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MACHINE LEARNING FOR RISK MANAGEMENT IN CONSTRUCTION PROJECTS

Doctoral Dissertation of Ania Khodabakhshian

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Extended Abstract

Background

Risks and uncertainties are inevitable in construction projects and can drastically change the expected outcome and negatively impact the project's success. This is due to their unique, uncertain, and complex nature, containing numerous activities, stages, and stakeholders with nonlinear relationships. Risk Management (RM), as a proactive approach to identify, assess, and mitigate these risks, can play a crucial role in ensuring the projects' on-time and on-budget delivery, meeting the project's objectives and constraints, and securing the workers' safety. However, it is still conducted in a manual, time-consuming, superficial, and ineffective manner. Moreover, risk identification and assessment, in their conventional forms, are conducted based on individual and experience-based expert judgments and seem highly personalized, qualitative, and context-dependent, making the knowledge transfer and model generalization critical issues for future projects. Therefore, more efficient and fact-based RM methods are being explored in literature, using the current advancements of data-driven methods and industry 4.0 technologies, such as Artificial Intelligence (AI) and Machine Learning (ML) algorithms.

With the increasing application of data-driven methods in construction research and practice, AI and ML algorithms, Bayesian inference, and fuzzy logic methods are being explored to automate and optimize the RM processes. ML-based models can improve analytical capabilities across the RM domain while offering a high granularity and depth of predictive analysis. Furthermore, they can significantly contribute to developing a holistic and integrated RM framework in construction companies, where risks are assessed based on factual knowledge inherited from previous projects concerning interrelated project variables and the effect of each on triggering different risks. However, their practical application is limited due to a) lack of structured data and infrequent documentation in the projects, b) overreliance on subjective expert judgment, c) isolated risk analysis and ignorance of causal inferences between variables in risk paths, d) improper choice of ML algorithms for a given problem regarding the data availability and requirements, the role of probability and expert judgment, and reasoning behind the analysis, and e) change-resistant culture of the construction industry and lack of technical knowledge on digital technologies.

Research Questions

Aiming to clarify the current status and challenges of RM methods in the industry and the scope and direction of this research to implement ML-based solutions, this dissertation seeks answers to the following questions, which have arisen after a Systematic Literature Review and analysis of real-world case studies:

a) What are the shortcomings of conventional RM practices, and in which capacities and by the application of which ML algorithms can the RM domain benefit? What are the advantages, disadvantages, application scope, data requirements, prediction accuracy, and limitations of Probabilistic and Deterministic ML approaches for RM?

b) How can an ML-based RM model be applied in real-world cases? What solutions can be proposed to overcome the data scarcity and uncertainty issues? How can the ML-based RM model be integrated with other project management processes? What are its practical application obstacles, ethical/moral issues, and bias harms in the industry?

Research Objectives

This research aims to propose an ML-based and systematic RM framework for construction projects to:

a) Identify and analyze the bottlenecks, problems, and inefficiencies in current RM practices, which ML algorithms can address and solve.
b) Define and implement proper ML algorithms based on data requirements, availability, and role of uncertainty in given RM issues.
c) Solve the data scarcity problem by eliciting experts' qualitative reasonings, synthesizing data using a Generative Adversarial Network (GAN), and integrating them with objective data from previous projects.
d) Represent the interdependencies and causal inferences in the enterprise risk network using probabilistic graphical models like Bayesian Networks (BNs).
e) Automate and optimize the construction risk identification and assessment processes using probabilistic and deterministic ML models and conduct a comparative analysis for their efficiency and accuracy.
f) Constantly assess and improve the RM system performance using real-time data in dynamic networks or post-mitigation intervention modeling of risks.
g) Address the ML-based model's real-world implementation requirements, challenges, ethics, and possible biases and harms in the system.

Research Methodology/Design/Approach

The research is conducted in systematic phases based on a case-study approach, given that the research has industry partners, Jacobs Engineering Group. The main phases of the research scheme, as presented in Figure a, are:

a) Systematic literature review and analysis of findings from state of the art, best practices, and Professional standards to find interactions between ML and RM realms, as well as the research gaps to be addressed,
b) Meetings with industry partners to determine the main focus area, expectations, and requirements,
c) Data gathering from 44 previous projects' documents, such as Monthly reports, Project charters, Risk registers, Cost reports, and Schedule baselines, as the research case studies,
d) Surveys and interviews with project managers and company representatives for data gathering and quantifying their subjective reasoning for risk identification and assessment,
e) Integrating the risk data from various sources in a probabilistic BN to create the risk network for each risk,

f) Solving the data scarcity problem through elicitation and synthetic data generation using GANs,
g) Implementation of deterministic models like Artificial Neural Networks and Decision Trees, as well as probabilistic models like Fuzzy Logic for results comparison and model validation,
h) Final validation of the models with actual project data and interviews with experts,
i) Integrating the proposed model with the current project management processes of the company,
j) Addressing the data privacy, ownership, and bias problems to facilitate the broader application of the model.

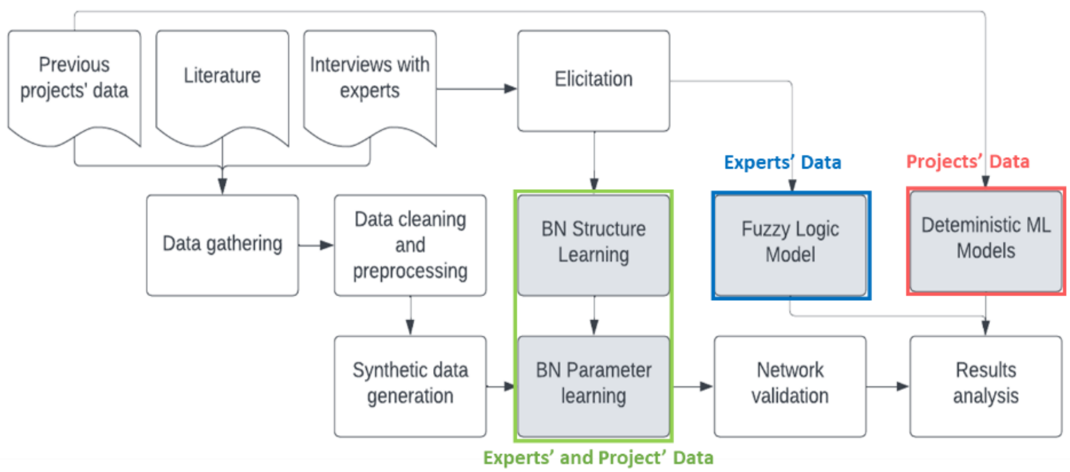

Figure a. Research Scheme

Research Findings

The findings of this study suggest that ML models, especially the probabilistic ones like BNs, can significantly facilitate, automate, and optimize the RM process of construction projects in all project knowledge areas, i.e., technical, financial, procurement, communication, etc. Being able to model the complex interrelationships and causal inferences between a project's key variables like budget, duration, delivery method, and built area, they can propose an accurate and realistic estimate of potential risks to upcoming projects, enabling project managers to proactively take preventive actions and make strategic decisions to mitigate their impacts for a more successful, safe, on-budget, and on-time project delivery.

Research Limitations/implications

The main limitation of this research is data scarcity, a common issue in construction companies due to the lengthy project completion process and unstructured and infrequent data documentation. Another limitation is the lack of similar previous studies on project-level risk modeling in the industry that could serve as a benchmark for result comparison, as a great share of literature in the RM realm focused on operation-level risks, the data of which is produced on a daily basis and is easier to model.

There is the risk of the proposed model's overfitting to entered data in the implication phase, as this study was developed for an actual client and based on their project database. Given the context-driven nature of risks and enormous variances between different types of projects, this is an inevitable issue. However, it is not considered a limitation since most companies have their specific portfolio of projects and services, and the model can be easily adjusted based on their requirements. Other issues to address during the implication phase are the social and ethical challenges of the AI technology application, enterprise infrastructural and organizational requirements, and necessary training to use the technology properly and efficiently.

Practical Implications/Motivation/Contribution

a) Determining the main features affecting risks in the industry and the characteristics of acceptable input risk data,
b) Providing a holistic comparative analysis between various probabilistic and deterministic ML algorithms for companies to choose from based on their data availability and scope of application,
c) Detecting practical implementation hinders and benefits, as well as moral-ethical challenges, to facilitate the integration of the proposed model with companies' project management systems.
d) Promoting the application of AI in the construction industry to facilitate, optimize, and automate project management services and increase projects' success rate.

This research project is funded and conducted in collaboration with Jacobs SPA, which is a leading construction and engineering consultancy firm worldwide. Therefore, the first practical implementation of the proposed model will be for Jacobs' project management services as the research industry partner. The topic of the research is motivated by the industry's leading firms' need to integrate AI advancements in their practices as a competitive advantage and as a driver for more efficient and sustainable projects.

Research Keywords

Risk Management, Artificial Intelligence, Machine Learning, Bayesian Network, Construction Projects

Organization and structure of the thesis

The thesis starts with an abstract and introduction and is followed by the main body consisting of a) Literature review and state of the art, b) Methodology and research scheme, c) Results and discussion, and d) Conclusion. Each chapter has some subchapters that are indicated in Table a.

Table a. Organization and Structure of the Thesis

Introduction	**State of the Art**	**Methodology**	**Results and Discussion**	**Conclusion**
Chapter 1: Introduction	**Chapter 2:** Systematic Literature Review Process on AI application for Construction Risk Management **Chapter 3:** Conventional Risk Management Models in Construction **Chapter 4:** AI application in Construction RM **Chapter 5:** Bayesian Networks and Elicitation	**Chapter 6:** Methodology **Chapter 7:** Case Studies	**Chapter 8:** Results and Discussion	**Chapter 9:** Conclusion

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Chapter 1: Introduction

1.1 Research Field

1.1.1 Architecture, Engineering, Construction and Operation (AECO) Industry

AECO industry plays a critical role in the economy of developed and developing countries (Yu et al., 2021), having a global output of 10.7 trillion USD in 2020, which is expected to grow by 42% by 2030 to reach 15.2 trillion USD, accounting for 14.7% of globular Gross Domestic Product (GDP) by 2030 (Global Construction Perspectives and Oxford Economics, 2021). In Europe, this industry contributes to 9% of the EU's GDP and provides about 18 million direct jobs (European Commission, 2016; Norouzi et al., 2021). However, besides all its contributions, it is one of the primary consumers of resources, with about 50% of the total raw materials use and 36% of the global final energy use, as well as one of the main environmental pollutants, accounting for 39% of the energy and process-related emissions (UN Environment Programme, 2019). All these attributes place the AECO industry in a critical position for policymakers and governments. One of the strategic shifts in the industry is its digitalization thanks to the advancements of Industry 4.0 technologies and digital innovations, which, despite having promising perspectives for increasing global construction sector productivity and efficiency by 15% (Barbosa et al., 2017), has not yet found its way in practice. Therefore, it is one of the least digitalized industries, specially respecting AI integration (Rampini and Re Cecconi 2022), with one of the lowest productivity improvement rates among all industries (1% compared to the 2.8% average rate) (Barbosa et al., 2017). Solutions to implement digital technologies in the AECO industry and improve its productivity have been the focus of numerous researchers recently, and this dissertation follows the same path.

1.1.2 Notion of Risk and Uncertainty

Prince2 standard defines risk as an uncertain event or set of events that, should it occur, will affect the achievement of objectives in a project. Project Management Institute (PMI) defined risk at two levels in projects:

- Individual project risk is an uncertain event or condition that, if it occurs, has a positive or negative effect on one or more project objectives.
- Overall project risk is the effect of uncertainty on the project as a whole, arising from all sources of uncertainty including individual risks, representing the exposure of stakeholders to the implications of variations in project outcome, both positive and negative" (Project Management Institute(PMI), 2017).

Risk is measured by a combination of the probability of a perceived threat or opportunity occurring and the magnitude of its impact on objectives (Axelos, 2017). Apart from the individual risk assessment based on probability and impact, the risk path method and scenarios analysis that consider the interrelations of various variables affecting the risks are proposed nowadays (Eybpoosh, Dikmen and Talat Birgonul, 2011).

1.1.3 Risks in the Construction Industry

The construction industry has some of the highest accident and fatality rates, delays, and cost overruns, which are caused primarily by uncontrolled risks. Construction projects, due to their uniqueness and multifaceted nature, the dynamic association and conflicting interests of numerous stakeholders, long generation terms, huge capital investment, exposure to the external environment, and various productivity constraints, experience many risks and vulnerabilities during their lifecycle (Taroun, 2014). Construction Risks, according to their sources, can be divided into the owner's, contractor's, third-party's, legal, social environment, and natural environment risk groups. They can occur at various levels, operational, project, portfolio, strategic, and business and enterprise levels, derived from external and internal factors (Khodabakhshian, Puolitaival and Kestle, 2023)

Although each project is unique, regarding the usual portfolio and project types of a specific contractor or a company, a standard Risk Breakdown Structure (RBS) can be composed. An RBS and risk evaluation indexing system should follow the following principles: (1) scientific, (2) system, (3) theory for practice, (4) operability, (5) independence, and (6) comparability (Chenyun, 2012). Fig 1.1 presents a typical project RBS based on previous studies.

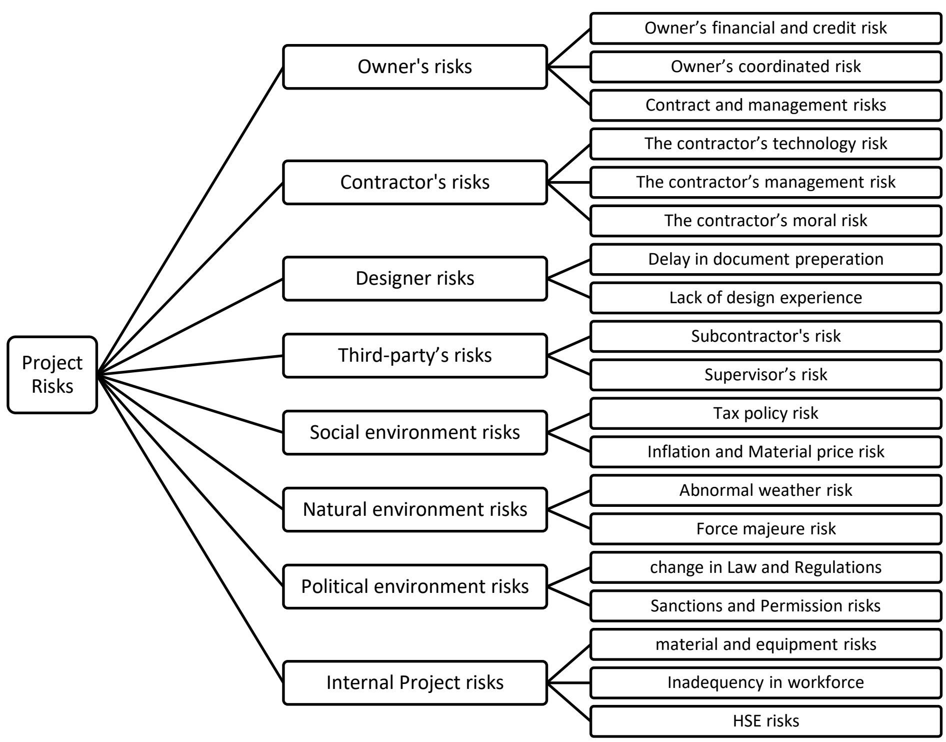

Figure 1.1 Construction Project Risk Breakdown Structure (Chenyun 2012; Ha, Hung, and Trung 2018) (Yaseen *et al.*, 2020)

1.1.4 Conventional Risk Management Methods and Processes

Project Risk Management aims to exploit or enhance positive risks (opportunities) while avoiding or mitigating negative risks (threats) through seven main steps: a) Plan Risk Management, b) Identify Risks, c) Perform Qualitative Risk Analysis, d) Perform Quantitative Risk Analysis, e) Plan Risk Responses, f) Implement Risk Responses, g) Monitor Risks (Project Management Institute(PMI), 2017). It is one of the main knowledge areas in project management standards, a brief comparative analysis of which is presented in Table 1.1.

Table 1.1 Comparison between PMBOK, PRINCE 2, and ICB standards in Risk Management practices

STANDARD	STRUCTURE	DEFINITION	STEPS
PMBOK 6	Among the main ten knowledge areas	Increase the probability and/or impact of positive risks and to decrease the probability and/or impact of negative risks, in order to optimize the chances of project success.	1) Plan Risk Management 2) Identify Risks 3) Perform Qualitative Risk Analysis 4) Perform Quantitative Risk Analysis 5) Plan Risk Responses 6) Implement Risk Responses 7) Monitor Risks (Project Management Institute(PMI), 2017)
PRINCE 2	One of the seven PRINCE2 themes	The systematic application of principles, approaches and processes to the tasks of identifying, assessing, and planning for risks and communicating risk management activities with stakeholders	1) Risk Identification 2) Probability, impact and timing (proximity assessment) 3) Response planning, Response implementation 4) monitoring and controlling (Axelos, 2017)
ICB 4.0	Categorized under the practice (project related) competence discussed in Project, Program, and Portfolio Management levels	Identification, assessment, response planning, and implementation and control of risks and opportunities around projects	No clear steps provided (International Project Management Association 2015)

RM is an important tactic to meet project targets like time, budget, and quality (Han *et al.*, 2008). Therefore, companies need to implement systematic risk management practices to identify, analyze, solve, and control the risks and integrate them into their organizational structure to increase their success rate. Furthermore, due to the advancements in digital technologies, a large volume of data is collected from construction, which can feed the RM models. However, conventional RM is conducted in an inefficient, subjective, and superficial form and based on individual and experience-based expert judgments (Li *et al.*, 2018). Furthermore, the data registry is not done in a structured, interoperable, and regular manner. Therefore, knowledge transfer, model generalization, and process automation remain critical issues for future projects' RM (Eybpoosh, Dikmen and Talat Birgonul, 2011).

1.2 Problem statement and approaches

1.2.1 Industry 4.0 Revolution in the Construction Industry

The construction industry is currently undergoing a significant transformation towards digitalization, which can be attributed to a) the generation of copious amounts of on-site and off-site data, b) the advancement of digital tools and technologies to capture and document this data such as wearable devices, sensors, and Internet of Things (IoT), and c) data-driven methods and decision-support systems, such as Artificial Intelligence (AI), Digital Twins, and Building Information Modelling (BIM), to process this data and extract insights for more efficient decision making and management of projects (Pan and Zhang, 2021). 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 that aims to make machines mimic human cognitive processes of learning, reasoning, perception, planning, and self-correcting (Darko *et al.*, 2020). AI is gaining a vast application for fostering, optimizing, and automating processes throughout the entire construction project life cycle for intelligent management of projects (Chenya, 2022).

Nowadays, AI algorithms can learn from enormous real-time data generated by cutting-edge technologies like 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 the construction projects (Zhong *et al.*, 2017). This data, if transformed into a structured and understandable form, can bring valuable insights for knowledge management in projects, and economic and social developments. The AI learning process takes 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. AI 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, nonlinear, and uncertain problems (Mellit and Kalogirou, 2008). Figure 1.2 presents the key pillars of the Industry 4.0 revolution in the construction industry.

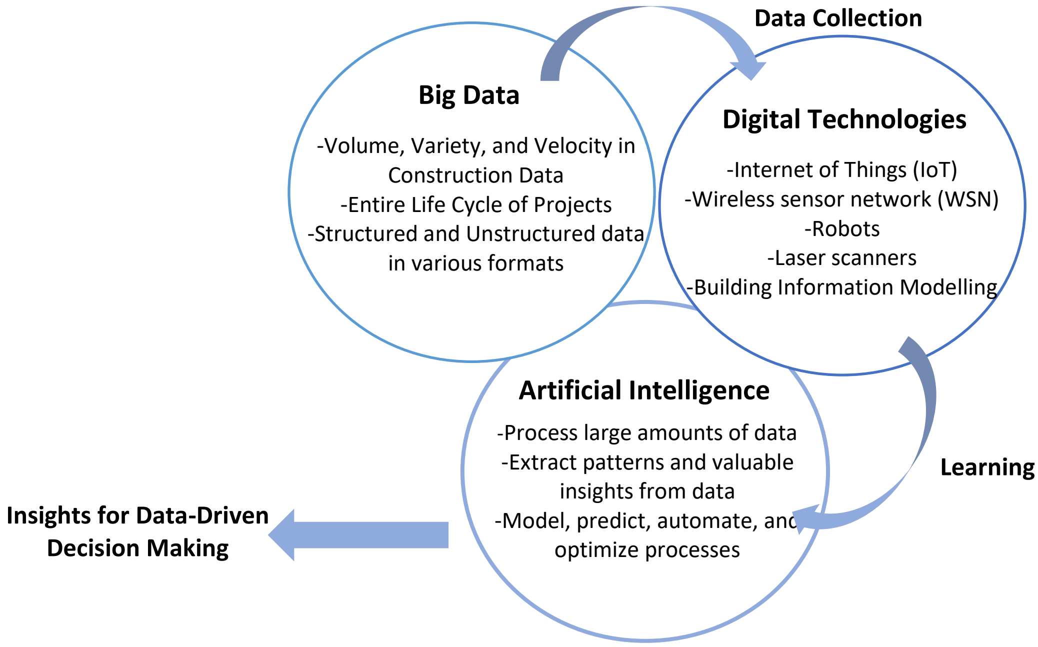

Figure 1.2 Pillars of Industry 4.0 Revolution in the Construction Industry (Khodabakhshian, Puolitaival and Kestle, 2023)

1.2.2 Machine Learning for Risk Management

The emergence of AI and ML has offered a promising avenue for addressing the shortcomings of conventional RM methods, enabling more accurate risk identification, assessment, and mitigation processes (Chenyun, 2012; Ha, Hung and Trung, 2018). AI models can improve analytical capabilities across the RM domain while offering a high granularity and depth of predictive analysis (Guzman-Urbina, et al. 2018), and provide accurate results in uncertain, dynamic, and complex environments (Yaseen *et al.*, 2020), like the construction industry. AI-based RM systems can function as a) Early-warning systems for risk control, b) AI-based risk analysis systems using algorithms like Neural Networks for identifying complex data patterns, c) Risk-informed Decision Support Systems for predicting various outcomes and scenarios of 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 in computer systems (Wu, Chen and Olson, 2014). However, their applications in construction RM have been limited and far behind other industries, and robust AI-based RM frameworks are missing (Chenya, 2022).

1.2.3 Machine Learning application benefits and hiders in construction enterprises

Though ML application can automate, optimize, and facilitate the RM processes, it requires a significant amount of data in a structured format to learn from and make a prediction for future projects. The most important hinders to the widespread application of ML in construction RM are:

a) lack of structured data or infrequent project documentation, with most data in text or image formats,
b) over-reliance to individual and experience-based judgment of experts for RM,
c) isolated risk analysis and ignorance of causal inferences between variables in risk path analysis (Eybpoosh, Dikmen and Talat Birgonul, 2011),
d) wrong choice of AI model for a given problem regarding the data availability and requirements, the role of probability and expert judgment, and the reasoning behind the analysis (An *et al.*, 2021; Chenya, 2022),
e) concerns about data privacy, confidentiality, and ownership,
f) lack of knowledge and training about ML methods in the industry

As there are a variety of risk types and individual experts might not have encountered or have sufficient knowledge of all of them, human-based risk analysis systems suffer from low accuracy, incomplete risk identification, and inconsistent risk breakdown structures (Siraj and Fayek, 2019).

1.3 Research Gap and Proposed Solution

While ML application in construction engineering and management has been widely studied and practical models have been developed for addressing challenges in design and execution processes (Jin, Zuo and Hong, 2019; Akinosho *et al.*, 2020), the RM domain, especially in project-level risk assessment, falls far behind. There is a research gap between the potentials and competitive advantages of AI-based models to facilitate and automate the RM processes in construction projects and their real-world application status quo. One of the most important issues hindering the widespread adoption of ML in RM practice is the lack of structure, comprehensive, and well-documented data in the construction industry (Maphosa and Maphosa, 2022). Construction projects are unique, lengthy, and complex, resulting in infrequent data generation and documentation from which the ML models can learn. Nevertheless, with the digitalization and data management trends caused by industry 4.0 technologies, data collection from construction projects is becoming faster, more standardized, and more frequent (Khodabakhshian and Re Cecconi, 2022; Regona et al. 2022; Kozlovska, Klosova, and Strukova 2021). The advancements of text mining methods like Natural Language Processing (NLP), preprocessing techniques, synthetic data generation using Generative Adversarial Networks (GANs), data clustering and classification methods like Support Vector Machine (SVM) and K-Nearest Neighbor (KNN), and models based on multiple sources and inferences like Bayesian Networks (BNs) can solve this problem. As a result, ML models can leverage more extensive databases, significantly enhancing their accuracy and effectiveness in construction research and practice (Ledig et al., 2017; Fan et al. 2019; Akinosho et al., 2020; Choi et al., 2021).

Seeing the proof of AI's effectiveness and productivity in other industries' risk domains, this research tries to bridge the gap of AI application for the construction RM domain by developing a systematic and holistic AI-based risk identification, assessment, mitigation, and control model, which can extract knowledge and insights from previous projects and expert judgment to predict risks for new projects efficiently and automatically. The proposed model can benefit from the advancements of digital technologies in various phases and integrate the produced knowledge in the project information systems, digital twin models, and documents for better knowledge management. Figure 1.3 presents the proposed AI-based RM framework that aims to a) mine and analyze real-time project data, historical records, or elicited experts' opinions (Hon *et al.*, 2021), b) conduct automatic identification, evaluation, and assessment of risks, c) conduct proactive decision-making on responses to mitigate these risks and d) share this insights and predictions in a collaborative environment for data integration like Cloud Building Information Modelling (BIM), and Digital Twin platforms (Pan and Zhang 2021). The main focus of this research is the ML algorithm learning part for automated risk identification and assessment.

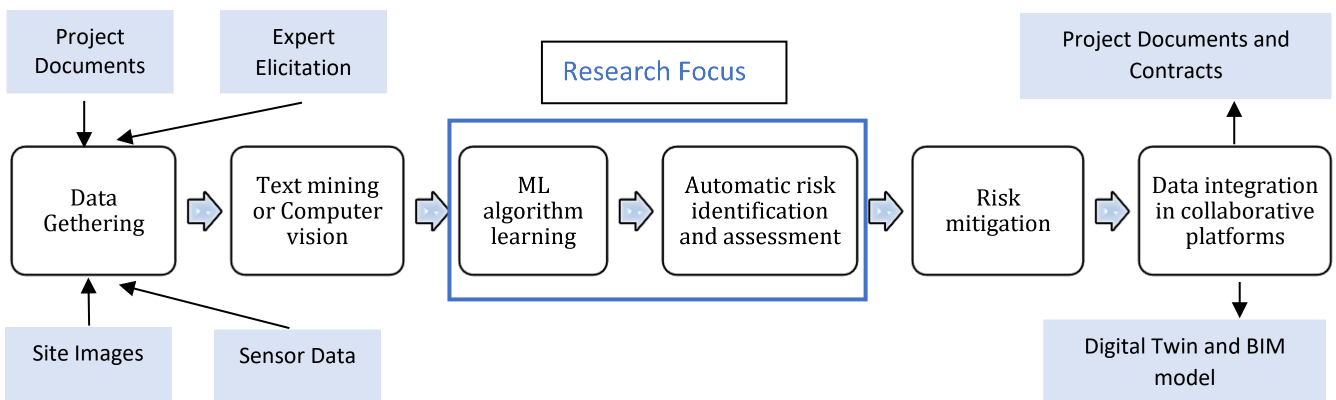

Figure 1.3 AI-based Risk Management framework (modified from (Khodabakhshian, Puolitaival and Kestle, 2023)

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Chapter 2: Systematic Literature Review Process on AI application for Construction Risk Management

2.1 Systematic Literature Review

This research used a Systematic Literature Review (SRM) approach on scientific libraries with various bibliometric analysis methods to find interrelations between RM, AI, and ML, and Project Management and Construction Industry, which serve as the theoretical basis of the developed model. The systematic literature review has a comprehensive, structured, reproducible, transparent, and quantitative nature. There are also some disadvantages, such as potential biases in the search. These have been minimized by following a systematic process throughout (Pickering and Byrne, 2014). An SLR requires the following stages: (1) question formulation; (2) localization and searching of the literature; (3) study selection and evaluation; (4) analysis and synthesis; and (5) reporting and interpretation of results. (Habibi Rad, Mojtahedi and Ostwald, 2021). 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 (Khodabakhshian, Puolitaival and Kestle, 2023). Figure 2.1 presents the main research areas of the State of Art, which served as the classification basis of the source papers.

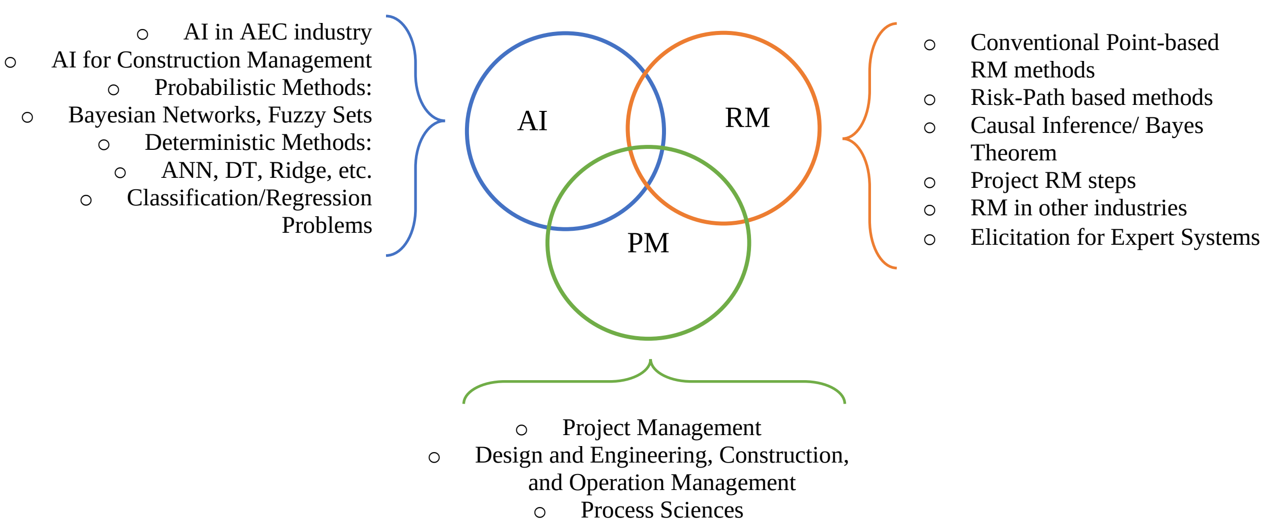

Figure 2.1 State of the Art areas

The literature search was conducted in Scopus and Web of Science, two of the most holistic scientific libraries. These sources provided relevant publications for the research themes mentioned in Figure 2.1. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were used to conduct the SLR, 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. The search rule is presented in Equation 2.1:

((Risk Management) OR (Risk Assessment) OR (Risk Analysis)) AND ((Construction industry) OR (AEC) OR (Construction Projects) OR (Building Sector)) AND ((Artificial Intelligence) OR (Machine Learning) OR (Deep Learning) OR (Bayesian Networks) OR (Deep Learning) OR (Neural Network) OR (Fuzzy Logic) OR (Statistical Model) OR (Data Mining)) (2.1)

Followingly, a thematic and bibliometric analysis was conducted using the VOSviewer and Bibliometrix applications on the source papers to identify the main areas of research concentration, common techniques, interrelation of topics, application scopes, and trending topics. Figure 2.2 presents the SLR workflow.

a) In the **Identification phase**, the search rule in equation 2.1 was used, and a massive amount of relevant literature was found.
b) In the **Screening phase**, a couple of criteria were used, such as the Engineering domain, publication date after 2013, and English language, after which 1143, 734, and 685 articles remained, respectively. Two groups of articles were the focus of the screening phase: a) review papers, as a result of which 71 articles were selected, and b) technical papers, as a result of which 245 papers were selected for the Eligibility phase. Review papers were used to extract general knowledge on various techniques and conduct a comparative analysis between them, and technical papers were used to get ideas about possible solutions to the research problems. They also served as a benchmark for the proposed model's accuracy evaluation and validation.
c) In the **Eligibility phase**, which had some overlaps with the Screening phase, abstracts and keywords of all 69 review articles and 614 technical papers 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 like data generation or structural design (Cao *et al.*, 2021), and some were focused on non-AI methods (Hualiang Li, Runzhong Liu, Li Li, Zhiting Liu, Shaoyan Lu and Lin, 2020), which was 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 review papers and 412 technical 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.
d) In the **Inclusion phase**, 48 review papers and 412 technical papers were selected as the source papers and were thoroughly studied and analyzed using quantitative and qualitative analyses to answer the research questions.

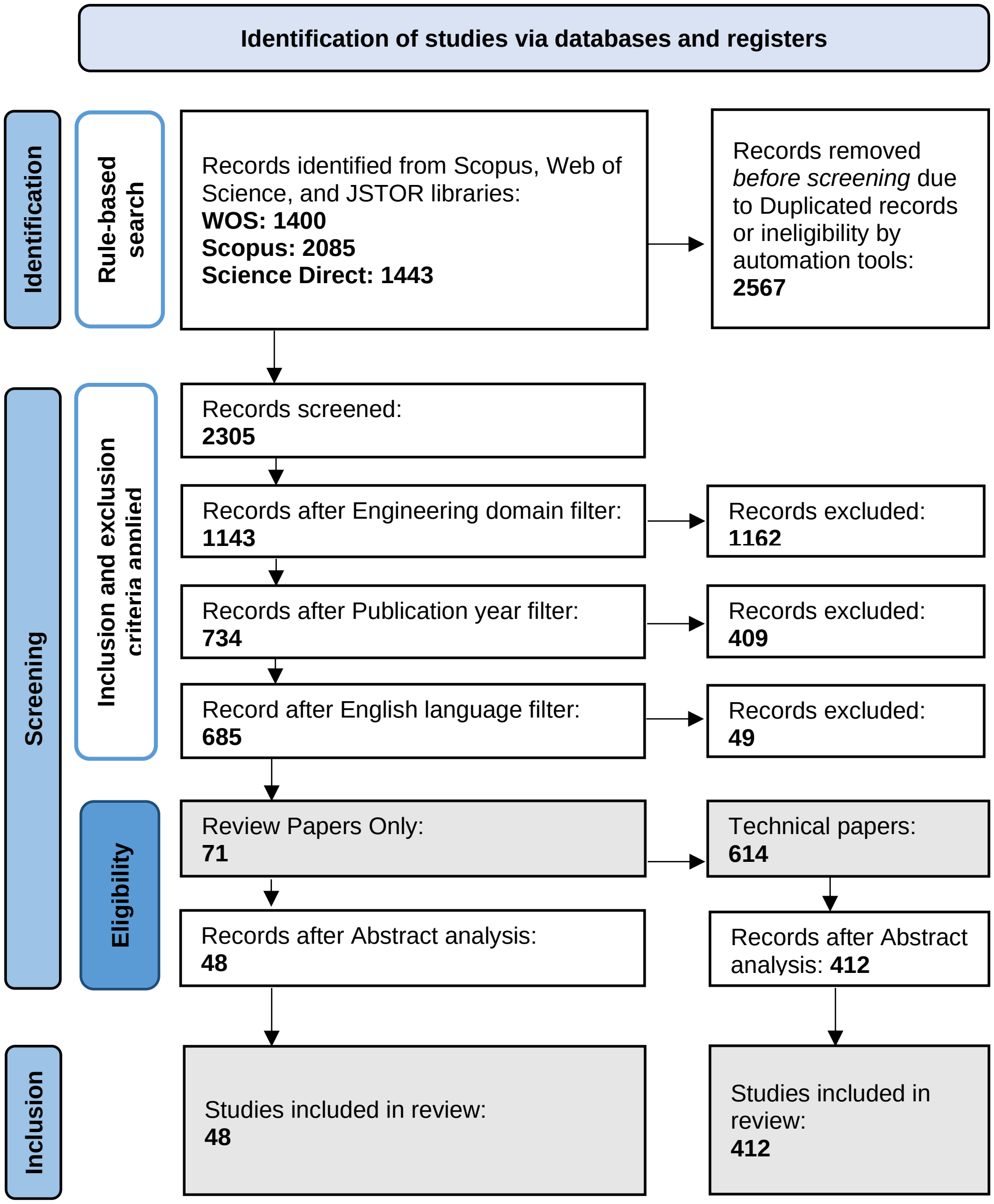

Figure 2.2 Systematic Literature Review flowchart based on PRISMA

The PRISMA checklist for Systematic Reviews is also addressed and filled to comply with the standard format of this study. However, the checklist is best suited for quantitative studies and analyses. Due to the qualitative nature of the primary analysis stage, some of the checklist items, such as risk ratio, risk of bias, mean difference, and sensitivity analysis, were not applicable to this study. The checklist consists of 5 stages, as well as sections of the paper addressing these stages are mentioned below:

- Framing the question: Introduction
- Identifying relevant publications: Systematic Literature Review
- Assessing study quality: Systematic Literature Review and Methodology
- Summarizing the evidence: Systematic Literature Review and Results
- Interpreting the findings: Results and Conclusion

2.2 Bibliometric Analysis

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; as well as research productivity and trends evaluation (Ali, Alhajlah and Kassem, 2022). Co-word analysis examines the content of the publications' "words" themselves (Donthu *et al.*, 2021). As an example, co-word analysis can show a thematic relationship between research keywords and research areas that frequently appear together. A keyword network displays the structure of the knowledge body by presenting the interrelations and organization of research topics (Zhao, 2022).

