

Article

Deterministic and Probabilistic Risk Management Approaches in Construction Projects: A Systematic Literature Review and Comparative Analysis

Ania Khodabakhshian ¹, Taija Puolitaival ²  and Linda Kestle ^{3,*}

¹ Department of Architecture, Built Environment and Construction Engineering, Politecnico di Milano, Via Ponzio, 31, 20133 Milan, Italy; ania.khodabakhshian@polimi.it

² Faculty of Built Environment, Tampere University, FI-33014 Tampere, Finland; taija.puolitaival@tuni.fi

³ School of Building Construction, Unitec Institute of Technology, P.O. Box 92025, Auckland 1142, New Zealand

* Correspondence: lkestle@unitec.ac.nz

Abstract: Risks and uncertainties are inevitable in construction projects and can drastically change the expected outcome, negatively impacting the project's success. However, risk management (RM) is still conducted in a manual, largely ineffective, and experience-based fashion, hindering automation and knowledge transfer in projects. The construction industry is benefitting from the recent Industry 4.0 revolution and the advancements in data science branches, such as artificial intelligence (AI), for the digitalization and optimization of processes. Data-driven methods, e.g., AI and machine learning algorithms, Bayesian inference, and fuzzy logic, are being widely explored as possible solutions to RM domain shortcomings. These methods use deterministic or probabilistic risk reasoning approaches, the first of which proposes a fixed predicted value, and the latter embraces the notion of uncertainty, causal dependencies, and inferences between variables affecting projects' risk in the predicted value. This research used a systematic literature review method with the objective of investigating and comparatively analyzing the main deterministic and probabilistic methods applied to construction RM in respect of scope, primary applications, advantages, disadvantages, limitations, and proven accuracy. The findings established recommendations for optimum AI-based frameworks for different management levels—enterprise, project, and operational—for large or small data sets.

Keywords: artificial intelligence; construction industry; machine learning algorithms; project management; risk management



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1. Introduction

The construction industry has some of the highest accident and fatality rates, delays, and cost overruns, which are caused primarily by uncontrolled risks. Risks occur at various levels, operational, project, portfolio, strategic, and business and enterprise levels, derived from external and internal factors, and can be: (a) a field-based risk, including financial, market, operational, political, reputational, and disaster risks, or (b) a property-based risk, including uncertainty, dynamics, interconnection and dependence, and complexity [1]. Risk management (RM), as depicted in best practices and project management standards, tends to be a proactive approach consisting of risk identification, analysis and assessment, mitigation planning, and control stages [2] to exploit or enhance positive risks (opportunities) while avoiding or mitigating negative risks (threats) and to ensure the project's success, to meet the project's objectives and constraints, and to secure the project's safety. However, it is still conducted in a manual, time-consuming, superficial, and ineffective manner. Risk identification and assessment, in their conventional ways, are conducted based on individual and experience-based expert judgments and seem highly personalized and context-dependent [3]. Therefore, knowledge transfer and model generalization remain critical issues for future projects.

On the other hand, the construction industry is experiencing a digitalization revolution thanks to the abundant production of data and the development of digital tools and data-driven decision-support systems such as artificial intelligence (AI), digital twins, and the Internet of Things (IoT). These technologies prepare the technical foundation for an intelligent and ever-improving construction industry. AI is one of the key pillars of the Industry 4.0 revolution and digitalization era, to create an active connection between the physical and digital worlds. It includes the science and engineering techniques that aim to make machines mimic human cognitive processes of learning, reasoning, perception, planning, and self-correcting [4]. AI is gaining vast applications for fostering, optimizing, and automating processes throughout the entire construction project life cycle for the “intelligent management” of projects.

AI models can improve analytical capabilities across the RM domain whilst offering a high granularity and depth of predictive analysis [5]. However, through its vital role in securing the project’s success and ability to solve the shortcomings of traditional RM methods, AI applications in construction RM have been limited and behind other industries. Robust AI-based RM frameworks are missing [6]. This study aims to analyze the AI algorithms and models from the risk reasoning and judgment point of view, for a functional classification addressable by practitioners and researchers in the field. This is a novel way of grouping the widespread AI algorithms’ applications in the construction industry. Unlike previous studies where the AI algorithm’s structure was the focus of analysis [7–11], this study bases the analysis and comparison of AI algorithms on the risk assessment statistical models and reasoning approaches that they utilize.

2. Background

Construction engineering and management are going through constant innovations toward digitalization and intelligence in the context of “Industry 4.0” [6]. AI is receiving increased attention due to its ability to provide increasingly accurate results in uncertain, dynamic, and complex environments [12], such as the construction industry. Having the intent of boosting labor efficiency by 40%, and doubling annual economic growth rates by 2035 [13], AI is becoming the focus for companies. The construction industry is experiencing a considerable boost in automation, productivity, and reliability and is reshaping itself along the whole life cycle of projects, including planning, construction, operation, and maintenance [10].

The advancement of AI and digital technologies can significantly change conventional risk assessment and management methods, making them factual, efficient, generalizable, and able to be performed in real time [6]. However, RM is a lesser studied and progressed domain in construction projects due to the complex and probabilistic nature of assessments, inferences, and the direct influence of RM on other knowledge areas such as stakeholders management [14]. The key reasons are (a) lack of structured data and infrequent documentation in the projects, (b) over-reliance on individual and experience-based judgement by experts in RM, (c) isolated risk analysis and ignorance of the causal inferences between variables in risk path analysis, and (d) incorrect choice of the AI model for a given problem, regarding data availability and requirements, the role of probability, expert judgement, and the reasoning behind the analysis [6,15].

AI is a vast umbrella term that includes various technologies, applications, types, and subfields. Based on a categorization provided by Abioye et al. [16], these subcategories are (a) machine learning, (b) knowledge-based systems, (c) computer vision, (d) robotics, (e) Natural Language Processing, (f) automated planning and scheduling, and (g) optimization. Machine learning (ML) algorithms can draw on extensive real-time data generated by cutting-edge technologies such as the Internet of Things (IoT), sensors, Cyber-Physical Systems (CPS), cloud computing, Big Data Analytics (BDA), text mining, and Information and Communication Technologies (ICT) for more reliable and smart management and decision making in construction projects [4]. This data, if transformed into a structured and understandable form, can serve as the basis of further data-driven analysis, which brings

valuable insights for knowledge management in projects and economical and societal development in the industry [17]. ML processes take place based on historical data records, in which the machine tries to recognize the relationships between input data and output data by constant weighting and correction [16]. ML algorithms can analyze large volumes of data to extract insights from previous data, recognize the data pattern, generalize the rules, and make a prediction for upcoming data entries in complicated, non-linear, and uncertain problems [18]. Figure 1 presents the key pillars of the Industry 4.0 revolution in the construction industry.

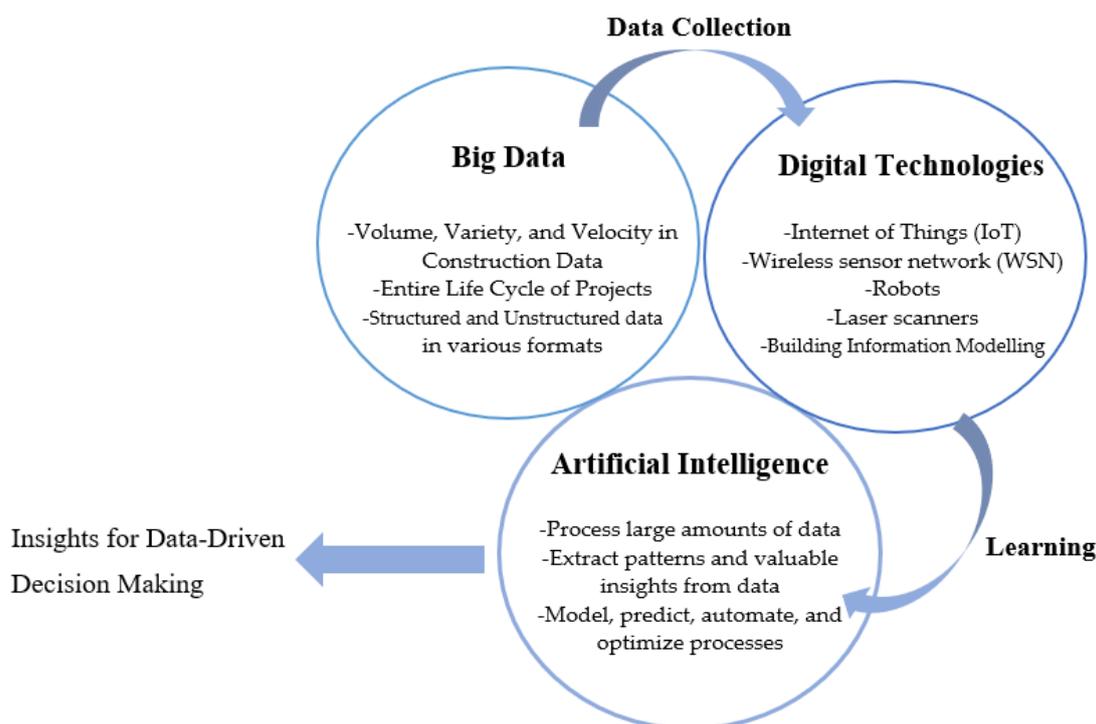


Figure 1. Pillars of Industry 4.0 Revolution in the Construction Industry [7,8,10,16,17,19].

