddus, M. Network-level accident-mapping: Distance-based pattern matching using artificial neural network. *Accid. Anal. Prev.* **2013**, *65*, 105–113. [CrossRef]
265. Mullai, A.; Paulsson, U. A grounded theory model for analysis of marine accidents. *Accid. Anal. Prev.* **2011**, *43*, 1590–1603. [CrossRef]
266. Chaher, Z.; Benseghir, H.; Ibrahim, A.; Kabir, M.N. A fuzzy-based risk model for construction project management. In Proceedings of the 2018 IEEE Conference on Systems, Process and Control (ICSPC), Melaka, Malaysia, 14–15 December 2018; pp. 129–134.
267. Cárdenas, I.C.; Al-jibouri, S.S.H.; Halman, J.I.M.; Van Tol, F.A. Capturing and integrating knowledge for managing risks in tunnel works. *Risk Anal.* **2012**, *33*, 92–108. [CrossRef]
268. Goh, K.C.K.; Currie, G.; Sarvi, M.; Logan, D. Bus accident analysis of routes with/without bus priority. *Accid. Anal. Prev.* **2013**, *65*, 18–27. [CrossRef]
269. Pinto, A.; Ribeiro, R.A.; Nunes, I.L. Fuzzy approach for reducing subjectivity in estimating occupational accident severity. *Accid. Anal. Prev.* **2011**, *45*, 281–290. [CrossRef] [PubMed]
270. Chen, Y.; Shu, L.; Burbey, T.J. An integrated risk assessment model of township-scaled land subsidence based on an evidential reasoning algorithm and fuzzy set theory. *Risk Anal.* **2014**, *34*, 656–669. [CrossRef] [PubMed]
271. Chen, S.M. Fuzzy group decision making for evaluating the rate of aggregative risk in software development. *Fuzzy Sets Syst.* **2001**, *118*, 75–88. [CrossRef]
272. Abduljabbar, R.; Dia, H.; Liyanage, S.; Bagloee, S.A. Applications of artificial intelligence in transport: An overview. *Sustainability* **2019**, *11*, 189. [CrossRef]
273. Bonano, E.J.; Apostolakis, G.E.; Salter, P.F.; Ghassemi, A.; Jennings, S. Application of risk assessment and decision analysis to the evaluation, ranking, and selection of environmental remediation alternatives. *J. Hazard. Mater.* **2000**, *71*, 35–57. [CrossRef]
274. Jamshidi, A.; Yazdani-Chamzini, A.; Yakhchali, S.H.; Khaleghi, S. Developing a new fuzzy inference system for pipeline risk assessment. *J. Loss Prev. Process Ind.* **2012**, *26*, 197–208. [CrossRef]
275. Huang, Y.; Bao, Y.; Wang, Y. Analysis of geoenvironmental hazards in urban underground space development in Shanghai. *Nat. Hazards* **2014**, *75*, 2067–2079. [CrossRef]
276. Ma, D.; Bai, H.; Wang, Y. Mechanical behavior of a coal seam penetrated by a karst collapse pillar: Mining-induced groundwater inrush risk. *Nat. Hazards* **2014**, *75*, 2137–2151. [CrossRef]
277. Karimi, I.; Hüllermeier, E. Risk assessment system of natural hazards: A new approach based on fuzzy probability. *Fuzzy Sets Syst.* **2006**, *158*, 987–999. [CrossRef]
278. Kuzu, A.C. Application of fuzzy DEMATEL approach in maritime transportation: A risk analysis of anchor loss. *Ocean Eng.* **2023**, *273*, 113786. [CrossRef]
279. Zio, E.; Baraldi, P.; Popescu, I.C. A fuzzy decision tree for fault classification. *Risk Anal.* **2008**, *28*, 49–67. [CrossRef] [PubMed]
280. Wang, Z.; Wang, R.; Deng, W.; Zhao, Y. An Integrated Approach-Based FMECA for Risk Assessment: Application to Offshore Wind Turbine Pitch System. *Energies* **2022**, *15*, 1858. [CrossRef]
281. Langeron, Y.; Barros, A.; Grall, A.; Bérenguer, C. Dependability assessment of network-based safety-related systems. *J. Loss Prev. Process Ind.* **2011**, *24*, 622–631. [CrossRef]

282. Özcan, E.; Danışan, T.; Yumuşak, R.; Eren, T. An Artificial Neural Network Model Supported with Multi-Criteria Decision-Making Approaches for Maintenance Planning in Hydroelectric Power Plants. *Eksploat. Niezawodn.—Maint. Reliab.* **2020**, *22*, 400–418. [CrossRef]