Figure 2.3. presents the keyword co-occurrence diagram in the 48 review papers that delineates areas of research concentration, common techniques, interrelation of topics, application scopes, and trending topics. For results visualization purposes, VOSviewer and Bibliometrix applications were used. It is noteworthy that a number of papers were particularly focused on health and safety risks, which are only analyzed regarding the AI algorithms they proposed (Kamari and Ham, 2022). Based on the bibliometric analysis, the topics covered in literature are grouped into 5 main areas, as presented in Figure 2.3: a) AI algorithms and techniques, b) Construction project disciplines, c) RM steps and areas, d) Decision support systems, and e) Health, safety, and occupational risks.

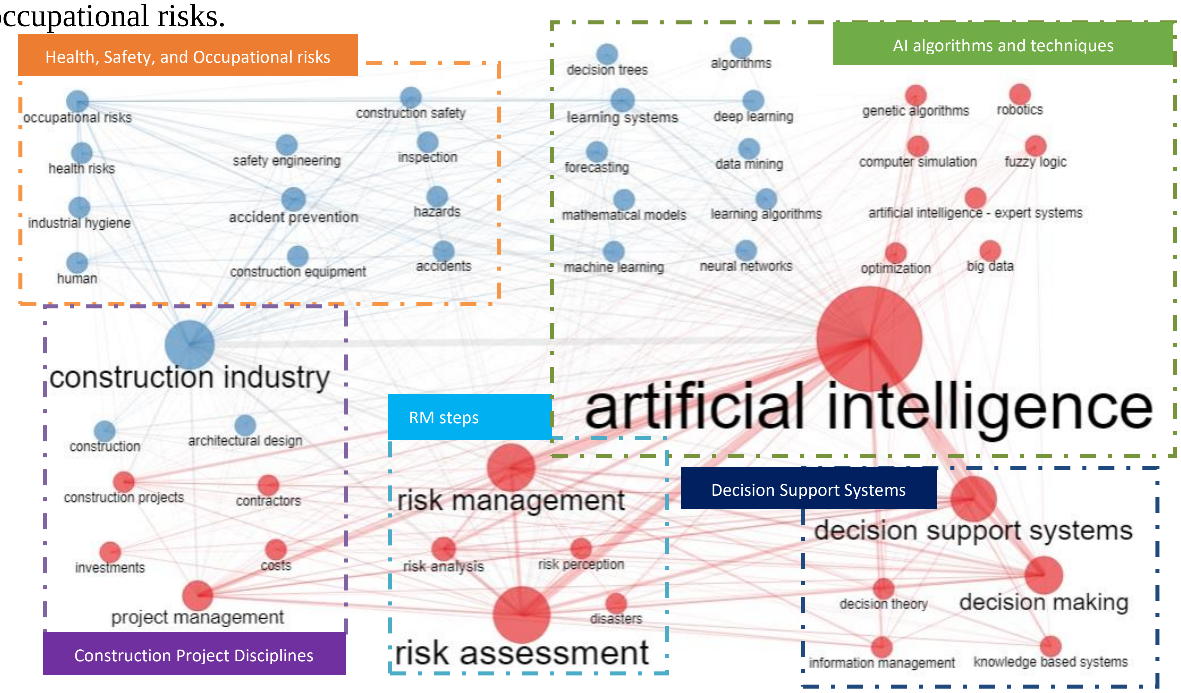

Figure 2.3 Co-occurrence diagram between keywords and research areas of source papers

Figures 2.4.a and 2.4.b present the co-occurrence diagram of keywords found in technical papers in WOS and Scopus, respectively, with their evolution over time. As evident in both figures, the focus of publications has shifted from classical and manual RM methods, such as AHP and Fuzzy Logic, to the use of novel and data-driven technologies, especially ML. Furthermore, the most common ML techniques are being repeated in keywords, such as Bayesian Belief Networks, Artificial Neural Networks, Random Forest, Fuzzy Logic, Genetic Algorithm, etc., which will be thoroughly analyzed in Chapter 4. The annual scientific publication rate and trending topics are presented in Figures 2.5 and 2.6, demonstrating a significant increase within the past couple of years. Big Data, Machine Learning, and Deep Learning lead the current trend of publications, followed by health, safety, and occupational risks. Decision Support Systems and knowledge-based Systems have been trending during the last decade but are substituted by AI-based techniques that foster the decision-making process. Figure 2.7. presents the co-occurrence diagram of countries that produced scientific articles in this domain, with China, the US, and Iran in the lead. However, interestingly, Italy has become one of the leading countries recently, indicating the interest of the Italian scientific community in AI-based RM methods.

As the bibliometric analysis is quantitative in nature and produced mainly background data, qualitative analyses were followed to answer the research questions in more detail and to analyze each ML algorithm and method, which is presented in Chapter 4. The data was first looked for AI-based risk data structuralizing and pre-processing methods through qualitative content analysis. Secondly, using a deductive approach, thematic content analysis was used to identify, analyze, and report repeated patterns (Bandura, 1989). Focusing mostly on ML algorithms and techniques and RM steps and areas groups and based on a contents analysis on applied techniques in technical papers, the ML-based techniques for risk identification, analysis, and mitigation planning were grouped under two general umbrella terms, deterministic and probabilistic models. A comparative analysis was used between probabilistic and deterministic models regarding their reasoning basis in risk assessment, advantages and disadvantages, application areas, and data requirements for each, which will be presented in Chapter 5. Moreover, given that Bayesian Approaches are the main solution proposed by the research, a separate chapter is designated to them, including structure and parameter learning methods for creating risk networks.

a)

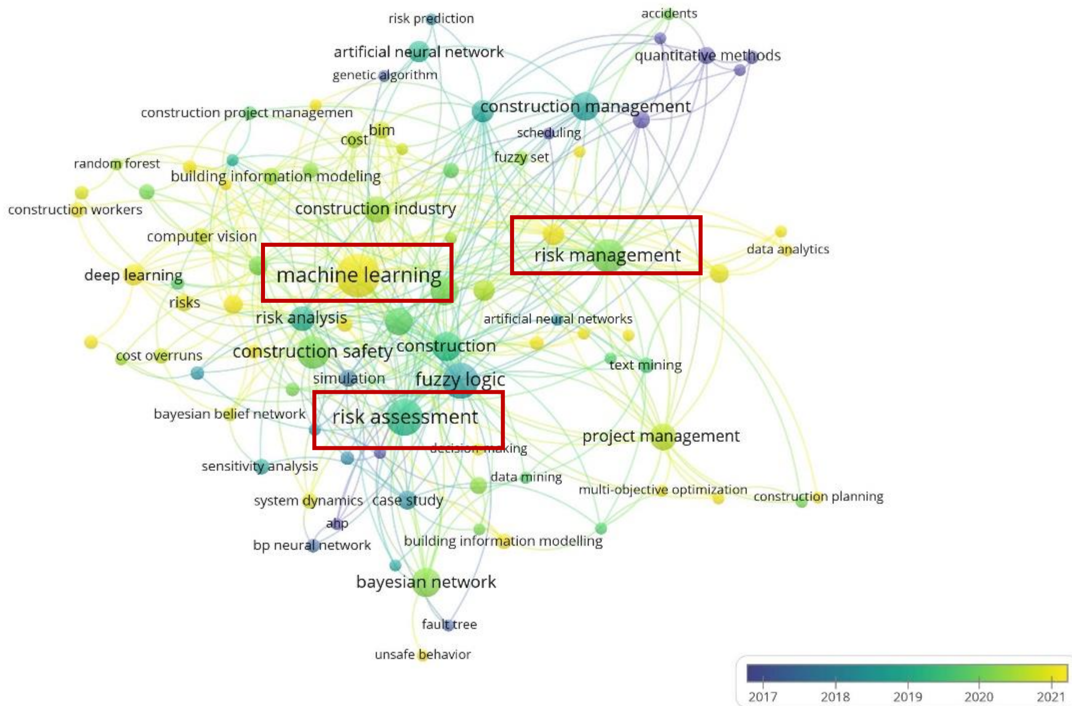

Figure 2.4a Keyword co-occurrence diagram and evolution during time in WOS source papers

b)

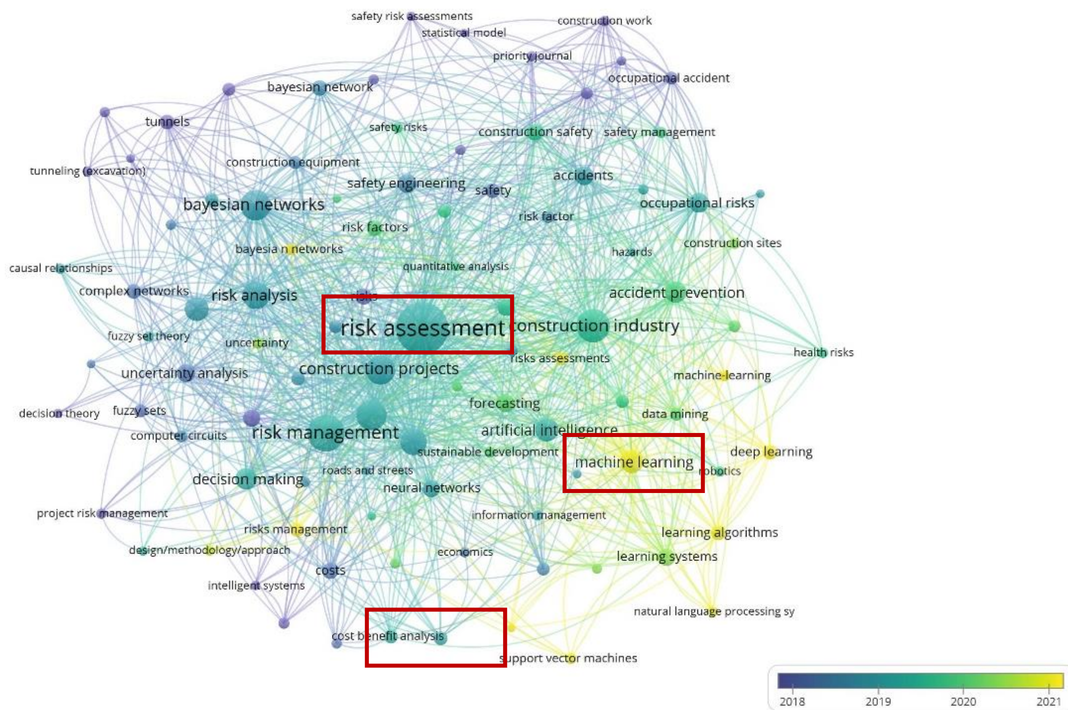

Figure 2.4b Keyword co-occurrence diagram and evolution during time in Scopus source papers

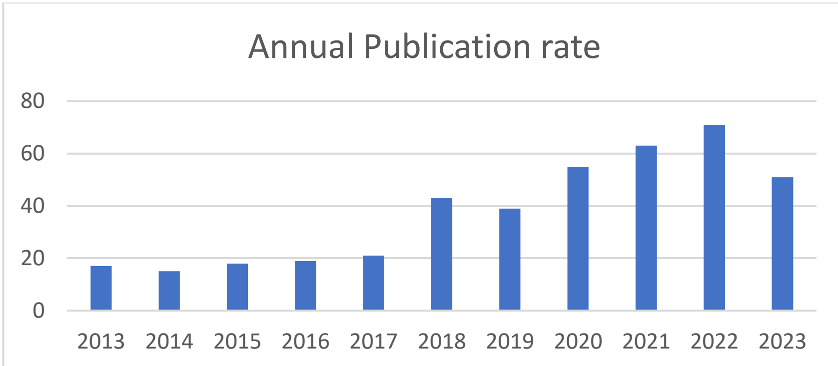

Figure 2.5 Annual Publication rate in AI-based RM models for the construction industry, based on the source papers

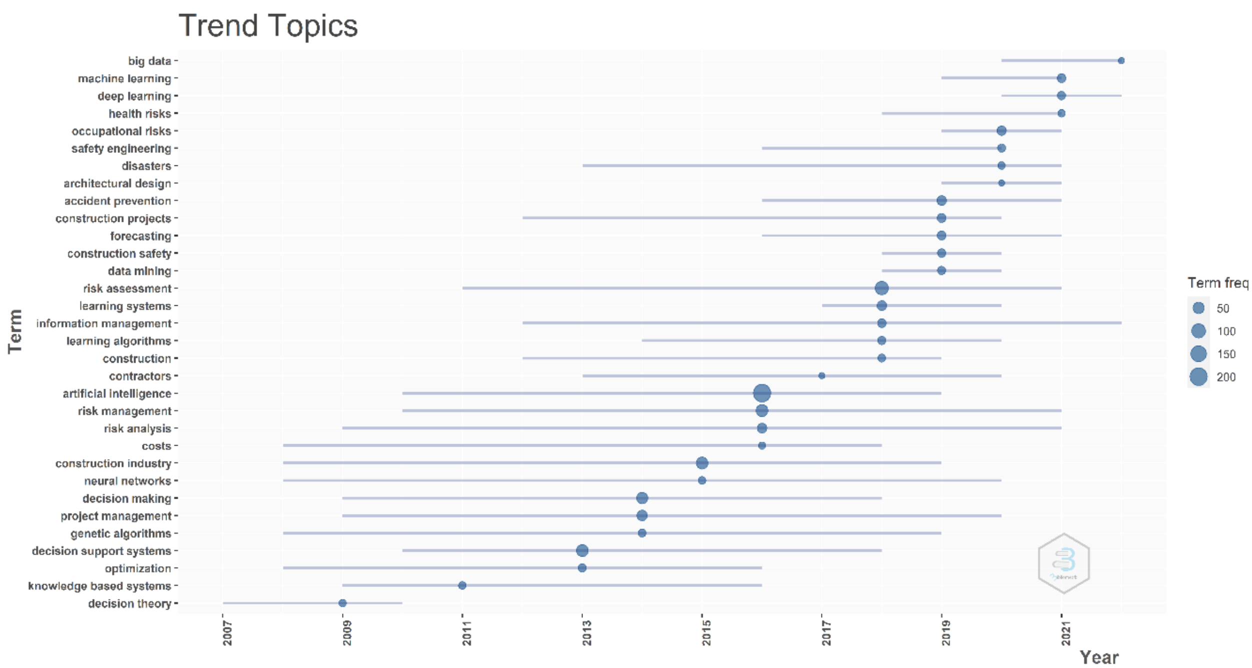

Figure 2.6. Trending topics and keyword dynamic

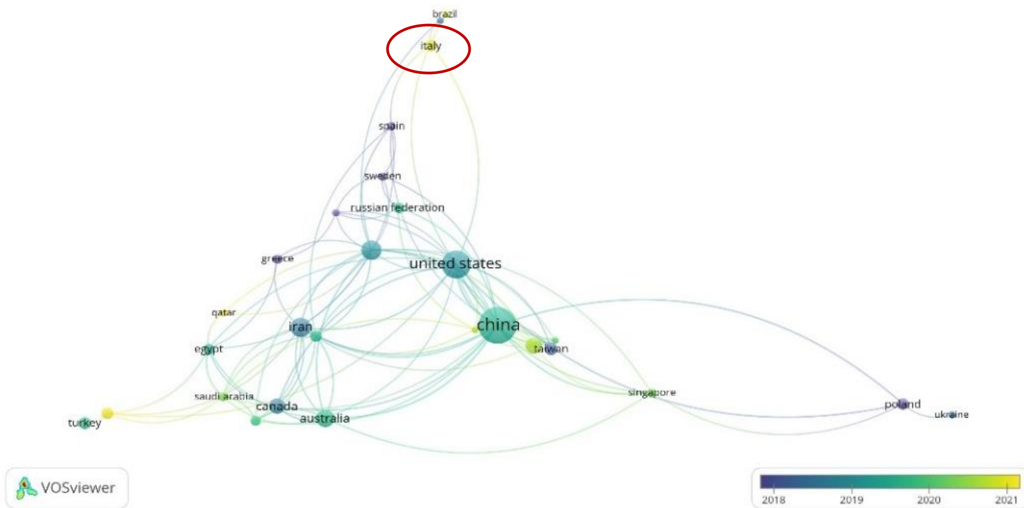

Figure 2.7. Co-occurrence diagram of countries

2.3 Statistical Analysis

In this subsection, a statistical analysis is conducted on the applied ML methods in technical papers, risk areas, and risks identified in the source papers. Figure 2.8. indicates the most frequent methods used with Hybrid Models (mostly Fuzzy+ another algorithm), Bayesian Belief Networks, Artificial Neural Networks, Fuzzy Logic, and Monte Carlo Simulation on top. These findings show the vast application of probabilistic models in the context of risk, unlike most other knowledge areas where deterministic approaches have more applications. Figure 2.9 indicates the RM steps covered in the source papers, with qualitative risk analysis on top, followed by risk identification, risk quantitative analysis, and mitigation planning. It is noteworthy that this categorization indicates the phase up to which these studies progressed. An interesting fact is the limited number of studies for risk intervention mitigation planning and post-intervention analysis, which is the case in real-world applications, too.

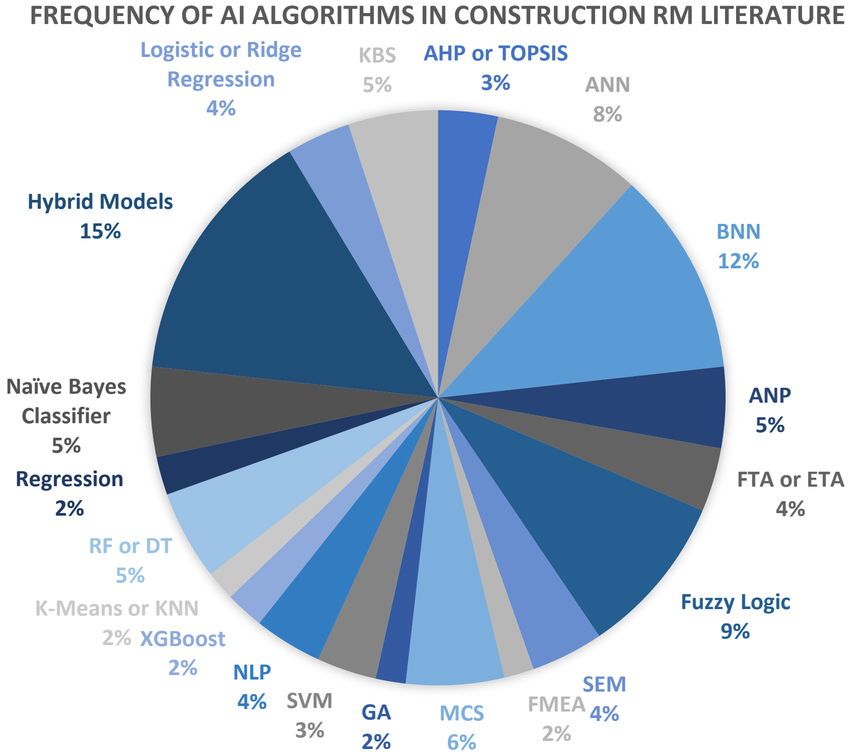

Figure 2.8. Most frequent AI methods used for construction RM in literature

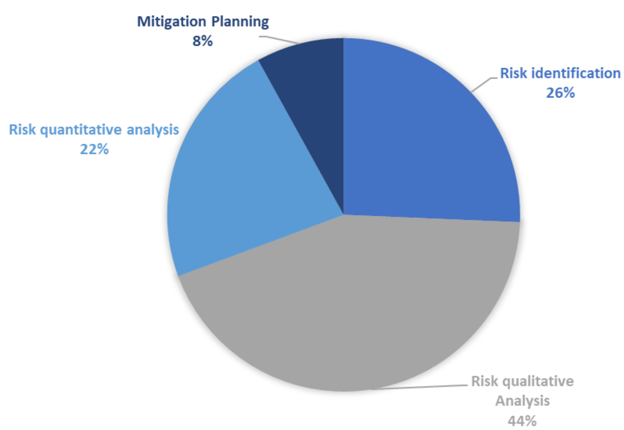

Figure 2.9. RM steps covered in source papers

Previous review studies aimed to identify factors leading to delays and disputes (Assaf and Al-Hejji, 2006), risks triggering cost performance in projects (Iyer and Jha, 2005), safety risk factors in the execution phase, international risk levels (Hastak and Shaked, 2000), and other topics. After reviewing previous articles, the most common risks were extracted and categorized into 11 groups: 1) Technical, Scope, and Management risks, 2) Administrative risks, 3) Communication risks, 4) Environmental risks, 5) Procurement risks, 6) Resource risks, 7) Safety risks, 8) Schedule risks, 9) Stakeholders risks, 10) Quality and change risks, and 11) financial risks. This categorization is based on the industry partner's documentation to be consistent in further research steps. This list of risks was compared with the company's risk list, and relevant risks were added to the study after interviews with the company representatives. Figures 2.10 to 2.12 present the most common risk factors identified in the financial, procurement, and safety categories.

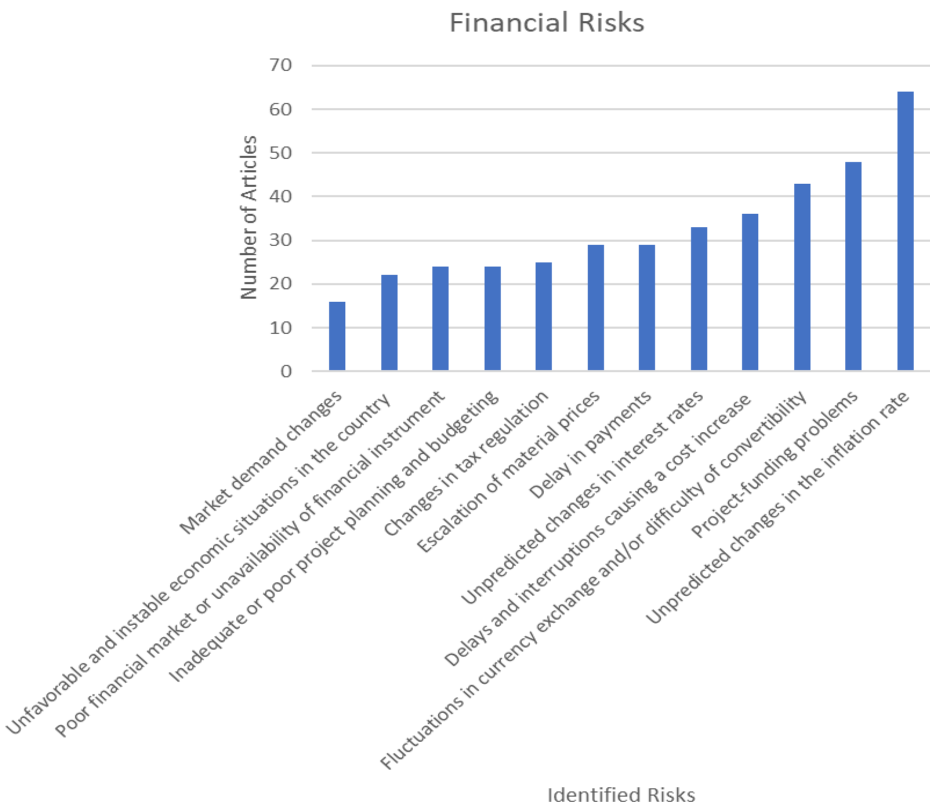

Figure 2.10. Frequency of appearance of each risk in the Financial Risk category in literature

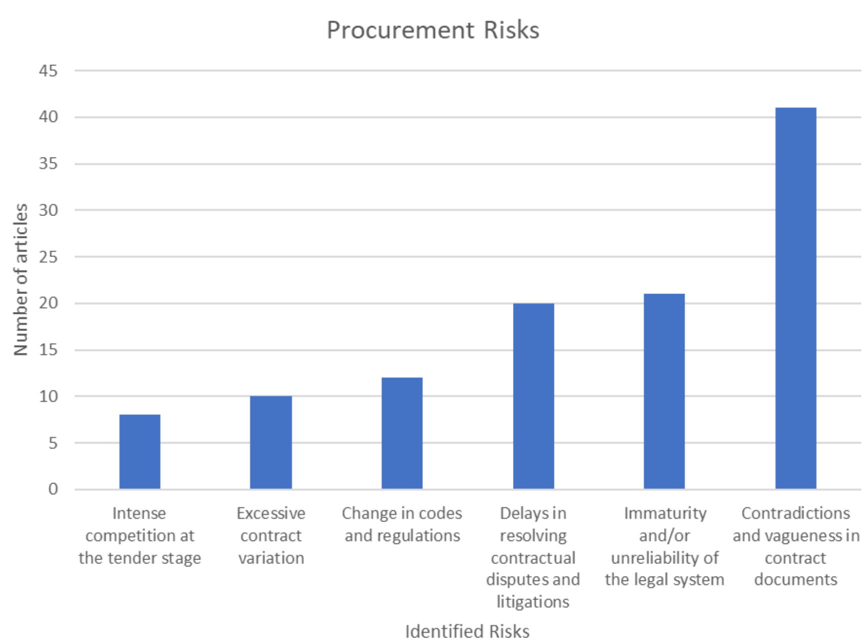

Figure 2.11. Frequency of appearance of each risk in the Procurement Risk category in literature

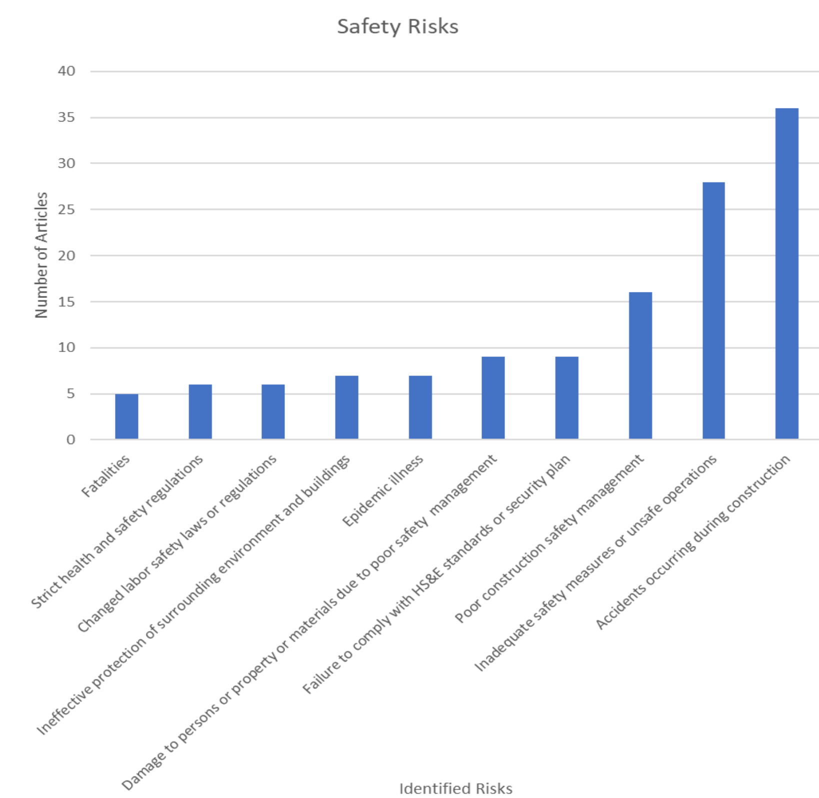

Figure 2.12. Frequency of appearance of each risk in the Safety Risk category in literature

2.4. Findings and Shortcomings of previous Review Studies

Many remarkable review studies have been published in recent years that present an extensive review of Industry 4.0 in formation of construction 4.0 (Kozlovska, Klosova and Strukova, 2021), different AI applications in the construction industry (Pan and Zhang, 2021) and in other industries (Wang and Siau, 2019), AI-based RM models for intelligent project management (Afzal *et al.*, 2019), and many more insightful topics. Contrasting with studies before 2009, which were largely centered on mathematical modeling or computer-aided design, the recent decade has seen a surge in the application of various quantitative methods and ICTs, especially BIM and AI, in the CEM field (Jin, Zuo and Hong, 2019).

The main foci of previous review studies were the structure of the AI algorithms or the data mining technologies (Rao and Chen, 2020), the classification of AI methods based on their structure, or the used technology, such as ML or computer vision (An *et al.*, 2021). The grouping of these technologies was based on their area of application in construction projects. For instance, Afzal *et al.* (2019) conducted a comprehensive review analysis on AI-based risk assessment methods and listed papers based on the technique used, identifying six key techniques used. Another critical review of available literature on AI applications in the construction industry, such as activity monitoring, risk management, and resource and waste optimization, was conducted by Abioye *et al.* (2021). Sharma *et al.* (2021) conducted an extensive review of the capability of various AI-based models to accurately predict and estimate preliminary construction cost, duration, and shear strength. In a similar study, Tayefeh Hashemi et al. (2020) analyzed the scientific papers on ML-based cost estimation over the past 30 years. In another study, the tree structure consisting of nodes in data mining was studied by Rao and Chen (2020) in the scope of construction risk control.

Islam et al. (2017) 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. In a similar study, Nguyen and Fayek (2022) conducted a comprehensive review study on the applications of hybrid fuzzy techniques in construction engineering and management research, providing a categorization of various hybrid models and their main application areas.

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 (Darko *et al.*, 2020; Yan *et al.*, 2020; Xu *et al.*, 2022) 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. (Xiong, Skitmore and Xia, 2015).

Notably, there are limited review studies specifically on BNs application for project management or RM in the construction industry, which generally aimed to predict the success of the projects (Martínez and Fernández-rodríguez, 2015; Afzal *et al.*, 2019). One of the comprehensive reviews on this topic that was not merely limited to the construction industry was conducted by Guinhouya et al. (2023), which focused on articles published within the last 20 years, categorizing them based on the project type (Construction & Infrastructure; Software & IT; Engineering & Manufacturing; and Others), project aspect (Challenges & Risks; Context & Process; and Outcomes), reasons for using BNs (Description; Prediction; and Prescription) and types of BNs (Basic BNs; Combined BNs; and Extended BNs).

As supported by these studies' findings, historically, risk analysis methods were primarily focused on ranking risks based on their relative importance. However, there has been a paradigm shift towards understanding the intricate interrelationships among various risks. This evolution is evident in how the objects of construction RM research have transitioned from generic construction projects to more specific types, such as small projects, underground constructions, green buildings, and prefabricated projects. Furthermore, there has been a heightened focus on individual risk categories, including political, safety, and social risks. The most studied type of risk in construction literature is safety risk. While most efforts have been directed toward technical developments, the management of construction personnel safety remains a primary concern. This attention to detail is complemented by the integration of RM into various management functions, such as cost, time, quality, safety, and environment, especially with the rising adoption of information and communication technologies (ICTs) (Zhao, 2022). Thanks to the Industry 4.0 revolution and the vast application of ICTs in the industry, the construction RM approach has evolved considerably, driven by technological advancements, innovative methodologies, and a deeper understanding of the intricacies of construction projects.

The application of ICTs in construction engineering and management (CEM) has been gaining momentum since 2009 (Jin, Zuo and Hong, 2019). This momentum is driven by the application of a plethora of quantitative methods, including algorithms, statistics, fuzzy sets, and neural networks. These methods have been pivotal in applying various data analytics approaches to perennial management issues, such as safety, sustainability, and risk assessment. The emergence of hybrid methods, which combine fuzzy techniques, MCDM, network analysis, and machine learning, signifies the industry's commitment to innovation (Zhao, 2022). ICTs, including building information modeling (BIM), the Internet of Things (IoT), virtual reality (VR), and digital twins, have been progressively integrated into RM. This integration is further underscored by the consistent focus on project performance indicators, such as cost, scheduling, safety, productivity, and risk management, in leading scientific journals (Adeleye *et al.*, 2013).

The recent decade has witnessed a harmonious integration of conventional research themes in construction with emerging topics. For instance, while cost, schedule, and productivity remain the top-studied topics, the methodologies have evolved. Traditional prediction methods have been replaced by advanced techniques like data mining and ML. Similarly, data analytics tools, such as the Bayesian decision tool, have found wider applications in construction safety research, with a growing emphasis on artificial intelligence and smart monitoring (Cho *et al.*, 2018).

Even though previous review studies provided lucrative insights on the evolution of the industry and RM processes, as well as highlighted the main ML applications for the RM domain, they rarely present a practical and problem-driven framework to implement these technologies in practice, and mostly focused on the underlying theoretical foundation of them. Once a practical approach is considered, many challenges come into the picture that need to be addressed, like ethical, moral, and social behaviors and responsibilities of autonomous agents like AI, industry acceptance, and trust building in these technologies (Emaminejad and Akhavian, 2022), data and model ownership and legal considerations, biases/harms/discrimination raised through data gathering phase, one-fit all model issues, conflicts of interest with current company practices, the requirement for training and education about AI, and many more prerequisites for a successful AI-based model application in practice.

One of the few studies that addressed the Opportunities and Adoption Challenges of AI in the Construction Industry was conducted by Regona et al. (2022), which identified fifty-seven key AI algorithms frequently mentioned in journal articles, namely, neural networks, fuzzy cognitive maps, genetic algorithms, Bayesian model, support vector machine, fast messy genetic algorithm, bootstrap aggregating neural networks, and adaptive boosting neural networks, which consequently are more likely to find a vast application in practice.

Although such studies provide helpful insights, they contain highly detailed and advanced information and formulas that might be far from the experience and roles of the audience and, in this 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.

This study, benefiting from the opportunity to work with real industry partners and encounter real-world problems when designing, optimizing, and implementing an AI-based model from start to finish, has a viewpoint and purpose different from the source review papers. In this study, the model is not merely a research case that can delineate the advantages of AI but also a practical example of how AI can alter already established and nonefficient RM practices, the challenges it can face, the ethical issues it can raise, and the solutions to these issues, with a problem-solving viewpoint. For instance, data scarcity, a widespread problem in almost every construction enterprise, has mainly not been appropriately addressed in previous studies as they did not focus on real-world case studies. To address such issues, this study explored AI-based solutions from other domains that are more advanced compared to construction. This is an opportunity offered by the advancements of Industry 4.0 technologies, which combine different technological approaches and models such as AI, Digital twins, Blockchain, and Cloud computing to expedite computerization and interconnectedness in diverse industries, leading to operational excellence (Habibi Rad, Mojtahedi and Ostwald, 2021).

Therefore, although the review papers gave significant insights and guidance toward the proper selection of algorithms and scope of applications, this study aims to go one step further and point out the areas that have not been extensively covered by such review studies, as the research gaps. Moreover, having the practical viewpoint, this research assesses previous review studies based on their practicality and compliance with actual industry challenges to choose the most optimum solution for the RM domain. The theoretical findings of this multidisciplinary study, alongside a comparative analysis of ML applications for construction RM, will be presented in Chapter 4, and the practical results will be presented in the results section in more detail.

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Chapter 3: Conventional Risk Management Models in Construction

3.1 Risk Management processes in construction projects

"The possibility of loss, injury, disadvantage or destruction" is the definition of risk in Webster's dictionary, which is measured by the combination of its probability of occurrence and the consequences of the occurrence (Subramanyan, Sawant and Bhatt, 2012). Risks can emerge from various origins, such as a) risk from outside the company—natural hazards, activities of suppliers, debtor customers, government policies; (b) risk from within the company—physical damage, accidents; and (c) risk that originates from company's activities—negligence (Assaf and Al-Hejji, 2006), which can be grouped under different Risk Breakdown Structures (RBS) (Mittnik and Starobinskaya, 2010), which can range from economic, scheduling, quality, and safety risks to macroeconomic, social, political, legal, contract, client-related, design, safety, procedural complexity, technical, material and equipment, project team, and cost overrun risks (Ganbat *et al.*, 2018). Furthermore, international risks can fall into three levels a) macro (nationwide), b) market, and c) project (Hastak and Shaked, 2000). Despite the various sizes and scopes of construction projects and their associated risks, RM remains an important tactic to ensure projects' success and deliver them on budget, on time, safely (Sousa, Almeida and Dias, 2014), and in compliance with the required quality and standards. It consists of some main steps, the most studied of which are:

- **Risk Identification:** Risk Identification is the process of identifying individual project risks as well as sources of overall project risk and documenting their characteristics for proper risk response in the future.
- **Qualitative Risk Analysis:** Qualitative Risk Analysis is the process of prioritizing individual project risks for further analysis or action by assessing their probability of occurrence and impact as well as other characteristics**.**
- **Quantitative Risk Analysis:** Quantitative Risk Analysis is the process of numerically analyzing the combined effect of identified individual project risks and other sources of uncertainty on overall project objectives like cost and schedule.
- **Mitigation Planning:** Mitigation Planning aims to take proactive actions to lower the possibility and impact of risks through risk reduction, risk avoidance, risk sharing, and risk acceptance (Project Management Institute(PMI), 2017).

Figure 3.1 presents the project risk management overview, containing the steps, input documents for each step, processing tools and techniques, and produced outputs, as proposed by the Project Management Institute (Project Management Institute(PMI), 2017).