AI-based RM systems can function as (a) early warning systems for risk control, (b) AI-based risk analysis systems, using algorithms such as neural networks for identifying complex data patterns, (c) risk-informed decision support systems for predicting various outcomes and scenarios of the decisions, (d) game-theory-based risk analysis systems, (e) data mining systems for large data sets, (f) agent-based RM systems for supply chain management risks, (g) engineering risk analysis systems based on optimization tools, and (h) knowledge management systems by integrating decision support systems, AI, and expert systems, to capture the tacit knowledge within organizations' computer systems [1].

As depicted in Figure 2, an AI-based RM system aims to (a) mine and analyze real-time project data, historical records, or elicited experts' opinions [20], (b) conduct automatic identification, evaluation, and assessment of risks, (c) conduct proactive decision making on responses to mitigate these risks, and (d) share these insights and predictions in a collaborative environment of data integration, such as Cloud Building Information Modelling (BIM), and digital twin platforms [10]. This research focuses specifically on the AI-based analytical models for risk assessment and management and aims to study the relevant aspects of a successful AI model, i.e., input data requirements, model structure and reasoning, application and scope, et cetera.

Most of the data-driven methods, such as ML algorithms, require a significant amount of data in a structured format to draw information from and make a prediction for future projects [21]. However, risk data are usually not frequently registered or updated in project documents. The data are often presented as unstructured text or in image formats, have missing values and scarcity problems, and are affected by different individual perceptions.

As there are a variety of risk types, individual experts might not have encountered, nor have sufficient knowledge on, all of them. Human-based risk analysis systems tend to suffer from low accuracy, incomplete risk identification, and inconsistent risk breakdown structures [22]. Therefore, AI-based methods for data structuralizing and pre-processing are required, such as Natural Language Processing for text mining, Generative Adversarial Networks (GANs) for synthetic data production, and clustering and classification methods such as Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) [23–26].

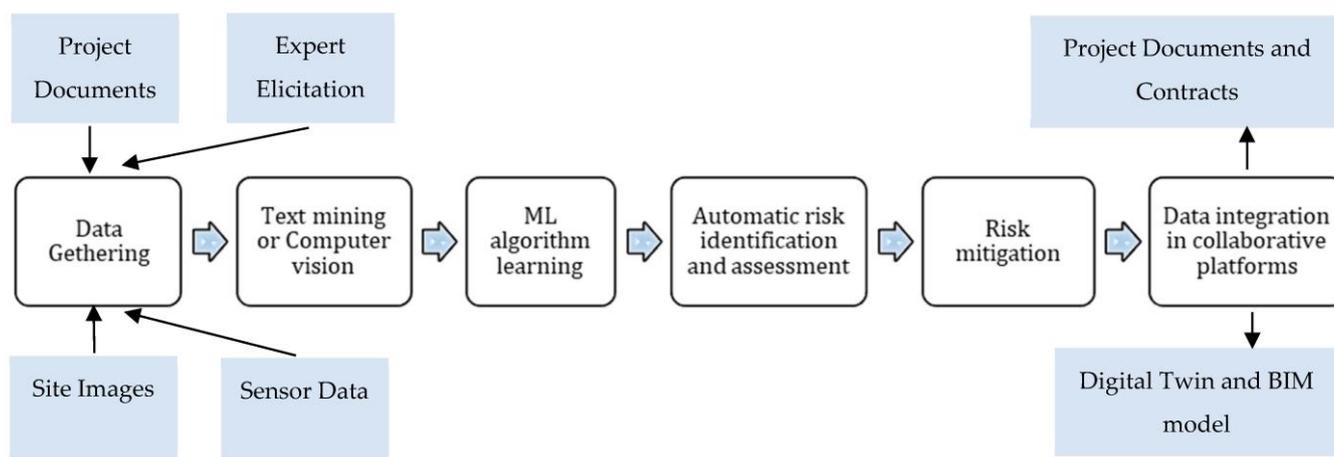


Figure 2. AI-based risk management framework [20,27,28].

ML algorithms' structures, processing formats, and the role of probability in the process are important issues to consider. Probability theory has been studied via various models within the past few decades, such as Gaussian models, Pareto distributions, stochastic process theory, Markov processes, and Monte Carlo simulations [1]. However, an important factor that is missing in many of the previous techniques is the isolated analysis of risks [14] and there is ignorance of the causal interrelations and correlations among risk factors. The assessment of the individual risk factor's magnitude, regardless of the occurrence, the probability of the risk events chain, and the effects each risk cause to the others, may result in an underestimation of the overall project risk level. Some previous studies have focused on the concept of risk paths and scenario analysis, rather than individual risk factors, which is a more accurate and realistic delineation [29].

The same concept is also applicable to the ML algorithms' structures and processing formats. ML algorithms can generally conduct deterministic or probabilistic analyses which are grouped under deterministic or probabilistic approaches. Deterministic models follow a frequentist statistic and provide a fixed prediction amount, simply based on historical data and the effects of input variables on the output. Therefore, they require high volumes of data to base the judgements on [10]. The probabilistic approaches mainly follow a Bayesian statistic and base judgement on multiple sources, such as experts' opinion, model simulation, and historical records [30–34]. Moreover, they provide a probability distribution of possible outcomes, considering the interrelation and causal inferences of input variables on each other. Therefore, they do not need a big database to draw from, and can update the probability distribution based on new observations or sources of judgement [35]. The first step, therefore, is to create a statistical analysis model, identify the problem to solve, and then decide which statistical approach to use, as improper choice of the statistical approach can result in the wrong influence of priors and variables, the wrong interpretation of results, and an improper reporting of results.

The same judgment-based and distribution-based grouping exists in conventional and non-AI-based RM methods, classifying them into deterministic and stochastic (probabilistic) models [36]. Deterministic models, such as the Probability–Impact matrix [37] or Pareto analysis [38], predict a fixed value and mostly follow a frequentist statistic. On the other

hand, the stochastic models represent the random behavior of risk factors through various types of distributions that emerge from data (frequentist) or expert opinion (Bayesian) and provide a probability distribution of each outcome. For instance, the Monte Carlo method runs multiple simulations on the model to reach a frequentist distribution of possible outcomes with an objective and data-based judgment [36], or Program Evaluation Review Technique (PERT) is a probabilistic method based on the assumption that the duration of a single activity can be described by a probability density function [39]. However, a main difference between these methods and AI-based algorithms is that they predict outcomes based on some rules, distributions, and formulas set by the model, whereas AI algorithms learn these rules by observing many samples of input and output data and detecting the patterns between them. Therefore, the processing process and structure are not comparable to the ML algorithms.

This research aims to address the above-mentioned issue through a thorough study of ML algorithms applied in the construction RM domain, which can have either a deterministic (frequentist inference) or probabilistic (Bayesian inference) approach. A systematic literature review and comparative analysis between AI models for RM domain was conducted to answer the following questions:

- (a) In which capacities, and through the application of which algorithms, can the RM domain benefit from AI?
- (b) What are the entry data requirements for each algorithm? In the case of data scarcity and uncertainty, which algorithms are the most applicable?
- (c) What are the advantages, disadvantages, applications, scope, prediction accuracy, and limitations of probabilistic and deterministic AI-based RM approaches?

3. Research Methodology

This research used a systematic literature review approach with various analysis methods to answer the research questions. The systematic literature review has a comprehensive, structured, reproducible, transparent, and quantitative nature [40]. There are also some disadvantages such as potential biases in the search. These have been minimized by following a systematic process throughout [40]. As topics and domains related to the scope of this research are numerous, the systematic literature review approach helped locate the most relevant inter-disciplinary publications, extract knowledge areas, and categorize their applied AI techniques, after some filtering. The publication search was conducted in Scopus and Web of Science libraries in July 2022, as the result of a preliminary search. These sources provided relevant publications for the research theme. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were used as required by the *Buildings* journal author guidelines, to conduct the systematic literature review, consisting of a 27-item checklist, and a 4-phase flow diagram consisting of (a) identification, (b) screening, (c) eligibility, and (d) inclusion for review. Following PRISMA provides a systematic structure for the review process and allows better and unbiased comparisons of findings, strengths, and weaknesses.