283. Wei, C.H.; Lee, Y. Sequential forecast of incident duration using artificial neural network models. *Accid. Anal. Prev.* **2007**, *39*, 944–954. [CrossRef]
284. Koivisto, R.; Kakko, R.; Dohnal, M.; Järveläinen, M. Accidental release. *J. Loss Prev. Process Ind.* **1991**, *4*, 317–331. [CrossRef]
285. Bersini, U.; Cacciabue, P.C.; Mancini, G. Cognitive modeling: A basic complement of human reliability analysis. *Reliab. Eng. Syst. Saf.* **1988**, *22*, 107–128. [CrossRef]
286. Helton, J.C.; Oberkampf, W.L.; Johnson, J.D. Competing failure risk analysis using evidence theory. *Risk Anal.* **2005**, *25*, 973–995. [CrossRef]
287. Hacibektasoglu, S.E.; Mertoglu, B.; Tozan, H. Application of a novel hybrid f-SC risk analysis method in the paint industry. *Sustainability* **2021**, *13*, 13605. [CrossRef]
288. Murè, S.; Comberti, L.; Demichela, M. How harsh work environments affect the occupational accident phenomenology? Risk assessment and decision making optimisation. *Saf. Sci.* **2017**, *95*, 159–170. [CrossRef]
289. Li, Z.; Liu, P.; Wang, W.; Xu, C. Using support vector machine models for crash injury severity analysis. *Accid. Anal. Prev.* **2011**, *45*, 478–486. [CrossRef] [PubMed]
290. Dubois, D.; Prade, H. Random sets and fuzzy interval analysis. *Fuzzy Sets Syst.* **1991**, *42*, 87–101. [CrossRef]
291. Wang, J.; Gu, X.; Huang, T. Using Bayesian networks in analyzing powerful earthquake disaster chains. *Nat. Hazards* **2013**, *68*, 509–527. [CrossRef]
292. Naderpour, M.; Lu, J.; Zhang, G. A situation risk awareness approach for process systems safety. *Saf. Sci.* **2014**, *64*, 173–189. [CrossRef]
293. Hsu, W.-K.; Chiang, W.-L.; Xue, Q.; Hung, D.-M.; Huang, P.-C.; Chen, C.-W.; Tsai, C.-H. A probabilistic approach for earthquake risk assessment based on an engineering insurance portfolio. *Nat. Hazards* **2012**, *65*, 1559–1571. [CrossRef]
294. Dubois, D. The role of fuzzy sets in decision sciences: Old techniques and new directions. *Fuzzy Sets Syst.* **2011**, *184*, 3–28. [CrossRef]
295. Azadeh, A.; Rouzbahman, M.; Saberi, M.; Valianpour, F. An adaptive algorithm for assessment of operators with job security and HSEE indicators. *J. Loss Prev. Process Ind.* **2014**, *31*, 26–40. [CrossRef]
296. Kaya, B.Y.; Dağdeviren, M. Selecting occupational safety equipment by MCDM approach considering universal design principles. *Hum. Factors Ergon. Manuf. Serv. Ind.* **2015**, *26*, 224–242. [CrossRef]
297. Lapa, C.M.F.; Pereira, C.M.N.A.; Melo, P.F.F.E. Surveillance test policy optimization through genetic algorithms using non-periodic intervention frequencies and considering seasonal constraints. *Reliab. Eng. Syst. Saf.* **2003**, *81*, 103–109. [CrossRef]
298. Wang, J.; Yang, J.B.; Sen, P. Safety analysis and synthesis using fuzzy sets and evidential reasoning. *Reliab. Eng. Syst. Saf.* **1995**, *47*, 103–118. [CrossRef]
299. Wang, J.; Han, S.; Li, X. 3D fuzzy ergonomic analysis for rapid workplace design and modification in construction. *Autom. Constr.* **2020**, *123*, 103521. [CrossRef]
300. Tepe, S.; Kaya, İ. A fuzzy-based risk assessment model for evaluations of hazards with a real-case study. *Hum. Ecol. Risk Assess. Int. J.* **2019**, *26*, 512–537. [CrossRef]
301. Cinar, U.; Cebi, S. A hybrid risk assessment method for mining sector based on QFD, fuzzy logic, and AHP. In *Intelligent and Fuzzy Techniques in Big Data Analytics and Decision Making: Proceedings of the INFUS 2019 Conference, Istanbul, Turkey, 23–25 July 2019*; Springer International Publishing: Cham, Switzerland, 2020; pp. 1198–1207.