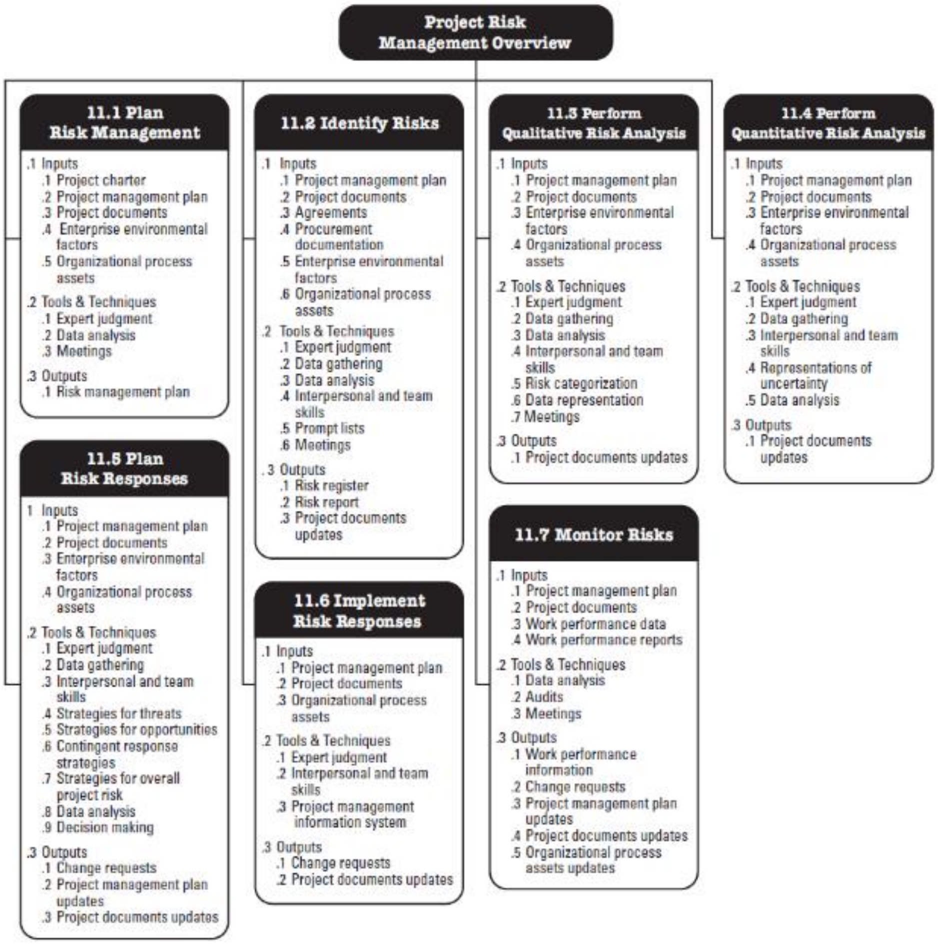

Figure 3.1 Project Risk Management Overview (Project Management Institute(PMI), 2017)

RM is one of the least developed knowledge areas in construction project management and falls behind other industries like finance. The probability theory has been studied through various models within the past decades, such as Pareto distributions, stochastic process theory, Markov processes, and Monte Carlo simulations (Wu, Chen and Olson, 2014) in conventional RM. However, an important factor that is missing in many of the previous techniques is the isolated analysis of risks and ignorance of the causal interrelations and correlations among risk factors. Assessment of the individual risk factor's magnitude, regardless of the occurrence probability of the risk events chain and the effects each risk causes 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 of reality (Eybpoosh, Dikmen and Talat Birgonul, 2011). Moreover, in most of these methods, the data is entered manually and in a time-consuming fashion, which reduces the productivity of the RM. In this section, an overview, pros, and cons of each of these techniques is briefly presented.

3.2 Conventional Risk Management Methods in Construction Projects

3.2.1 Checklists and Information Systems

Checklists and questionnaire surveys are some of the basic, comprehensive, and comprehensible methods in small and mid-sized construction companies (Ganbat et al., 2018). Checklists are valuable planning and assessment tools when carefully developed, regularly updated, validated, and applied. A sound checklist should offer formative and summative evaluations, specifying and clarifying the criteria that should be considered when assessing a phenomenon in a particular context, enhancing the objectivity and credibility of the evaluation process, and guiding practitioners in planning for the outcomes of the evaluation. As a part of companies' information systems, checklists can serve as a risk identification ontology that aims at supporting risk assessment, decision-making concerning risk control, and the planning of risk mitigation strategies (Zhou, Vasconcelos and Nunes, 2008). This method is particularly effective in the construction industry due to its reliance on practical experience. A reliable assessment can be achieved by selecting experts through scientific methods and determining risk categories and their impacts through expert interviews (Ganbat *et al.*, 2018). They are comprised of some main steps:

1. Risks and hazards identification, and if the company has a list of previous risks, the Project Manager or the Risk controller should only check the ones that apply to that specific project.
2. Deciding who might be harmed and affected and how.
3. Risk Evaluation based on its magnitude, possibility of occurrence, and severity of consequences.
4. Decision on the mitigation method and resource allocation.
5. Implement preventive or corrective actions.
6. Control the remaining and secondary risks.
7. Record and review the findings as a lessons-learned registry.

Some of the common checklist-based risk identification methods in construction projects are:

a. Industrial checklists prepared by a documentation specialist for various project and product documents.
b. Interviews with key project participants or analysis of historical data for similar projects like lessons learned.
c. Database systems that actively manage and report the progress of projects
d. Brainstorming with the project team (Tadayon and Jaafar, 2012).

The downside of this technique is that checklist preparation and update require much time and precision, which is usually overlooked in construction companies. Moreover, filling the checklists is a tedious task that project managers might not be willing to do each month for each monthly report.

3.2.2 Probability-Impact Matrix

The Probability-Impact matrix is a common risk assessment and ranking technique to elicit from the core team and experts on the likelihood and consequences of a risk, to grade the probability and impact of each identified risk, and to calculate the risk criticality as the product of these two values. Once risks' criticality is assessed and risks are ranked based on their criticality, the project management team can prioritize them and allocate project resources to mitigate the ones with higher priority. It is also a useful and comprehensible technique that ensures consistency of assessment between team members (Chapman, 2001). Usually, a liker scale from 1 to 5 (1 being the lowest and 5 being the highest) or descriptive terms (such as very high, high, medium, low, and very low) can be used, and the severity of each risk is determined according to its position on the graph is identified (El-Sayegh et al. 2021). The specific combinations of probability and impact that lead to a risk being rated as ''high,'' ''moderate,'' or ''low'' importance – with the corresponding importance for planning responses to the risk – are usually set by the organization. They are reviewed and can be tailored to the specific project during the risk management planning process (Mojtahedi, Mousavi and Makui, 2010).

Besides the ease of calculation and standardized process as the advantages of this technique, it has a time-consuming and repetitive process, which despite requiring constant updates as the project progresses, is not usually updated or reproduced after project initiation. Moreover, it evaluates risks isolated and ignores the interdependence of risks, which is not the case in real-world applications. Figure 3.2 presents the scheme of the P-I matrix as offered by the Project Management Institute (Project Management Institute(PMI), 2017).

Probability	Threats					Opportunities					Probability
Very High 0.90	0.05	0.09	0.18	0.36	0.72	0.72	0.36	0.18	0.09	0.05	Very High 0.90
High 0.70	0.04	0.07	0.14	0.28	0.56	0.56	0.28	0.14	0.07	0.04	High 0.70
Medium 0.50	0.03	0.05	0.10	0.20	0.40	0.40	0.20	0.10	0.05	0.03	Medium 0.50
Low 0.30	0.02	0.03	0.06	0.12	0.24	0.24	0.12	0.06	0.03	0.02	Low 0.30
Very Low 0.10	0.01	0.01	0.02	0.04	0.08	0.08	0.04	0.02	0.01	0.01	Very Low 0.10
	Very Low 0.05	Low 0.10	Moderate 0.20	High 0.40	Very High 0.80	Very High 0.80	High 0.40	Moderate 0.20	Low 0.10	Very Low 0.05	
	Negative Impact					Positive Impact					

Figure 3.2 Probability-Impact Matrix Scheme for Risk Ranking (Project Management Institute(PMI), 2017)

3.2.3 Critical Path Method

Critical Path Method (CPM) [3] is a useful tool for schedule risk assessment. It is a network-based approach to estimate the minimum project duration and determine the amount of schedule flexibility on the logical network paths within the schedule model (Project Management Institute(PMI), 2017). This visualization of the interdependence of project activities enables project managers to monitor critical activities closely and ensure project success. Additionally, CPM can calculate the expected completion time, estimate the impact of schedule changes, and allocate resources effectively.

The technique of schedule network analysis calculates the early start, early finish, late start, and late finish dates for all activities, irrespective of any resource limitations. This is done by analyzing the schedule network in both forward and backward directions. The amount of time that an activity can be delayed or extended from its early start date without affecting the project finish date or violating any schedule constraint determines the total float or schedule flexibility on any network path. A critical path typically has zero total float. However, with the precedence diagramming method sequencing, critical paths may have positive, zero, or negative total float depending on the constraints applied. The variance on the critical path has a direct impact on the project end date. Potential schedule risks can be identified by monitoring the progress of activities on near-critical paths (Equation 3.1). Figure 3.3 illustrates the critical path method scheme. However, despite its many benefits, it assumes deterministic activity durations and does not account for the uncertainty present in construction projects, potentially leading to overestimating project completion time and underestimating risk (Iromuanya, C., Hargiss, K. M., & Howard, 2015).

$$Schedule\ Variance = Earned\ Value - Planned\ Value \quad (3.1)$$

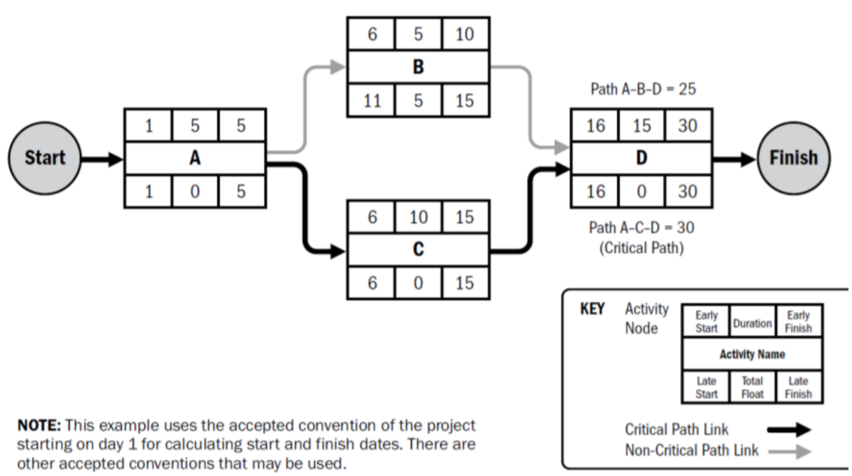

Figure 3.3 Critical path method scheme (Project Management Institute(PMI), 2017)

3.2.4 Multiattribute Utility Theory (MAUT), Analytical Hierarchy Process (AHP), and Analytic Network Process (ANP)

The evolution of project delivery selection methods has seen the introduction of more sophisticated decision-making tools such as the Multiattribute Utility Theory (MAUT) and Analytical Hierarchy Process (AHP). These tools help improve the objectivity of the selection process and make it less subjective. The MAUT allows the project manager to identify a utility function for each criterion, based on their assigned weights, which is then used to compute the utility score of each project delivery method. Finally, the project delivery method with the highest global utility score is selected (Ahmed and El-Sayegh, 2021).

The AHP, on the other hand, involves identifying different project delivery methods and developing a hierarchy of the selected criteria in which the risk factors play a significant role. The process then involves conducting a pairwise comparison of project delivery methods, after which these ratio scales are used to measure the manager's comparative preferences and integrated to compute an overall weight for each project delivery method (Farnsworth *et al.*, 2016).

A later and more expanded version of AHP is the Analytic Network Process (ANP), which aims to overcome AHP limitations regarding the assumption of independence between criteria. ANP model allowed for complicated interrelations between various criteria elements (Khademi, Behnia and Saedi, 2014), using control hierarchies, clusters, nodes, the interrelationship among nodes and the interrelationship among clusters (Yucelgazi and Yitman 2020). Figure 3.4. shows the structure of ANP models.

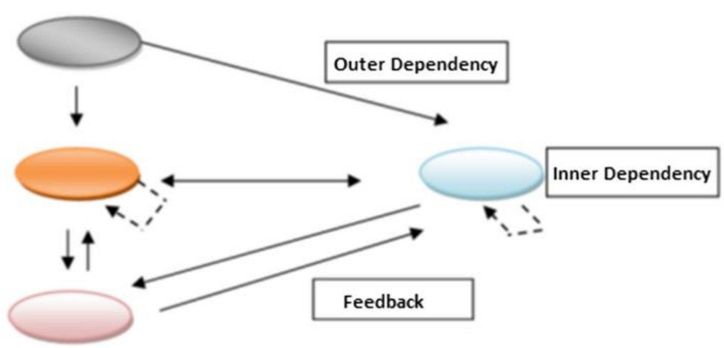

Figure 3.4. Structure of ANP models (Yucelgazi and Yitman 2020)

3.2.5 Monte Carlo Simulation

Monte Carlo Simulation is a statistical sampling and simulation technique for quantitative risk analysis, where a computer model is iterated many times, with the input values chosen at random for each iteration driven by the input data, including probability distributions and probabilistic branches (Kokkaew and Wipulanusat, 2014). Outputs are generated to represent the range of possible outcomes for the project. It is an excellent way to solve uncertain problems, especially problems like construction schedule management(Kurihara, 2002). Unlike CPM, it can include the notion of uncertainty is estimations, which is more in alignment with reality.

Monte Carlo Simulation is mainly used for schedule and cost risks; therefore, the input values are usually cost and duration estimates. Outputs represent the range of possible outcomes for the project (e.g., project end date, project cost at completion). Typical outputs include a histogram presenting the number of iterations where a particular outcome resulted from the simulation or a cumulative probability distribution (S-curve) representing the probability of achieving any particular outcome or less. Figure 3.5. presents a probability distribution and a S-curve generated by Monte Carlo simulation. The theoretical basis of Monte Carlo was the law of large numbers and the central limit theorem; the practice method of it was repeated sampling and high-speed computation. Therefore, it requires accurate data and an understanding of project processes, which is a complex and tedious task for project managers (Liu, 2014). It has also been applied for probabilistic safety risk assessment in construction projects in combination with ML methods (Lin, Wu and Zhang, 2023).

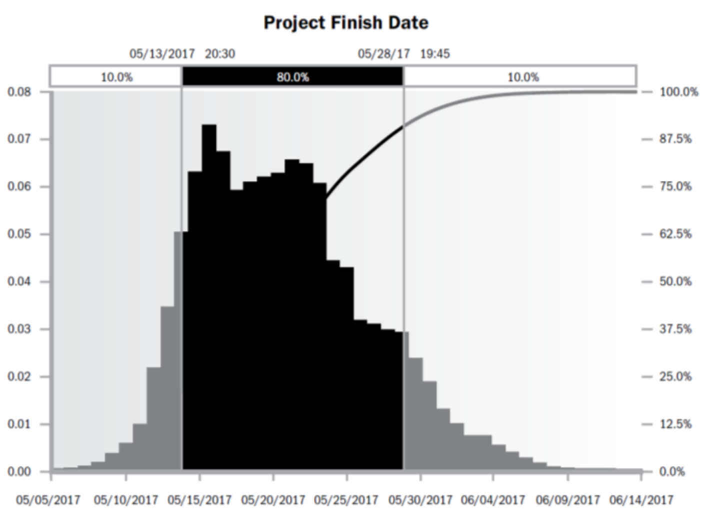

Figure 3.5. Probability distribution and a S-curve generated by Monte Carlo simulation (Project Management Institute(PMI), 2017)

3.2.6 Program Evaluation Review Technique (PERT)

Program Evaluation and 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 (Liu, 2013). It helps predict a project's completion time and potential risks using a network diagram to represent the interdependence of various tasks in a project and calculates the expected completion time by considering the optimistic, most likely, and pessimistic scenarios. The project duration can be calculated by the sum of the "expected" durations of each activity in the critical path. Then, According to the central limit theorem, the project duration can be shown to follow a normal distribution, uniquely defined by the parameters computed from each activity parameter. Therefore, PERT analysis helps identify a project's critical path and the tasks that impact the completion time. Figure 3.6. presents the PERT scheme. PERT considers the uncertainties during the construction process to plan, schedule, and control complex projects with many uncertainties. This technique can predict delays and cost overruns by monitoring critical tasks and progress and ensuring they are completed on schedule. However, PERT assumes that all activities in a project are independent and can be completed within the estimated time frame, which may not always be the case in the real world. It also does not consider the uncertainties associated with the project that can impact the outcome.

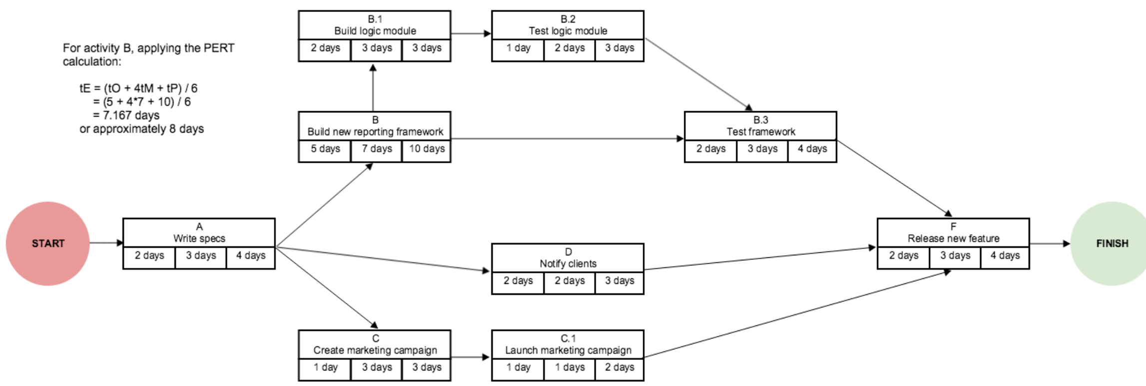

Figure 3.6. PERT methods scheme

3.2.7 Graphical evaluation and review technique (GERT)

GERT, proposed by Pritsker (Pritsker, 1966) is a technique for the analysis of a class of networks that have two characteristics: 1) a probability that a branch of the network is indeed part of a realization of the network, and b) and elapsed time or interval associated with the branch if the branch is part of the network. These networks are stochastic and can be used for modeling risk and probabilistic activity duration.

While CPM and PERT fall short in many practical situations, GERT is performing well due to its ability to address probability branches and loops. GERT makes it easy to identify project tasks, dependencies, and alternative paths. This can help streamline project planning and ensure that all tasks are completed in the most efficient manner. However, due to its complex structure it is not as commonly used as CPM and PERT (Tao *et al.*, 2017). Figure 3.7 presents an example of GERT structure.

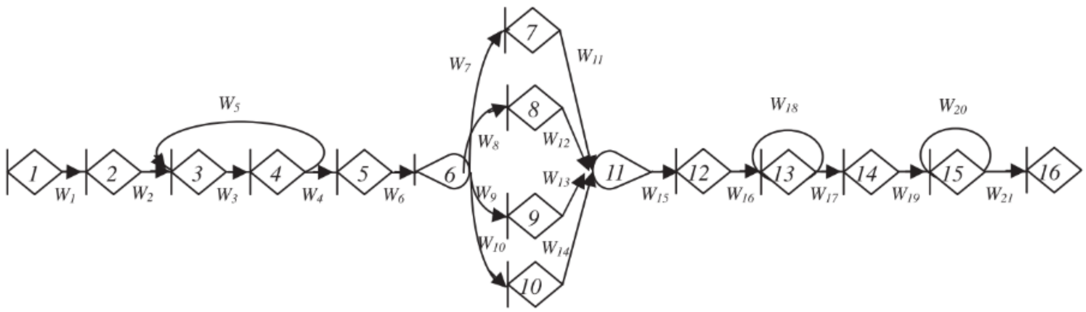

Figure 3.6. A GERT sample (Tao *et al.*, 2017)

3.2.8 Pareto Analysis

It is a useful technique to determine risk factors that are more frequent or more critical in projects, based on historical data. Inspired by the Pareto "80-20" rule, this method seeks to find the 20% most significant factors that cause 80% of the risks. Therefore, it statistically separates a limited number of input factors-either desirable or undesirable- with the greatest impact on an outcome, like the root causes of a risk, to prioritize for mitigation planning (Pareto, 1964). In order to make a Pareto chart a few steps should be taken:

a) Develop a list of problems to be compared.
b) Develop a standard measure for comparing the items like the frequency, duration, and cost.
c) For each item, assess its frequency, duration, or cost, in a cumulative way.
d) Find the percent of each item in the grand total by taking the sum of the item.
e) List the items being compared in decreasing order of the measure of comparison on the horizontal axis of a graph, with the left vertical axis labeled with numbers of occurrence.
f) Label the right vertical axis with the cumulative percentages (cumulative total equal to 100%).
g) Draw in the bars for each item.
h) Draw a line graph of the cumulative percentages. The first point on the line graph should line up with the top of the first bar.
i) Determine the point where the cumulative percentage equals to 80%, with all the items before that determined as vital items. Figure 3.8. presents a Pareto chart example (Kenton, 2022).

As it is a useful method to identify and determine the main root causes of problems and risks and optimize the resource allocation to solve them, Pareto analysis can significantly foster problem-solving and decision-making processes in companies. However, it does not provide solutions by itself. Also, it mainly focuses on past data and does not consider of future possible scenarios.

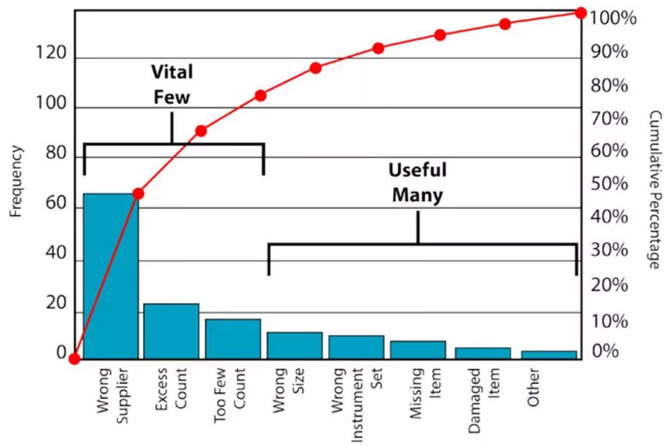

Table 3.8. Example of Pareto chart analysis (Kenton, 2022)

3.2.9 Stochastic Process Theory

Stochastic models are used to represent the random behavior of risks and are widely used for quantitative analysis in financial risk management. A stochastic process is defined as a family of random variables $\{X_t\}_{t \in T}$ defined on a given probability space and indexed by t belonging to a parameter set T (Edirisinghe, Setunge and Zhang, 2015). There are some important theories and processes used, like random walk, Brownian motion, and geometric Brownian motion, which help simulate a problem in a stochastic model, considering the different logics, reasonings, and distribution types to model the expected outcomes. The random walk, which is one of the simplest and most used techniques, tries to predict the path a pedestrian will take and when he will be positioned after N steps, given that the probability to move a step forward is p and the probability to move a step backward is 1-p. Therefore, the aim is to answer the following question: What is the probability p(m,N) that the walker will be at position m after N steps? It is answered through complicated formulas or computer simulation and can give a probabilistic and realistic prediction about the future behavior of a risk factor or possible scenarios over time (Paul and Physics, no date). The geometric Brownian motion (GBM), a more advanced modeling theory, describes the random behavior of the asset price level S(t) over time. The GBM is specified as Equation 3.2 (Brigo and Dalessandro, 2007). Figure 3.9. presents an example of GBM sample paths and distribution statistics.

$$dS(t) = \mu S(t)dt + \sigma S(t)dW(t) \quad (3.2)$$

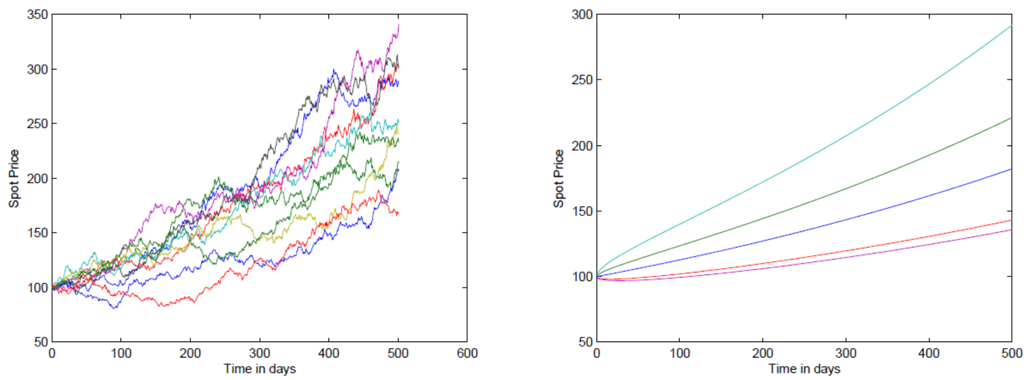

Figure 3.9. GBM Sample Paths and Distribution Statistics (Brigo and Dalessandro, 2007)

The downside of stochastic techniques is the approximate decisions on the distribution techniques and parameters that can fit a complex problem well. Especially in construction problems, where there are many variables engaged in the process, and each can have a different distribution type, the stochastic modeling can become very complex and, if simplified, would grow far from reality.

3.2.10 Markov Process

Markov process is a widespread type of random process that pertains to situations where a system has a finite number of states, and the system's state in the next moment is dependent solely on the current state but not on any previous state. The process by which the system transitions from one state to another is known as a Markov process. If the process is unchanging over time and the probability of state transitions is not dependent on time, it is considered to be a homogeneous Markov process. Markov processes can be either state-discrete Markov processes, which have a discrete state space, or state-continuous Markov processes, which have a continuous state space. When both the state and time are discrete, the Markov process is called a Markov chain (Sun and Li 2007).

The analysis of the Markov chain can reflect dynamic changes of the system state by the state transmission probability as p_{ij}. p_{ij} is the probability that from state i to state j and $0< p_{ij} <1$ (i =1,2,…,n). The matrix that is made of state transmission probability is called one-step state transmission probability matrix of the Markov chain. We use P to represent it and the sum of elements in every line is 1. Figure 3.10. shows the transmission probability matrix, and Figure 3.11. presents an example of the Markov chain model (Edirisinghe, Setunge and Zhang, 2015). Once the steps grow in number and the experiment is repeated many times, with the transmission probability matrixes being produced by each other, the variables get closer to their stationary value. The stationary distribution of a Markov chain describes the distribution of X_t after a sufficiently long time that the distribution of X_t does not change any longer.

In the building sector, it can be used for creating a building deterioration prediction model based on different variables (Edirisinghe, Setunge and Zhang, 2015), or predict the final probability of some risks in a dynamic mode. The downside of this method is the complicated mathematical calculations that require special technical knowledge.

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots & p_{1n} \\ p_{21} & p_{22} & p_{23} & \cdots & p_{2n} \\ p_{31} & p_{32} & p_{33} & \cdots & p_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & p_{n3} & \cdots & p_{nn} \end{bmatrix}$$

Figure 3.10. One-step transition probability matrix (Edirisinghe, Setunge and Zhang, 2015)

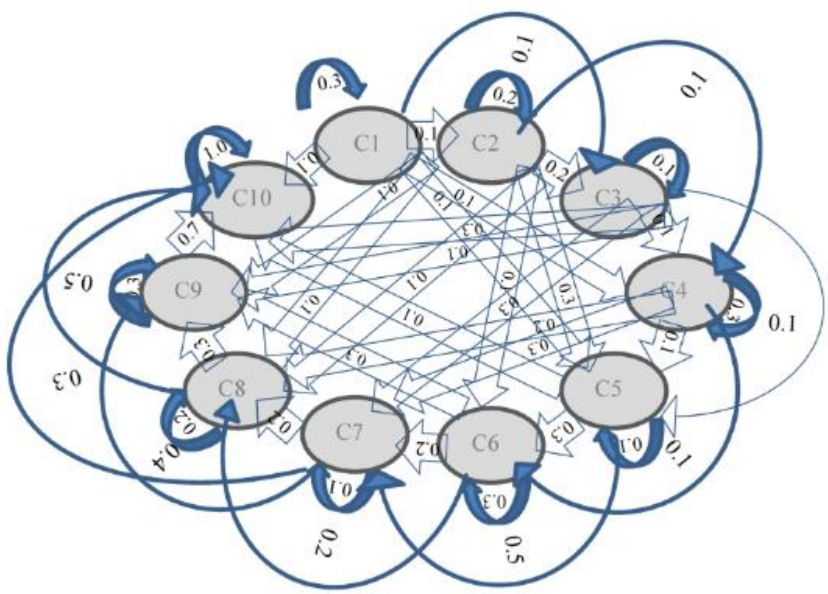

Figure 3.11. Example of Markov chain model (Edirisinghe, Setunge and Zhang, 2015)

3.2.11 Earned Value Management

Earned Value Management (EVM) is one of the most used project management techniques to check the progress of the projects compared to the budget and schedule baselines and predict the expected budget and duration for project completion. EVM integrates the scope baseline with the cost baseline and schedule baseline to form the performance measurement baseline and develops and monitors three key dimensions for each work package and control account:

- **Planned value (PV)** is the authorized budget assigned to scheduled work for an activity or work breakdown structure (WBS) component, which defines the physical work that should have been accomplished at a given point of the schedule. The total planned value for the project is also known as the budget at completion (BAC).

- **Earned value (EV)** is a measure of work performed and completed at a certain point of the schedule expressed in terms of the budget authorized for that work. It is the budget associated with the authorized work that has been completed. EV determines current status and can cumulatively determine the long-term performance trends.
- **Actual cost (AC)** is the realized cost incurred for the work performed and completed on an activity during a specific period or the measured work related to the EV.

The comparison of these three measures gives insights into project performance and future time and cost trends and variances on baselines, which are caused by uncontrolled risks (Sruthi and Aravindan, 2020). Figure 3.12. presents the S-curve for comparison of PV, EV, and AC. Although it is not a specific risk management method, its techniques, listed in Table 3.1, like schedule variance, are used to estimate the consequences of the risks on the project (Project Management Institute(PMI), 2017).

EVM provides an analytical evaluation of the project by considering both the schedule and cost performance and helps detect possible risks and issues early, thus enabling corrective actions to be taken on time and the baselines to be updated accordingly (Project Management Institute, 2011). However, EVM does not consider the impact of changes in scope, schedule, and resource availability, which can result in inaccurate predictions (Sruthi and Aravindan, 2020).

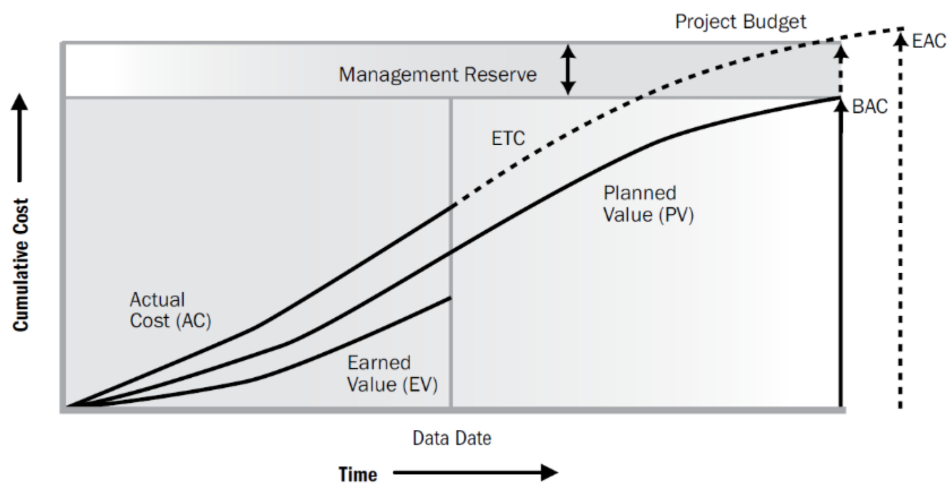

Figure 3.12 Earned Value, Planned Value, and Actual Costs on the project S-curve (Project Management Institute(PMI), 2017)

Table 3.1 Earned Value Calculations Summary Table (Project Management Institute(PMI), 2017)

Name	Lexicon Definition	How Used	Equation
Planned Value (PV)	The authorized budget assigned to scheduled work.	The value of the work planned to be completed to a point in time, usually the data date, or project completion.	
Earned Value (EV)	The measure of work performed expressed in terms of the budget authorized for that work.	The planned value of all the work completed (earned) to a point in time, usually the data date, without reference to actual costs.	EV = sum of the planned value of completed work
Actual Cost (AC)	The realized cost incurred for the work performed on an activity during a specific time period.	The actual cost of all the work completed to a point in time, usually the data date.	
Budget at Completion (BAC)	The sum of all budgets established for the work to be performed.	The value of total planned work, the project cost baseline.	
Cost Variance (CV)	The amount of budget deficit or surplus at a given point in time, expressed as the difference between the earned value and the actual cost.	The difference between the value of work completed to a point in time, usually the data date, and the actual costs to the same point in time.	CV = EV – AC
Schedule Variance (SV)	The amount by which the project is ahead or behind the planned delivery date, at a given point in time, expressed as the difference between the earned value and the planned value.	The difference between the work completed to a point in time, usually the data date, and the work planned to be completed to the same point in time.	SV = EV – PV
Estimate At Completion (EAT)	The expected total cost of com- pleting all work expressed as the sum of the actual cost to date and the estimate to complete.	If the CPI is expected to be the same for the remainder of the project, EAC can be calculated using: If future work will be accomplished at the planned rate, use: If the initial plan is no longer valid, use: If both the CPI and SPI influence the remaining work, use:	EAC = BAC/CPI EAC = AC + BAC – EV EAC = AC + Bottom-up ETC EAC = AC + [(BAC – EV)/ (CPI x SPI)]
Estimate to Complete (ETC)	The expected cost to finish all the remaining project work.	Assuming work is proceeding on plan, the cost of completing the remaining authorized work can be calculated using: Reestimate the remaining work from the bottom up.	ETC = EAC – AC ETC = Reestimate

3.2.12 Risk Use Case and Risk Class Diagrams

A use case diagram provides a visual representation of the typical interactions between a user and a computer system. It includes actors, which represent essential 'players' in the system, and use cases, which represent the routines the system must perform to achieve its actions. A risk use case diagram specifically focuses on modeling the interactions and relationships related to risk management within a system or project. It helps to identify and visualize the various use cases or scenarios involving risks and how different actors interact with the system to manage those risks effectively, as depicted in Figure 3.13. On the other hand, a class diagram depicts the types of classes used in an object-oriented system and defines the relationships that exist between them, which are of two types: associations and subtypes. It showcases attributes, methods, and constraints for each class. Class diagrams are part of the Unified Modeling Language (UML) and are widely used in software development to represent the static structure of a system. A risk class diagram can contain various classes of risk types, risk categories, risk assessments, and risk treatments (Tah and Carr, 2000).

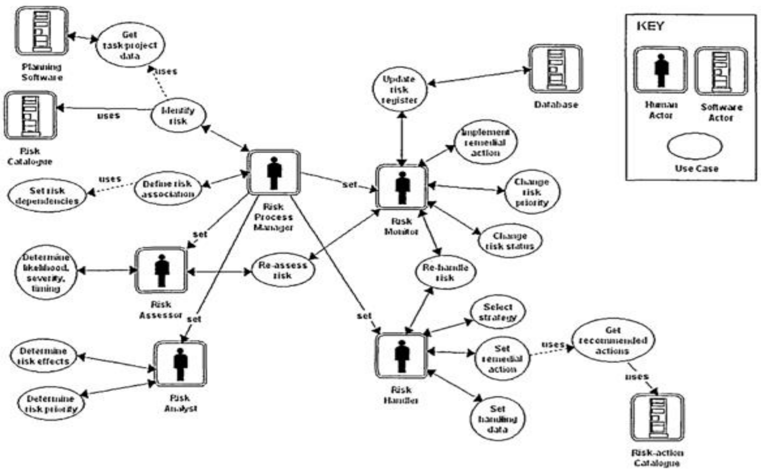

Figure 3.13. Risk Use Case Diagram sample (Tah and Carr, 2000)

3.2.13 Software Systems

Various project scheduling software systems, such as Microsoft Project, Oracle Primavera P6, Open Plan Professional (OPP), FastTrack Schedule, ZOHO Projects, @risk, Workfront, eResource Scheduler, ConceptDraw Project, Resource Guru, Smartsheet, and many other software, packages, and platforms are used for time control and risk management in the construction industry (Sepasgozar *et al.*, 2019). Moreover, various packages in Python, R studio, and Mathlab have been developed for Monte Carlo simulation or fuzzy logic modeling, which are some of the first attempts to digitalize the risk assessment process. It is noteworthy that some standardized tools such as Hierarchical Risk Breakdown Structure (HRBS) and strength–weakness–opportunity–threats (SWOT) analysis have been developed over the years as a complementary part of other RM methods (Tah and Carr, 2000).