Figure 3, which was created based on the PRISMA guidelines, presents the literature search scheme, including the four phases which are further elaborated in the following paragraphs. The findings serve as the source papers to identify and classify AI algorithms for RM. The algorithms are classified into two groups of probabilistic and deterministic approaches. These are based on their analytical reasoning, input data requirements, and level of intaking uncertainty, and helped shape an important component of the AI-based RM framework in Figure 2.

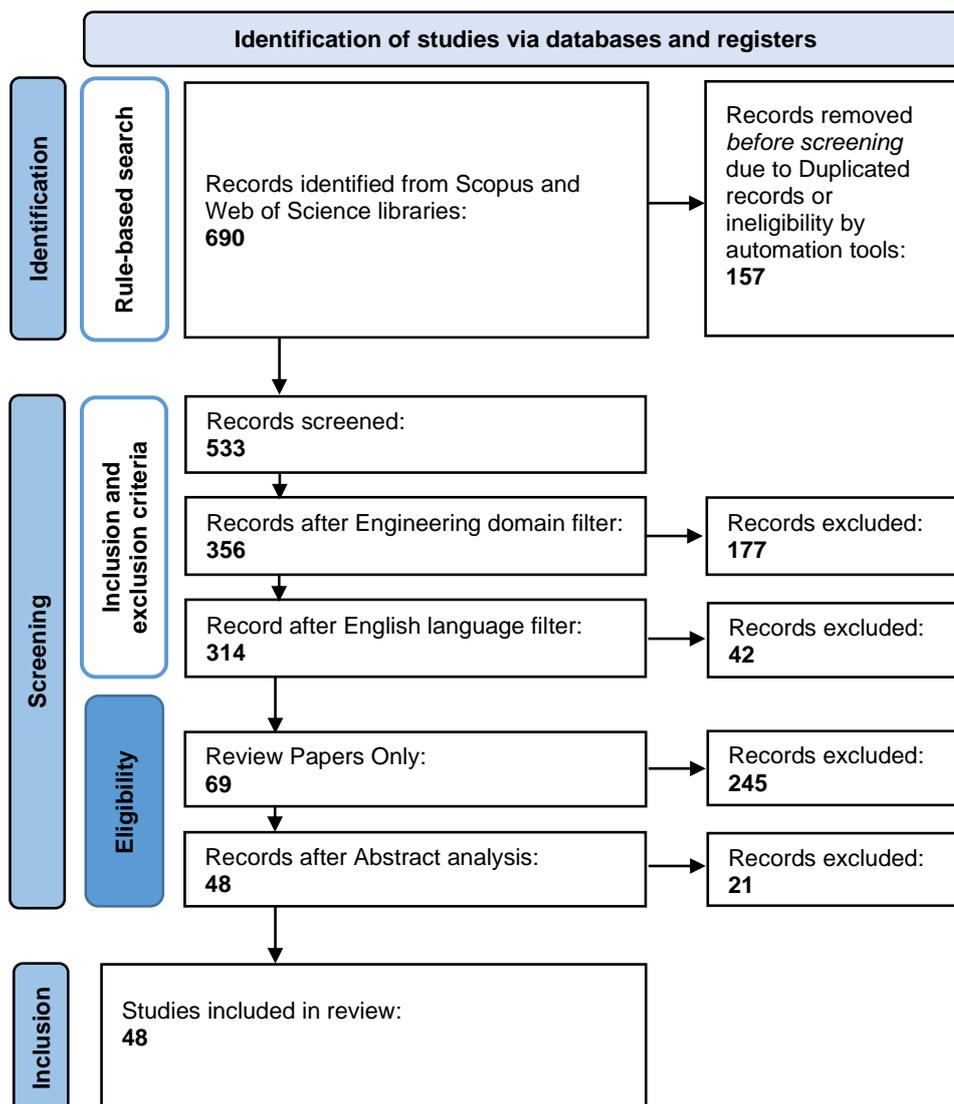


Figure 3. Systematic literature review flowchart based on PRISMA.

In the identification phase (Figure 3), the search rule in the scientific databases was (“construction”) OR (“AEC”) OR (“construction industry”) OR (“construction project”) AND (“risk”) OR (“risk assessment”) OR (“risk management”) OR (“risk evaluation”) AND (“Artificial Intelligence”) OR (“Machine Learning”) OR (“Data Mining”). As a result of which, and after duplicates removal, 533 articles remained.

In the screening phase (Figure 3), the criteria used included the engineering domain, English language, and the type of review paper. Among the 533 papers in this phase, only 356 were in the engineering and building domain, and the rest in other domains were excluded. Moreover, only 314 of these 356 were in English, only 69 of which were review papers. As a result, 69 articles were selected for this phase. Review papers were the focus, as they had a wider variety of techniques included, often had had a comparison conducted, and had the correct level of detail for each method for our research scope. It is noteworthy that the exclusion process up to this point was fully automatic and based on the filtering rules of the scientific libraries. Therefore, any potential biases or errors were out of the control of the researchers.

In the eligibility phase (Figure 3), which had some overlaps with the screening phase, abstracts and keywords of the 69 documents were reviewed to remove the outlier publications. For instance, some publications were studying RM in other industries, some were focused on AI methods for other purposes such as data generation, and some were focused on non-AI methods. As an example, Li et al. [41] developed an occupational risk assessment

indicators system of power grid enterprises using AHP, which, although containing valuable insights, was out of the scope of this study. A similar case was the review study conducted by Cao et al. [42] on AI algorithm applications in civil engineering issues, such as determining the compressive strength of concrete and predicting and evaluating the different parameters of composite beams and shear connectors, which was also out of this study's scope. The exclusion process at this point was manual and based on the researcher's judgment. There might have been some mistakes caused by incomplete abstracts, which could have led to the wrong exclusion or inclusion of papers. However, the final 48 source papers were fully reviewed to guarantee their compliance with the research questions and objectives and to reduce selection errors. There might have been other insightful papers not included in the analyzed scientific libraries, which is an inevitable issue in any literature review study.

In the inclusion phase (Figure 3), 48 final documents were selected as the source papers, and these were thoroughly studied and analyzed using quantitative and qualitative analyses to answer the research questions. For the quantitative analysis, a bibliometric analysis was conducted as it includes many techniques, such as science mapping and particularly co-word analysis—both considered to be applicable for this research. Co-word analysis examines the content of the publications' "words" themselves [43]. As an example, co-word analysis can show a thematic relationship with words that frequently appear together. It also shows keywords' and research areas' co-occurrence. Main areas of research concentration, common techniques, interrelation of topics, application scopes, and trending topics were identified. It is noteworthy that a number of papers were particularly focused on health and safety risks, which were only analyzed regarding the AI algorithms that they proposed. For instance, Kamari and Ham [33] presented a vision-based digital twinning and thread assessment framework for natural disaster risk modeling at a construction jobsite and analyzing the impacts of potential windborne debris in construction site digital twin models.

As the bibliometric analysis is quantitative in nature and produced mainly background data, qualitative analyses followed to answer the research questions in more detail. AI-based risk data structuralizing and pre-processing methods through qualitative content analysis were undertaken first. Then, secondly, thematic content analysis was carried out, using a deductive approach to identify, analyze, and report repeated patterns [44]; in this case, these were deterministic and probabilistic approaches for risk identification, analysis, and mitigation planning. Thirdly, a comparative analysis was performed between probabilistic and deterministic approaches regarding their reasoning basis in risk identification, assessment, and mitigation planning stages, advantages and disadvantages, application areas, and data requirements.

The PRISMA checklist is best suited for quantitative studies and analyses. Due to the qualitative nature of the main analysis stage, some of the checklist items, such as risk ratio, risk of bias, mean difference, and sensitivity analysis, were not applicable for this study. However, the reporting herein does follow the PRISMA checklist topics: rationale and objectives can be found in the Introduction and Background, methods in the Research Methodology, results and discussion in the Findings and Discussion sections and finally in the Conclusions and Further Research section.

4. Findings and Discussion

4.1. Background Data

All the 48 source papers served as references for the bibliometric analysis of the findings. Figures 4–6 were created for a visual presentation of trending topics and research areas, technologies, and publication rate. Figure 4 illustrates the co-occurrence diagram between keywords and research areas in the source papers created by the Bibliometrix application, providing the big picture of the interdisciplinary research in the field. The circles represent the keywords in articles, and their colors are assigned by the clustering algorithms in Bibliometrix. Moreover, the authors grouped these keywords into five main areas based on their similarity and content, represented by the colored squares. As indicated on the diagram, the papers introduce a number of AI algorithms applicable to various steps of RM, such as risk identification and analysis and for decision making on different aspects

of construction projects, such as contracts or cost. There are a number of papers particularly focused on health and safety risks, which were only analyzed regarding the techniques they proposed. Figure 5 records the annual scientific publication rate in the research area and demonstrates a significant increase within the past couple of years. Figure 6 indicates the various topics' trends within the past 15 years. Big Data, machine learning, and deep learning lead the current trend, followed by health, safety, and occupational risks. Decision support systems and knowledge-based systems used to be trending during the last decade, but have now been superseded by AI-based techniques that foster decision making.