302. Labeau, P.E.; Smidts, C.; Swaminathan, S. Dynamic reliability: Towards an integrated platform for probabilistic risk assessment. *Reliab. Eng. Syst. Saf.* **2000**, *68*, 219–254. [CrossRef]
303. Cai, B.; Liu, Y.; Liu, Z.; Tian, X.; Zhang, Y.; Ji, R. Application of Bayesian networks in quantitative risk assessment of subsea blowout preventer operations. *Risk Anal.* **2012**, *33*, 1293–1311. [CrossRef]
304. Liu, H.C.; Fan, X.J.; Li, P.; Chen, Y.Z. Evaluating the risk of failure modes with extended MULTIMOORA method under fuzzy environment. *Eng. Appl. Artif. Intell.* **2014**, *34*, 168–177. [CrossRef]
305. Azadeh, A.; Farmand, A.H.; Sharahi, Z.J. Performance assessment and optimization of HSE management systems with human error and ambiguity by an integrated fuzzy multivariate approach in a large conventional power plant manufacturer. *J. Loss Prev. Process Ind.* **2012**, *25*, 594–603. [CrossRef]
306. Paltrinieri, N.; Comfort, L.; Reniers, G. Learning about risk: Machine learning for risk assessment. *Saf. Sci.* **2019**, *118*, 475–486. [CrossRef]
307. Lapa, C.M.F.; Pereira, C.M.N.A.; De Barros, M.P. A model for preventive maintenance planning by genetic algorithms based on cost and reliability. *Reliab. Eng. Syst. Saf.* **2005**, *91*, 233–240. [CrossRef]
308. Podofillini, L.; Dang, V.; Zio, E.; Baraldi, P.; Librizzi, M. Using expert models in human reliability analysis: A dependence assessment method based on fuzzy logic. *Risk Anal.* **2010**, *30*, 1277–1297. [CrossRef]

309. Zhang, Y.; Yang, N. Development of a mitigation strategy against the cascading propagation of risk in R&D network. *Saf. Sci.* **2014**, *68*, 161–168.
310. Weng, J.; Meng, Q. Analysis of driver casualty risk for different work zone types. *Accid. Anal. Prev.* **2011**, *43*, 1811–1817. [CrossRef] [PubMed]
311. Bani-Ahmad, S.; Sa'adeh, S. Scalability of the DVFS power management technique as applied to 3-tier data center architecture in cloud computing. *J. Comput. Commun.* **2017**, *5*, 69–93. [CrossRef]
312. Gul, M.; Guneri, A.F. A fuzzy multi-criteria risk assessment based on decision matrix technique: A case study for aluminum industry. *J. Loss Prev. Process Ind.* **2015**, *40*, 89–100. [CrossRef]
313. Aqlan, F.; Ali, E.M. Integrating lean principles and fuzzy bow-tie analysis for risk assessment in chemical industry. *J. Loss Prev. Process Ind.* **2014**, *29*, 39–48. [CrossRef]
314. Lee, H.M. Group decision making using fuzzy sets theory for evaluating the rate of aggregative risk in software development. *Fuzzy Sets Syst.* **1996**, *80*, 261–271. [CrossRef]
315. Mohsen, O.; Fereshteh, N. An extended VIKOR method based on entropy measure for the failure modes risk assessment—A case study of the geothermal power plant (GPP). *Saf. Sci.* **2016**, *92*, 160–172. [CrossRef]
316. Abdel-Aty, M.; Pande, A. Identifying crash propensity using specific traffic speed conditions. *J. Saf. Res.* **2005**, *36*, 97–108. [CrossRef]
317. Rusli, R.; Shariff, A.M. Qualitative assessment for inherently safer design (QAISD) at preliminary design stage. *J. Loss Prev. Process Ind.* **2009**, *23*, 157–165. [CrossRef]
318. Marhavilas, P.K.; Koulouriotis, D.E.; Mitrakas, C. On the Development of a New Hybrid Risk Assessment Process Using Occupational Accidents' Data: Application on the Greek Public Electric Power Provider. *J. Loss Prev. Process Ind.* **2011**, *24*, 671–687. [CrossRef]

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