3.3. Summary

Although various techniques have been developed to identify, analyze, and evaluate risks qualitatively and quantitatively (Zou, Kiviniemi and Jones, 2017), which are being widely applied in the industry these days, they are confined to static control management and play only a limited role in practice (Zhang *et al.*, 2014). They are mainly conducted manually and inefficiently, frequently based on knowledge and experience-based intuitions. Moreover, the assessment is greatly reliant on mathematical analysis and experience, ignoring the interdependencies between risks and project variables, which makes the model unlearnable and ungeneralizable by the machines (Shim *et al.*, 2012). Finally, most of the abovementioned methods fail to address risks in multidisciplinary knowledge areas and project sections to create a unified and communicative environment. As depicted in Figure 3.14. RM scope expands throughout the entire lifecycle of the projects, and if an RM method cannot create a link between various phases of the project, it cannot provide a realistic and applicable assessment of risks.

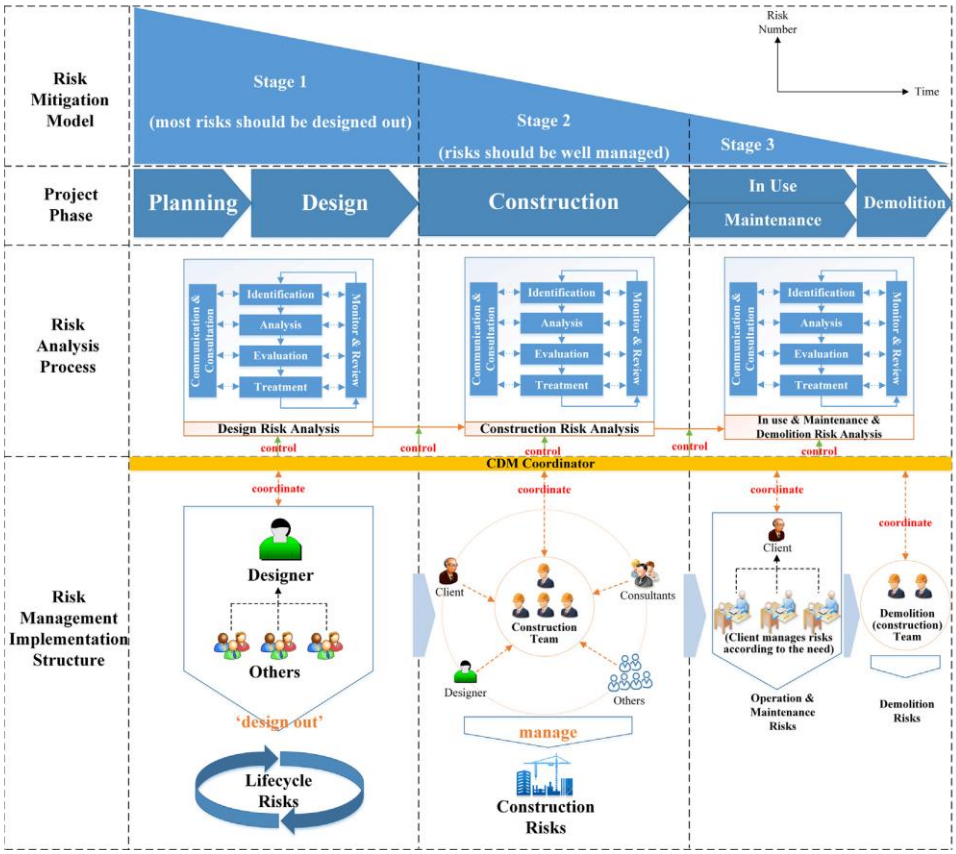

Figure 3.14. General RM framework during the lifecycle of construction projects (Zou, Kiviniemi and Jones, 2017)

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Chapter 4: AI application in Construction RM

4.1. Industry 4.0 Revolution in the Construction Industry

The Architecture, Engineering, Construction, and Operation Industry (AECO) occupies the center stage in a nation's socio-economic development and industrialization, with a worth estimated about $8.7 trillion, accounting for 12.2% of the world's economic output and providing employment for about 200 million people worldwide (Zou and Sunindijo, 2015). Traditionally, it is a slow-shifting industry with a change-resistant nature. However, recently, and thanks to the fourth industrial revolution, it is going through constant innovations and a considerable shift toward digitalization and intelligence, aiming to significantly enhance automation, productivity, reliability, sustainability, and effective RM (Fernández-Mora, Navarro and Yepes, 2022; Wu et al., 2022). The concept of Construction 4.0 represents the industry's digital transformation through the use of advanced tools such as laser scanning, drones, robots, AI, IOT, and Digital Twins, which improve the management of construction projects across all phases of their lifecycles, leading to the creation of smarter and more sustainable buildings (Ahmed and El-Sayegh, 2021). Figure 4.1. presents various industry 4.0 technologies in construction projects. Based on a classification offered by Sepasgozar et al. (2019), some of these key digital technologies used for different purposes in construction projects are:

a) Digital design communication tools: Digital Twin, Building Information Systems (BIM) including Revit, ArchiCAD, Navisworks, BIMx, BricsCAD, Archibus, Constructor, IntelliCAD, VisualARQ, Revizto; Geographic Information Systems (GIS) including QGIS, ArcGIS, and ArcMap (Shirowzhan and Sepasgozar, 2019).
b) Digital communication systems: cloud-based tools, emails, smartphones, and radio communication systems (Adam, Josephson and Lindahl, 2017).
c) Digital scheduling and planning tools: Microsoft Project, Oracle Primavera P6, FastTrack Schedule, ZOHO Projects, @risk, Workfront, eResource Scheduler, Concept Draw Project, Resource Guru, Open Plan by Deltek, Smartsheet, and other software, packages, and platforms.
d) Digital progress monitoring and job-site controlling tools: laser scanner, lidar, Internet of Things sensors, and photography camera (Sepasgozar et al., 2019).
e) Digital contract management tools: intelligent or smart contracts. The literature shows that many projects suffer from weak contract administration (Asiedu, Adaku and Owusu-Manu, 2017).
f) Digital devices to increase the productivity of heavy equipment: real-time locating systems, Global Positioning System (GPS), and radar.
g) Digital production technologies: 3D printers (Tahmasebinia et al., 2018).

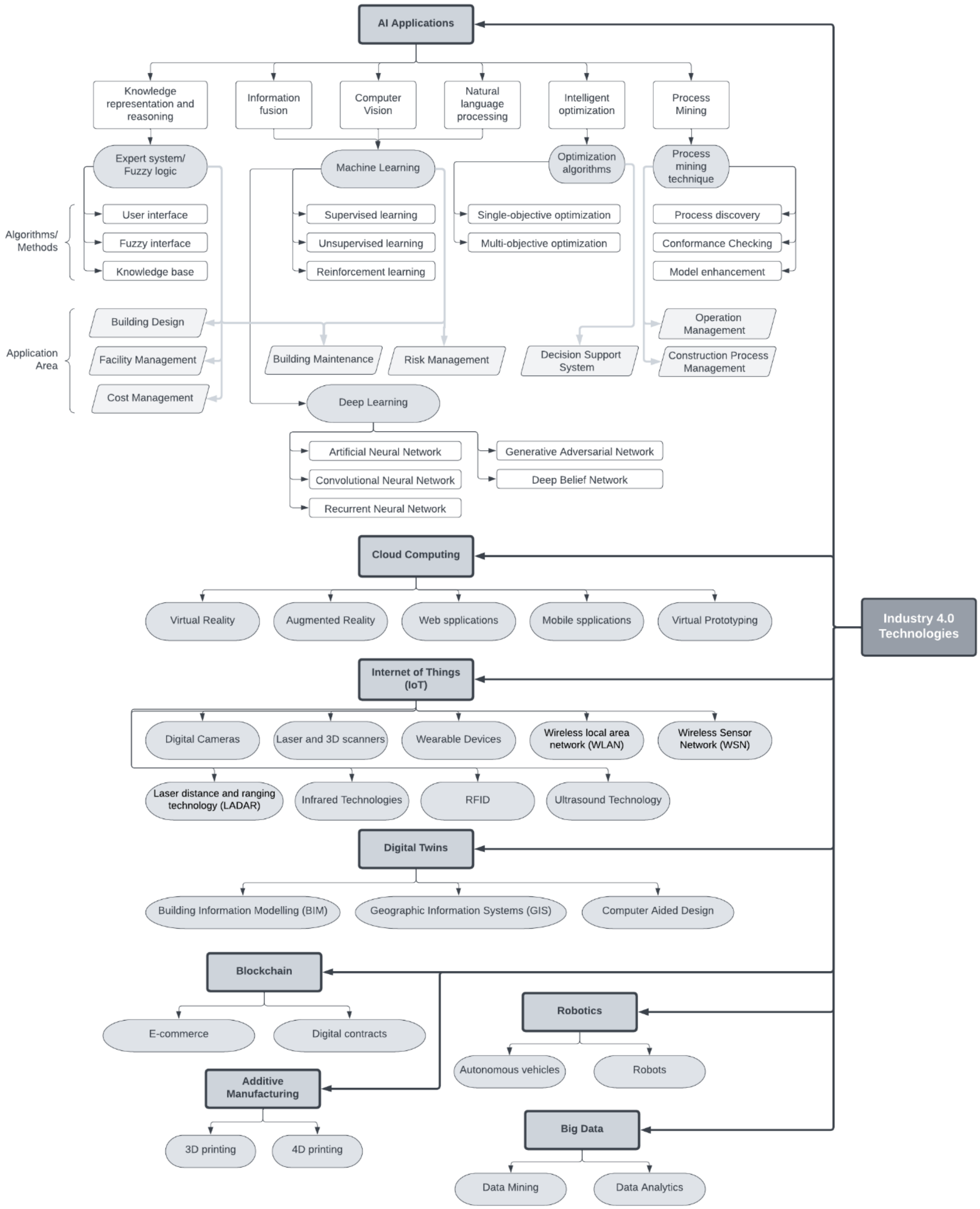

Figure 4.1. Industry 4.0 technologies in construction projects (Abioye et al., 2021; Pan and Zhang, 2021)

4.2 AI Applications in Construction Engineering and Management

Artificial Intelligence (AI), a concept that emerged in the late 1950s, found its way into the construction industry as a support of activities like construction management, architecture, structural design, etc. (Oh et al. , 2019). European Commission (EC, 2019) defines AI as: "Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behavior by analyzing how the environment is affected by their previous actions." Having the insight into boosting labor efficiency by 40% and doubling annual economic growth rates by 2035 (M. Purdy 2016), AI is becoming the center of companies' attention.

AI has a wide range of applications, especially in fostering, optimizing, and automating processes throughout the entire lifecycle of construction projects, thereby enabling intelligent project management. With the advent of 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), AI algorithms can now learn from large volumes of real-time data, enabling more reliable and intelligent decision-making and management of construction projects (Zhong et al., 2017). AI models can improve analytical capabilities across the construction engineering and management domains while offering a high granularity and depth of predictive analysis (Guzman-Urbina, Aoyama and Choi, 2018), and provide accurate results in uncertain, dynamic, and complex environments (Yaseen et al., 2020), like the construction industry. A dominant number of AI applications are already operational in the financial sector (fintech), where data is available in great quantity and good quality. The broad usage of complex AI applications in the construction industry started only later, mostly because of data collection and data quality problems.

The thriving application of AI, and especially ML algorithms, in construction projects, has proven to be effective in solving the shortcomings of traditional project management methods, automating repetitive and tedious tasks, optimizing resource allocation, making a factual prediction on projects' trends, and data-driven decision-making for managing construction projects (Sanni-Anibire, Zin and Olatunji, 2021), during all phases of projects like:

a) Planning and Control phase for schedule optimization based on available resources and the work breakdown structure (WBS),
b) Generative design for design optimization and increasing engineering performance in an iterative manner (Newton, 2019),
c) Claim Analysis to reduce the claim-based delays in the project,
d) Predicting the Environmental Performance of buildings to promote improvements if necessary (Fernandes, Rocha and Costa, 2019),

e) Health and safety assurance of the workforce (Wu et al., 2019) using images from trucks, cranes, and other construction machinery or sensor data for predicting safety measures such as injury severity, injury type, body part impacted, and incident type,
f) Maintenance and operation management, retrofitting of existing buildings (Rampini and Re Cecconi, 2022), and more.

Despite all the advantages and potentials of AI, there is a practical gap in applying AI, Big Data, ML, and the Internet of Things (IoT) into well-known construction practices, which, if solved, would place industry among the top productive sectors (Gledson and Greenwood, 2017). Blanco et al. (2018) stated that AI is the next frontier for construction technology as they survey the applications and algorithms to help bridge the technology gap (Basaif et al., 2020). However, the industry practitioners are generally reluctant to trust new technologies, and the use of antiquated work processes is prevalent (Manuel et al., 2019; Zhang et al., 2021). Small businesses comprise the vast majority of the industry with a share of 82.3% (compared to 44.4% for manufacturing and 35.1% for retail) (Kobe, 2022) and smaller companies are known to be often the "late majority" and "laggards" in technology adoption (Peltier, Zhao and Schibrowsky, 2012). Other determining factors for AI's vast application in the industry are enterprises' attitude toward change, technology switching costs, market uncertainty and environmental hostility, demographical characteristics like Age, Education, Gender, and Ethnicity of business owners, knowledge about the technology, and relative advantage of AI compared to already established methods (Schepers and Wetzels, 2007).

AI is a vast umbrella term that includes various technologies, applications, types, and subfields. AI itself is a subcategory of digital technologies alongside cloud-based applications, augmented reality, virtual reality, digital twin, artificial intelligence, cyber–physical systems, big data, blockchain, laser scanners, robotics and automation, sensors, Internet of Things, actuators, and sensors (Forcael, Ferrari and Opazo-vega, 2020), all of which have found their way in construction research and practice over the last decades. Based on comprehensive literature reviews on AI applications in construction engineering and management by Pan and Zhang (2021) and Chenya (2022), AI applications can be grouped into six main categories: (a) machine learning, (b) knowledge-based systems, (c) computer vision, (d) robotics, (e) Natural Language Processing, (f) automated planning and scheduling, and (g) optimization, as depicted in Figure 4.2, and can cover a variety of purposes such as construction process management, facility management, and RM. Another classification of AI applications in construction was provided by Abioye et al. (2021), depicted in Figure 4.2. Moreover, Figure 4.3 categorizes the components, types and subfields of AI. Three types of AI based on their level of autonomy and authority are: a) Artificial Narrow intelligence (ANI), b) The artificial general (or "strong") intelligence (AGI), and c) The artificial super-intelligence (ASI). ANI aims to automate some repetitive and learnable activities without the ambition to substitute human intelligence, authority, or decision-making. AGI aims to match human-level intelligence in any field and type of human activity and is capable of complex decision-making (Wang and Siau 2018). ASI aims to exceed human intelligence and faculties, staying unbeatable by any human mind (Müller and Zalta, 2020). The current state of AI application in the AEC industry is mostly the ANI and, to some extent, the AGI.

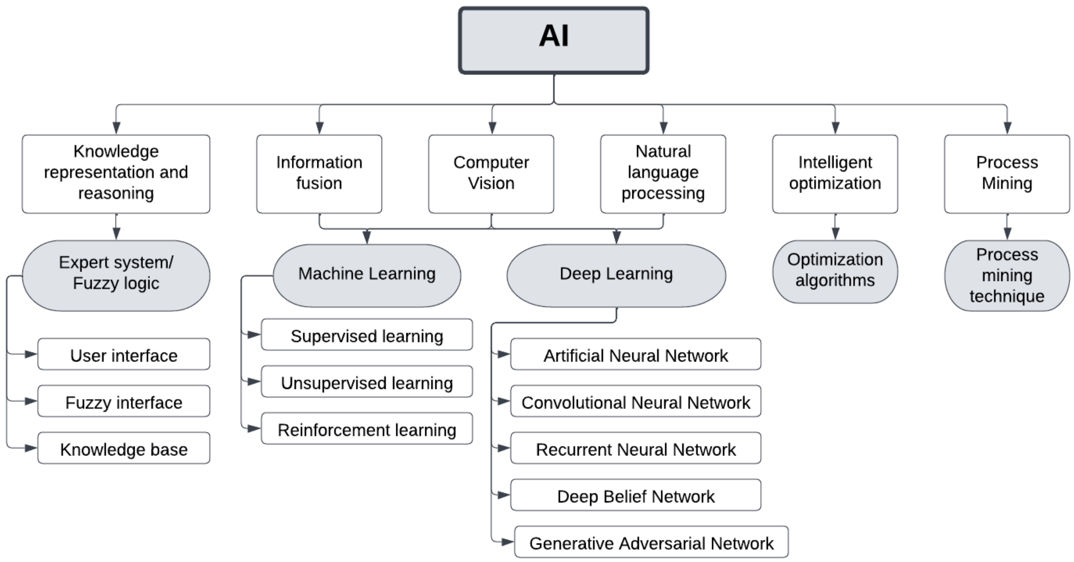

Figure 4.2. AI application groups in Construction Engineering and Management (Abioye et al., 2021; Pan and Zhang, 2021)

AI has four types of applications in construction based on their level of automation, which are listed below (PWC, 2017). Automation is a technology that actively selects data, transfers information, makes decisions, and controls processes, having significant potential to extend human performance and improve safety (Lee, See and City, 2004).

a) **Automated Intelligence,** which is the automation of manual and cognitive tasks and does not involve innovative ways of doing things, like automated welding systems.
b) **Assisted Intelligence,** which includes accurate and efficient tracking, analysis, and visualization of data, like AI surveillance systems for construction personnel performance improvement on particular tasks, and project monitoring systems using Industry Foundation Classes-based BIM (Golparvar-Fard et al., 2015).
c) **Augmented Intelligence,** which includes algorithmic decision-making to enable construction personnel to do things they could not do and make better decisions, decision support systems for contractor selection، and design alternatives selection to enhance occupation health and safety in construction design (Awad and Fayek, 2012).
d) **Autonomous intelligence,** which supports decision-making processes without human intervention, like a construction robot that can assemble pre-designed modular structures by autonomously identifying the prismatic building components like brick and blocks (Feng et al., 2015).

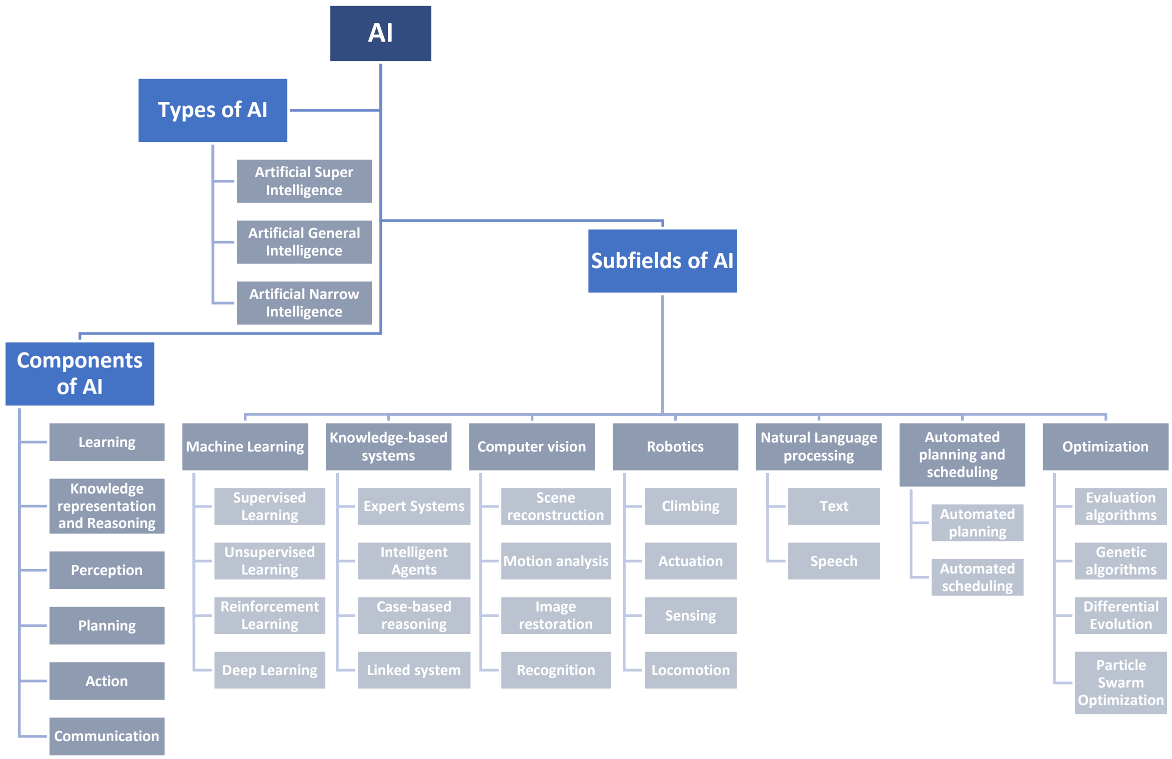

Figure 4.3. Components, types and subfields of AI (Abioye *et al.*, 2021)

4.3. Classifications of AI applications in Risk Identification, Analysis, and Mitigation Planning domains

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 (Chenya, 2022). 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 sup-port systems, AI, and expert systems, to capture the tacit knowledge within organizations' computer systems (Wu, Chen and Olson, 2014).

ML, a branch of AI, combines methods from statistics, database analysis, data mining, pattern recognition, and AI to extract trends, interrelationships, patterns of interest, and valuable insights from complex data sets (Flath et al., 2012). ML techniques have been widely studied in construction RM research, aiding in hazard and risk identification, vulnerability assessment, consequence prediction, and mitigation strategy development (Habibi Rad, Mojtahedi and Ostwald, 2021), which can bring numerous benefits to construction projects, including preventing cost overruns, enhancing site safety, and managing projects efficiently (Regona et al., 2022). 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 stakeholder management (Xia et al., 2018). The key reasons are:

a) Lack of structured data and infrequent documentation in the projects
b) Over-reliance on individual and experience-based judgment 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 (An et al., 2021; Chenya, 2022).

In this subsection, the different ML algorithms applications for construction risk identification, assessment, and control, which previous researchers studied, are listed and analyzed, such as Artificial Neural Networks (Heravi, Asce and Eslamdoost, 2015), Decision Trees (Chou and Lin, 2013), Logistic Regression (Hwang and Kim, 2016), Naïve Bayesian Models (Gerassis et al., 2017), Support Vector Machines (Huang and Tserng, 2018), Genetic Algorithm (GA), Structure Equation Modelling (SEM), Fuzzy Hybrid Methods (FHMs) (Afzal et al., 2019).

4.3.1 Phase-based classification of AI applications

Construction Risk identification has been conducted by various methods such as construction drawing, meta-network, Monte Carlo simulation, ontology, and BNs (Liu et al., 2021). Moreover, various techniques have been used to model the interdependencies of project risks in literature, including Structural Equation Modeling (SEM) (Eybpoosh, Dikmen and Talat Birgonul, 2011), Analytic Network Process (ANP) (Prince Boatenga and Ogunlana, 2015), causal mapping (Ackermann and Alexander, 2016) systems thinking (Loosemore and Cheung, 2015), and Bayesian Belief Networks (BBNs) (Yildiz et al., 2014), among which BBNs have gained much popularity due to benefiting from a robust theoretical framework and the ability to capture uncertainty and update beliefs upon the availability of new information, which is a considerable advantage in ongoing projects. Qualitative Risk Analysis is the process of prioritizing individual project risks for further analysis or action by assessing their probability of occurrence and impact as well as other characteristics (Project Management Institute(PMI), 2017). Various AI techniques such as multilevel regression (SEM) (Ebrat and Ghodsi, 2014), MCDM, probability models, FHM, NNs, and genetic algorithm (GA) have been used in previous research for both qualitative and quantitative analysis. Quantitative Risk Analysis is the process of numerically analyzing the combined effect of identified individual project risks and other sources of uncertainty on overall project objectives like cost and schedule. Quantitative Risk assessment tools are based on different linear and non-linear approaches. However, since construction projects have stochastic behavior, non-linear probabilistic models of AI, such as ANNs, ANP, and BBN, are dominant to address this phenomenon of interdependency (Dekker, 2013), which can be used independently or in a hybrid manner. Few studies have adopted hybrid methods based on the FST and other AI tools to design flexible risk assessment tools under high uncertainty (Afzal et al., 2019).

4.3.2 Other AI applications classifications in literature

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 (2021), RM falls under a) the category of Expert Systems/Fuzzy logic for Knowledge Representation and Reasoning mainly formed on probabilistic, qualitative, and linguistic analysis, and b) Machine Learning for supervised learning based on either probabilistic or deterministic analysis. Samantra, Datta and Mahapatra (2017) classified construction risk assessment approaches as a) Probabilistic approach, dealing with risk probability and impact estimation based on historical numeric data, including Sensitivity analysis, Decision Tree analysis, Bayesian Networks, Monte Carlo simulation, etc. (Zhang, et al., 2014), and b) Possibilistic approach, dealing with risk probability and impact estimation based on qualitative or descriptive data including fuzzy logic (Dikmen, Birgonul and Han, 2007). The advantage of possibilistic models is that they can embrace the uncertain and vague definition of risk factors and their magnitude in a linguistic and subjective human description (Samantra, Datta and Mahapatra, 2017). Although called by various names, the notion and reasonings for classifying all of the methods are the same. For ease of reference, this research calls them Probabilistic and Deterministic models. 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.

Probabilistic models are mostly based on Bayesian Inference, which allows making judgments on prior and posterior probabilities in random variables based on various sources, like expert judgment, model simulation, or historical data (Phan et al., 2016). 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 (Zhang et al., 2016). 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. This is a huge advantage in situations with limited data, as the application of multiple sources compromises the data limitation.

On the other hand, Deterministic models are mostly based on the Frequentist approach, which can be merely 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 straightforward and simpler compared to the Probabilistic methods, 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 overreliance on experts' opinions if not appropriately calibrated (Bar-hillel and Neter, 1993). A comparative analysis of deterministic and probabilistic ML methods is presented in subchapter 4.

4.3.3 ML Classifications

Machine learning (ML) is a computational approach that enables machines to mimic human learning, gaining knowledge and experience from real-world data (Gibert, Mateu and Planes, 2020), which is used for modeling, control, or prediction using statistical techniques, without the need for explicit programming. The ML methods, as presented in Figure 4.4., can be categorized as:

a) Supervised Machine Learning, which involves machines making decisions based on labeled datasets (input and desired output pairings). It is further divided into classification and regression (Kotsiantis, Zaharakis and Pintelas, 2006),
b) Unsupervised Machine Learning, which involves machines learning the underlying structure in unlabeled datasets, categorized into clustering and dimension reduction techniques (Xie et al., 2020);
c) Reinforcement Learning (RL), defined as learning a mapping from situations to actions to maximize a scalar reward or reinforcement signal]. RL is a computational approach that involves learning from the outcome of interactions with the environment; and,
d) Deep Learning, the current state-of-the-art in ML, which has proven to provide more accurate predictions than conventional ML techniques (Schmidhuber, 2015; Abioye et al., 2021; Sharma et al., 2021).

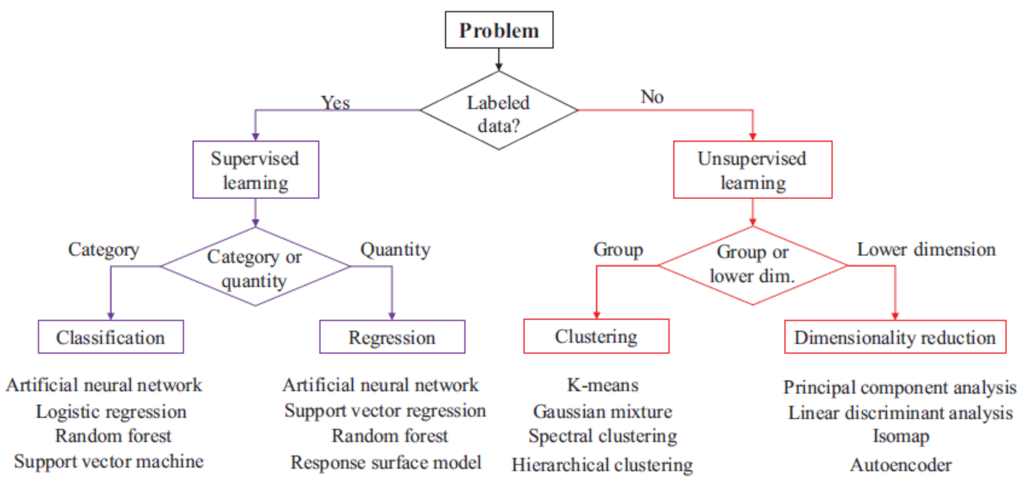

Figure 4.4. Types of ML algorithms based on type of data (Kong et al., 2019)

For a successful application of ML methods, transparent, accessible, and high-quality data are needed to be compiled in a computer-readable form. In ML applications, although significant expertise and effort are required in model tuning, training, validation, and interpretation, generally, the time spent running ML is much less in comparison with the time to gather data, integrate it, clean it, and pre-process it (Domingos, 2012). However, challenges arise mainly in two cases:

a) When the data is large-scale, high-dimensional, nonlinear, non-stationary, and heterogeneous, challenging the capabilities of existing ML methods, where more advanced ML techniques, such as active learning, reinforcement learning, and deep learning are required (Nguyen and Medjaher, 2019) to characterize the higher-order correlation and dependencies within the data, perform efficient and reliable imputation and prediction for decision making, and develop scalable learning models for large-scale and time-dependent problems (Xie et al., 2020), and

b) When the data is limited, scarce, and unstructured, or there are missing data, outliers, and imbalanced class distribution (Dietrich et al., 2020), which makes the application of advanced and black box models inefficient and unprecise.

In order to overcome these challenges, alongside assuring the proper data quality, quantity, and format, methods like Principal Component Analysis (PCA) and Feature Importance are super helpful. PCA is used to address dimensionality problems, breaking down large variable data sets into smaller classes without losing valuable data (Koc, Ekmekcioğlu and Gurgun, 2021). It can also reduce the chance of overfitting the developed models by eliminating features with high correlations. On the other hand, features importance in ML techniques captures complex relationships between variables, providing insights for decision-makers by determining the relative significance or contribution of each feature or input variable in a given model's predictive performance. (Allah Bukhsh et al., 2020).

ML methods offer numerous advantages, including speed, cost-effectiveness, high performance, and ease of validation. The hybridization of standard models and the introduction of new ones has become a common practice among researchers for solving engineering and construction problems (Munawar, Hammad and Waller, 2021). One of the common hybrid models is the aggregation of Monte Carlo Simulation with ML models, used for risk and reliability assessment and construction and excavation projects (Lin, Wu and Zhang, 2023). Moreover, BIM has been paired with ML methods in numerous previous research (Pan and Zhang, 2023). The Auto-ML technologies have been introduced to solve the requirement for manual interventions, such as data normalization, feature selection, model selection, and hyperparameter optimization in traditional ML, automating the ML pipeline, eliminating manual operations, and allowing designers to train optimal models with minimal effort (Chauhan et al., 2020).

Comparative analysis between various ML algorithms has been the topic of many studies. For instance, Koc and Gurgun (2022) implemented various methods including logistic regression (LR), decision tree (DT), random forest (RF), and Extreme Gradient Boosting (XGBoost) for predicting construction accident severity assessment. ML algorithms have been widely studied for construction risk assessments (Lin et al., 2021b), construction accident severity assessment (Koc and Gurgun, 2022), safety enhancement, injury type prediction (Alkaissy et al., 2023), cost overrun and delay prediction, human error reduction, and ensuring the performance of the project in terms of quality, cost, and on-time completion (Sharma et al., 2021). While traditional statistical models have been used to analyze construction accidents, schedule trends, or project progress, ML techniques offer high potential for predicting future events (Alkaissy et al., 2023). Most applied classes of ML methods in general are ANN, support vector machine (SVM), response surface model (RSM), logistic regression (LR), decision tree (DT) and random forest (RF), hybrid methods that couple two or more soft computing algorithms, and all other methods (e.g., evolutionary computing (EC) and genetic expression programming (GEP)) that are not significant in the number of applications. (Xie et al., 2020)

4.4. Introductions to Various AI and ML Methods for Construction RM

In this section, various methods used for the construction of RM in literature are introduced. Initially, non-ML methods like Big Data techniques, Process Mining, and NLP are introduced, and then ML algorithms are listed, starting from deterministic algorithms and continuing with probabilistic ones.

4.4.1. Big Data

In the rapidly evolving landscape of information technology, "Big Data" has emerged as a ubiquitous and complex pool of diverse data (Meng et al., 2022). The construction industry, already dealing with large volumes of heterogeneous data, is expected to see an exponential increase in data volume with the commoditization of technologies like the IoT and Cloud Computing (Bilal et al., 2016), which can be considered Big Data due to having the three features of variety, velocity, and volume. Traditional and manual data collection and processing methods are inadequate to handle the vast and varied data generated in construction projects. Hence, the use of Big Data technology is necessary to collect, classify, and process data effectively.

Big Data application for Construction RM has been studied by numerous scholars. Ayhan and Tokdemir (2020) developed a model to predict engineering construction accidents and suggested preventive measures using class clustering analysis and ANN. Guo et al. (2016) developed a Big Data-based worker behavior observation platform to identify unsafe behavior patterns and improve safety on site. Other researchers like Su et al. (2021) proposed a data-driven approach using Convolutional Neural Network (CNN)-based image recognition techniques for automated fire detection and alarm systems.

Big Data analysis techniques such as text mining, audio analytics, video analytics, and predictive analytics are being increasingly used to improve safety and mitigate accident risks on construction sites. Zhu et al. (2020) applied different ML methods to classify the severity of construction safety accidents, emphasizing the critical role of predictive analysis. Among ML and DL methods, Neural Networks, simulating certain intelligent activities of the human brain, are widely used in Big Data analysis techniques, particularly in engineering construction risk assessment (Hegde and Rokseth, 2020). The advent of Big Data technology has also facilitated the observation of workers on job sites, with researchers using motion sensors, cameras, and ML to monitor worker behavior and unsafe movements, as well as the incompliance of activities with safety measures (Yu et al., 2021). However, controlling unsafe human behavior remains the primary challenge in construction safety management, necessitating the development of AI-based Big Data systems (Tibaut and Zazula, 2018). The efficient collection of multi-sourced, heterogenous, time-constrained, spatially correlated, concurrent, and synchronized Big Data in construction projects and the integration of it with construction site domain knowledge present ongoing challenges that require new theories and methods for data processing (Meng et al., 2022). Disaster Risk Management is another area that can significantly benefit from the advancement of Big Data technologies by improving the speed and effectiveness of linkages between disaster information and systemic response to increase resilience (Habibi Rad, Mojtahedi and Ostwald, 2021).

4.4.2. Process Mining

Process Mining is an analytical, evidence-based, and data-driven method to detect, monitor, and improve business or project processes (Kulakli and Birgun, 2021). As a theme of Business Project Management, Process Mining is a combination of data-mining and traditional model-driven Business Project Management that analyses processes simply and systematically by exploiting current and historical process data stored as event logs in the information systems. For this purpose, Machine Learning and Data Mining algorithms are used to understand the current performance of the processes and their deviations concerning a normative model (Van der Aalst, 2016). In contrast to traditional methods like process mapping, Process Mining is fact-based, objective, continuously enhancing, self-operating, efficient, less time-consuming, holistic, and detailed (Miller, 2014).

PM has an outstanding performance in ever-changing and uncertain environments like construction projects and can take advantage of Industry 4.0 novel technologies for the digital transformation of the industry. Like Project Management, PM has standard implementation steps based on the application objectives, e.g., 1) process discovery, 2) process conformance checking, and 3) process enhancement (Van der Aalst, 2016).

Integration of PM and RM has been limitedly studied in previous research works. Taroun, (2014) studied different risk models and measures in construction projects by assessing the various definitions, risk elements, and allied concepts of risk models. Caron, Vanthienen and Baesens (2013) provided a full exploration of the applicability of PM in the context of the eight components of the COSO Enterprise RM Framework, which was illustrated based on the risks involved in insurance claim handling processes. Lamine et al. (2020) researched to establish the Business Process-Risk Integrated Method (BPRIM) framework to address risks considering enterprise engineering. In PM integration with enterprise and project processes, Liu et al. (2012) proposed a generic approach of business process simulation for operational decision support by simulating credit card applications. Khodabakhshian and Re Cecconi (2022) proposed a PM-based project-level RM framework for a number of Italian construction projects, developing PM workflows for each of the process discovery, conformance checking, and performance enhancement levels, as depicted in Figure 4.5.