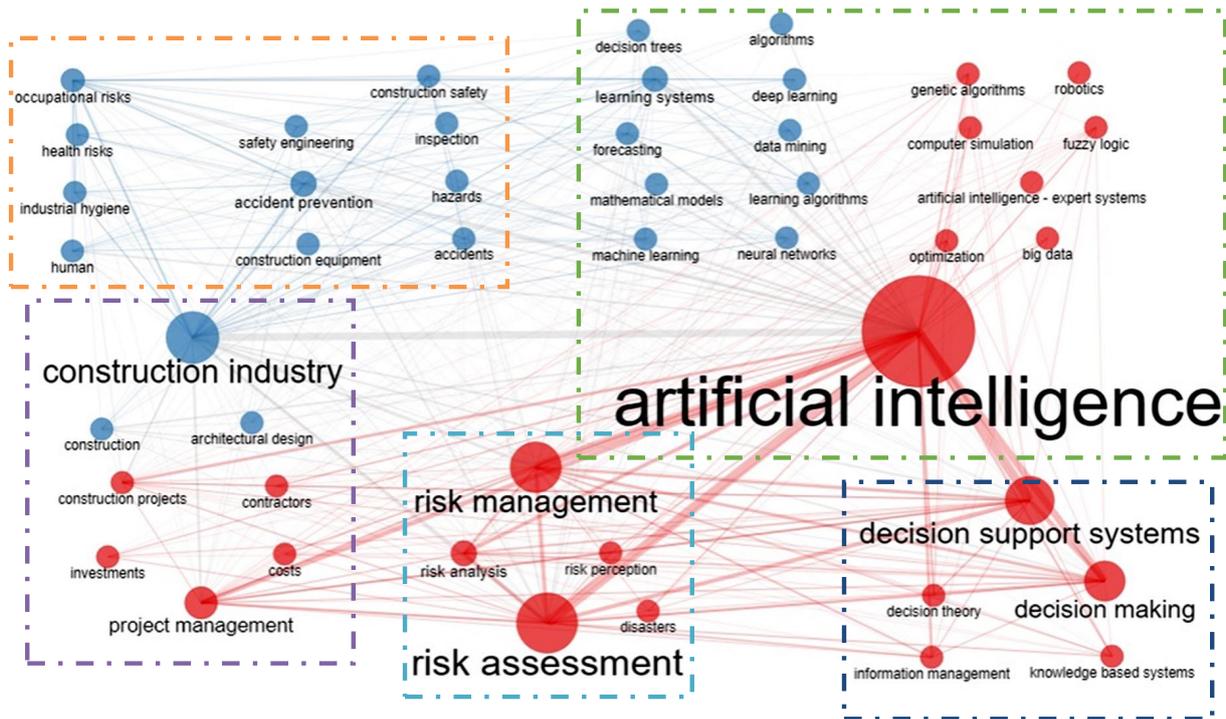


Figure 4. Co-occurrence diagram of keywords/research areas of source papers. ● AI algorithms, ● decision support systems, ● RM domains ● construction project disciplines, ● health and safety.

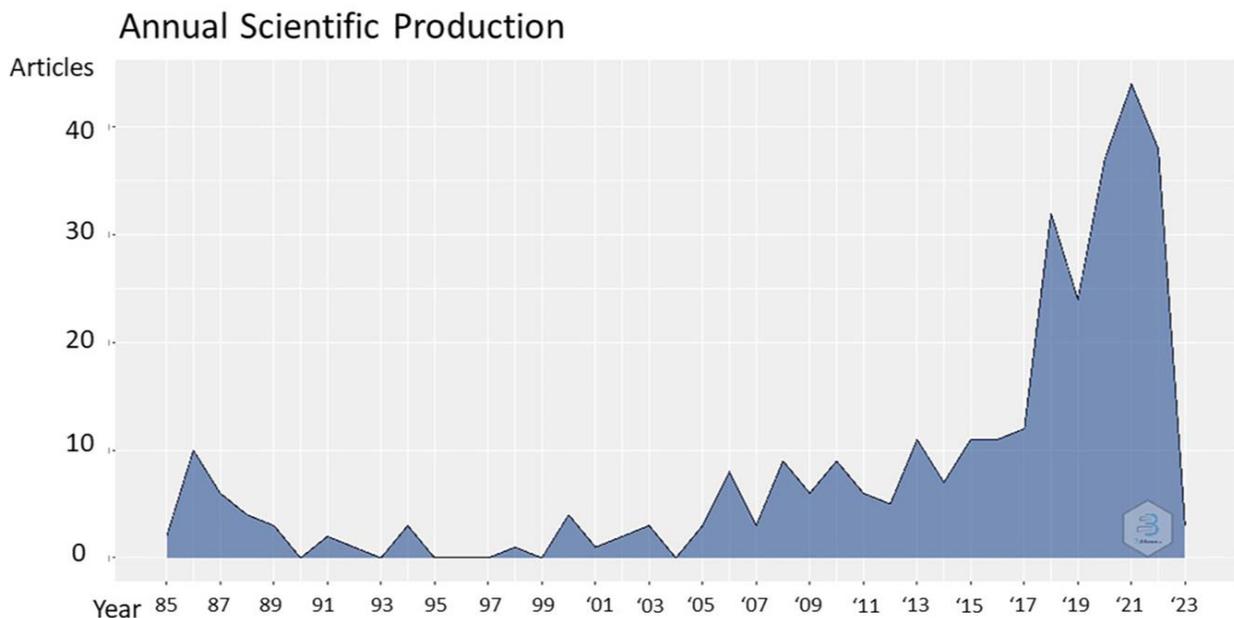


Figure 5. Annual scientific publication rate in the research area.

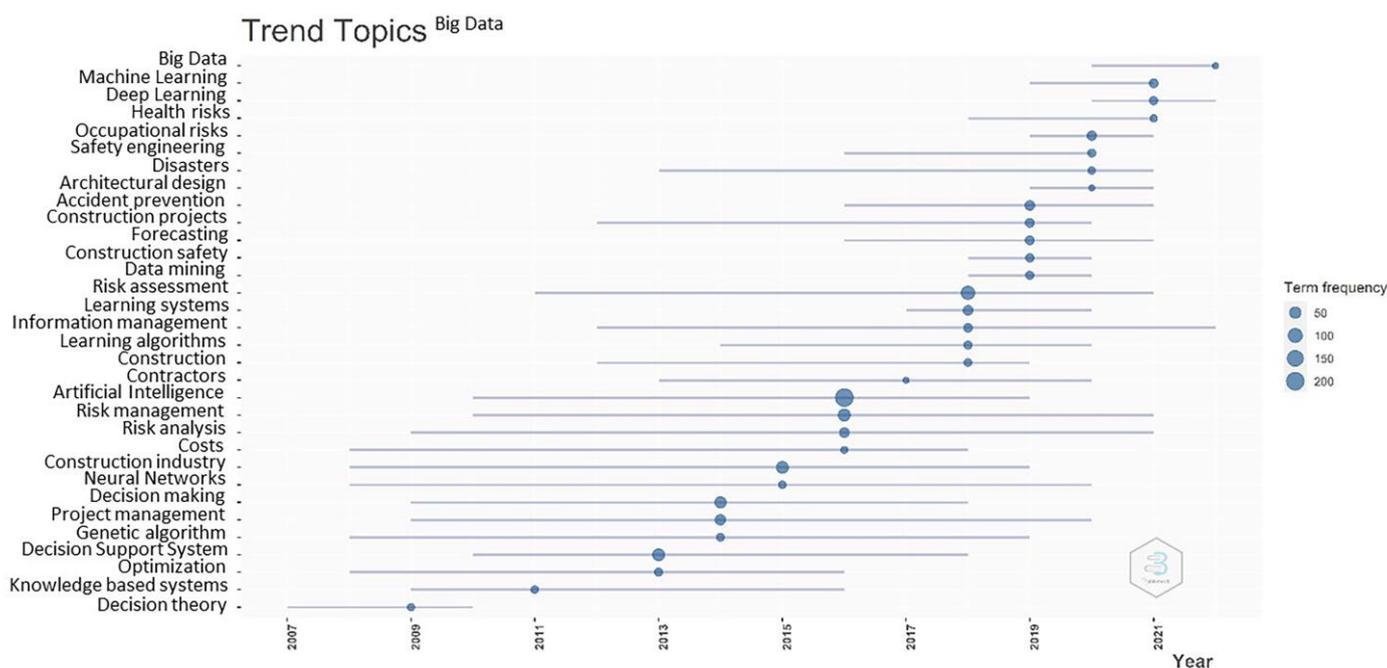


Figure 6. Trending topics in the domain within the past 15 years.