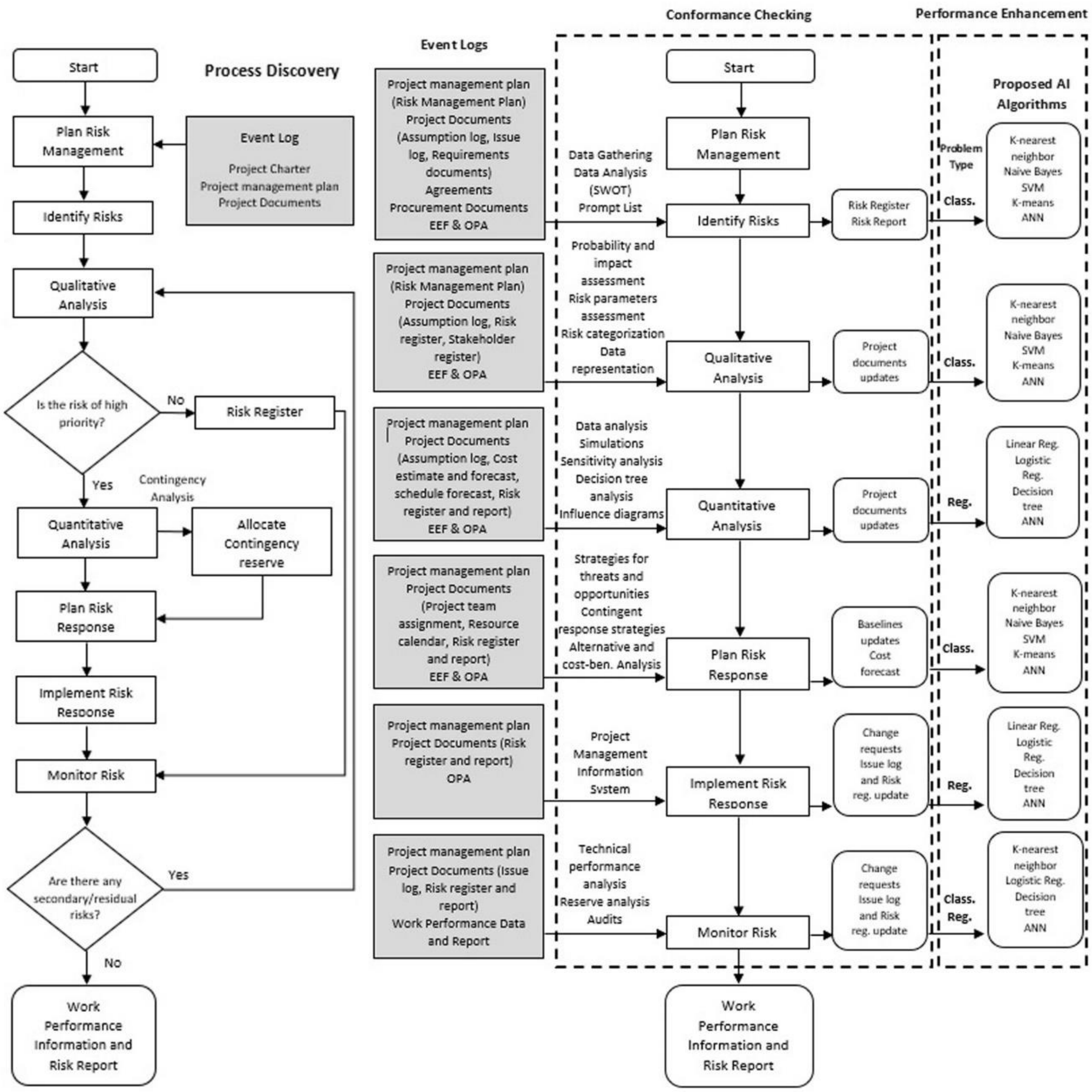

Figure 4.4. Framework workflow for in Process Discovery, Conformance Checking, and Performance Enhancement Phases (Khodabakhshian, and Re Cecconi, 2022)

4.4.3. Natural Language Processing (NLP), Text Mining, and Data Structuralizing Techniques:

Natural Language Processing (NLP), a subfield of AI, focuses on creating computational models that emulate human linguistic abilities (Bilal et al., 2016). It has applications in machine translation, text processing, user interfaces, speech recognition, and expert systems (Chowdhury, 2003). NLP techniques transfer human language to the structured text and then to numeric data for further analysis and modelling (Di Giuda et al., 2020). Text tokenization is a key process in NLP, a preprocessing step involving tokenization, stop word removal, and stemming (Zou, Kiviniemi and Jones, 2017).

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 research is data scarcity and missing values, which hinders the application of Deep Learning algorithms requiring huge amounts of data to have proper performance. Therefore, NLP-based Text Mining applications have been the center of attention to convert textual and unstructured data, consisting of 80% of construction data, into structured format proper for AI algorithms (Fan and Li, 2013). TM can run an automatic analysis of construction documents (Malsane et al., 2015) and extract valuable data for identifying contract risks from contract conditions, socio-technical risks from licensee event reports, and safety risks from accident reports (Xu et al., 2021), which can bridge the gap between manual and automated processes for reviewing construction specifications. Clustering and Classification methods, such as Support Vector Machine (SVM), Linear Regression (LR), K-Nearest Neighbour (KNN), Decision Tree (DT), and Naïve Bayes (NB) models, are used to categorize risks and can be integrated with TM methods as a proceeding step of text structurization (Zhang et al., 2019). Moreover, NLP has been used to develop automated specification reviewing models, such as the one proposed by (Moon et al., 2021), which includes a Named Entity Recognition (NER) model based on bidirectional long-short-term memory architecture.

NLP can greatly benefit the RM domain by extracting the acquired knowledge from similar previous projects through risk registers and documents, aiding project teams and public agencies to be well-equipped with a risk identification model instead of starting from scratch (Erfani and Cui, 2022). It has also been applied to other construction management areas, such as contract management (Hassan, Le and Lv, 2021), litigation and claim management, and safety management (Baker, Hallowell and Tixier, 2020). The study by Erfani introduced an NLP-based model for risk register template generation using historical data, offering flexibility, efficiency, and reduced subjectivity compared to expert judgment-based approaches (Erfani and Cui, 2022). Moreover, NLP provides the opportunity to generate risk register templates and conduct sensitivity analysis, resulting in a more accurate analysis of risks. The importance of NLP extends to addressing problems like increased risk of accidents, rework, wasted resources, and conflicts in construction projects (Zhang and El-Gohary, 2017).

4.4.4. Artificial Neural Networks and Generative Adversarial Networks (GANs)

Categorized in the Deep Learning group, Artificial Neural Networks (ANNs) are intelligent systems designed to emulate human brain functions, handling intricate information processes while not needing to understand cause-and-effect relationships. Inspired by human biological neurons, ANN consists of processing units called neurons with weighted connections, which are located in three sections, namely the input layer, several hidden layers, and the output layer (Sharma et al., 2021). The forward flow of information, moving from input data through hidden nodes to the output result, is a key feature of NNs. The number of input nodes corresponds to specific risk parameters, while the number of hidden neurons is guided by training data (Lin et al., 2021b). There has been a noticeable trend over the past 20 years (Xu et al., 2022).

Applications of NNs in construction management date back to the early 1990s and cover a range of topics like construction scheduling and management, resource allocation, and construction litigation. Based on a review study conducted by Hegde and Rokseth (2020) on applications of ML methods for engineering risk assessment, ANNs are the most applied method to aid in engineering risk assessment, followed by SVM, Decision Trees, and RF. Moreover, the format of the input data for Risk Assessment in NNs can be numeric data, categorical data, video data, sensor data, and textual data, and input data acquisition approaches could be historical, real-time, or a combination of historical and real-time data. NNs offer advantages such as the capability to deal with large and complex data, self-organization, fault tolerance, adaptive learning, large data handling, quick processing, and multitasking (Sharma et al., 2021). However, their application in construction engineering and management is challenged due to data collection, cleaning, and storage difficulties, black box structure resulting in difficulty to explain, lack of transparency, data privacy and cybersecurity challenges, lack of on-size-fits-all model (Akinosho et al., 2020), weak collaboration among stakeholders, and lack of systematic design for required platforms (Xu et al., 2022).

ANN can greatly reduce risks through their on-time identification, evaluation, and mitigation in complex and uncertain construction environments by capturing the interdependence between accidents and their causes in historical data, which effectively avoids the limitations of traditional risk analysis, such as the vagueness and subjectivity of expert experience. ANN is considered one of the most optimal tools for predicting various types of risks in construction projects, such as finance (Lhee, Issa and Flood, 2012), site safety (Yang, Ahn and Kim, 2020), Structural health, contract (Jin, 2011), and quality, disputes and claims, bidding and procurement; and evaluating risks such as deep excavation risks like wall deflection and ground surface settlement (Zhou et al., 2019), project success prediction, organizational capability assessment, accident analysis, environmental disasters and flood prediction (Munawar, Hammad and Waller, 2021), and optimal risk allocation. Project managers can benefit from the automated and efficient ANN-based risk prediction to quickly determine the priority of possible risks and to proactively plan for preventive actions, such as simplifying the work site operation, adjusting personnel arrangements (Xu et al., 2022), and directing their limited resources and time towards the bigger risk factors through recognizing project milestones (Pedroso, 2017).

Despite the black box structure of ANNs, making them unexplainable, they are the most applied AI methods in many fields (Tayefeh Hashemi, Ebadati and Kaur, 2020). However, their data-driven nature can lead to low prediction performance with small data sets; moreover, their sensitivity to input data and the number of input neurons affect system performance. Developing hybrid models of backpropagation NNs will lead to more accurate predictions and prevent the model from presenting erroneous performance and hence can overcome the abovementioned shortcomings. For instance, ANFIS is a fuzzy system that uses NN-based learning to find parameters and is considered a powerful hybrid model for RM (Munawar, Hammad and Waller, 2021).

On a broader scope, the application of deep learning techniques, particularly Convolutional Neural Networks (CNN), has seen significant advancements in the construction industry, being the most applied type of deep learning method in literature based on Akinosho et al. (2020). CNN is instrumental for object detection and monitoring for construction site safety purposes, with Multi-view deep learning and voxel-based 3D CNN as its two pioneering research areas (Lin, Wu and Zhang, 2023). Moreover, computer vision technology provides conditions for CNNs to further realize accurate object and personnel detection in real-time mode (Fang et al., 2018; Seo et al., 2015). Figure 4.6. presents the structure and learning process of a typical ANN.

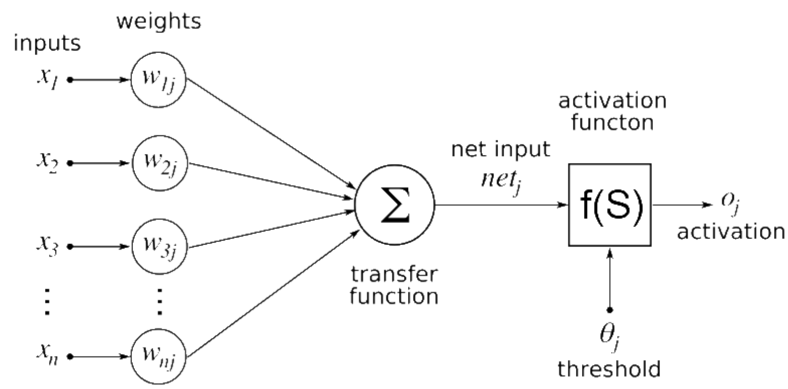

Figure 4.6. Structure and Learning process of ANNs (Keerthana, 2021)

Another solution to overcome data scarcity in construction research is data augmentation techniques like Generative Adversarial Networks (GANs), which are applied to improve the quantity and distribution of data by producing synthetic data through learning from the training sample (Goodfellow et al., 2020). GANs are a type of NNs in which two sub-networks, namely the generator and the discriminator, compete with each other by using deep learning methods to become more accurate in their predictions (Akinosho et al., 2020). The generator is a conventional multilayer perceptron, and the discriminator is a binary classifier that finds the differences between the original data and the generated data (Zhang et al., 2018). GANs typically run unsupervised and use a cooperative zero-sum game framework to learn, where one person's gain equals another person's loss. Although GANs have broader applications in creating synthetic images, they are recently being applied to tabular data as well, which is the common form of risk data registration. GANs' application in generative design cannot be overlooked, even if it has been studied broadly yet. Newton (2019) argues that GANs are an emerging research area in deep learning that has demonstrated impressive abilities to synthesize 2D and 3D designs from specific architectural styles and design requirements. Figure 4.7. presents the structure of GANs.

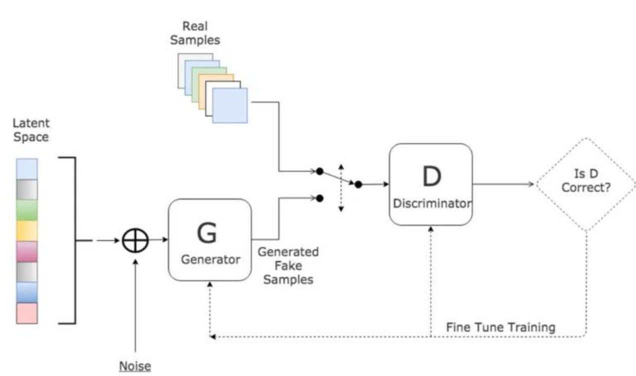

Figure 4.7. Structure of GANs (Ganz, 2020)

4.4.5. Random Forest and Decision Tree

Decision Tree is an analytical method that partitions data based on essential variables, offering a top-down algorithm to explain complex problems in construction safety and risk prediction (Delen et al., 2017). It is a widely used non-parametric supervised learning algorithm for classification and regression tasks, consisting of a hierarchical structure with a root node, branches, internal nodes (decision nodes), and leaf nodes. Starting from the root node, the tree is constructed by recursively partitioning the data based on available features, creating homogeneous subsets represented by leaf nodes to find optimal split points within the tree. This process is then performed iteratively for each branch (Tayefeh Hashemi, Ebadati and Kaur, 2020). The Decision Tree Regressor is employed for regression tasks, aiming to predict continuous numerical values, which can fit each subspace in the case of regression. It recursively partitions the data into subsets, minimizing the variance of predicted values (Ferreira and Vasilyev, 2015; Mistikoglu et al., 2015). Known for its accuracy, interpretability, and efficiency, DT can handle unrelated features and produce feasible results for large data sources (Poh, Ubeynarayana and Goh, 2018).

Developed by Breiman (2001), Random Forest is adept at demonstrating nonlinear relationships without statistical assumptions and can address classification and regression problems. The RF algorithm consists of numerous trees for training and predicting sample data, with critical considerations for splitting tree nodes and applying randomness. The formation of classification and regression trees (CARTs) is a significant part of the RF model, with applications demonstrated in construction and excavation projects (Lin et al., 2021a). Figure 4.8. illustrates the DT and RF structures. A cost function is applied together with a greedy construction procedure to find the optimal partitioning of the data. RF further enhances DT by constructing multiple trees and using bootstrap aggregating or bagging to overcome overfitting and instability (Alkaissy et al., 2023). Both algorithms have high explainability and transparency and have an understandable reasoning and learning process, which is a great advantage compared to black box methods.

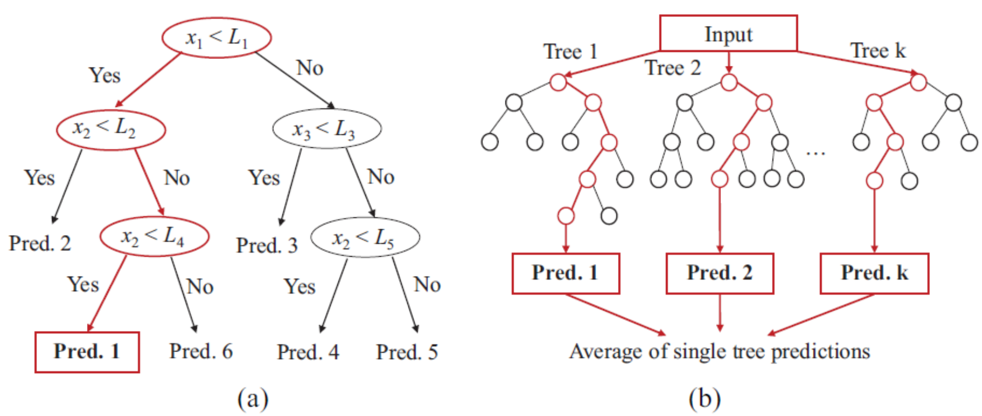

Figure 4.8. Structures of a) binary DT, and b) RF (Xie *et al.*, 2020)

4.4.6. Extreme Gradient Boosting (XGBoost)

The XGBoost algorithm, proposed by Chen and Guestrin (2016), is an integrated learning method based on gradient boosting, which aims to achieve an accurate classification via calculations of weak classifiers iteratively. The structure of XGBoost consists of an ensemble of decision trees, where each tree corrects the errors made by its predecessors. The objective function of XGBoost is defined by two main concepts: training error and regularization (Dong et al., 2020). The method utilizes gradient descent optimization (Munkhdalai et al., 2019) to find optimal values and employs parallel computing to reduce learning time and improve based on the prediction error (Chen and Guestrin, 2016). It utilizes column and row block data structures for efficient tree construction, handles sparse data using a sparsity-aware learning algorithm, reflects linearity and non-linearity of data, and incorporates regularization to enhance model robustness (Khodabakhshian et al., 2023; Elmousalami, 2020). It also adds a regularization term to the loss function to penalize model complexity and address overfitting (Dong et al., 2020). Algorithm performance is evaluated using metrics like confusion matrix, precision, recall, and F1-score (Baker, Hallowell and Tixier, 2020).

Koc and Gurgun (2022) proposed a tree-based ensemble ML model, combining XGBoost and Genetic Algorithm, to predict potential future accidents and their severities in construction projects. Wu and Lu (2022) adopted XGBoost to evaluate the degree of each structural reliability index and feature importance analysis in bridge construction risk assessment. Dong et al. (2020) proposed an XGBoost algorithm-based prediction model for structural health monitoring and electrical resistivity measurement, which considered all potential influential factors simultaneously. XGBoost has been widely applied for RM in other industries as well, such as real-time driving risk assessment (Shi, Qian and Guo, 2022), credit risk analysis (Tang, Guorui Zhu and Li, 2023), environmental risk assessment (Iban and Bilgilioglu, 2023). These applications highlight the versatility and robustness of XGBoost in assessing various types of risks across different domains; however, its application in construction RM is relatively new and understudied. Figure 4.9. presents the structure and learning process of XGBoost.

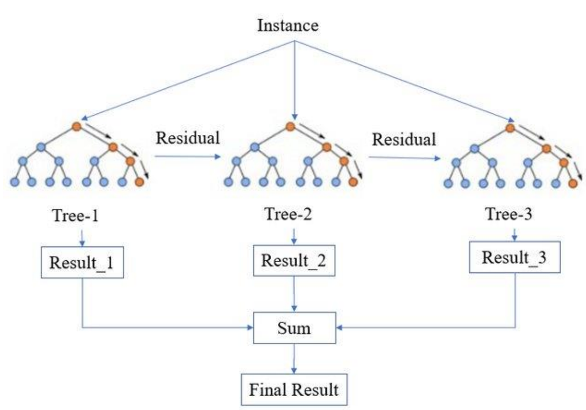

Figure 4.9. Structure and Learning process of XGBoost (Wang, Chakraborty and Chakraborty, 2021)

4.4.7. Support-Vector Machine (SVM)

The Support-Vector Machine (SVM), a concept grounded in statistical learning theory and structure risk minimization, was pioneered by Corinna Cortes (1995). SVM is a versatile tool for classification and regression problems, aiming to enhance predictive accuracy while preventing overfitting. SVM's structure consists of three layers: input data, hidden, and output, each serving specific classification rules. The process involves inputting vectors into the model, transforming them into a high-dimensional feature space using the training data, and utilizing kernel functions like polynomial, linear, sigmoid, or radial basis functions (Skala, Karim and Zabran, 2020). The high-dimensional space is divided into positive and negative instances by a hyperplane. To classify new instances, their location in this space concerning the hyperplane is determined. The optimal classification hyperplane and kernel functions are the two main principles of SVM (Corinna Cortes, 1995; Xie et al., 2020). It can also be used as a regression method, known as Support Vector Regression (SVR), by applying minor changes to the algorithm, basically involving the determination of a regression model for describing the relationships among sample data (Sharma et al., 2021). Figure 4.10. illustrates the structure of SVM.

SVM has been applied for risk assessment in various domains. Zhou et al. (2017) used SVM to identify excavation risks in subway projects. It is also a popular method for flood analysis, where SVM training models assign binary linear classifiers to minimize errors and maximize geometric margins (Xue et al., 2020). SVR has been introduced as a regression tool for flood risk assessment (Gibert, Mateu and Planes, 2020). In geotechnical engineering, SVM is used for pattern recognition, matter classification, and soil and rock classification, aiding in landslide susceptibility analysis and the identification of deformed rocks and soil (Sharma et al., 2021). It is also applied in construction safety assessment since it can solve high-dimensional problems and nonlinear features, such as worksite accidents (Alkaissy et al., 2023).

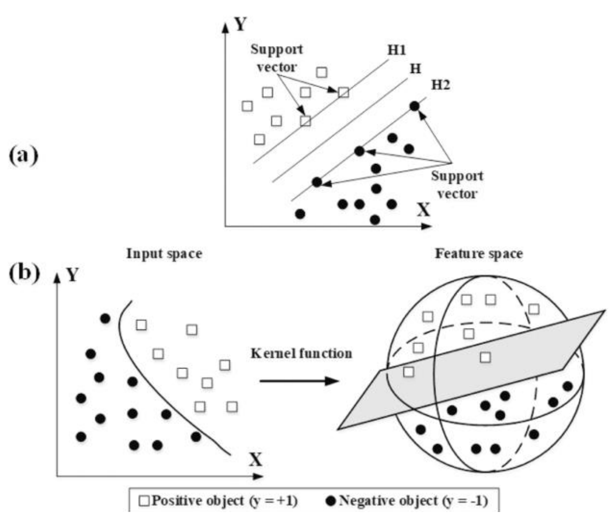

Figure 4.10. Structure and learning process of SVM (modified from (Huang and Zhao, 2018))

4.4.8. K-Nearest Neighbor, K-Means, and Naïve Bayes Classifiers

The K-nearest neighbors (KNN) classifier is a non-parametric supervised ML algorithm used for classification and regression tasks. KNN finds a predefined number of training samples (denoted by the parameter 'K') closest in distance to a new sample, which is yet to be classified. The label of the new sample is then determined by a majority vote of its K-nearest neighbors (Santos et al., 2017). It has been widely applied in construction RM and safety research. Farid et al. (2018) propose the K-nearest neighbor (KNN) method for calibrating safety performance functions to evaluate road safety for four states in the USA (Farid, Abdel-Aty and Lee, 2018). Goh et al. (2018) used the established algorithms commonly used in supervised learning, including KNN and Naïve Bayes classifiers, to evaluate the relative importance of different cognitive factors within the Theory of Reasoned Action (TRA) in influencing safety behavior. Figure 4.10. presents the learning process of KNN.

K-means is another widely used clustering ML algorithm, aiming to partition a set of data points into "K" distinct clusters based on their features, which was first published in 1955. The goal of K-means, which is a greedy algorithm, is to minimize the sum of the squared error over all K clusters; thus, it can only converge to a local minimum (Jain, 2010). (Chattapadhyay, Putta and Rao (2021) developed a risk prediction system based on a cross analytical ML model was developed for construction megaprojects, using a genetic-algorithm-based K-means clustering algorithm (GA–K-means) with dual-objective functions to segment high-risk factors and allied sub-risk components.

The Naive Bayes Classifier is one of the most applied Bayesian learning methods, which is a statistical classifier based on Bayes' theorem. It is a probabilistic ML algorithm called naïve due to a fundamental assumption that variables or features are conditionally independent given the class label. In other words, the presence or absence of a particular feature does not influence the presence or absence of any other feature, given the class variable (Naji, Ibrahim and Hassan, 2018). Mathematically, it is expressed as Equation 4.1. It has been widely used in construction research like other Bayesian approaches. Gondia et al. (2020) used NB classifier and DT to facilitate accurate project delay risk analysis and prediction using objective data sources. NB was chosen for this purpose since it is suited to small-sized data sets.

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \quad (4.1)$$

Where:

P(A|B) is the posterior probability of class A given predator B.
P(B|A) is the likelihood which is the probability of predictor B given class A.
P(A) is the prior probability of class A.
P(B) is the prior probability of predictor B.

4.4.9. Logistic and Ridge Regression

Logistic Regression (LR) analyzes the relationship between a categorical dependent variable and independent variables to estimate values and probabilities using a logistic distribution function, such as the sigmoid function (Xie et al., 2020). Proposed by Cox (1958), LR is a favored classification model, especially in safety risk assessment, as it correlates items and simplifies the resulting formula. It is mainly used for binary predictions, but extensions like One-vs-rest logistic regression (OvR LR) and multinomial logit (M LR) can handle multi-class problems (Abramovich, Grinshtein and Levy, 2021). Figure 4.11 presents the structure and learning process of LR.

Ridge Regression, also known as L2 regularization, is a technique used to address multicollinearity in multiple regression data. By adding a degree of bias to the regression estimates, Ridge Regression stabilizes them, thus providing a solution to ill-posed problems or reducing variance in the predictions (Hoerl and Kennard, 1970). Incorporating a penalty term ensures that the model does not overfit the data, allowing for more robust predictions of potential risks in construction projects. This method has been particularly useful in handling high-dimensional data where traditional regression models may falter. Ridge Regression has been applied to develop predictive models for continuous values such as cost estimation, project delays, and safety risk evaluation in construction, providing valuable insights and decision-making tools for project managers and engineers (Dobriban and Wager, 2018).

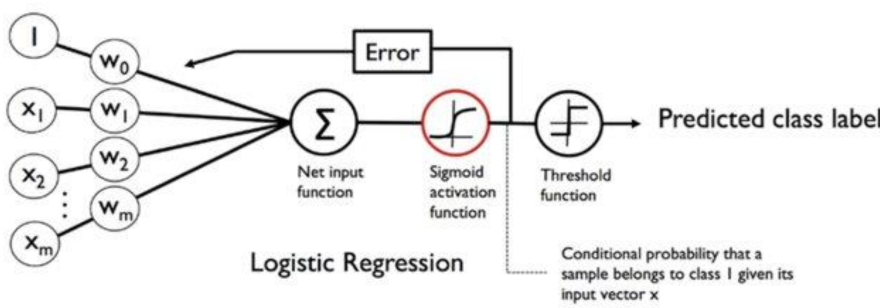

Figure 4.11. Structure and learning process of Logistic Regression (Torres, Ohashi and Pessin, 2019)

4.4.10. Genetic Algorithm

A Genetic Algorithm (GA), a family of evolutionary computation models (Tayefeh Hashemi, Ebadati and Kaur, 2020), is a search heuristic inspired by Charles Darwin's theory of natural evolution, reflecting the process of natural selection where the fittest individuals are selected for reproduction (Morano et al., 2018). It consists of Initialization or candidate solutions generation, selection of individuals based on their fitness in the problem domain, crossover (recombination) for randomly choosing pairs of individuals from the population to create one or more offspring, mutation for introducing small random changes in the offspring, replacement of some of the less fit individuals with new offspring to the population, and termination of the process when some stopping condition like minimum fitness threshold is met (Koc, Ekmekcioğlu and Gurgun, 2021).

GAs are used in various applications where exact solutions are hard to find. They can be applied to optimization and search problems, including scheduling, data modeling, RM, and many engineering design problems (Magnier and Haghighat, 2010). The strength of GAs comes from their ability to explore a large solution space efficiently and often find good enough solutions to complex problems where other methods might struggle. In the context of construction, GAs have been applied to credit risk evaluation in construction enterprises utilizing a combination of Radial Basis Function (RBF) Neural Network and Ant Colony Algorithm (Wu and Si, 2008), predicting the risk of contractor default using GA and ANN (Al-Sobiei, Arditi and Polat, 2005), quantitative assessment of technology choices in building retrofit projects (Asadi et al., 2014), resource optimization and management (Ugwu and Tah, 2002), and optimal income taxation (Małecka-Ziembińska and Ziembiński, 2020).

4.4.11. Fuzzy Logic and Hybrid Models

Zadeh's fuzzy set theory, developed in 1965, has been instrumental in handling uncertainty and vagueness in risk assessment practices (Zadeh, 1965). Contrary to crisp values with deterministic nature, fuzzy sets indicate a membership function between 0 and 1 for each variable and can utilize linguistic terms by experts, allowing for uncertain reasoning (Yazdanbakhsh and Dick, 2018). The probabilities 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 (Pokoradi, 2015). Methods like AHP, developed by Saaty (1980), and TOPSIS, created by Hwang and Yoon (1981), are based on fuzzy set theory. Therefore, FL models are easily comprehensible for experts and project managers to utilize in their RM processes. Their white-box and explainable nature is a great advantage in comparison to black-box deep learning methods.

Fuzzy hybrid techniques, such as FANP, FBBNs, FMCS, and FANNs, have been employed as hybrid models in Construction Engineering and Management (CEM), specifically the RM domain, to handle subjective uncertainty and vagueness through combining qualitative assessments with quantitative ones (Chan, Chan, and Yeung, 2009) These techniques combine fuzzy logic with standard methods like Multi-Criteria Decision Making, Monte Carlo Simulation, and ML to enhance their capabilities in performing dynamic modeling and computing processes (Fayek et al., 2020; Seresht et al., 2018). Moreover, they have been coupled with advanced technologies like BIM, GIS, sensors, modular construction, alternative reality technologies (e.g., augmented reality / AR, virtual reality / VR), and emerging innovations (e.g., big data analytics) in construction research (Chen, Lu and Zhao, 2022). Optimization and prediction of time performance (e.g., project durations), cost performance (e.g., cost controls), productivity performance (e.g., estimation of productivity), RM, disputes and claims, and client satisfaction are the primary application areas of these hybrid models (Tran, Cheng and Pham, 2016).

Based on an extensive literature review conducted by Nguyen and Robinson Fayek (2022), Fuzzy Hybrid ML techniques represent the majority (38%) of fuzzy hybrid applications in construction problems, aiming to handle subjectivity, incomplete data, and ambiguity (Seresht et al., 2018). These techniques, with fuzzy ANN and fuzzy clustering in lead (Soares, Barroso and

Al-Fahdawi, 2020), are used in data classification, predictive modeling, and pattern recognition (Qi et al., 2021). Fuzzy ANN has been mainly applied for construction materials' strengths prediction, project cost estimation, and evaluation of subcontractor and project manager (Rashidi, Jazebi and Brilakis, 2011), while Fuzzy clustering techniques (e.g., fuzzy c-means, context-specific fuzzy inference systems) have also been utilized for structural damage detection, development of control systems for pavement deflection tests, pavement design, monitoring project schedules, and predictive modeling (Yu, Zhu and Yu, 2013).

Fuzzy Hybrid MCDM models have been mainly applied for construction material selections, project risk management, supplier selection, and sustainability analysis (Beltrão and Carvalho, 2019). Fuzzy hybrid simulation techniques, like fuzzy Monte Carlo simulation (FMCS), fuzzy discrete event simulation (FDES), fuzzy system dynamics (FSD), and fuzzy agent-based modeling (FABM), handle the dynamic nature of construction problems (Raoufi, Gerami Seresht and Robiinson Fayek 2016). They have been used in risk analysis, project scheduling, resource management, quality management, and construction crew performance modeling (Attarzadeh et al., 2017; Nguyen and Fayek, 2022). In particular, Fuzzy Monte Carlo Simulation has been implemented primarily on construction RM because of its ability to simultaneously model and process various uncertainties, including probabilistic and subjective uncertainty of project risk factors (Seresht et al., 2018). In general, Fuzzy hybrid MCDM techniques are recommended for decision-making problems, fuzzy hybrid simulation techniques for capturing dynamism in process and system modeling, and fuzzy hybrid optimization techniques for solving complex multi-objective optimization problems.

A fuzzy Cognitive Map (Wee et al., 2015) is a combination of fuzzy Logic and cognitive map, which uses subjective and vague linguistic variables from domain experts, perform a Root Cause Analysis, and model 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 for imprecision and uncertainty (Chen, Zhang and Wu, 2020). Figure 4.12. presents the structure of a Fuzzy Cognitive Map. Ensemble Risk Analysis Fuzzy-based Framework (ERAFF) is another type of fuzzy models used to enhance the safety of construction operations. The ERAFF's novel contributions are threefold: (1) determining critical causal factors by considering their significance and influence levels, (2) identifying and prioritizing risks that threaten workers' lives by examining the association of causal factors and risks, and (3) providing and prioritizing beneficial control measures (Sadeghi, Zhang and Mohandes, 2023). Unlike traditional methods that rely on accident data, which may have limitations such as underreporting (Dewlaney, Hallowell and Fortunato, 2012), ERAFF can be implemented prior to accidents, using expert feedback (Hallowell and Gambatese, 2009). It overcomes subjectivity and ambiguity in decision-making by utilizing fuzzy set theory, systematically identifying causes, prioritizing risks, and ranking control measures.

The main challenge in FL implementation, especially in prediction problems, is the requirement of highly dimensional and complex data, accommodating a mix of quantitative and qualitative inputs, and capturing uncertainty and vagueness of model outputs (Tiruneh, Fayek and Sumati, 2020; Subramanyan, Sawant and Bhatt, 2012). Moreover, once the number of parameters and input variables increases, the scenario modeling and analysis becomes complicated and burdensome.

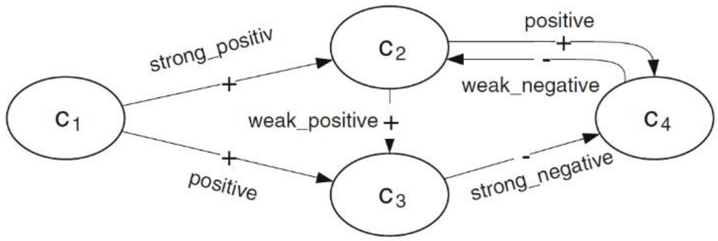

Figure 4.12. structure of a Fuzzy Cognitive Map (Szwed, Skrzynski and Chmiel, 2016)

4.4.12. Knowledge-based Systems

Construction RM often depends on tacit knowledge, making the exploitation of corporate risk memory crucial. This memory includes lessons learned from previous projects, allowing for precise forecasts about risks and their consequences (Dikmen et al., 2008). As pinpointed by Atkinson, Crawford and Ward (2006), risk-related experience gained throughout past projects is fundamental for accurate risk estimations in upcoming projects. However, capturing and utilizing this knowledge in a quantified and interpretable form is challenging (Okudan, Budayan and Dikmen, 2021). Knowledge-based Systems seem to be the perfect solution for this issue, which has been widely discussed in the literature (Abu Bakar et al., 2016).

Knowledge-based Systems (KBS) is a branch of AI used for machine decision-making, relying on existing knowledge in the field. A KBS is comprised of a knowledge base, an inference engine, and a user interface. The knowledge base can be created from expert knowledge, past experiences, or other relevant sources, enhancing productivity, efficiency, and transparency of the decision-making process. KBS can be classified into four categories: (A) Expert Systems, which imitate human decision-making process; (B) Case-based Reasoning (CBR) Systems, using past experiences to interpret new situations, requiring expert knowledge for case selection; (C) Intelligent Tutoring Systems, employing AI techniques for personalized tutoring; and (D) DBMS with intelligent user interfaces and linked systems, including Hypertext manipulation systems (HMS) for easy traversal of complex information networks (Abioye et al., 2021).

Despite the recognized benefits of knowledge-based RM, implementation is low due to a lack of learning culture and ineffective knowledge management (KM) processes/tools in the industry (Abu Bakar et al., 2016). Construction companies can barely capture, store, and disseminate knowledge to optimize the RM of forthcoming projects (Alashwal and Abdul-Rahman, 2014). Knowledge management strategies can be categorized as techniques and technologies (Eken et al., 2020). Techniques are defined as non-information Technology (IT) tools, while technologies are IT tools that require the development of a system to manage the knowledge, providing a platform for articulating, storing, and sharing knowledge (Alavi and Denford, 2011). However, the majority of these tools are generic knowledge management tools and usually do not offer a particular technological solution to support the RM process. A critical review of knowledge-based RM tools for construction projects conducted by Okudan, Budayan and Dikmen (2021), reveals that an ideal tool should support all RM steps, capture and formalize tacit knowledge, support live risk knowledge capture, enable inter-project learning, and have a systematic case retrieval mechanism (Fan et al., 2014). Existing tools, particularly web-based platforms, often lack these features. Web-based organizational learning tools using Case-based reasoning (CBR), which can be used for capturing, storing, retrieving, and disseminating risk-related knowledge, have been proposed as an alternative to address the abovementioned challenges (Okudan, Budayan and Dikmen, 2021). Moreover, the use of fuzzy linguistic variables, hybrid similarity measurement, and comprehensive definition of project features are critical for increasing accuracy in KBS (Zou, Kiviniemi and Jones, 2017).

CBR has been identified as a promising method for knowledge-based RM, which has been studied by previous researchers for construction projects and safety management (Lu, Li and Xiao, 2013). The web-based tool CBRisk can facilitate knowledge-based RM by developing a corporate risk memory to store risk-related knowledge of construction projects. CBRisk represents a continuous learning platform, enabling inter-project learning and live capture of newly created risk-related knowledge (Ayhan and Tokdemir, 2019). CBR recalls prior knowledge to provide a starting point for solving new problems (Zou, Kiviniemi and Jones, 2017), and is preferred due to its transparency and performance compared to black box methods like ANN. Figure 4.13. presents a holistic process model for knowledge-based RM activities throughout the project life cycle, including risk identification, response planning, monitoring, and cataloging risks and responses. As depicted in the figure, some of the main features and benefits of an RM KBS are a) Risk identification based on similar projects and the risk catalog, b) Knowledge capture, c) RM at every stage of the project, d) Guidance on different RM processes (Dikmen et al., 2008).