4.2. AI-Based Risk Data Structuralizing and Pre-Processing

Text mining tools such as Natural Language Processing and adaptive lexicon have been implemented to convert textual and unstructured risk data into a proper structured format for AI algorithms [45]. Given that 80% of construction data are stored in text format in project reports, TM can extract valuable data for identifying contract risks from contract conditions, socio-technical risks from licensee event reports, and safety risks from accident reports [46] for the further analysis of risks. Computer vision techniques are for detecting hazardous objects and situations that might trigger safety risks through images. Clustering and classification methods are used to categorize risks and can be integrated with text mining methods as a next step in text structurization. These methods are widely applied in the safety and contract risk domains, for instance, various ML methods, such as Support Vector Machine (SVM), Linear Regression (LR), K-Nearest Neighbor (KNN), Decision Tree (DT), and Naïve Bayes (NB) models, are used in the literature to classify the causes of accidents [47].

As construction companies and institutions do not document frequently and do not share their data in the form of open sources, a common issue in construction is data scarcity and missing values, which hinders the application of machine learning and deep learning algorithms requiring huge amount of data to have proper performance. Therefore, data augmentation techniques such as Generative Adversarial Networks (GANs) are applied to improve the quantity and distribution of data by producing synthetic data through learning from the training sample [48]. Although GANs have broader application in creating synthetic images, which can be highly beneficial in analyzing safety risks and hazards in construction sites, they are recently being applied on tabular data as well, which are the common form of risk data registration. However, advanced GANs' algorithms for tabular data generation are still missing and the produced data might face an overfitting problem. Another solution to the data scarcity problem is elicitation. Elicitation is the process of obtaining knowledge and subjective assessment about the underlying relationships and dependencies between variables and their probabilities from domain experts, which is being vastly used in learning structure and parameters in Probabilistic Graphical Models such as Bayesian Networks [49].

4.3. AI Algorithms Classification for Risk Identification, Analysis, and Mitigation Planning

Various categories have been proposed for AI-based risk analysis and reasoning methods in the literature. Based on the categorization for AI application areas in the construction industry proposed by Pan and Zhang [10], RM falls under the category of expert systems/fuzzy logic for knowledge representation and reasoning mainly formed on probabilistic, qualitative, and linguistic analysis, and machine learning for supervised learning based on either probabilistic or deterministic analysis. Samantra et al. [50] classified construction risk assessment approaches as (a) probabilistic, dealing with risk probability and impact estimation based on historical numeric data, including sensitivity analysis, Decision Tree analysis, Bayesian Networks, Monte Carlo simulation, etc. [51], and (b) possibilistic, dealing with risk possibility and impact estimation based on qualitative or descriptive data including fuzzy logic [52]. The advantage of the possibilistic approach is that it can embrace the uncertain and vague definition of risk factors and their magnitude in a linguistic and subjective description [50]. Although called by various names, the notion and reasonings for classifying the methods are the same, in most cases. For ease of reference, this paper called them probabilistic and deterministic approaches. It is noteworthy that this classification basis is the risk reasoning itself, which is applicable to all phases of the RM process from risk identification to assessment and mitigation planning. This classification aims to bridge the gap in previous studies and provide a standardized and holistic grouping applicable to all ML algorithms in the realm. Furthermore, unlike previous studies that focus mostly on the structure of the ML algorithms and their theoretical backgrounds, this study has a practical and problem-driven approach, assessing and grouping the algorithms based on their potential to fit different situations and scenarios in real-world projects.

The probabilistic approach is mostly based on Bayesian inference, which allows for making judgements on prior and posterior probabilities in random variables based on various sources, such as expert judgement, model simulation, or historical data [53]. Prior probability is the likelihood of a particular state of a variable happening without seeing any evidence, and posterior probability is the updated belief or likelihood of that state of a variable happening after seeing evidence [54].

Benefitting from multiple sources of data in probabilistic approaches, the priors can be learned based on one source and the posteriors can be updated by another source. On the other hand, the deterministic approach is mostly based on the frequentist approach, which can be based on historical records and the priors are learned based on the frequency of an event happening in the database. These methods perform best when a huge amount of data is available. The learning and development processes are much more straight forward and simpler compared to the probabilistic approach, as the elicitation process to obtain information on probabilities from experts is usually challenging and time-consuming. However, the downside, in contrast to probabilistic approaches, is the inability to assign probability to a particular event happening after witnessing evidence, i.e., the posterior update. The downside of the probabilistic approaches, on the other hand, is the subjectivity, bias, and over reliance on experts' opinions if not calibrated properly [55].

4.3.1. Probabilistic Approach

The probabilistic approach is used by Structural Equation Modelling (SEM), Bayesian Network (BN), fuzzy logic, and fuzzy cognitive map that can be integrated with other methods such as fault tree analysis. These methods have a vast application in expert systems and knowledge representation and can have one of the below-mentioned risk reasonings [56]:

1. Probability-based reasoning, referring to probability theory to indicate the uncertainty in knowledge, including fault tree analysis (FTA), SEM, and BNs.
2. Rule-based reasoning, deploying a set of rules in the "if <conditions>, then <conclusion>" format with logical connectives, such as AND, OR, and NOT, for analyzing the qualitative and linguistic data of expert opinion, including fuzzy logic.

3. Fuzzy cognitive map (FCM) learned from data or expert opinions, in which the fuzzy graph structure enables interpreting complex relationships and systematic causal propagation for the immediate identification of risks' root causes in uncertain conditions.

SEM is a versatile multivariate statistical technique consisting of a schematic diagram representing causal structural relationships among multiple variables [57], and has a vast application in construction safety risk analysis with Exploratory Factor Analysis (EFA). EFA can uncover the underlying structure of a large set of variables when there are no hypotheses about the nature of the underlying structure of a model [58].

Bayesian Networks are the most applied Probabilistic Graphical Model in the construction industry [20], and are statistical techniques based on probability and graph theory that represent the causal relationships between the variables and their probabilities in a risk networks. BNs are presented as graphs consisting of nodes, as random variables, and directed arcs, as causal relationships among these variables, which is referred to as the Directed Acyclic Graphical model (DAG) [59] and includes a Conditional Probability Distribution (CPD) for continuous variables or a Conditional Probability Table (CPT) for categorical variables, representing the influences between the nodes. The structure and parameters for CPD or CPT can be learned through algorithms from extensive historical data, expert opinion, or both. BNs have a wide application in modelling, identifying, and analyzing project-related risks such as claims and contract risks, structural health, operation quality, cost and schedule overruns, and safety hazards [60,61].

Fuzzy logic has wide application in modelling qualitative and subjective data extracted from expert opinion, which allows reasoning with ambiguous information. The probability of verbal expressions are transformed into fuzzy numbers, with degrees of truthfulness or falsehood represented by a range of values between 1 (true) and 0 (false), using triangular, trapezoidal, or Gaussian fuzzy membership functions, and through four subprocesses of fuzzification, inference, composition, and defuzzification [62]. Fuzzy logic integration with Bayesian Network, Analytic Hierarchy Process (AHP), and TOPSIS is proven to be a robust risk assessment and decision-making approach, especially when the problems are characterized by subjective uncertainty, ambiguity, and vagueness [63]. A fuzzy cognitive map [56] is a combination of fuzzy logic and cognitive map, which uses subjective and vague linguistic variables from domain experts, performs a Root Cause Analysis, and models complex and dynamic systems with numerous indicators, causal dependencies, and weights. FCM forms a what-if scenario analysis for the prediction and evaluation of risks in a fuzzy weighted graph model with a tolerance of imprecision and uncertainty [64].

There are some interesting previous studies that proposed probabilistic and subjective RM models for construction projects. Afzal et al. [65] proposed a hybrid method of fuzzy logic and BBN based on a systematic literature review on subjective RM methods for cost overrun risk in construction projects, which proved to have better performance compared to other AI-based methods. The integration of Monte Carlo simulation (MCS) and multi-criteria decision model (MCDM) techniques for measuring complexity and risk relationship for cost overrun in construction projects was studied and proposed by Floyd et al. [66] and Qazi et al. [67]. Cardenas et al. [31] addressed the data unavailability and incompleteness problem in tunneling projects through expert elicitation in BBNs. Lee and Kim [68] proposed a Failure Mode and Effects Analysis (FMEA)-based method to find primary factors responsible for causing cost increases throughout the modular construction life cycle. Ferdous et al. [69] developed a Quantitative Risk Analysis model based on event tree analysis (ETA) and fault tree analyses (FTA) to handle and describe the uncertainties in the input event likelihoods. Kim et al. [70] conducted a comparative analysis between SEM, multiple regression, and ANN and developed an SEM-based model to predict the project success of uncertain international construction projects.