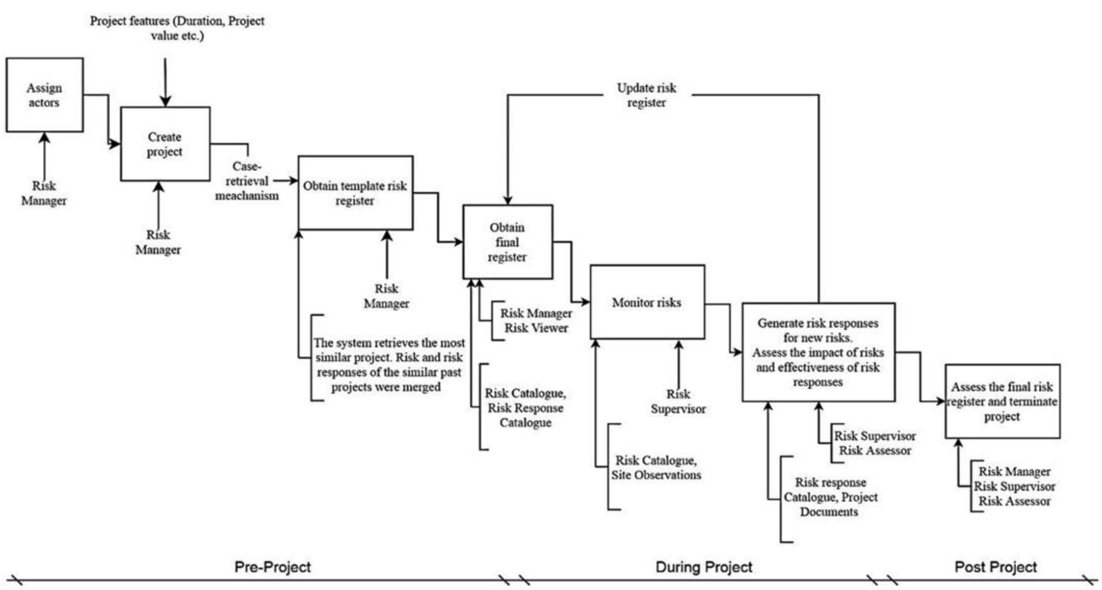

Figure 4.13. RM Knowledge-based system Process Model (Okudan, Budayan and Dikmen, 2021)

4.4.13. Fault Tree Analysis and Event Tree Analysis

Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) are essential tools in engineering and construction RM and for handling uncertainties in process systems risk analysis. These methodologies provide systematic ways to identify and evaluate potential failures and risks in complex systems. Fault Tree Analysis (FTA) is a top-down approach that starts with an undesired event and systematically identifies the various reasons that event can occur. It is a deductive method that enables an investigation of causal relations between basic events or factors and an undesired event. It uses Boolean logic to combine different failure events, allowing for the calculation of the probability of the top event (Guan et al., 2020). A study by Shu, Li and Qiu (2008) applied FTA based on fuzzy reasoning in risk analysis of construction quality, providing a more nuanced understanding of the potential failures in construction projects. Event Tree Analysis (ETA), on the other hand, is a bottom-up approach that starts with an initiating event and explores possible outcomes through different branches, representing various scenarios. It is an inductive method that describes accident scenarios through a sequence of events. It helps in understanding the sequence of events that can lead to different consequences (Wang et al., 2014). FTA/ETA requires the assessment of single probability values for events so that the probability of occurrence of a failure accident can be calculated through the logical or functional relationships predefined in the diagram. Figures 4.14. and 4.15 present the structures of Faul Trees and Event Trees, respectively.

In construction projects, ETA can be combined with FTA to create a hybrid framework for assessing risks. Moreover, the integration of fuzzy logic and hybrid frameworks further enhances these tools, allowing for a more nuanced understanding of complex risks in construction projects (Wang et al., 2014). Abad and Naeni (2020) proposed a hybrid framework using fuzzy fault tree and fuzzy event tree analysis to assess the risk of change and scope creep in construction projects. Ferdous et al. (2011) explored the uncertainty handling formulations in Fault and Event Tree Analyses for process systems risk analysis, emphasizing their applicability in complex systems. Abdollahzadeh and Rastgoo (2017) used FTA and ETA methods based on Fuzzy Logic for risk assessment in bridge construction projects. Guan et al. (2020) integrated FTA and Fuzzy set theory with BNs to create a risk assessment model for international construction projects.

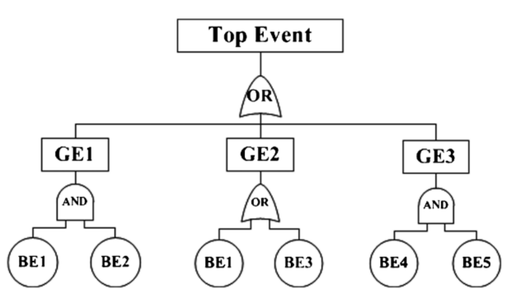

Figure 4.14. structure of Fault Trees (Abdollahzadeh and Rastgoo, 2017)

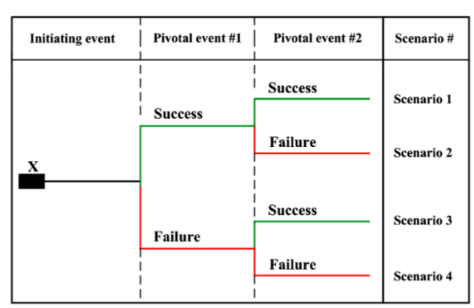

Figure 4.15. structure of an Event tree (Abdollahzadeh and Rastgoo, 2017)

4.4.14. Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is a multivariate statistical analysis technique used to analyze structural relationships between measured variables and latent constructs (Eybpoosh, Dikmen and Talat Birgonul, 2011). It combines factor analysis and multiple regression analysis, allowing researchers to test complex relationships between observed and unobserved variables (Xiong, Skitmore and Xia, 2015). SEM has many advantages including a) the ability to handle complex relationships among variables, including those that are hypothetical or unobserved, b) estimating all coefficients in the model at the same time and assessing the significance and strength of any particular relationship in the context of the full model, and c) the possibility to statistically test the model in a simultaneous analysis of the entire system of variables to determine the fitness of the model (Liu et al., 2018).

SEM's ability to model complex relationships makes it particularly suitable for analyzing the multifaceted nature of construction risks, although its application in construction research is relatively new. Malesios and Dey (2019) utilized SEM to assess both external and internal risk factors in projects, providing a comprehensive understanding of how different risks interact and influence each other. Kassem (2022) applied SEM, specifically Partial Least Squares Structural Equation Modeling (PLS-SEM), to assess RM in oil and gas construction projects, allowing for a nuanced understanding of the relationships between various risk factors and their impacts. Moreover, SEM can incorporate various aspects such as government acts, laws, and policies, and their influence on effective communication and construction risk, as explored in a recent study (Adeel et al., 2022). It can also be used for risk paths' identification in international construction projects (Eybpoosh, Dikmen and Talat Birgonul, 2011), resulting in a more accurate and realistic assessment of risks. It can also be combined with Exploratory Factor Analysis (EFA) for safety risk factors analysis in construction projects (Liu et al., 2018). 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 (Liu et al., 2018). GA and multi-variate SEM have also been found to be useful in measuring project risk interdependencies for the optimal cost solution under uncertainties (Liu, Yang and Zhang, 2013).

4.4.15. Bayesian Networks (BNs)

Bayesian Networks are the most implemented type of Probabilistic Graphical Models, statistical techniques based on probability and graph theory that enable modeling of stochastic systems and representing causal relationships between variables to perform risk and probability analysis (Hon et al., 2021). BNs, developed based on the Bayes Theorem of Thomas Bayes, are graphical representations of knowledge with intuitive structures and parameters to solve complex and uncertain problems (Lee, 2021). 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) (Borujeni et al., 2021); and include 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 on CPD or CPT can be learned through algorithms from enormous historical data, expert opinion, or both.

BNs have a wide application in modelling, identifying, and analysing project-related risks like claims and contract risks, structural health, operation quality, cost and schedule overruns, and safety hazards (Khodabakhshian and Re Cecconi, 2022; Liu, Jiao and Key, 2021). They can analyze causal influences between project variables and risks in construction projects, offering several advantages, including the ability to model uncertainty and dynamic risks, handle large amounts of data and model complexity, and perform sensitivity analysis and validation. However, there are limitations, such as over-reliance on expert knowledge and a lack of validation guides for BN models (Hon et al. 2022).

The application of Bayesian approaches in Construction Management (CM) research has been extensively mapped across almost all functional areas, as defined by Kang et al. (2018). These applications demonstrate the ability of Bayesian methods to handle uncertainties and multifactor interdependencies, with a particular focus on safety management, risk management, contract management, and process control. Since BN is the proposed method of the research, chapter 5 is completely designated to analyze its structure, learning process, and background in more detail.

4.5. Probability-based ML Algorithms Classification

ML algorithms' structures, risk reasoning, processing formats, data requirements, and the role of uncertainty in the assessment process are the criteria to categorize them into Probabilistic and Deterministic groups. Such categorization enables the comparison of the advantages and limitations of each group and the choice of the proper method for the given problems.

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 (Wu, Chen and Olson, 2014). However, an important factor that is missing in many of the previous techniques is the isolated analysis of risks (Xia et al., 2018) and 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 (Eybpoosh, Dikmen and Talat Birgonul, 2011).

The same concept also applies 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 (Khodabakhshian, Puolitaival and Kestle, 2023). 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 their judgments on (Pan and Zhang, 2021). The probabilistic approaches mainly follow a Bayesian statistic and base judgment on multiple sources, such as experts' opinions, model simulation, and historical records (Choy, O'leary and Mengersen 2009; Karimiazari et al., 2011; Cardenas et al. 2014; Debnath et al., 2016). 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 an extensive database to draw judgment from and can update the probability distribution based on new observations or data (Gelman et al., 2013). 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 an 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. Figure 4.16 provides an overview of the probability-based classification of ML algorithms.

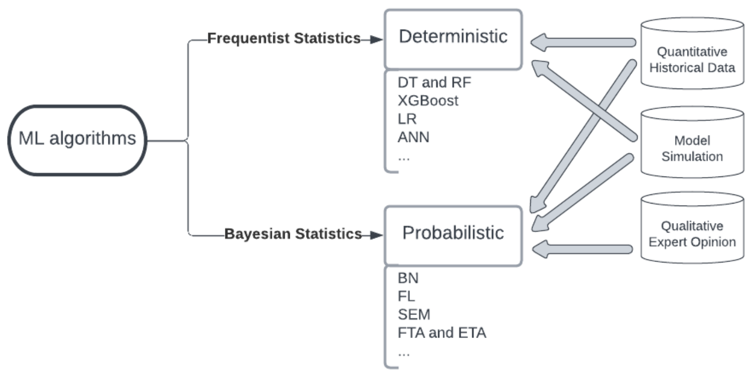

Figure 4.16. Probability-based ML algorithms' classification

The same probability-based grouping exists in conventional and non-AI-based RM methods, classifying them into deterministic and stochastic (probabilistic) models (Senova, Tobisova and Rozenberg, 2023). Deterministic models, such as the Probability–Impact matrix (El-Sayegh et al., 2021) or Pareto analysis (Pareto, 1964), predict a fixed value and mostly follow a frequentist statistic. On the other hand, the stochastic models represent the random behaviour 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 (Senova, Tobisova and Rozenberg, 2023), 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 (Liu, 2013). However, the main difference between these methods and ML-based algorithms is that they predict outcomes based on some rules, distributions, and formulas set by the model, whereas ML 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.

4.5.1. Probabilistic ML approaches for RM

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 aforementioned risk reasonings (Wee et al., 2015):

1. Probability-based reasoning refers to probability theory to indicate the uncertainty in knowledge, including fault tree analysis (FTA), SEM, and BNs. Figures 5.1 and 5.2 present the structures of a fault tree and an event tree.

2. Rule-based reasoning, deploying a set of rules in the "if <conditions>, then <conclusion>" format with logical connectives, like AND, OR, NOT, for analysing 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 immediate identification of risks' root causes in uncertain conditions. Figure 5.3 presents the structure of an FCM.

Some remarkable previous studies have proposed probabilistic and subjective RM models for construction projects. Afzal et al. (2019) 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. (2017), and Qazi et al., (2016). Cardenas et al. (2014) addressed the data unavailability and incompleteness problem in tunneling projects through expert elicitation in BBNs. Lee and Kim (2017) 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. (2011) 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. (2009) conducted a comparative analysis between SEM, multiple regression, and ANN and developed an SEM-based model predict the project success of uncertain international construction projects.

Moreover, the biggest portion of construction RM literature is based on hybrid models, the integration of Fuzzy Logic with other AI-based methods, which are among the probabilistic models group. Fuzzy logic application 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 (Chan et al., 2009). For instance, Zhao, Hwang and Gao (2016) 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, Sadiq and Tesfamariam (2015) incorporated fuzzy logic into BBN and proposed a Fuzzy Bayesian belief network (FBBN) model to represent dependencies of events and uncertain knowledge (such as randomness, vagueness, and ignorance) for safety analysis of Oil and Gas Pipeline projects. In another study, Shafiee (2014) 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, Li and Chen (2021) proposed a project risk prediction model using the entropy weight method (EW), fuzzy analytic hierarchy process (FAHP), and 1D Convolutional Neural Network for risk indexing. Cheng and Lu (2015) 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) with the level of criticality of risks. Liu and Ling, (2005) 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, like the one Islam et al. (2017) conducted, which delineated the advantages of Fuzzy Bayesian Belief Networks (FBBNs) over other hybrid models like FANP, due to overcoming the systematic constraints like lengthy calculations required for the pairwise comparisons. Petroutsatou, and Vagdatli (2023) proposed a probabilistic model for pre-estimating the life cycle cost of road tunnels' construction using multiple regression analysis and Monte Carlo simulation.

4.5.2. Deterministic ML approaches for RM

Deterministic Models include most of the ML algorithms, including a) Regression to predict continuous numerical outcomes like delay caused by a risk, including Linear Regression, Decision Trees, Support Vector Machines (SVM), and Neural Networks (NN) techniques, b) Classification to present the class of the output based on some input features like risk identification including NNs, Random Forest, SVM, and Genetic Algorithm, c) Clustering to explore data for natural groupings like 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 like identifying the most significant causes of accidents including Decision Trees and Random Forest, e) Anomaly detection to identify unusual cases based on deviation like identifying accident risks including SVM and Deep Neural Networks (Ajayi et al., 2019). Deterministic models provide a definite prediction of output value without assigning a probability distribution to it, which is their main difference from Probabilistic models. 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 (Hegde and Rokseth, 2020). They have a great performance in the presence of abundant data, capturing linear and nonlinear relationships of the data and serving as a predicting model for industrial RM control and accident severity assessment (Gondia, Siam, et al., 2020).

Deterministic ML applications have been studied mainly for predicting delay risks in construction, predicting the impact of contract changes on time and quality performance, and analyzing and modeling incident databases for predicting health and safety risks. The format of the input risk data for risk assessment in deterministic models can be numeric, categorical, video data, sensor data, and textual data, and input data acquisition approaches could be historical, real-time, or a combination of historical and real-time data (Hegde and Rokseth, 2020). Jallan and Ashuri (2020) 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, Putta and Rao (2021) used cross analytical ML model with K-means clustering and Genetic Algorithm to exploit different risk factors and their impacts on the performance aspects of construction megaprojects. Valpeters, Kireev and Ivanov (2018) determined the probability of contract execution risk at a given stage of its establishment using Logistic Regression, Decision Tree, and Random Forest algorithms. Creedy, Skitmore and Wong (2010) benefited from Multivariate Regression Analysis for evaluating risk factors that lead to cost overruns in delivering highway construction projects. Yaseen et al. (2020) developed a hybrid artificial intelligence model called integrative RF classifier with GA optimization (RF-GA) for delay problem prediction. Joukar and Nahmens (2016) extracted and forecasted volatilities of the Construction Cost Index (CCI) in the short term by assessing the cost risk of construction projects with respect to price volatilities and quantifying the risk of overestimation or underestimation, using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and ARIMA. Gondia, Asce, et al. (2020) used the DT and Naive Bayes Model to analyze and predict project delay risk using objective data from previous projects. Alshboul et al. (2022) 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.

Moreover, the integration of NNs with other methods, as hybrid models, has been widely studied for construction RM. Goh and Chua (2013) used NN analysis in 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 (2013) proposed 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 (2011) developed an ANN-based Risk allocation decision-making process in public–private partnership (PPP) projects. Chenyun (2012) conducted an Analysis and evaluation of project cost risk and identification of critical factors based on NN.

4.6. Comparative Analysis between Probabilistic and Deterministic ML Models

Following determining and listing the probabilistic and deterministic algorithms based on the source technical papers, 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 4.1. 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.

In general, algorithms with a deterministic approach have advanced structure, quicker processing time, and higher precision of results in complex problems. However, they require a large amount of structured data with no missing values or uncertainties. Given that documentation is in a non-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, is more appropriate for RM in construction due to functioning in the state of data scarcity and missing values and being closer to reality, considering the inter-dependencies between risk variables. They can integrate subjective and experience-based experts' opinions through elicitation with objective historical data gathered from previous projects or simulations to overcome the data scarcity issue. Moreover, they benefit from the risk path approach instead of isolated risk assessment, which makes the assessment process closer to reality. However, the structure and parameter learning are daunting and complicated tasks as the model becomes more complex, containing more variables and risk factors.

Probabilistic models are based on Bayesian Inference, as mentioned in Equation 4.2, and Deterministic models are based on Frequentist Inference, as mentioned in Equation 4.3. 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.

Referring to Table 4.1., and considering the circumstances of the case study, the Probabilistic Models, specifically BNs, were chosen as the primary solution of the research. However, for validation and comparative analysis purposes, a number of Deterministic models and Fuzzy Logic will be applied to the case study as well.

$$\mathrm{P}_{\mathrm{Posterior}}(\mathrm{H}|\mathrm{D}) = \frac{\mathrm{P}(\mathrm{D}|\mathrm{H})\mathrm{P}_{\mathrm{Prior}}(\mathrm{H})}{\mathrm{P}(\mathrm{D})} \quad (4.2)$$

$$\text{Likelihood } \mathrm{L}(\mathrm{H};\mathrm{D}) = \mathrm{P}(\mathrm{D}|\mathrm{H}) \quad (4.3)$$

This research aimed to overcome the shortcomings of previous review articles, which mostly focused on one type of ML application or its computational structure, by applying a practical classification for the proposed ML algorithms from the risk reasoning and judgment point of view. Such a functional and right-to-the-point classification is easily comprehensible and can be addressed by practitioners and researchers in the field, and they can choose the algorithm that best fits their requirements, research problem, available data, and resources. This is an interdisciplinary and novel way of grouping the widespread ML algorithms already implemented in the construction RM research. Furthermore, this practical viewpoint assisted the integration of the heterogeneous findings of previous review studies, which had differing scopes.

Apart from this theoretical comparative analysis, the results obtained from different probabilistic and deterministic ML algorithms on the research case study are compared in Chapter 8, which is the practical complementary part of the provided analysis. It is noteworthy that different algorithms have varying accuracy and performance in different contexts and problems due to the context-drivenness of RM; therefore, it is only possible to evaluate their overall performance and validate them by knowing the context and scope of their application, which in this case is the research case study.

Table 4.1. Analytical comparison between Probabilistic and Deterministic RM models(Khodabakhshian, Puolitaival and Kestle, 2023)

Comparison Criteria	Probabilistic Approach	Deterministic Approach
Reasoning basis	Probability-based reasoning Rule-based reasoning Fuzzy logic (Samantra, Datta and Mahapatra, 2017; Valpeters, Kireev and Ivanov, 2018)	Forward propagation and backpropagation Loss function Weights and biases (Hosny, Elbarkouky, and Elhakeem, 2015; Habbal et al., 2020)
Structure	Interconnected graphs (Khakzad, NKhan and Amyotte, 2013; Qazi et al., 2016; Lee and Kim, 2017)	Layers of neurons or branches (Jin and Zhang, 2011; Gajzler, 2013)
Data Source	Historical Data, model simulation Experts' opinion (Butler, Thomas and Pintar, 2015; Mkrtchyan, Podofillini and Dang, 2015)	Historical data, model simulation (Hosny, Elbarkouky, Elhakeem, 2015; Habbal et al., 2020; Re Cecconi, Khodabakhshian and Rampini, 2022)
Inference	Bayesian inference (Nguyen and Tran, 2016)	Frequentist inference (Lele and Allen, 2006)
Data Requirements	Limited amount of data Able to deal with missing values Numerical, categorical, and linguistic data (Regan, Colyvan and Burgman 2002; Mohamed and Tran, 2021)	High amount of data Partial ability to deal with missing values (Fan et al., 2019)
Probability and dependencies' role	Embrace probability in assessments Considering variables interdependencies with each other and final output (Omondi, Lukandu and Wanyembi, 2021; Wang et al., 2021)	Does not embrace probability in assessments Considering variables interdependencies on final output (Valpeters, Kireev and Ivanov, 2018; Anysz, Apollo and Grzyl, 2021)
Prediction precision	Mid-high (Tardioli et al., 2020)	Very high (Akinosho et al., 2020)
Application scope	Subjective and uncertain problems with limited data (Yang, Bonsall and Wang, 2008)	Objective and complex problems with abundant data (Gondia, Asce, et al., 2020)
Application in RM processes	Risk identification Qualitative analysis Risk control (Karakas, Dikmen and Birgonul, 2013; Islam et al., 2019; Yucelgazi and Yitmen 2020)	Risk identification Qualitative and quantitative analysis Mitigation planning Risk control (Fang, C. and Marle, 2013; Chattapadhyay, Putta and Rao, 2021)
Advantages	Flexibility to various problems Ability to integrate qualitative and quantitative data (subjective and objective) Risk path approach Ability to include dynamic data (Serpella et al., 2014; Zhang, Wu, et al., 2014)	Quick processing and learning Ability to consider linear and nonlinear relationships among data Ability to include dynamic data (Sherafat et al., 2020; Von Platten et al., 2020)
Disadvantages	Takes longer time to create the structure Not high precision if merely based on historical data High processing time in complex problems (Wisse et al., 2008; Qazi et al., 2016)	Individual risk analysis approach (isolated) Not flexible toward change Requirement of high data volume (Giannakos and Xenidis, 2018; Lamine et al., 2020)

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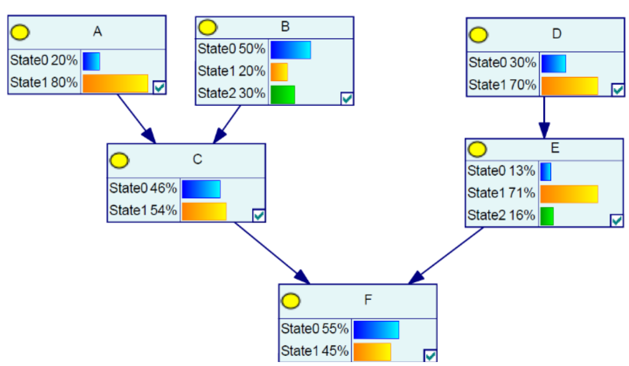
Chapter 5: Bayesian Networks and Elicitation

5.1. Bayesian Networks

Probabilistic models and Bayesian approaches enable the integration of subjective expert data as background knowledge on priors and posteriors for a more precise structure and parameter learning with objective project data. Probabilistic networks have become a widely accepted method for representing knowledge for reasoning under uncertainty (Yoon, Weidner and Hastak, 2021), and have been successfully applied in various domains such as medical diagnosis, prognosis, planning, information retrieval, and natural language processing. BNs, as the most applied probabilistic graphical models (Odimabo and Oduoza, 2017), have been widely used for accident root cause analysis, workers' safety risk assessment, and defect risk analysis in construction research (Nguyen, Tran and Chandrawinata, 2016; Gerassis et al., 2017). However, their application in practice, dynamic risk modeling, and proper network validation is still in infancy (Piao et al., 2021; Nguyen, Tran and Chandrawinata, 2016). BNs are comprised of two main components:

a) A Directed Acyclic Graph (DAG) is used to qualitatively present the interdependency among variables and encode conditional independence assumptions, which is also referred to as the structure of the BN. In DAG, nodes present the variables, and the arc oriented between variables presents the dependency between them, starting from the parent node toward the child node (Guinhouya, 2023).
b) Conditional Probability Tables (CPTs) or Conditional Probability Distribution (CPD) quantitatively represent the relationship between the child node and its parent nodes in discrete or continuous variables, respectively (Wang and Chen, 2017), which are also referred to as the parameters of the BN. Figure 5.1. presents a BN example, indicating both the DAG and the CPT.



C	State0			State1		
E	State0	State1	State2	State0	State1	State2
State0	0.7	0.2	0.6	0.4	0.9	0.3
State1	0.3	0.8	0.4	0.6	0.1	0.7

Figure 5.1. Bayesian Network and CPT example

The structure and causal relationships between variables or the parameters are determined by learning algorithms from objective project data, elicitation of subjective expert opinion, or both (Garvey, Carnovale and Yeniyurt, 2015). BNs have huge advantages compared to other ML algorithms for risk analysis, given their ability to combine different sources of information (e.g., expert knowledge, field data, simulation models, and databases) (Qazi et al., 2016), handling incomplete data, which is a common challenge in the industry (Zhang et al., 2016), and updating the interdependency among risks when new information is available, which contribute to their broad application in construction risk-related research (Liu et al., 2019).

Among the four types of BN reasoning, i.g. a) Predictive Reasoning, b) Diagnostic Reasoning, c) Predictive+ Diagnostic reasoning, and d) Predictive+ Intercausal reasoning, Predictive reasoning is the most popular type and is mainly used for predicting the probability of cost overrun, time performance, and workplace accidents. Moreover, diagnostic reasoning seeks to diagnose the risk or accident scenarios and causes of poor performance as the output (Hon et al. 2022).

BNs can aggregate various project objectives and model a holistic risk network in which the general impact of each risk is depicted and calculated across the network. This approach focuses on the "Risk Path" connecting the causal effect of various risks instead of isolated assessment of individual risk points, The risk path approach, despite delineating what happens in reality (Yildiz et al., 2014), has been limitedly studied (Eybpoosh, Dikmen and Talat Birgonul, 2011). To depict the risk path and increased learning by BNs, a thorough analysis of lessons learned, risk events, and previous projects' documents is required. However, the main challenge is that in most companies, there is no consistency or standard in the lessons learned in terms of style, language, metrics, and detail. Additionally, concerning general project risks, each project that lasts at least a couple of months is counted as one data entry in the database, leading to a data scarcity problem. Therefore, relying merely on the project data limits the choice of algorithms to implement. For instance, deterministic and black-box models like artificial neural networks, which perform significantly in huge databases, are inapplicable for small datasets. For this reason, this study relied on probabilistic models as the first step, which handles data scarcity problems through integrating various sources of information and uncertainty.

5.1.1. BN Literature

In order to identify the main application areas, applied techniques, and learning processes of the Bayesian approaches, another filter was added to the source technical papers, filtering merely papers that used the BNs or hybrid models containing Bayesian approaches in construction, resulting in 78 articles. These articles were thoroughly analyzed to identify BN application areas and were complied with similar review studies for a systematic classification (Hon et al., 2021), as mentioned below:

- Safety Management covers four main areas: a) Analyzing factors that affect the safety performance in projects (Chan et al. 2017), b) Selecting Safety Management Strategies and Interventions (Mofidi et al., 2020), c) Safety Supervision and workforce monitoring (Nath, Behzadan and Paal, 2020), d) Other Safety-Related Topics, including lifecycle safety control, safety design, and accident diagnosis (Abdat et al., 2014).

- Risk Management in building, infrastructure, excavation projects, and energy (e.g., buildings, bridges, tunnels, power plants) (Wang et al., 2014).
- Contract and Procurement Management is used to analyze construction contractual risks, handle disputes, and improve bidding (Abotaleb and El-adaway, 2017). Particularly, the Naïve Bayes method has been employed to extract the required contractual text for decision-making (Hassan and Le, 2020).
- Process Control for managing project schedules, predicting schedule performance, productivity management, and other areas like progress monitoring and performance measurement (Golparvar-Fard, Peña-Mora and Savarese, 2015; Sabillon et al., 2020)
- Project Cost Management, for cost prediction, forecasting errors in cost estimation, and dynamic monitoring of construction costs (Nasrazadani et al., 2017).
- Quality Management, including evaluating the impacts of stakeholders on quality defects, evaluating operator welding-quality performance, and examining building materials compliance for fire safety (Yu et al., 2019).
- Other CM Research and Practice, such as design management, project information management, environment management, materials management, and stakeholder management (Hu and Castro-Lacouture, 2019).

Figure 5.2. presents the co-occurrence diagram of the keywords in the source technical papers, indicating the Bayesian modelling techniques, application areas, and risk factors, which are developed in Bibliometrics. Moreover, BNs have been applied in one of the forms mentioned below (Guinhouya, 2023):

a) Basic BNs, which are the most prevalent type in literature.
b) Combined BNs, with methods like Fuzzy Set Theory, Fault Tree Analysis, and Project Evaluation and Review Technique, etc.
c) Extended BNs, including Hybrid BN (HBN), Dynamic BN (DBN), and Object-Oriented BN (OOBN).

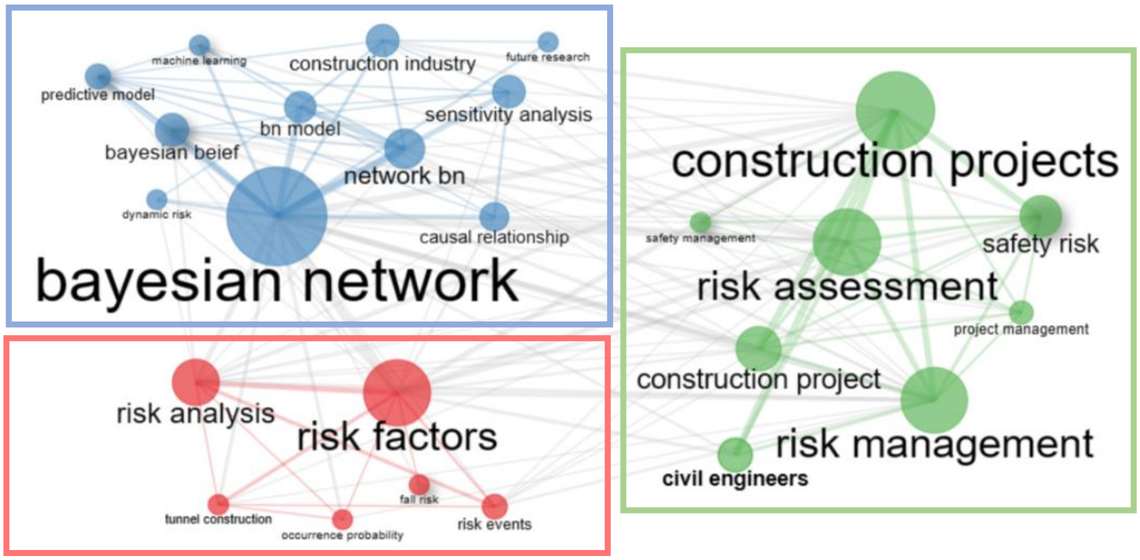


Figure 5.2. Co-occurrence diagram of keywords-main domains of literature review
Modeling technique
Application
Risk factors

There are remarkable studies on BN applications in construction RM. Liu et al. (2021) proposed a BN-based construction risk assessment method for PPP projects of urban rail transit, using offline interviews and surveys and online questionnaires and result correction by leaky noisy-OR gate model (Zhansheng Liu, Yueyue Jiao and Key, 2021). Mittnik and Starobinskaya (2010) presented a hybrid BN-based operational-risk taxonomy for modeling common shocks and mapping causal dependencies between frequencies and severity of risk events. Qazi and Dikmen (2019) developed a BNN-based methodology and an aggregative process of risks mapped on a risk matrix in order to assess the holistic impact of each risk across the risk network, using a new risk metric called Network Propagation Impact (NPI). Wang et al. (2014) proposed a hybrid model using BN and Relevance Vector Machine (RVM), which identifies risk scenarios and quantifies the probability and severity of possible risks. Asrar and Adi (2021) measured safety performance using a BN-based probabilistic model for a Dam construction project. Xia et al., 2017 proposed a modified BN to consider risk propagation in different stages of a construction project life cycle using ranked nodes/paths and Bayesian truth serum. Qazi et al., (2016) introduced a comprehensive risk management process, namely "Project Complexity and Risk Management (ProCRiM)," which is based on the theoretical framework of Expected Utility Theory and BNs. It establishes causal paths across project complexity attributes, risks, and their consequences affecting the project objectives.

Though all the previous studies added valuable insights to the field, the specific BN-based models for risk identification and assessment that rely on a limited number of input data are missing. Even the research works that benefitted from experts' opinions are more focused on the risk qualitative analysis, which is a more tangible objective for fuzzy set implementation. This research aims to fill this research gap by proposing practical solutions to overcome the data scarcity problem in the construction industry, i.e., elicitation-based structure and parameter learning in BN and synthetic data generation by Generative Adversarial Networks (GANs). The obtained results will be compared to merely data-based BN models, like Naïve Bayes model, and will be validated by experts and cross-validation. The Naïve Bayes classifier model was first proposed by Pearl (Pearl, 1988) and widely adopted in ecology, sociology, economics, and construction projects (Wang and Zhang, 2018). It takes a top-down approach to proceed from risk factors to risk events, where the joint probability distribution of a risk system can be decomposed into the product of specific conditional probabilities and marginal probabilities in the DAG, considering all the risk factors independent. Although it is easier to learn a Naïve Bayes model from data due to variables' interdependencies ignorance, it cannot represent a real-world situation where all project variables somehow affect each other.

5.2. Elicitation-based RM Models

There are many decisions to be made in each construction project, which intrinsically have a high level of risk and uncertainty. Risks are known events that might or might not happen in the future and can be integrated into the decision models in the form of probabilities or probability distributions. The probability of an uncertain event or condition can be assessed based on various sources, like historical records, model simulation, analogues, theories, physical principles, etc. (Druzdzel and van der Gaag, 2000). On the other hand, the uncertainties in the risk assessment process stem from a) information deficits and limited size of observations and data samples due to difficulty or costliness of the data acquisition, or the unstructured and infrequent data registration (Butler, Thomas and Pintar, 2015), known as informal uncertainty, or b) the use of linguistic variables by experts, when they are engaged in the probability assessment procedure due to lack of project data (Hora, 2018), known as Lexical uncertainty (Andrić et al., 2019). This process is called elicitation, which, although being a lucrative method in RM, can be full of uncertainties and fuzziness, as already mentioned.

Elicitation is the process of obtaining knowledge and subjective assessment about the underlying relationships and dependencies between variables and their probabilities from domain experts, based on which the priors and posteriors of a network are estimated (Laitila and Virtanen, 2016). This is the main advantage of the Bayesian approach over the Frequentist one, in which the priors and posteriors are merely based on historical data, and no other source of information can be included. Elicitation is the most common source for BN development, structure learning, and parameter learning in previous research, and case studies are the most common source for network validation (Hon et al., 2022). Bayesian methods necessitate a prior distribution to derive a posterior distribution for variables when evidence is observed. The prior distribution is intrinsically subjective and based on a judgment, which is in alignment with the subjectivity of probabilities derived from experts. It is noteworthy that the prior can have a uniform distribution in case of a lack of prior knowledge of the event. Therefore, the prior does not limit the application of the Bayesian theorem in case of lack of an informative prior.

Butler, Thomas and Pintar (2015) conducted a systematic literature review on expert elicitation studies on enteric illness and their key considerations and identified five main themes for designing an elicitation-based system: a) the expert panel, b) the background material supplied, c) the elicitation model, e) analysis methods, and f) research design. Careful consideration of these themes reduces bias, produces the best possible results, and synthesizes the available knowledge on the field from different experts. Monti and Carenini, (2000) discussed four methods in the knowledge acquisition task of probability elicitation from experts for BN construction for the clinical domain of chronic nonorganic headaches, three of which were extracted from literature, and the fourth one was developed by adapting the Analytic Hierarchy Process (AHP), which allowed the analyst to measure reliably the degree of inconsistency in the expert's assessments. Kuhnert, Martin and Griffiths (2010) provided a guideline for using expert knowledge in ecological models and natural resource and conservation decision-making, examining the impact of expert knowledge through priors in Bayesian modeling with the aim of minimizing potential bias. Although there is a rich literature of elicitation-based BN development in other realms, similar examples in construction research are missing.

In spite of the advantages of elicitation, the main challenge is the huge amount of probability assessments needed when the model is complex and contains many nodes with multiple states, as the CPT grows exponentially with the number of parent nodes (Laitila and Virtanen, 2016). The easiest type of elicitation is for binary problems, for instance, the possibility of a risk event happening or not. However, the elicitation can get more complicated when there are multiple possible states for each variable or the variables can take continuous values, for which the experts need to provide a probability density function or its integral, the distribution function. Therefore, elicitation in its conventional form can be time-consuming, costly, difficult to understand, and contain inconsistencies in the expert's assessments (Monti and Carenini, 2000). Furthermore, a number of errors might arise during the elicitation process, which will be discussed in the methodology section.