There is a trend of integrating fuzzy logic with other AI-based methods in the literature. Fuzzy logic applications in construction management literature can be divided into two main fields (a) fuzzy set/fuzzy logic and (b) hybrid fuzzy techniques, with the applications

in four main categories, including decision making, performance, evaluation/assessment, and modeling [71]. For instance, Zhao et al. [72] developed a risk assessment model using a fuzzy synthetic evaluation approach for green building projects in Singapore, which grouped and calculated the likelihood of each risk factor's occurrence, risk magnitude, and criticality. Kabir et al. [73] incorporated fuzzy logic into BBN and proposed a fuzzy Bayesian belief network (FBBN) model to represent the dependencies of events and uncertain knowledge (such as randomness, vagueness, and ignorance) for the safety analysis of oil and gas pipeline projects. In another study, Shafiee [74] proposed a fuzzy analytic network process (FANP) approach to select the most appropriate risk mitigation strategy for offshore wind farms with regard to four criteria: safety, added value, cost, and feasibility. Zhong et al. [75] proposed a project risk prediction model using an entropy weight method (EW), a fuzzy analytic hierarchy process (FAHP), and a 1D convolutional neural network for risk indexing. Cheng and Lu [76] presented a hybrid risk analysis model combining fuzzy inference with failure mode and effect analysis (FMEA) to improve the existing risk assessment methods for pipe jacking construction by mapping the relationship between occurrence (O), severity (S), and detection (D) and the level of criticality of risks. Liu and Ling [77] constructed a fuzzy-logic-based artificial neural network model, or fuzzy neural network (FNN), to facilitate the decision-making process for contractors, providing a clear explanation to justify the rationality of the estimated markup output. There are also some remarkable literature review studies on fuzzy and hybrid risk assessment methods in construction projects, such as the one that Islam et al. [78] conducted, which delineated the advantages of the fuzzy Bayesian belief network (FBBN) over other hybrid models such as FANP, due to overcoming systematic constraints such as the lengthy calculations required for the pairwise comparisons. Petroutsatou et al. [79] proposed a probabilistic model for pre estimating the life cycle cost of road tunnels' construction using multiple regression analysis and Monte Carlo simulation. A detailed table of related papers and their techniques can be found in Appendix A.

4.3.2. Deterministic Approach

A list of ML techniques applied in construction-related disciplines includes artificial neural networks (ANN), Decision Trees, Logistic Regression, Naïve Bayesian Models, and Support Vector Machines. ML combines methods from statistics, database analysis, data mining, pattern recognition, and AI to extract trends, inter-relationships, patterns of interest, and useful insights from complex data sets [80]. A deterministic approach is used by most of the machine learning algorithms. These algorithms can be used for one of the following applications in RM: (a) regression to predict continuous numerical outcomes such as delay caused by a risk, including Linear Regression, Decision Trees, Support Vector Machines (SVM), and neural network (NN) techniques; (b) classification to present the class of the output based on some input features, such as risk identification, including NNs, Random Forest, SVM, and Genetic Algorithm; (c) clustering to explore data for natural groupings, such as finding related events causing a risk, including K-means and SVM; (d) attribute importance to rank attributes based on their relationships to the target variable, such as identifying the most significant causes of accidents, including Decision Trees and Random Forest; (e) anomaly detection to identify unusual cases based on deviation, such as identifying accident risks, including SVM and deep neural networks. In contrast to other realms in construction, ML applications have been limited and mainly related to predicting delay risks in construction, predicting the impact of contract changes on the time and quality performance, and analyzing and modeling incident databases for predicting H&S risks. The format of the input risk data for risk assessment in the deterministic approach can be numeric, categorical, video data, sensor data, textual data, etc., and input data acquisition approaches could be historical, real-time, or a combination of historical and real-time data [81].

ANNs are the most applied ML method in engineering risk assessment, followed by SVM, Decision Trees, RF, CART, Naïve Bayes, K-means, KNN, Linear Regression, and BRT [81]. NNs are formed by layers of interconnected nodes using activation function, weight, and bias, which simulate the human brain structure and behavior for solving problems such as recognition, classification, and regression [82]. The reasoning behind these layers relies on the weights and biases assigned to each node, being learned and optimized, based on forward propagation and backpropagation processes, with an objective to minimize the loss function as an indicator of prediction precision. They provide notable performance in the presence of abundant data, capturing linear and nonlinear relationships of the data. They also act as a predicting–analytical model for industrial RM control and accidents’ severity assessment, firstly to estimate the S-curve in a construction project, secondly to analyze the causes of accidents, and to also predict delay risk in construction logistics [83].

DT is a supervised learning method that explores the relationships of many input attributes to an output attribute by creating a top-down branching structure consisting of a root node splitting into branches as probable outcomes. DTs do not need any assumptions regarding the independence of variables or variable values. They can process both numerical (continuous) and categorical (discrete) data and perform regression and classification. Support Vector Machines (SVM) perform regression and classification by mapping data to a high-dimensional feature space. This is to categorize the data points by forming a separator between the categories in the form of a hyperplane. Genetic Algorithm, which is an optimization and complex problem-solving method using an adaptive heuristic search, is also useful in measuring project risk interdependencies for the optimal cost solution under uncertainties [84].

The deterministic approach has been widely studied in the RM literature. Jallan and Ashuri [85] used text mining and Natural Language Processing techniques to identify and classify risk types and trends affecting publicly traded construction companies by leveraging their 10-K reports filed with the Securities and Exchange Commission. Chattapadhyay et al. [86] used a cross-analytical machine learning model with K-means clustering and Genetic Algorithm to exploit different risk factors and their impacts on the performance aspects of construction megaprojects. Valpeters et al. [87] determined the probability of contract execution risk at a given stage of its establishment using Logistic Regression, Decision Tree, and Random Forest algorithms. Creedy et al. benefited from Multivariate Regression Analysis for evaluating risk factors that lead to cost overruns in delivering highway construction projects. Yaseen et al. [12] developed a hybrid artificial intelligence model called integrative Random Forest classifier with Genetic Algorithm optimization (RF-GA) for delay problem prediction. Joukar and Nahmens [88] extracted and forecasted the short-term volatilities of the Construction Cost Index (CCI), like price volatilities, by assessing the cost risk of construction projects, and quantified the risk of overestimation or underestimation, using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and ARIMA. Gondia et al. [83] used Decision Tree and Naïve Bayes model to analyze and predict project delay risks using objective data from previous projects. Alshboul et al. [89] implemented an ensemble machine learning technique combining various ML algorithms, such as XGBoost, Categorical Boosting, K-Nearest Neighbor, Light Gradient Boosting, ANN, and DT, to predict the liquidated damages in highway construction projects.

Neural networks are the most used algorithms in this group and have been integrated with other algorithms in hybrid models as well. Goh and Chua [90] used NN analysis in a quantified occupational safety and health management system audit with accident data obtained from the Singaporean construction industry in order to predict accidents and identify safety critical factors. Gajzler [91] developed a method for supporting the decision-making process of materials and technology selection for repairing industrial building floors using knowledge-based NN and fuzzy logic. Jin and Zhang [92] developed an ANN-based risk allocation decision-making process in public–private partnership (PPP)

projects. Chenyun and Zichun [93] conducted an analysis and evaluation of project cost risk and the identification of critical factors based on NN. A detailed table of the related studied papers and their techniques can be found in Appendix A.

4.4. Comparative Analysis between Probabilistic and Deterministic Models

Following determining and listing the probabilistic and deterministic algorithms based on the source papers in Figure 3, an analytical comparison was performed between them regarding their reasoning basis in risk identification, assessment, and mitigation planning stages, advantages and disadvantages, application areas, and data requirements for each, presented in Table 1. The basis of this comparison was the points mentioned in the sourced papers of the systematic literature review regarding the precision, problem type, analytical reasoning, input data requirements, level of probability included, and characteristics of each of these methods.

Table 1. Analytical comparison between probabilistic and deterministic RM models.

Comparison Criteria	Probabilistic Approach	Deterministic Approach
Reasoning basis	Probability-based reasoning Rule-based reasoning Fuzzy logic [44,50,87,94]	Forward propagation and backpropagation Loss function Weights and biases [95,96]
Structure	Interconnected graphs [67,68,97]	Layers of neurons or branches [91,92]
Data Source	Historical Data, model simulation Experts' opinion [98,99]	Historical data, model simulation [95,96,100]
Inference	Bayesian inference [101]	Frequentist inference [102]
Data Requirements	Limited amount of data Able to deal with missing values Numerical, categorical, and linguistic data [103,104]	High amount of data Partial ability to deal with missing values [24]
Probability and dependencies' role	Embrace probability in assessments Considering variables interdependencies with each other and final output [105,106]	Does not embrace probability in assessments Considering variables interdependencies on final output [87,107]
Prediction precision	Mid-high [108]	Very high [25]
Application scope	Subjective and uncertain problems with limited data [109]	Objective and complex problems with abundant data [83]
Application in RM processes	Risk identification Qualitative analysis Risk control [110–112]	Risk identification Qualitative and quantitative analysis Mitigation planning Risk control [86,87,113]
Advantages	Flexibility to various problems Ability to integrate qualitative and quantitative data (subjective and objective) Risk path approach Ability to include dynamic data [114,115]	Quick processing and learning Ability to consider linear and nonlinear relationships among data Ability to include dynamic data [116,117]
Disadvantages	Takes longer time to create the structure Not high precision if merely based on historical data High processing time in complex problems [67,118]	Individual risk analysis approach (isolated) Not flexible toward change Requirement of high data volume [119,120]

In general, algorithms with a deterministic approach have advanced structure, quicker processing time, and higher result precision in complex problems, but they require a large amount of structured data with no missing values or uncertainties. Given that documentation is in a less than optimum condition in the industry, data scarcity and infrequent data updates are the main challenges in these models. The probabilistic approach, on the other hand, due to functioning in the state of data scarcity and missing values and being closer to reality regarding the inter-dependencies between risk variables, is more

practical. It can integrate subjective and experience-based experts' opinions through the elicitation of objective historical data gathered from previous projects or simulations to overcome the data scarcity issue. Moreover, it benefits from the risk path approach instead of isolated risk assessment. However, the structure and parameter learnings are daunting and complicated tasks as the model becomes more complex, containing more variables and relationships. The probabilistic approach is based on Bayesian inference, as mentioned in Equation (1), and the deterministic approach is based on frequentist inference, as mentioned in Equation (2). These equations are the basis of risk reasoning and assessment for different AI algorithms, which can lead to different results and accuracies in the RM process. Construction firms can refer to this study and Table 1 to choose the most appropriate AI model to foster their RM processes, their enterprise requirements, and data availability.

$$P_{\text{Posterior}}(H|D) = \frac{P(D|H)P_{\text{Prior}}(H)}{P(D)} \quad (1)$$

$$\text{Likelihood } L(H; D) = P(D|H) \quad (2)$$

4.5. Results Comparison with Previous Studies

The main foci of previous review studies were the structure of the AI algorithms or the data mining technologies [121], the classification of AI methods based on their structure, or the used technology, such as ML or computer vision [15]. The grouping of these technologies was based on their area of application in construction projects. For instance, Afzal et al. [65] conducted a comprehensive review analysis on AI-based risk assessment methods, and listed papers based on the technique used, identifying six key techniques used. In another study, the tree structure consisting of nodes in data mining was studied by Rao and Chen [121] in the scope of construction risk control. Islam et al. [78] conducted an extensive review of hybrid and fuzzy models' structures and then explored the areas of their applications, such as roads and highways and building projects [122]. A few articles just focused on one type of risk, such as safety risk, and one type of project, such as urban railway construction. Some other studies [7–11] highlighted the RM domain, focusing on the types and structures of AI technologies applied in construction. In other studies, a specific method, such as the SEM, was analyzed thoroughly regarding technical aspects, sample size issues, data screening and reliability testing, model evaluation and validation processes, etc. [57].

Although such studies provide helpful insights, they contain highly detailed and advanced information and formulas that might be from the experience and roles of the audience and, in our case, the practitioners and industrial researchers in the field. Most of the technologies discussed in these papers are at the research stage. Their future potential application in practice is therefore still unknown. Applying a practical approach to the topic, this study aims to analyze the ML algorithms from the risk reasoning and judgment point of view, and classify the methods based on the established statistical reasonings in probability studies, i.e., frequentist and Bayesian approaches. Such a functional and right-to-the-point classification is easily comprehensible and able to be addressed by practitioners and researchers in the field, meaning they can choose the method that best fits their requirements and resources. This is an interdisciplinary and novel way of grouping the widespread ML algorithms already implemented in the construction industry. Furthermore, this practical viewpoint assisted the integration of the various, heterogeneous findings of previous studies in the literature, which had differing scopes. Underlying similarities between this study and previous investigations in terms of the systematic literature review process are inevitable and expected in part.

It is noteworthy that the validation of results produced by different ML algorithms is outside the scope of this study. However, previous studies proved the higher accuracy, efficiency, and processing speed of the ML algorithms compared to traditional methods. Their accuracy is assessed using performance metrics such as Root Mean Square Error

(RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of Determination (R2) [89], which compare the estimated value with the actual value of outcomes. Different algorithms are of varying accuracy and performance in different contexts; therefore, it is only possible to evaluate their overall performance and validate them by knowing the context and scope of their application.

5. Conclusions and Further Research

The construction RM process benefits significantly from AI in terms of automation, optimization, fostering decision making, and standardization, as supported by the systematic literature review findings. Machine learning and deep learning algorithms, with ANN, SVM, BN, and fuzzy logic in the lead, have found significant applications in RM research. However, in order to implement these methods in practice, and to identify the causes of various risks and to analyze them in construction projects, experience, prior knowledge, and historical data are required. In most cases, those experiences are not always well documented nor easily accessible. Therefore, the data requirements, reasoning, and structure of each AI model needs to be thoroughly analyzed to select the most appropriate one based on the requirements and data availability in an organization. Furthermore, AI-based methods, such as text mining and computer vision, can assist in structuring the risk data and overcome the data scarcity problem.

This study provided a systematic literature review based on the PRISMA guidelines provided for classifying AI algorithms that can be applied during different phases of the RM process. The source papers were studied thoroughly to extract insights on common AI algorithms used for risk management, as well as their main areas of application. These algorithms were grouped under probabilistic and deterministic groups based on their risk reasoning, learning process, data requirements, flexibility toward data scarcity, uncertainty, integration of qualitative and quantitative data, and application scope.

The deterministic approaches are mostly based on frequentist statistics and can predict an outcome without attaching a likelihood to it. Moreover, ML algorithms with a deterministic approach, such as deep learning algorithms, have a black-box structure; that is, the workflow between input and output variables is complex and incomprehensible to users. Therefore, there is no room for subjective expert judgment in the process. The relationships between inputs and outputs are merely learned from historical data and simulations, making the model require a huge amount of data for learning and adjusting weights.

Alternatively, the probabilistic approaches are based on Bayesian statistics and predict the likelihood of different possible outcomes. While black-box models are being programmed with minimum human guidance, probabilistic models such as Bayesian Networks and SEMs are the closest examples to the Explainable AI (XAI) concept, being more comprehensible for users due to their transparent and graph-based structure indicating the inter-relationships between input variables and the output. Therefore, they can serve as knowledge-based systems representing domain knowledge and expert opinions through elicitation, integrating subjective expert judgment with objective historical data. This is an advantage when there are not enough data available to base the entire learning process on. It is noteworthy that hybrid models, such as fuzzy neural networks or Bayesian neural networks, combine the two approaches and benefit from both linear and non-linear relationships between input variables. They usually have more robust performance and better flexibility and are becoming more widespread in construction research.

The contribution of this paper is providing an analytical comparison between different AI algorithms for practitioners and researchers to choose the appropriate AI model for a targeted risk, which, as proven by the results of previous studies in the literature, can bring many advantages in terms of automation, optimization, digitalization, and decision making, increasing the RM processes' performance and projects' success rate. This comparison is made from a practical and problem-driven viewpoint and highlights the most influential features when choosing and implementing a model in practice. That is, instead of focusing

on the structure of each algorithm and trying to fit them into the RM problem, which can often fail, this study focuses on the situations and problems in which each algorithm can work best regarding data availability, the emphasis on uncertainty, the existence of different data sources, etc. The algorithms' categorization provided by this study is also based on risk reasoning statistics to bring the theoretical topics one step closer to practical processes. It is the main difference from previous literature review studies, which put their focus on the algorithms' structures and types with great theoretical detail and formulas rather than their practical capacities, reasonings, and challenges. An AI-based RM framework is presented, in which this study focuses on the data analysis phase. Future phases will be the subject of further studies.