5.3. BN Advantages

Bayesian approaches seem to be the ideal methods for RM in construction projects for their ability of:

a) **Modeling complex problems and relationships between variables.** CM problems, like safety, business, and legal risks, have multiple inter-dependent factors and uncertainties that need to be tackled by complex modeling, which BN can facilitate due to its graph-based structure, DAGs and CPTs, and benefiting from graphical representation to show relationships among project variables (Baudrit et al., 2019) for easier understanding,
b) **Representing and dealing with high levels of uncertainty and complexity** (Phan et al., 2016).
c) **Combining different sources of information,** e.g., export knowledge, field data, synthetic data, and model simulations, which can be used for prior and posterior distributions. Most problems in construction projects, e.g., safety, tendering, and financial management, need implicit knowledge from field experts to serve as priors. Bayesian approaches can converge these complex models, which cannot be done in other ways (Van De Schoot et al., 2017),
d) **Incorporating subjective and objective data in quantitative form,** which are derived from experts and previous case studies. Bayesian approaches can turn qualitative assessments like linguistic terms into crisp values through elicitation and quantitatively represent the relationships among variables in the form of probabilities and beliefs, which can be updated when new information is available (Xia et al., 2017).

e) **Handling incomplete data, missing values, and data scarcity.** This is due to the Bayesian inference and the ability of combining different data sources and reasonings, which can update beliefs and compensate for the data scarcity (Leu and Chang, 2015; Zhang et al., 2016),
f) **Performing different tasks of quantitative relationship analysis, diagnosis, prediction, and monitoring** (Chua and Goh, 2005; Chan et al., 2017). As RM is consisted of various stages, i.e., Risk Identification, Qualitative Risk Analysis, Quantitative Risk Analysis, Mitigation Planning, Control Risk, and Monitor Risk, and can be applied on various levels, i.e., Operational, Project, Portfolio, and Enterprise, with different purposes and requirements for each, BNs are proper methods able to perform all the tasks in one single application.
g) **Flexibility to be integrated with other methods to improve the accuracy and reliability of risk assessments.** On the one hand, BNs are flexible to import mathematical methods like Markov chain Monte Carlo (MCMC) to improve the data organization and processability. For instance, MCMC is commonly used with Bayesian approaches to determine the posterior distribution and draw random samples, which strengthens the predictive ability and statistical quality of Bayesian approaches (Ji and Abourizk, 2017). On the other hand, BNs can be combined with other common applications in CM, such as BIM, the Geographic Information System (GIS), Multi-Agent Systems, ML algorithms, and Decision Support Systems (Qazi et al., 2016; Rongchen et al., 2020). As combined applications could benefit from the advancements of each method, it also improves the applicability of Bayesian approaches in CM, providing even more powerful tools to tackle complex CM issues.
h) **Ability to conduct both forward and backward inference.** BNs can model both potential hazards (forward inference) and most likely causes of an adverse outcome (backward inference) according to different roles/trades in the construction industry.

5.4. BN Limitations and Research Gaps

Despite all the advantages of BNs, there are several challenges and research gaps that need to be addressed in order to benefit from their full potential in construction research and practice, including:

a) Most of the issues studied in RM literature are not multifaceted, while the advantage of Bayesian approaches is fully realized in more complex multifaceted and multi-factorial problems.
b) Limited application of dynamic BNs in CM research, while construction projects are based on constant change and progress along their lifecycle.
c) Over-reliance on expert knowledge for structure and parameter learning due to lack of availability and accessibility of project data.
d) Most of the issues addressed in the literature are operational-level issues, such as safety management. However, BNs have the potential to address problems on project and strategic levels as well, which could be even more critical in construction projects.
e) Major focus on risk assessment rather than entire stages of risk management.
f) Lack of attention to the diagnostic reasoning of BN, such as construction fault diagnosis and energy/materials consumption diagnosis.

g) Difficulty and biases in the elicitation process and in turning experts' tacit knowledge into quantitative data, such as complexity, biases, unreliability and subjectiveness, inconsistency between two expert opinions, and overconfidence (Low-Choy et al., 2011).
h) Lack of established validation methods for BNs due to insufficient data applications (Mkrtchyan, Podofillini and Dang, 2015). Most previous studies used case studies in model validation, which, although performing acceptable when data is insufficient, cannot be generalizable to a larger set of projects. Sensitivity analysis or expert evaluation are better validation methods to improve this step's comprehensiveness and reliability (Liao Ma and Chong, 2018; Hon et al., 2022). Sensitivity analysis is used to determine the impact of changes in the state of a variable on the overall risk of a system. Decision analysis is used to determine the optimal decision in a risk management problem, considering the uncertainties associated with the variables in the system.

5.5. Future potential CM topics for BN applications

The application of BNs for RM can be improved and expanded in terms of:

a) Detailed analysis level by including more in-depth root causes of risks and accidents like workers' psychological factors, containing entire project phases,
b) Dynamic modelling of interactions between incidents and their causes using temporal nodes and time series, meaning performance at time T will affect those at time T+1 (Nwadigo et al., 2020),
c) More advanced Bayesian modeling techniques in combination with other statistical, mathematical, and simulation methods, like BIM, Digital twins, and multi-agent systems (Wu et al., 2014),
d) Integration with other project knowledge areas like stakeholder management and resource management for more optimized risk responses,
e) Real-time safety monitoring, benefiting from digital technologies such as IoT, sensors, and wearable devices,
f) More systematic validation methods, which mitigate the biases in the model, such as evaluating the reliability of data elicited from expert knowledge before modeling (Zhang et al., 2016),
g) Better documentation and reporting of best practices, research results, and methods for future reference (Van De Schoot et al., 2017).

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Chapter 6: Methodology

6.1. Research scheme and framework

This research follows a systematic methodology consisting of several phases developed for an industry partner. Therefore, the steps are slightly different from regular research projects and are revised through a back-and-forth feedback process from the industry partners, available data and case studies, and the results obtained. The main phases are:

a) Systematic literature review and analysis of state-of-the-art findings, best practices, and Professional standards to find interactions between AI and RM realms, as well as the research gaps to be addressed,
b) Meetings with industry partners to determine the main application area and scope, expectations and requirements, data and tools available, and status quo on RM practices,
c) Data collection from previous projects' documents, such as Monthly reports, Project charters, Risk registers, Cost reports, and Schedule baselines, Standards and best practices, and Literature,
d) Surveys and interviews with experts, project managers, and company representatives for data collection and inference, quantifying their subjective judgments and risk reasonings,
e) Data cleaning, preprocessing, and categorizing, and standardized data collection templates creation,
f) Integrating the risk data from various sources (objective project data and subjective experts' opinions) using probabilistic Bayesian Networks (BNs) to create the risk network for each risk,
g) Solving the data scarcity problem by synthetic data generation using Generative Adversarial Networks (GANs) and repopulating the BN model with the new synthetic data,
h) Implementation of advanced deterministic models like Artificial Neural Networks, XGBoost, and Decision Trees to compare the results obtained merely based on objective project data,
i) Developing a Fuzzy Logic-based risk assessment model based on the opinions of experts to compare the results obtained merely based on subjective elicitation,
j) Comparative analysis of results obtained from the three techniques mentioned above to validate the proposed BN-based model,
k) Implementing both probabilistic and deterministic ML models on another risk database with a significantly higher number of data to compare the performance of each algorithm with respect to the size of the database,
l) Final validation of the model using ongoing project data and experts' opinions,
m) Integrating the proposed model with the company's current project management processes,
n) Addressing the potential data privacy and ownership challenges, biases, and ethical and moral issues raised during the implementation phase to facilitate the wider application of the model in practice.

The overall research scheme and phases, data sources, and used tools and methods are presented in Figure 6.1.

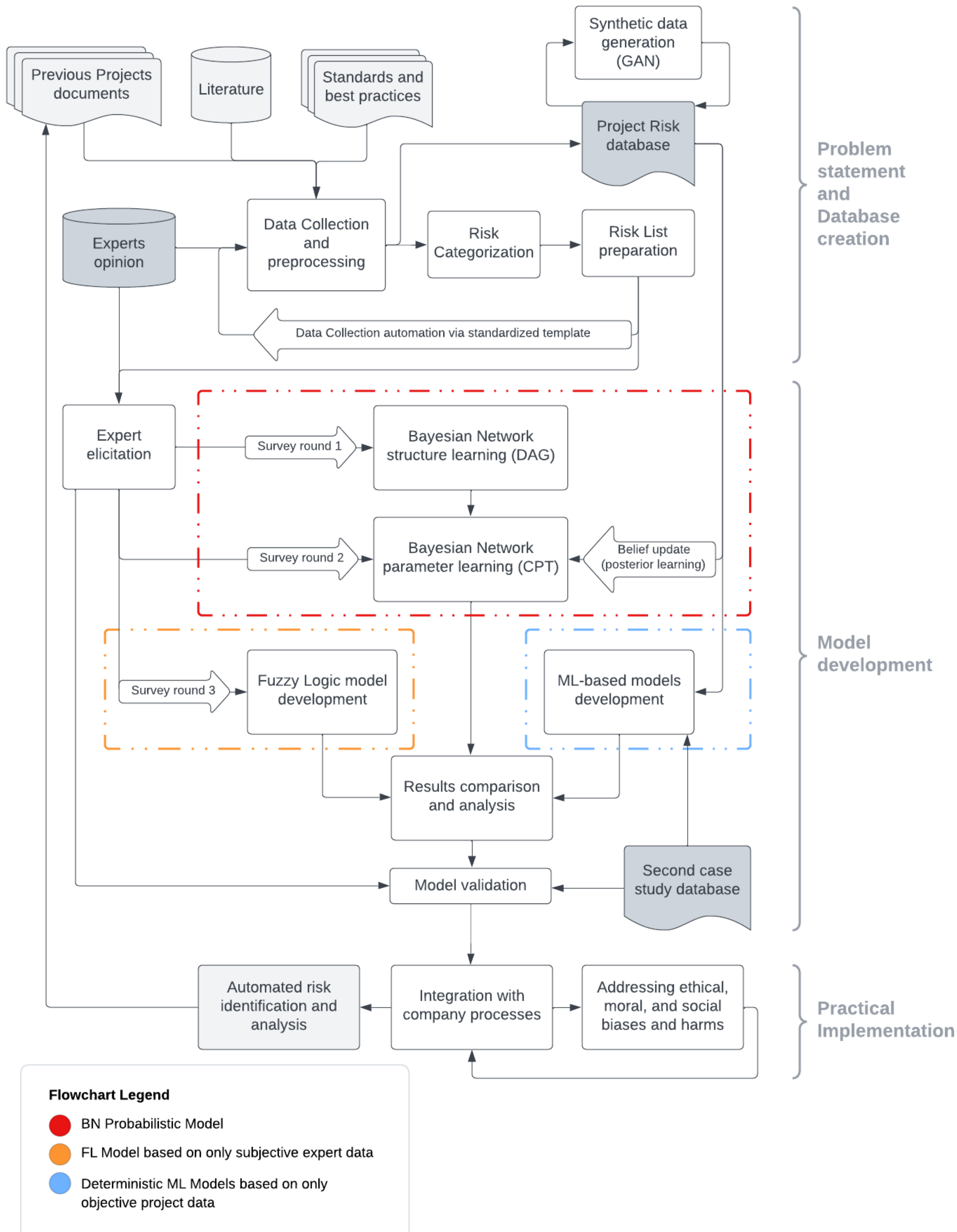

Figure 6.1 Research Scheme and phases

The proposed computational model and its components and processes are developed based on a Process Mining framework presented in Figure 6.2. Process Mining provides an ever-improving platform and workflow for the model in a standardized fashion. It is an optimal approach to tailor RM steps on the available data sources on various levels with the requirements of the case study regarding the maturity and performance of its RM processes. Initially, only 44 project data were available; therefore, only probabilistic models like BNs were applicable. Hence, the research started with BN development and integrated data and inferences from three different sources of previous project data, literature, and citations from experts to compensate for the data limitation issue. Experts' subjective data was gathered through a three-step elicitation process using surveys and interviews, a detailed overview of which is presented in the following subchapters. Later, synthetic data was generated using GANs based on the available database, doubling its size and enabling the application of other deterministic ML methods. Moreover, a Fuzzy Logic-based model was developed based on surveys from 11 experts to compare the differences in obtained results and predicted probabilities if the judgment is merely based on subjective data, objective project data, or a combination of both.

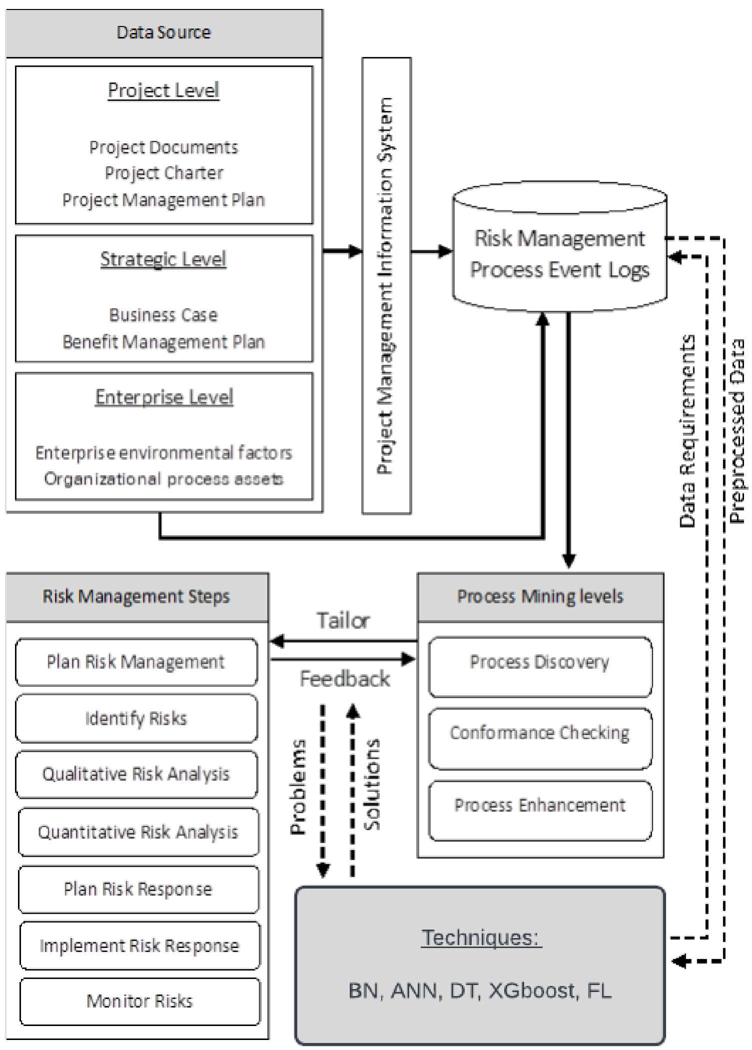

Figure 6.2 Process Mining Architecture for the proposed ANN-based risk management framework

This research aims to develop an automated and optimized RM framework using the three proposed solutions, namely a) BNs, b) Deterministic ML models, and c) Fuzzy Logic model. The project variables/features and risks serve as the input of these models, and the portfolio of Jacobs' projects serves as the training and testing datasets. Finally, the probability of each risk happening or the existence of each risk in the project risk list is the output of the model. Figure 6.3 presents the proposed framework, which will be implemented for each new project. Based on the project variables/features of the given project, the ML model will automatically predict the risks and their probabilities in that project.

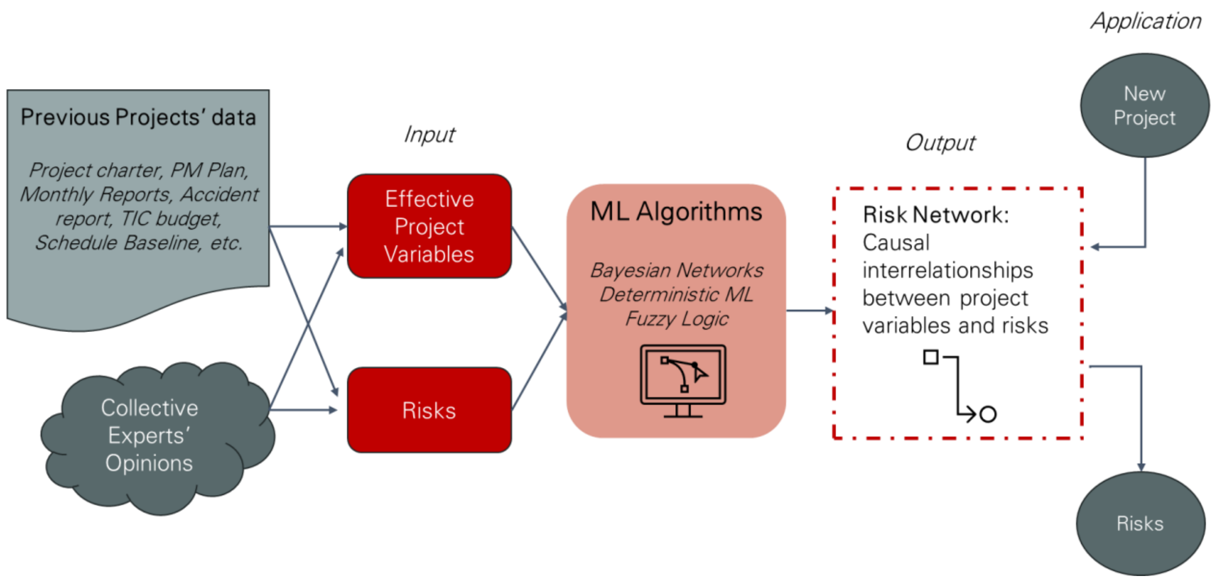

Figure 6.3 Proposed application framework of the ML-based models

6.2. Data Collection

Project Risk Data requires specific attributes attached when being registered to be usable in systematic analysis; for instance, the type of risk, area of influence, owner of the risk, probability of the risk, impact, and consequences of the risk, cost and time contingency assigned to the risk. However, in reality, risk data registration is conducted in an unstructured and infrequent manner in construction projects, including several missing values and inconsistent entries. Moreover, due to the context-specific nature of risks, it is highly probable that only specific types of risks are identified and registered in a company's documents. Therefore, with the purpose of creating a holistic database of risks in construction projects, three main sources were probed as data sources:

a) Previous projects' documents, including Project Charters, Monthly Reports, Accident Reports, Progress Reports, Risk Registers, Schedule Baseline, Budget Baseline, etc.;
b) Literature on research conducted by other scholars on construction-related risks;
c) Interviews with experts, including project managers, engineers, and program directors at the company.

Data gathering is followed by the risk categorization step, for which both project knowledge areas identified by PMBOK and the company's registration formats were considered, as a result of which the identified 65 risks were categorized into 11 categories 1) Technical, Scope, and Management risks, 2) Administrative risks, 3) Communication risks, 4) Environmental risks, 5) Procurement risks, 6) Resource risks, 7) Safety risks, 8) Schedule risks, 9) Stakeholders risks, 10) Quality and change risks, and 11) financial risks. As the documents' review is a time-consuming process, a standardized format for data collection was developed in Excel, including all the necessary information on the project like duration, contract type, number of contractors, etc., as well as all the risks identified in each risk category, which was sent to project managers of the studied projects to fill. This solution significantly expedited the data collection process. Ultimately, all this data was documented in tabular format in a unified Excel spreadsheet consisting of 44 rows of data as projects and 47 columns of data as project features.

6.3. Data Preprocessing and Synthetic Data Generation

Data preprocessing is a critical part of the ML pipeline that helps improve the quality, relevance, reliability, and compatibility of the input data with ML algorithms. It aims to make data cleaner, more manageable, and more suitable for ML application by transforming the initial raw data, usually in an unstructured format including errors, outliers, and missing values, into a suitable format for analysis in ML, and includes the following steps:

a) Data Cleaning for handling missing values, outliers, and noise in the dataset
b) Data Integration among multiple sources
c) Data Transformation into a suitable format, preferably numerical format proper for mathematical and statistical methods
d) Feature Selection to identify the most influential features and reduce dimensionality, noise, and redundancy
e) Feature Engineering for deriving new features from existing ones or binning, discretization, and aggregating data
f) Synthetic Data Generation to increase the database size
g) Data Splitting into train, validation, and test datasets

In this study, data preprocessing had a significant positive impact on the developed models. Given the small size of the database and the existence of missing values, projects with missing values were dropped off the table, and data-filling methods like average value replacement were used. Moreover, synthetic data generation was conducted in order to increase the size of the database with an initial 44 projects or rows of data. Synthetic data generation refers to the process of creating artificial data that mimics the characteristics, patterns, and statistical distribution of the initial data using different approaches such as Rule-based or parametric methods, Simulation-based methods, and Generative Adversarial Networks (GANs). This study used GANs, which is a deep learning technique.

GANs are a type of deep learning algorithm (Akinosho *et al.*, 2020) that can learn the probability distribution in a collection of training samples and generate more examples with the same probability distribution (Goodfellow *et al.*, 2020). Data Augmentation techniques like GANs are applied to improve data quantity, diversity, and distribution by producing synthetic data through learning from the training sample (Berthelot, Milanfar and Goodfellow, 2020). GANs are composed of two subnetworks: a) the Generative Network, which generates the synthetic data, and b) The discriminative network, which is a binary classifier aiming to find the differences between the original and generated data by the network (Akinosho *et al.*, 2020). Although GANs have broader applications in creating synthetic images and unlabeled dataset learning (Zhang *et al.*, 2017), which can be highly beneficial in analyzing safety risks and hazards in construction sites, they are recently being applied to tabular data as well, which is 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. The complete code using GANs for data augmentation on the case study database can be found here.

6.4. Probabilistic Risk Model Development

Once the data is collected, cleaned, and prepared for analysis, ML-based models must be developed to learn from the data, detect patterns, generalize the rules and relationships between data features, and predict outcomes for new data. Due to the limited size of the database and the uncertain nature of the risk domain, probabilistic models are initially developed. Benefitting from probability and graph theory, they enable modeling of stochastic systems and causal relationships between variables. Furthermore, they can benefit from Bayesian Inference to integrate various sources of information and judgments and make the input dataset stronger and more diverse. As the most applied Probabilistic Graphical Model (PGM), the Bayesian Network (BN) was chosen for modeling the risk network in the company, which can graphically represent the influential project attributes, potential risks in projects, the relationships between these variables, and the existing knowledge and uncertainty in the area (Lee, 2021).

Each BN consists of three parts: a) The nodes representing the variables; b) the DAG, representing the structure and the interrelationships between the nodes in the network, and c) the Conditional Probability Table (CPT) or the Conditional Probability Distribution (CPD), representing the strength of these interrelationships between variables (Nasir, Mccabe and Hartono, 2003). Hence, the development of BNs includes two parts: the development of the topology or the structure, which is the qualitative part, and the parameterization, which is the quantitative part. The next chapter presents a comprehensive overview of various structure and parameter learning approaches.

Furthermore, there are three types of probability data or parameters in a BN: prior probability, conditional probability, and posterior probability. Prior probabilities are the probability distribution before taking into consideration any evidence, and posterior probability is calculated after observing evidence (Mohamad and Tran, 2021). Conditional probabilities are the probabilities that reflect the degree of influence of the parent nodes on the child node. For BNs with discrete nodes, the probabilistic dependence is often represented via a table called a Conditional Probability Table (CPT). To obtain the CPT, first, the possible combination values of the parent nodes need to be found, which is called an instantiation. For each instantiation, the probability that the child node will take a possible value is the conditional probability. They could be calculated using statistical or computational methods or elicited from domain experts (Zhang *et al.*, 2020).

6.4.1. Structure and Parameter Learning in BN

The structure and parameters of a BN can be learned from different sources, e.g., Expert knowledge (the judgment of academics and industry professionals), Objective data (field or observational data derived from databases, records, and the scientific literature), Model simulation (outputs of other established models or frameworks, such as FTA, ETA, and Influence Diagrams), and the combination of two or three of them (Phan *et al.*, 2016).

There are three ways to build a BN: manually, automatically or a combination of both (Fenton, Neil and Caballero, 2006). One can elicit both the structure and parameters of the network, or elicit the structure only and learn the parameters from historical data, or learn both the structure and the parameters based on objective data (Low Choy, O'leary and Mengersen, 2009; Kjærulff and Madsen 2008). The probabilities elicited from domain experts are called subjective probabilities. When multiple experts are used, we can either elicit the experts' opinions individually and then combine them or achieve the group consensus. Elicitation-based BN models are thought to carry biases and uncertainty while learning BBN is considered evidence-based (Mazaheri, Kujala and Montewka, 2014), since the model is built on real data.

Structure-learning methods proposed in the literature are a) based on conditional independence test, or b) based on a scoring metric and a search algorithm. The first group (Campos, 1998) analyzes the dependent and independent relationships among variables via conditional independence tests such as X2 tests and constructs the networks that characterize these relationships. The second group (Lam, Bacchijs and Bayesian, 1994) consists of two components: 1) a scoring function that assesses how well a network fits the data and 2) a search method to find networks with high scores. Moreover, the structure learning research mainly focuses on two problems a) Evaluation, which involves developing scoring functions that can measure the fitness of a Bayesian network structure to the given data, using various principles, such as Bayesian Methods, Minimum Description Length, or Entropy Methods, and b) Identification, that involves finding the network structures that optimize the scoring functions, which typically involves searching through a large space of possible network structures and evaluating them using the scoring function. Various algorithms can be used for this task, such as the K2 algorithm, the PC algorithm, or Genetic Algorithms (Chen *et al.*, 2008).

When extensive objective data is available, structural learning can be performed merely based on the data and by algorithms like PC algorithm, K2 algorithm, Naïve Bayes algorithm, and Tree Augmented Naïve Bayes algorithm (Abdat, et al., 2014). Furthermore, parameter learning can be performed by Expectation-Maximization (EM) and Maximum Likelihood Estimation (MLE) algorithms (Fang et al., 2023). EM algorithm is suitable for incomplete data, while MLE is a common strategy for parameter learning of complete data (Ji, Xia and Meng, 2015). Moreover, Fault Tree Analysis, Event Tree Analysis, and Influence diagram can be used to build BN structure based on types of random variables and inferences.

Among the numerous algorithms proposed to learn the structure and parameters of BNs, the K2 algorithm for structure learning and the Expectation-Maximization (EM) algorithm for parameter learning are the most applied ones in CM research (Chen et al., 2008). K2 is a greedy search algorithm that learns the network structure from the data, aiming to maximize the posterior probability of the learned network structure (Chen *et al.*, 2008). K2 is a greedy search algorithm that learns the network structure from the data, aiming to maximize the posterior probability of the learned network structure (Cooper, Herskovits and Edu, 1992). The algorithm assumes that the variables in the network have been ordered beforehand so that all the parents of a variable occur prior to the variable itself. This ordering reduces the search space for the algorithm and makes it computationally efficient. However, the performance of the algorithm is highly dependent on the correctness of the ordering. If the order is incorrect, the algorithm may yield poor results (Chen *et al.*, 2008). Unfortunately, in many real-world applications, the correct ordering of variables may not be available. In such cases, other algorithms may be used, such as the PC algorithm or the Greedy Equivalence Search algorithm. These algorithms do not require an ordering of variables but may be more computationally expensive than the K2 algorithm.

The EM algorithm, however, is an iterative parameter learning algorithm that alternates between estimating the expected sufficient statistics of the data, given the current estimates of the parameters, and then updating the parameters based on these statistics. One advantage of the EM algorithm is its computational speed, which makes it well-suited for large and complex problems, such as those encountered in the construction industry (Ji and Xia, 2015). Another advantage is its ability to impute missing data, which is often a common problem in real-world applications. However, it is important to note that the EM algorithm assumes a fixed network structure, which may not always be known or correct. In such cases, other algorithms may be used to learn the network structure from data, such as the K2 algorithm or the PC algorithm.

If extensive previous data is not available, the elicitation method is used to extract insights from expert judgment for structure learning and prior and posterior assignment. Even though the involvement of experts' judgment brings uncertainty and biases, and empirical data-based BN is considered more objective, the fully objective BN application is not always viable due to data limitation and the rare occurrence of specific accidents or situations, which are not represented in the available databases. As a result, experts' knowledge continues to be an important source for risk modeling. Reducing the elicitation workload and facilitating the elicitation of individual conditional probabilities are the two most important tasks for BN modeling based on experts' knowledge (Zhang *et al.*, 2020)

The computational complexity of learning BN structures can be a major challenge, especially for networks with a large number of variables as the number of possible network structures and the number of CPT entries grow exponentially with respect to the number of variables and their states (Achumba et al., 2013), making the exhaustive search and CPT calculations impractical. The sheer number of probabilities would not only lead to heavy elicitation loads but will also cause inconsistency in the judgment. Therefore, as exact structure-learning methods fail to model risk networks efficiently, various inexact search-based methods have been developed using Machine Learning, which is computationally efficient and can handle moderately sized networks. Heuristic search techniques, such as the K2 algorithm, Genetic algorithms, Simulated Annealing, and Markov Chain Monte Carlo (MCMC)-based methods are some of these models (Castelo and Koˇcka, 2003). Moreover, when new evidence (observation) is obtained, inferences can be made, i.e., posterior probabilities could be calculated, which brings the model closer to reality. Making inferences is also called probability propagation, conditioning or belief updating (Fang *et al.*, 2023).

This study uses elicitation method for manual structure learning and EM for parameter learning based on previous projects' data. Equations 6.1. to 6.3. present the formulas used for Maximum Likelihood Estimate (MLE), Expectation, and Maximization steps, respectively, which are automatically run on the input data in GENIRE software. A comprehensive overview of various elicitation methods, potential issues and errors that need to be addressed, and eventually, the elicitation methods used in this research are presented in the next subsections.

$$L\ (\theta; X) = p\ (X|\theta) = \int p\ (X, Z|\theta) dZ = \int p(X|Z, \theta) p(Z|\theta) dZ \quad (6.1)$$

$$Q\big(\theta\big|\theta^{(t)}\big) = E_{Z\sim p(.|X,\ \theta^{(t)})}[\log p(X, Z|\theta)] \quad (6.2)$$

$$\theta^{(t+1)} = arg\ _{\theta}\max Q\big(\theta|\theta^{(t)}\big) \quad (6.3)$$

Where:

X is the set of observed data,
Z is the set of unobserved latent data,
θ is a vector of unknown parameters,
L (θ;X)=p (X|θ) is the likelihood function,
Q(θ ⎜θ^(t)) is the expected value of the log likelihood function of θ with respect to the current conditional distribution of Z given X and the current estimates of the parameters.

6.4.2. Elicitation Methods

There are several elements to consider when selecting an elicitation method. First, a proper issue needs to be selected, formed, and analyzed, which should be compatible with the elicitation process. That is, the posed issue should be resolvable within the assigned time and resources, be within the available knowledge area of the experts, and has to have a firm basis for judgment. The research question frames the problem, structures the model, and identifies the data (expert and ⁄or empirical) required for input into that model (Kuhnert, Martin and Griffith, 2010).

Second, the elicitation methods and means should be selected, which can be either a loose and informal method or a structured and rigorous one. Some of the common means are questionnaires, surveys, interviews, round tables, etc., which can be used in online or in-person formats regarding the physical accessibility of the experts. Another important element in elicitation is the type of variables (continuous or categorical) and scale used to obtain information, e.g., Likert scale and linguistic terms. Although crisp values (i.e., numbers) are more precise than linguistic terms, defining a crisp value for occurrence probability and severity is not easy. On the other hand, although linguistic terms are easier to comprehend and evaluate by experts, translating qualitative responses to a quantitative probability measure is challenging. In this case, Fuzzy Logic is used, by which the subjectivity of experts can be modeled. In FL, variables have degrees of truthfulness or falsehood, or degree of membership to a specific class, represented by a range of values between 1 (true) and 0 (false), which are calculated through four steps: fuzzification, inference, composition, and defuzzification (Pokorádi, 2015). Therefore, the probability of verbal expressions needs to be transformed into fuzzy numbers, denoted by P(Θ), using triangular, trapezoidal, or Gaussian fuzzy membership functions (Li *et al.*, 2012). Although fuzzy logic-based risk assessment (Bowles and Peláez, 1995) has been studied widely, its integration with Bayesian Networks is limitedly explored (Mohamed and Tran, 2021).

Generally, the elicitation methods and reasonings used are divided into direct methods, asking experts for quantitative numbers, and indirect methods, asking experts for qualitative statements. The common elicitation methods include but are not limited to Betting method, Equivalent lottery method, Analytical Hierarchy Process (AHP) method (Monti and Carenini, 2000; Bielza, Gómez and Shenoy, 2010), Probability Wheel, Probability Scale (Renooij, 2001), Fuzzy Logic (Ren et al., 2009). It is considered the most human-friendly and comprehendible method.

Third, the experts need to be selected based on their professional skills, current position or role, experience with the issue, preferability in terms of citations and published works, and recommendations from respected bodies. An expert is someone who has superior knowledge about the subject of interest and its rules (Bonano et al., 1990) gained through their life experience, education, or training. Another important factor to consider is the expert's willingness and motivation to take part in the experiment and their openness to share their names or affiliations. Furthermore, the number of experts involved in the process needs to be determined based on the problem type. If more than one expert is invited to the experiment, there is a chance of redundancy, assuming they are performing the same task. Selecting experts from different backgrounds and fields can both solve this issue and add a diversity of viewpoints to the table, which are important teamwork elements. One of the most common methods in group elicitation is the Delphi approach, which begins with eliciting information from each expert independently and sharing the collated results amongst the group as feedback for helping experts understand the elicitation task, ensuring their response addresses the question adequately (Macmillan and Marshall, 2006). The risk though, is that the answers might have massive inconsistencies, needing to be calibrated. The common way to aggregate the responses is to take a mean, where the variance of the mean is a measure of uncertainty among the expert responses (Kuhnert, Martin and Griffith, 2010). Methods like sensitivity analysis or selectivity curve are useful to present the impact of an expert's priors on the network.

The forth step is the training of experts about the whole elicitation process regarding forming the probability judgments and responses, the role of their subjective judgment on the analysis, background information about the elicitation questions, and judgment biases. The scales used to assess the probability, either in numeric or linguistic formats, should be clearly explained, and the confidentiality of their responses should be assured. It is also essential to ask for feedback from experts on the process and adjust it accordingly to be more comprehensible and accurate. If the elicitation is conducted in groups, then a coordinator should lead the sessions to use the time efficiently (Hora, 2018).

The eight most widely used elicitation focuses were summarized by Kuhnert et al. (2010), i.e., elicitation of (1) probability, (2) frequency, (3) quantity, (4) weighting, (5) quantitative interval, (6) probability distribution, (7) categorical measure, and (8) relative measure. The first six are to elicit quantitative values, while the last two deal with qualitative values (Kuhnert, Martin and Griffith, 2010). Low Choy, O'leary and Mengersen (2009) highlighted six key elements for conducting an elicitation: a) the purpose and motivation for the use of prior information, b) Specify available prior knowledge from experts or other sources, to define an appropriate and achievable goal of elicitation, c) Formulate a statistical model representing the conceptual model, d) Design numerical encoding (measurement technique) for effective elicitation of prior information and representation as a statistical distribution, e) Manage uncertainty, biases, and inconsistencies for accurate and robust elicitation, and f) Design an elicitation protocol to manage logistics of implementing elicitation. Moreover, based on a guide provided by Martin, Kuhnert and Mengersen (2005), there are eight key processes in an elicitation exercise: a) Clearly articulate the research question, b) Consider the resources available to help address the research question, c) Consider the modeling framework and data requirements carefully for the process under investigation, d) Identify what types of expert(s) are available to determine the form of elicitation required, e) Structure the elicitation such that the information supplied by experts can be translated into something (e.g., prior probabilities, prior distributions) that can be used for the model, f) Incorporate a feedback mechanism with some form of graphical aid, and g) Ensure a structured sensitivity analysis is conducted to investigate the impact of priors..

The review of previous research in the realm is useful in terms of providing a general framework and examples for the elicitation structure. However, the research gap remains for a holistic and detailed elicitation process for real-world problems in the construction industry.

6.4.3. Elicitation Challenges and Errors

Even though elicitation seems like a solution to many problems in BN application, the selection of the elicitation method, determination of experts, and the training process could be daunting (Kuhnert, Martin and Griffith, 2010). Furthermore, when the BN gets bigger and contains more nodes, the number of conditional probabilities grows exponentially, which require great workload from the experts to provide data, as well as from the research to assure the quality or consistency of the elicited result. There are two solutions to overcome this challenge:

Reducing the number of conditional probabilities to elicit by simplifying the model structure, i.e., reducing the number of nodes, reducing the number of node states, restricting the model by node divorcing, or exploiting the causal independence between the parent nodes, e.g., the Noisy-OR rule (for binary variables) and its extension Noisy-Max rule (for nominal variables). There are also methods to generate a full CPT from a few probability items and functions, e.g., the ranked node method (Fenton, Neil and Caballero, 2006), the likelihood method, the EBBN method (Wisse *et al.*, 2008), and the weighted sum algorithm, all of which could be applied to nominal variables and reduce experts' elicitation workload.

Facilitating the elicitation of individual probability entry using direct methods, asking experts to give quantitative numbers or indirect methods, asking experts to give qualitative statements (Knochenhauer, Swaling and Dedda, 2013). Methods such as the probability wheel, probability scale, gambling analogy, and Fuzzy BN are used for direct quantitative probability elicitation, and AHP is used for indirect elicitation.

Another issue is the uncertainties derived from experts' elicitation, which are a) the aleatory uncertainty, the uncertainty associated with the randomness of systems, and b) the epistemic uncertainty, the uncertainty caused by lack of knowledge of systems (Merrick, van Dorp and Dinesh, 2005). In BNs, the aleatory uncertainty is represented by the probability concept itself; however, the epistemic uncertainty, which is caused by experts' lack of knowledge about the parameters of the model, is neither asked nor addressed, assuming the experts have full knowledge about the issue (Brooker, 2011).