One of the limitations of this research was the paucity of publications when validating the proposed analytical comparison. Being a highly specialized topic, many previous studies were out of the scope of this study and could not serve as a benchmark for comparing results. Another limitation was using English language as one of the filters. This might have excluded some relevant studies. Further, the classifications provided by previous researchers for the AI algorithms were based on different criteria, such as the project phase, the algorithms' efficiency levels, supervised or unsupervised learning, etc., which in some cases were incompliant, contradictory, or partial. Therefore, this study grouped them under probabilistic and deterministic approaches to include the majority of these criteria. A more detailed classification would provide a more accurate comparison. Another limitation is the variety of methods and techniques, both AI-based and non-AI-based; each has a different scope and target process. Therefore, not all of the techniques could be analyzed within one article, and most of them applied to other phases such as data gathering and digital twin integration. However, these topics will be the focus of future research work to complete the AI-based RM framework proposed in this study.

In addition to analyzing the AI-based data gathering and preprocessing tool, a further study can involve the discussion and validation of the comparative table by experts in the field and/or through case studies for the implementation of algorithms and comparison of the results. The systematic literature review could also be expanded into other generic AI-based RM framework phases, such as data production and documentation techniques, integration with digital twins, etc. Moving toward a fully automated RM process, the findings of the practical application of AI in real-world case studies throughout different phases of the proposed framework, for instance, the data gathering, data analysis, and automating document update, would be the topic of further studies.

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Appendix A

Table A1. References of source papers and partially used papers for the systematic literature review.

References	Model	Technique	Context
Love et al. (2021) [123]	Review Paper		Review on risk and uncertainty of rework in construction
Afzal et al. (2019) [65]	Review Paper		Systematic literature review and content analysis on AI-based risk assessment methods
Cao et al. (2021) [42]	Review Paper		Review on AI algorithms, e.g., ANN, GA, SVR, etc., applications in civil engineering domains such as predicting and evaluating the different parameters of composite beams and shear connectors
Chenya et al. (2022) [6]	Review Paper		Systematic literature review on research gaps and future trends of intelligent risk management in construction projects
Saka et al. (2023) [124]	Review Paper		Review on conversational AI systems, e.g., Natural Language Processing
Xiong et al. (2015) [57]	Review Paper		Critical review of SEM applications in construction
Basaif et al. (2020) [27]	Review Paper		Study on technology awareness of AI application for risk analysis in Malaysian construction projects
An et al. (2021) [15]	Review Paper		Literature review on five type of popular AI algorithms, including Primary Component Analysis, Multilayer Perceptron, fuzzy logic, Support Vector Machine and Genetic Algorithm
Okudan et al. (2021) [125]	Review Paper		Review of knowledge-based RM tools in construction projects using AI, ML, and fuzzy set
Abioye et al. (2021) [16]	Review Paper		Review on AI status, opportunities and future challenges in the construction industry
Adams (2008) [126]	Review Paper		Review on risk identification and analysis techniques in construction projects in the UK
Pan and Zhang (2021) [10]	Review Paper		A systematic literature review and qualitative analysis on the current state of AI adoption in the context of construction engineering and management and discussion on its future trends.
Wu et al. (2021) [122]	Review Paper		Safety risk investigation framework in urban rail transit engineering construction using AI algorithms and data clouds
Yucelgazi and Yitmen (2020) [112]	Probabilistic	Analytical network processing (ANP)	Risk assessment for large infrastructure projects
Khodabakhshian and Re Ceconi (2022) [60]	Probabilistic	BN, process mining	Risk identification in construction projects
Chen et al. (2012) [127]	Probabilistic	Expert system Knowledge management	Evaluating performance heterogeneity through a knowledge management maturity test in the building sector
Khademi et al. (2014) [128]	Probabilistic	ANP and AHP	Construction risk analysis
Liu et al. (2016) [129]	Probabilistic	SEM	International construction projects risk assessment
Lu et al. (2022) [130]	Probabilistic	BN, fuzzy logic	System risk management
Qazi et al. (2016) [67]	Probabilistic	ANP and BN	Risk path measuring and modeling project complexity in construction projects
Khakzad et al. (2013) [97]	Probabilistic	BN	Risk analysis of offshore drilling operations
Boughaba and Bouabaz (2020) [131]	Probabilistic and Deterministic	ANN, fuzzy logic, RNN	AI-based tendering decision-making model considering the success and failure factors
Islam et al. (2017) [78]	Probabilistic	MCS	Hybrid methods for risk assessment in construction projects
Samantra et al. (2017) [50]	Probabilistic	Fuzzy Set	Fuzzy-based risk assessment module for an underground metro rail station construction project
Tian et al. (2022) [132]	Probabilistic	BN	Crossed risk assessment of construction safety
Adeleke et al. (2018) [133]	Probabilistic	SEM	Nigerian companies' construction risk management
Chen et al. [94]	Probabilistic	BN, fuzzy logic	Catenary construction risk assessment based on expert fuzzy evaluation and BN
Kabir et al. (2016) [134]	Probabilistic	ANN, BN, and FTA	Risk assessment in energy projects

Table A1. Cont.

References	Model	Technique	Context
Chen et al. (2020) [135]	Probabilistic	Fuzzy set, ELECTRE III, multi-attribute decision making	Fuzzy- and ELECTRE III-based construction bid evaluation framework under uncertainty
Moradi et al. (2022) [136]	Probabilistic	Bayesian neural networks, BN	Condition and operation risk monitoring of complex engineering systems
Karakas et al. (2013) [110]	Probabilistic	Multiagent systems, BN, fuzzy set	Multiagent system to simulate risk-allocation and cost-sharing processes in construction projects
Eybpoosh et al. (2011) [29]	Probabilistic	SEM	Risk rath identification of international construction projects
Vagnoli and Remenye-Prescott (2022) [137]	Probabilistic	BN	Expert knowledge elicitation into system monitoring data
Omondi et al. (2021) [105]	Probabilistic	MCS, Markov chain model, Bayes' theorem	Investigate how the capacity of probabilistic reasoning to handle uncertainty can be combined with the capacity of Markov chains to map the stochastic environmental phenomena to improve performance of tuning decisions under uncertainty
Valipour et al. (2016) [138]	Probabilistic	Fuzzy ANP	Hybrid fuzzy cybernetic model to identify shared risks in projects
Senova et al. (2023)	Probabilistic	MCS	Financial risk assessment using Monte Carlo simulation
Kamari and Ham (2022) [33]	Deterministic	Computer vision, point cloud segmentation, digital twinning	Deep-learning-based digital twinning framework for construction siter disaster preparedness
Fang et al. (2013) [113]	Deterministic	GA	Risk planning under resource constraints
Choi et al. (2021) [26]	Deterministic	NLP, text mining	Developing a digital EPC contract risk analysis tool for contractors, using AI and text mining techniques
Wu and Lu (2022) [139]	Deterministic	RF, XGBoost, Bagging Regressor, SVR,	AI-based for accident and safety risk assessment in bridge construction
Alshboul et al. (2022) [89]	Deterministic	XGBoost, KNN, ANN, DT, LightGBM, CatBoost	Liquidated damages prediction in highway construction projects
Esmaeili and Hallowell (2012) [140]	Deterministic	Delphi method, SSRAM	Developing a decision support system called scheduled-based safety risk assessment and management (SSRAM)
Habbal et al. (2020) [95]	Deterministic	ANN	ANN-based planning risk forecasting model in construction projects
Yaseen et al. (2019) [12]	Deterministic	RF, GA	Risk delay prediction in construction projects by hybrid an AI model
Choi and Lee (2022) [141]	Deterministic	NLP, bi-directional long short-term memory (bi-LSTM)	Contractor's risk analysis of Engineering Procurement and Construction (EPC) contracts Using Ontological Semantic Model and bi-long short-term memory (LSTM) technology
Hosny et al. (2015) [96]	Deterministic	NN	Development of an NN-based predictive and decision awareness framework for construction claims using backward optimization.
Chattapadhyay et al. (2021) [86]	Deterministic	Cross-analytical machine learning model, K-means clustering, GA	Exploiting different risk factors and their impacts on the performance aspects of construction megaprojects
Valpeters et al. [87]	Deterministic	Logistic Regression, DT, Random Forest	determination of the probability of contract execution at a stage of its establishment
Fan et al. (2020) [142]	Deterministic	NN, AHP	Development of a credit risk index system of water conservancy projects
Anysz et al. (2021) [107]	Deterministic	Decision Tree, ANN	Predicting the result of a dispute
Zhong et al. (2021) [75]	Deterministic and Probabilistic	CNN, fuzzy AHP, entropy weight method	Cost and schedule risk prediction model for construction projects using 1D-CNN, EW, and FAHP.

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