Expert judgment can turn into probabilities using different methods and scales. One of the most comprehendible approaches is using the verbal descriptors of likelihoods such as probable, rare, and virtually certain. However, there is the risk of different interpretation by various individuals, which can lead to inconsistency between the results. Common types of errors when expressing one's knowledge in terms of probabilities, which are detected and classified using cognitive psychologists, are Extension Error, Conjunction Error, Disjunction Error (Bar-hillel and Neter, 1993), Judgmental Errors (Representativeness and Availabilities heuristics), Overconfidence/conservatism (Hora, 2018), Support theory error (Tversky and Koehler, 1994), Epistemic uncertainty (due to lack of knowledge) (Kuhnert, Martin and Griffith, 2010), Misunderstanding of conditional probabilities, Translation of scales, Affect error, Hindsight bias, Law of small numbers, and Linguistic uncertainties such as ambiguity, context dependence, under specificity, and vagueness (Regan, Colyvan and Burgman 2002).

6.4.4. Elicitation Process of the Study

This research follows a case study method and is developed based on a database of projects conducted by an Italian construction company; hence, the experts interviewed for elicitation are the representatives of the company. Structure learning of BN is done through elicitation, and Parameter learning is done based on elicitation and previous projects' data using the EM method. Experts identified the effective project variables on common risks as the network parent nodes, the risks as the child nodes, and their connection as the DAG, forming the BN structure. Afterward, they quantified the causal inferences, nodes' interconnections, and probabilities as the parameter learning and finally validated the network. Previous projects' objective data was later inserted into the BNs to update the beliefs and posteriors. The second round of validation was conducted using cross-validation based on the database. The success of the methodology depends on the quality of the data, the expertise of the experts, the compatibility of the elicitation method, and the rigor of the modeling process.

Figure 6.4 presents the elicitation process used by this study. It starts with analyzing the issue, determining the scope of elicitation, and consequently, selecting experts and the proper elicitation method. The elicitation was conducted in 3 phases presented in Figure 6.5 Before starting the elicitation process, previous project documents were thoroughly analyzed, key project variables were determined, and common risks were extracted and grouped into 11 categories. This classification significantly simplified and structuralized the elicitation process.

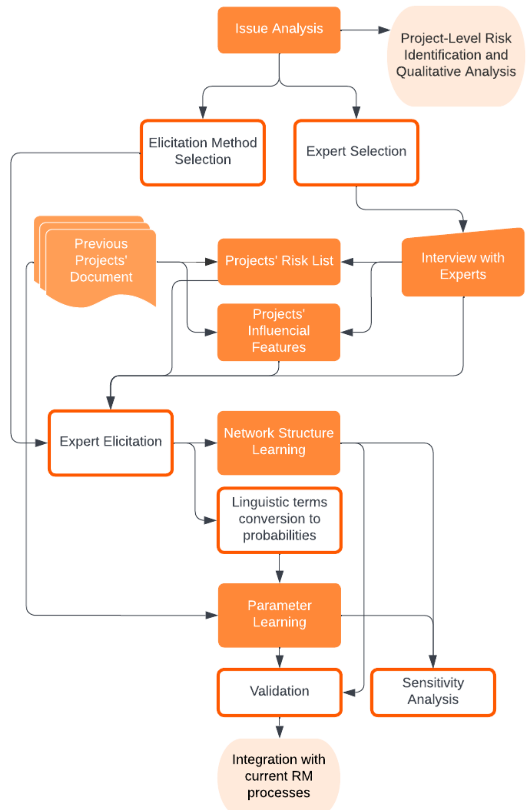

Figure 6.4 Elicitation and Structure Learning Process of the study

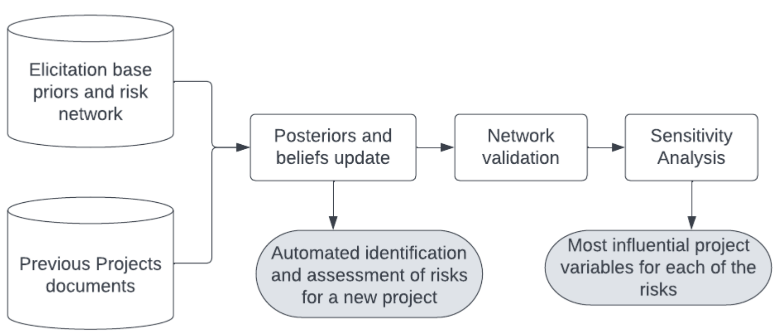

Figure 6.5 Integration of Elicitation and Project data for risk network parameter learning

The first round of elicitation was through a poll survey sent to all the Project Managers and directors of the company, which aggregated to 30 people. 16 of these experts responded to the survey, and alongside their evaluation of relationships between project variables and consequent risk categories, they provided their educational level, position in the company, and years of experience. This questionnaire had risk categories as columns and different project variables as rows. Experts were asked to select if any of these project variables, like budget, delivery method, etc., had an effect on that specific risk category or not, providing a yes or no answer. If more than 60% of the answers were yes, that variable would be added to the structure of that risk category network. Based on the findings, the overall structure of the risk networks was created in GENIE software, a specific tool for BNs development and validation, with parent nodes as project variables, child nodes as risks, and arcs as their relationship with each other. This process is presented in Figure 6.6.

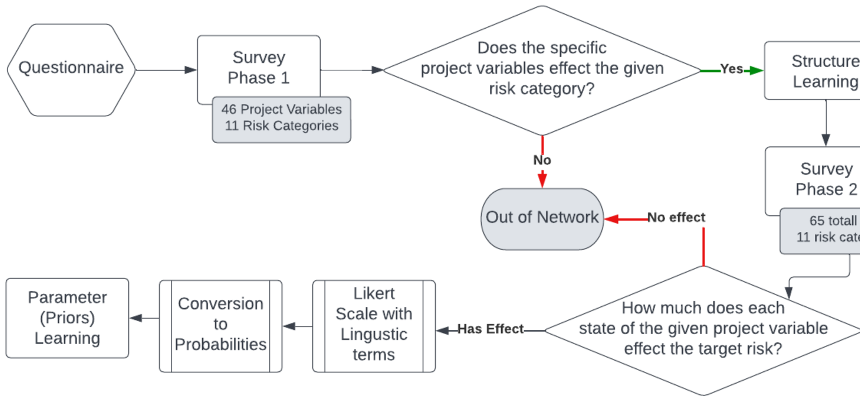

Figure 6.6. Elicitation-based learning process

In the second phase, the experts were interviewed individually on one or two specific risk categories. They were asked to select the likelihood of each risk in the risk category happening given a specific state of the affective variables on a scale of 1-5. For instance, given the evidence that the project type is residential, how likely it is that it faces a delay risk due to authorization and permit issues, and so on for all other types of projects. Then, these numbers were turned into numbers between 0 and 1, presenting the posterior probability of the risks given the realization of any of the conditions questioned, using the equation 6.4. Since most child nodes, in this case, the risks, have more than one parent, in this case, influential project variables, the joint distributions of collective posteriors are calculated by a geometric mean presented in Equation 6.5. These priors shape the background knowledge of the BNs derived from years of experience. Afterwards, the projects' data was inserted into the model and the beliefs or posteriors were updated based on these observations. Combining two sources of data and judgement, this research succeeded in compensating for the data scarcity problem, as depicted in Figure 6.7.

{IF Answer = "very low", x=0.1}
{IF Answer = "low", x=0.3}
{IF Answer = "medium", x=0.5}
{IF Answer = "high", x=0.7}
{IF Answer = "very high", x=0.9}
(6.4)

$$\left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}} = \sqrt[n]{x_1 x_2 \dots x_n} \quad (6.5)$$

Where:

Answer is the linguistic assessment of experts,

x_i is the posterior inserted from i[th] parent node to the child node.

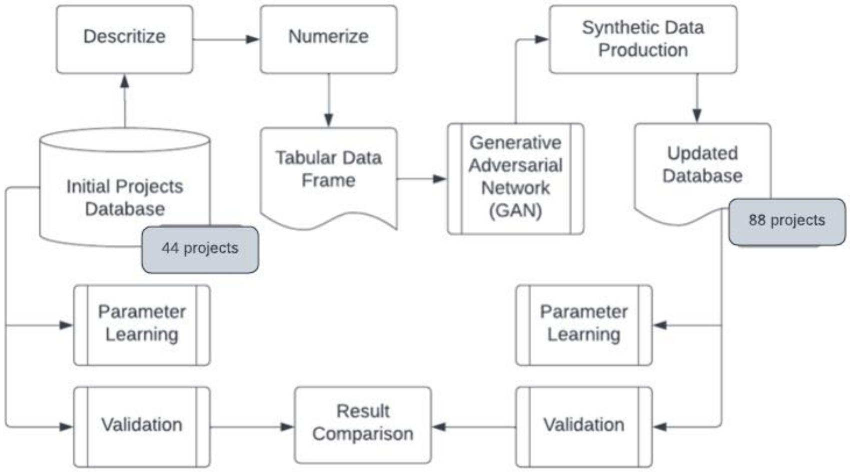

Fig. 6.7. Beliefs Update and Parameter Learning

The third phase of elicitation was conducted after the project data insertion into the model. Experts were asked to validate the networks based on one of their ongoing projects, the data of which was not inserted into the network. Their feedback was registered, and minor changes were made to the model to make it more accurate and user-friendly. Afterward, a cross-validation based on the projects' database was conducted, and the results were registered.

Finally, the proposed probabilistic RM model for this study was developed, as presented in Figure 6.8, consisting of a) input data, including the independent project variables, which are the ones not influenced by choice of any other variable, and the dependent project variables somewhat affected by the independent ones, b) process layer, including the interrelations and influences of the project variables on each other and on the project risks, categorized in 11 groups, each having a number of risks, and c) output layer, that is the identification and assessment of the likelihood of the risks. It is noteworthy that for the ease of elicitation, the structure learning was based on the 11 risk categories, but the parameter learning was conducted separately for each single risk.

It is noteworthy that, although this probabilistic BN-based model is the primary alternative proposed for the research problem, Other deterministic ML-based RM models and Fuzzy logic-based models are developed as well in order to conduct a comparative analysis and model validation, examining the variances in results if they are merely based on experts' opinions or on projects' data. Moreover, the same methods are applied to another database of construction projects with a higher number of values to assess the influence of database size on the obtained results from the ML models.

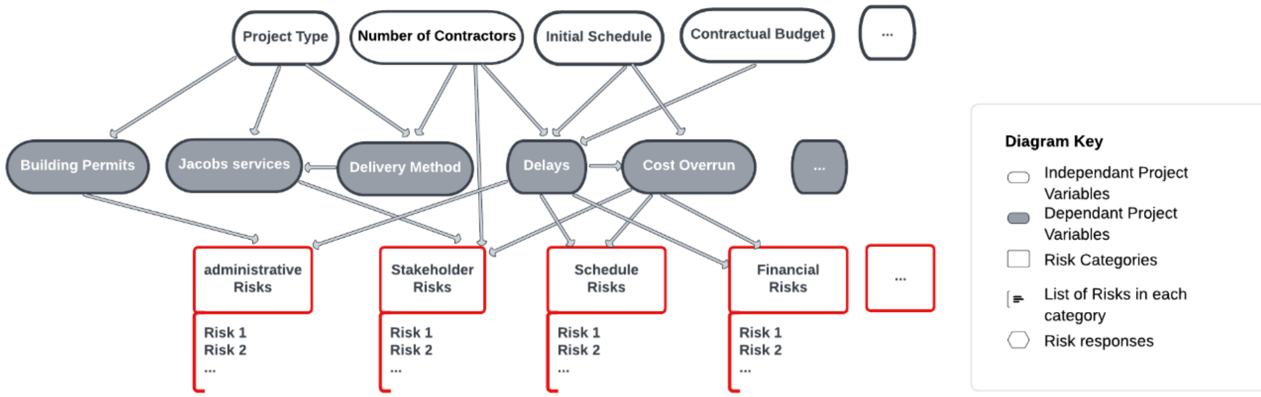

Fig. 6.8. General Risk Network of the study using BN

6.5. Fuzzy Logic Model Development

Fuzzy logic is a mathematical framework that deals with uncertainty and imprecision in using the fuzzy values and degree of membership between 0 and 1 instead of crisp and deterministic values, enabling a more flexible and nuanced representation of subjective and vague information like linguistic terms. In risk analysis for projects, fuzzy logic can be applied to handle the inherent uncertainties and imprecisions and representation and manipulation of linguistic variables and fuzzy sets, which are defined by membership functions. Fuzzy logic has a close relationship with the elicitation process of experts' subjective opinions. While asking experts about their assessment of the probability of some risks happening, it is much easier for them to express it using linguistic terms such as "low," "medium," or "high", which needs to be transformed into quantified and numeric values for analysis, pattern detection, and learning by the machine. Fuzzy sets, providing a distribution of membership values to each linguistic term, can capture the uncertainty associated with them and allow the incorporation of qualitative and expert knowledge in the risk assessment process.

Fuzzification and defuzzification are two fundamental steps in the fuzzy logic process. Fuzzification involves mapping crisp input values into fuzzy sets by assigning membership degrees to relevant linguistic terms. This step converts precise measurements or data into fuzzy representations using different memberships like Triangular, Trapezoidal, Gaussian, and Sigmoid. If more than one expert is involved in the process, their answers should be aggregated. Defuzzification, on the other hand, is the process of converting fuzzy output values into crisp values that can be easily understood and used for decision-making, using different methods like centroid maximum membership value methods. These methods determine how the fuzzy sets are transformed into crisp values or how the aggregated fuzzy outputs are converted into a single crisp output value.

The aim of this phase of the research is to assess the potential of Fuzzy logic in providing a formal framework to capture and represent these expert opinions in the form of linguistic variables and fuzzy sets in the RM context. By incorporating fuzzy logic, the process of eliciting experts' opinions can be more systematic and structured, allowing for a more effective integration of their knowledge and expertise into the decision-making process. Fuzzy logic facilitates the modeling of subjective assessments, uncertainties, and imprecisions, providing a powerful tool for incorporating expert opinions in a quantifiable and interpretable manner. Therefore, it provides insightful results if the risk assessment is merely based on experts' subjective opinions, which is later compared to results of ML methods merely based on project objective data and results of the BN model based on both experts' and projects' data.

In this study, the fuzzy logic model was developed for the Procurement Risks category. Therefore, the input variables were the ones identified by experts on the first round of the survey as following:

- "Project Type": states= {"Building: Residential", "Building: Commercial", "Industrial/Data Science/Logistic", "Pharma: vaccine and fill finish", "Pharma: other types"}
- "Delivery Methods": states= {"DB", "Design+GC", "EPCM"}
- "Number of Contractors": states= {"1", "more than 1"}
- "Initial TIC budget": states= {"more than 15M", "between 15 and 60M", "more than 60M"}
- "Cost Contingency": states= {"sufficient", "insufficient"}
- "Cost Overrun": states= {"low", "mid", "high"}
- "Project Duration": states= {"less than 2y", "between 2 and 3y", "more than 3y"}
- "Project Delay": states= {"low", "mid", "high"}
- "Covid Suspension": states= {"yes", "no"}
- "Jacobs Service Type": states= {"A_E", "EPCM", "PM_CM"}
- "Jacobs Collaboration With the Headquarters": states= {"yes", "no"}
- "Existence of Sustainability certificates": states= {"yes", "no"}

11 experts participated in the survey where they were asked to assess the probability of each of the four risks in the Procurement Risks category, given different states of the abovementioned project variables based on their experience, using the Linguistic Terms: {"very low", "low", "medium", "high", "very high"}. Then, the triangular membership function was used to fuzzify each answer using the following membership ranges:

Membership_ranges={
"very low": [0.0, 0.166, 0.332]
"low": [0.166, 0.332, 0.498]
"medium": [0.332, 0.498, 0.664]
"high": [0.498, 0.664, 0.83]
"very high": [0.664, 0.83, 1.0]
}

Figure 6.9. presents the fuzzy membership function of each range using triangular distribution.

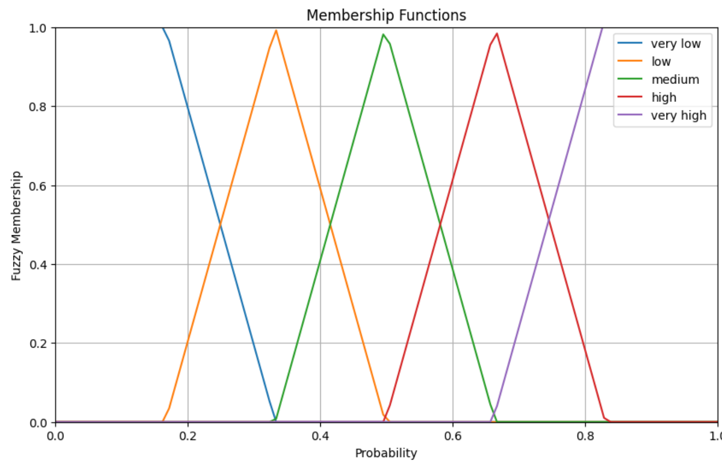

Figure 6.9. triangular fuzzy membership function used by the study

Then the aggregation of the 11 answers for each probability was assessed using weighted average method and the value was defuzzified into a crips value between 0 and 1, showing the probability of that risk happening given specific states of each project variable. These values are comparable to the posteriors learned from 1 expert opinion and updated by project data in the BN model.

There are two possibilities for completing the model. The first one is conducting risk assessment using Fuzzy Rules, which relate the input variables to the output risk probability. However, given that 12 input variables affect the risks and each of them has 2 or more states, the total number of rules required will be 116640 (5*3*2*3*2*3*3*3*2*3*2*2), which is almost impossible to model. Therefore, the integration of FL with the structure already learned in the BN model is suggested, where the CPT connecting child and parent nodes is filled with the probabilities learned through the Fuzzy Logic process. The structure consists of parent nodes (the project variables), intermediate nodes, and child nodes (the risks), as depicted in Figure 6.10., which greatly simplifies the rule-based analysis.

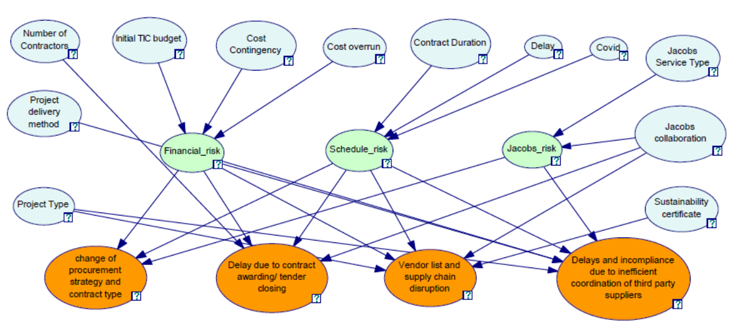

Figure 6.10. BN graph structure for the procurement risks

First, the membership functions for each part of the graph are simulated in Mathlab using the Fuzzy library. Then, all the rules for the rule-based analysis are inserted into the model. Each rule consists of if statements, in which different combinations of input variables' states are noted, and the aggregated defuzzified values calculated from experts' opinions are assigned to them as the probability of different outcomes based on the noted rules. The overall number of rules for each part of the model equals the multiplication of the number of input variables' states. Based on these rules and their output probabilities, the model can predict the probability of each of the intermediate nodes happening once the input values are inserted.

However, Mathlab does not provide the probability distribution among all scenarios, which indicates the final value for each of the states ("yes"/"no") of the nodes. Therefore, the probability distribution of the overall model, considering all the possible rules and scenarios, is calculated using the SciKit Fuzzy library in Python. The algorithm calculated the probability distribution of each rule and calculated the integral of its figure. Afterward, it sums up all the values and provides their average as the final probability of each of the states ("yes"/"no") of the studied node, the code of which can be found here. Following this graph structure, it is possible to divide the overall risk network into smaller pieces and apply the FL model. In the end, and with the same process, the probability of each of the risks having a "yes" state is calculated. It is noteworthy that the prior distributions of different states of the child nodes are assumed equal since this model does not use any previous project data. Moreover, the aggregated values from experts serve as the posteriors of the network.

6.6. Deterministic Machine Learning-based Models Development

After developing the BN model based on both experts' opinions and project data, and FL merely based on experts' opinions, several other ML algorithms and methods were used to learn from only the project data and identify the Procurement risks. Since the inference is based on one source of judgment, frequent statistics is used instead of Bayesian statistics, and the probability of events is directly associated with the repetition in the database. Hence, instead of probabilistic models, deterministic ML models are developed to predict one certain output without assigning a probability distribution to it. In other words, these algorithms follow a fixed set of rules and computations to make predictions or classify data, and their outcomes are entirely determined by the input data and the algorithm itself. Deterministic algorithms do not incorporate randomness or probability in their decision-making process.

For this purpose, 8 different ML algorithms, mostly deterministic ones, including Decision Tree, XGBoost, Logistic Regression, Support Vector Machine, Random Forest, K-Nearest Neighbor, Naïve Bayes Classifier, and ANN are applied to the already augmented database of projects, consisting of 88 rows. Although this is a very limited number of data, which negatively affects the performance of the ML algorithm, the obtained results provide lucrative insights into the influence of inference sources and the role of uncertainty in the risk identification assessment process, which are compared to results obtained from BN and FL models. While deterministic models are of higher reproducibility and stability, they may struggle to handle complex and uncertain data patterns or capture inherently probabilistic phenomena. In such cases, stochastic or probabilistic algorithms, which incorporate randomness or uncertainty, may be more appropriate. This is a good exercise to realize what type of inference and statistics fits the RM domain best and for limited databases like the research case study. As all the used algorithms have been thoroughly introduced in Chapter 4, no additional information on their structure is provided here. The Python code used for the abovementioned algorithms in the first case study can be found here.

The results obtained from each algorithm are registered for comparative analysis based on the data requirements, structure, the role of uncertainty and non-linearity, and inference of each of them in the results section. It is noteworthy that the performance and accuracy of the algorithms highly depend on the input data quality and quantity. Even if GANs have augmented the first case study database, it is still very small and limited, which can challenge the successful application of the deterministic ML algorithms and may result in overfitting.

6.7 Implementation of the Probabilistic and Deterministic ML Models on another Database with a Higher Volume of Data

In order to assess the effect of database size on the performance and accuracy of ML algorithms and to evaluate the effectiveness of each algorithm with respect to its unique structure, a second case study with a considerably larger database was examined, which aimed to predict the delay and cost overrun risks in construction projects using 6 ML algorithms a) Artificial Neural Network, b) Decision Tree, c) XG Boost, d) Linear Regression, e) Ridge Regression, and f) Bayesian Network. It is an open-access real-world database of 13570 New York City school building construction projects, which is retrieved from "the Capital Project Schedules and Budgets" database available on the City of New York's Open Data Portal (https://data.cityofnewyork.us/Housing-Development/Capital-Project-Schedules-andBudgets/2xh6-psuq), maintained by the New York City government.

Linear regression is applicable to this case study since, in contrast to the previous one, the type of the problem is regression. It is a widely employed ML algorithm that predicts a continuous output variable based on input variables. Often used as a benchmark, it fits a straight line or plane through the data to capture the underlying relationship between inputs and output. The objective is to estimate coefficients that effectively predict the output variable from input variables. These coefficients can then be used to make predictions for new input values. The method of Least Squares is commonly used to estimate the coefficients by minimizing the sum of squared errors between predicted and actual values (Sanni-Anibire, Zin and Olatunji, 2021). Ridge Regression, a variation of linear regression, addresses multicollinearity issues caused by highly correlated input variables. It achieves this goal by incorporating a penalty term in the least squares method (Khodabakhshian et al., 2023).

Before data cleaning the database had 13570 rows or projects and 14 columns or project attributes, including: Project Geographic District, Project Building Identifier, School Name, Project Type based on funding, Project Description (Description of construction/ retrofit services and work packages), Project Phase Name, Project Status (completed, ongoing), Project Phase Actual Start Date, Project Phase Planned End Date, Project Phase Actual End Date, Project Budget Amount ($), Final Estimate of Actual Costs Through End of Phase Amount ($), Total Phase Actual Spending Amount ($), DSF reference Number(s). The substantial number of rows and influencing attributes enables ML algorithms to capture patterns in data more effectively, leading to more accurate predictions. Specific attributes, such as the type of construction work, planned and actual project end dates, and total costs, were considered particularly important for differentiating construction projects and allowing the algorithms to generate meaningful predictions. However, only 1489 records with 17 data columns remained in the database after the data cleaning and filtering phase, during which irrelevant columns such as “Project School Name,” “DSF Number(s),” “Project Building Identifier,” and “Project Type”, incomplete projects with missing values specially in actual end date and total spending costs columns, errors and outliers like negative value for time and cost-related attributes, and duplicates were dropped from the database. Furthermore, date attributes were converted into Python’s datetime objects with the "%m/%d/%Y" format, and “Week Delay” and “Week Duration” values were calculated based on the difference between "Project Phase Actual End Date" and "Project Phase Planned End Date”, and the difference between "Project Phase Actual End Date" and "Project Phase Actual Start Date" respectively. The categorical variables were transformed into numerical values using Label Encoding, which is super useful when the order of the categories is not essential. A similar procedure was conducted for the "Project Description" column, which usually contains different types of work separated by a delimiter and is not interpretable for ML algorithms. For this purpose, a one-hot encoding approach was applied, creating ten new columns, each for a specific work package; the value of the value of each could be 0 or 1. Finally, projects with no work package identified, with delays exceeding 80% of the duration, and with cost overruns of more than 75% of the total budget were dropped from the database as outliers, deteriorating the accuracy and generalizability of the ML model. Following the data preprocessing steps, redundant columns such as 'Project Status Name' and 'Project Description' were removed, as their information had been effectively captured in new binary variables.

Figure 6.11. presents the research scheme and steps of this case study, with the ultimate goal of conducting a comparative analysis between the performances and prediction precision of different ML algorithms for delays and cost overruns, two of the most significant construction risks concerning each algorithm's structure and learning process.

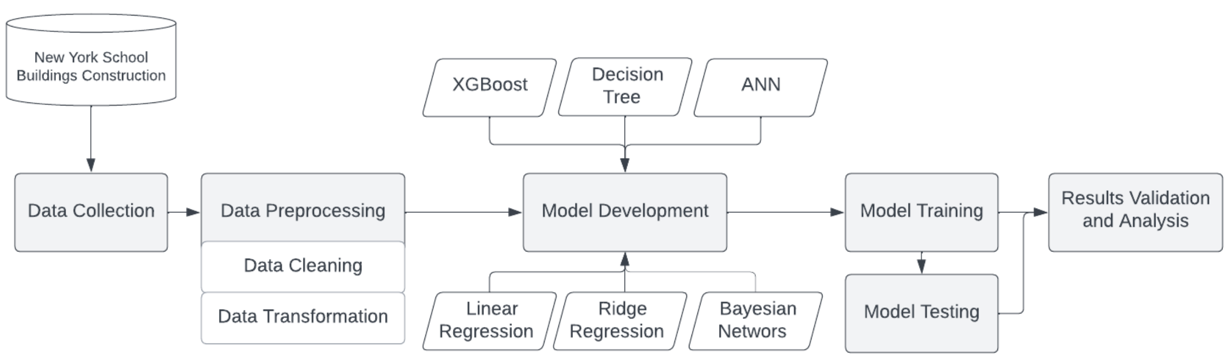

Figure 6.11. Second Case study research scheme and flowchart

Five models based on the five abovementioned algorithms are developed. The target variables are the "Week Delays" and "Total Phase Actual Spending Amount," the precision to predict which indicates the performance of the ML algorithms. The dataset is divided into train and test datasets with an 80%-20% proportion, so that the model can be trained on one subset and evaluated on another, providing an unbiased assessment of its performance. The primary goal of model training is to learn underlying patterns and relationships between the predictor and target variables through an iterative process wherein the algorithm minimizes prediction errors by adjusting its internal parameters, while testing enables the evaluation of the model's generalizability to unseen data. The input data is scaled and normalized before the training process for the ANN model to ensure that it has a similar range and variance to prevent specific features from dominating the learning process.

Several metrics, such as R squared, Mean Absolute Error (MAE), Mean Squared Error (MSE), and cross-validation (CV) scores, are employed to evaluate the performance of the models in the testing process. R-squared, also known as the coefficient of determination, is a statistical measure ranging from 0 to 1, representing the proportion of the variance in the dependent variable that can be explained by the model's independent variables. Mean Absolute Error (MAE) measures the average magnitude of the errors in the predicted values, irrespective of their direction, while Mean Squared Error (MSE) calculates the average squared differences between actual and predicted values. Cross-validation (CV) is a technique used to evaluate a model's performance by partitioning the dataset into k subsets or folds. The model is trained on k-1 folds and tested on the remaining folds. This process is repeated k times, with each fold used as the test set once. Analyzing these metrics makes it possible to identify each model's strengths and weaknesses and select the most suitable model. Moreover, using multiple evaluation techniques helps to mitigate the risk of overfitting and ensures that the chosen model can generalize well to new, unseen data. Ultimately, a thorough model testing process guarantees the reliability and validity of the findings of the study.

As the last step, the results obtained from each algorithm are compared to identify the most accurate and well-performing one. The structure and data requirements of each algorithm are briefly stated and analyzed to identify the reason behind their performances. This step is super important to facilitate the ML algorithm selection based on available risk data, database size, application scope and target, and computational complexity of each model.

6.8. Models Validation and Results Comparison

The learning process of each algorithm is followed by the validation and testing phases, where the results obtained from the algorithm are compared to the actual data in the test dataset to assess its precision and performance. Moreover, a comparative analysis was conducted between all the algorithms based on the precision and accuracy of results and the variances between the predicted probability of each of the risks.

6.8.1. Model Validation Methods

In machine learning model development, validation refers to the process of evaluating the performance and generalization ability of a trained model beyond the training data using unseen data and identifying potential issues such as overfitting or underfitting. The purpose of validation is to estimate how well the model is likely to perform on new, unseen examples. Validation can be conducted using various methods, such as:

a) Holdout validation is done by splitting the dataset into two parts: training and validation sets. The model is trained on the training set and evaluated on the validation set. The performance metrics obtained on the validation set provide an estimate of how the model will perform on unseen data.

b) K-fold cross-validation, where the dataset is divided into K subsets or folds. The model is trained and evaluated K times, with each fold used as the validation set once while the remaining folds are used for training. The performance results from each fold are then averaged to provide an overall estimate of the model's performance.
c) Stratified cross-validation, when dealing with imbalanced datasets where the distribution of classes is uneven. It ensures that each fold has a representative proportion of examples from each class, helping to obtain more reliable performance estimates.
d) Leave-One-Out Cross-Validation (LOOCV), using all but one sample for training and using the single left-out sample for validation. This process is repeated for each sample in the dataset.
e) Time Series cross-validation, used for time series data, where the temporal order of the data points is important. It involves creating training and validation sets by using data from earlier time periods for training and data from later time periods for validation.
f) Experts' validation, where experts implement the model on their ongoing projects or unseen data and evaluate its performance.

These validation methods help assess the model's performance and make informed decisions regarding hyperparameter tuning, model selection, and potential improvements in the training process. This research initially used experts' validation to validate the structure of the BN and the FL model, then used K-fold cross-validation for the BN model and Holdout and K-fold cross-validation for other ML algorithms.

6.8.2. Model Scalability and Adaptability

The risk realm is highly context-driven and subjective, as the types and probabilities of risk can greatly differ from one location to another and from one type of project to another. Furthermore, as the three solutions are originally designed for the project portfolio of a specific client, they are not automatically scalable to other types of portfolios. However, it possesses a high degree of adaptability and can be customized for other companies with distinct project portfolios by making minor adjustments in the models. The overall framework and application steps remain consistent, while the variables in the developed BN or deterministic ML models can be easily modified and updated when new data is introduced. This flexibility allows the models to be applied to various databases. However, the scalability of the FL model is comparatively limited. Its effectiveness heavily relies on the implicit knowledge and expertise of specific professionals, which can significantly vary between companies or even across different countries. Therefore, data-driven models like ML have a higher scalability in comparison to expert systems like FL. On the other hand, integrating subjective experts' opinions helps tailor the developed model better to the requirements of the company. Therefore, the BN model benefits from both scalability and the ability to be tailored to the specific context of the projects.

6.9. Integration of the Proposed Model with the Company's Project Management Processes

There are many drivers and benefits in using digital technologies on a broad scale that interests construction companies including a) lower business costs of manpower with reduced need for human intervention, b) real-time collection, processing, and monitoring of data compared to human agents, c) faster prediction of risks, delays, and clashes, due to simulating the digital version of the project in advance, d) enhancing workers' safety by using robots in dangerous activities, and e) allocating machinery and resources to the activities Optimizely (Yaseen et al., 2020). AI specifically aims to boost labor efficiency by 40% and double annual economic growth rates by 2035 (Purdy and Daugherty, 2016). Nevertheless, to obtain these benefits, companies have to bear high implementation costs, immensely change their established process and organizational structures, secure data privacy and cyber security, and educate their personnel (Oesterreich and Teuteberg, 2016). Moreover, AI applications can lead to numerous challenges, harm and biases, and ethical and social issues, which need to be studied and addressed for a successful and harmless application in the industry, which are thoroughly analyzed in the next subchapter. In general, AI's application in construction companies has its advantages and disadvantages, or the opportunities and challenges, which are briefly listed in Table 6.1.

The main aim of this industrial research is to integrate the proposed AI-based method with the current company's project management processes, such as RM tools for risk identification and assessment automation, quality control tools for project success and KPIs prediction, and procurement and sales unit processes for bid/no bid decision making. The integration is based on produced outputs by the model that can serve as input for other departments' information systems. Through an integrated and synced platform, information on new projects is automatically inserted into the developed ML-based RM model from project database, and the output of the model, the predicted risks, and their probability are inserted into cost management, time management, quality management, resource planning, and HSE services software to be considered for decision making and resource allocation. Moreover, the frequent updates and surveillance of risks will make constant progress reporting possible in monthly reports to keep all the stakeholders informed and engaged in the risk mitigation process.

An important issue to take into account is that even though this model is developed through a Ph.D. research framework, it will be implemented and used in the company for long after the project is finished and the model is finalized. Therefore, strategic decisions need to be made on model ownership, confidentiality, and copyright. Moreover, training sessions will be held to educate the users with basic ML knowledge and guidelines for the use of the model. Model surveillance and maintenance are issues that need to be discussed with the company management to either assign people from the company to take care of them or outsource the responsibility.

Table 6.1. AI application Opportunities and Challenges in construction firms (Regona, Yigitcanlar and Xia, 2022)

Opportunities	Challenges
Provide a competitive advantage to businesses that use AI, as it will reduce economic costs	AI applications are highly specialized and need constant algorithms training to identify patterns
Increase productivity and efficiency of on-site personnel	The fragmented nature of the construction industry may result in data scarcity
Reduce the time spent on repetitive tasks by using big data	High initial costs in the research and development of AI platforms
Identify high-risk issues and automatically classify them into actionable categories	AI platforms need investment constantly to keep data up to date
Improve current work processes	Implementation of AI requires businesses to move away from traditional ideas
Increase the consistency in project related work that will result in higher quality	Security and reliability of a large amount of data
Avoid possible delays through predictive modeling	Multi-point responsibility between stakeholders may reduce accountability
Extract data from the complex document and categorize them based on patterns easily	Non-standardization of a construction project makes it difficult to implement AI
Reduce the probability of on-site accidents and mitigate safety risks	Require an AI expert that will involve additional costs
Increase accuracy of plans and allow for better verification	High resistance from industry bodies
Produce outcomes that can be easily understandable by all stakeholders, which enhances efficient communication	Ethical, moral, and legal issues that are yet to be addressed by the government or institutional bodies
Enhance consistency and reliability, as AI is highly unlikely to make mistakes (provided data are correct)	High impact on traditional skills and may impact job availability

6.10 Addressing the Potential Ethical, Moral, and Social Harms and Biases of the Proposed Model in Practice

Being overwhelmed with the numerous advantages of AI and industry 4.0 technologies in construction, the potential harms, biases, and discriminations embedded in and caused by such technologies in ethical and social contexts are usually overlooked. As creators of the built environment, engineers, architects, and construction managers have a vital social responsibility to represent the needs of all social groups, regardless of ethnicity, race, and gender, in their projects to serve sustainable development goals. Therefore, the proposed technology should be human-centric and socially harmless to them and the environment they live in. Hence, the social, ethical, and moral responsibilities of such technologies, beyond the technical standards, should be addressed as prerequisites to implement them in the design, construction, and operation phases of projects (Weber-Lewerenz, 2021). This initiative gives rise to the concept of Industry 5.0 for a transition toward a sustainable, human-centric, and resilient industry that looks beyond productivity and efficiency as end goals (European Commission, 2021; Kozlovska, Klosova and Strukova, 2021). However, the tradeoff between delivering building projects faster, cheaper, and higher quality while following ethical and moral regulations is not always easy, considering the great capital, lengthy process, numerous stakeholders, and complex data environment in construction projects.

The inherent complexity, bureaucracy, and change-resistant culture in the construction industry, as well as technology switching costs and market uncertainty, slow down the industrial evolution and digital-data-driven systems integration in projects, which can be perceived both as a threat and an opportunity (Manuel *et al.*, 2019; Zhang, Pan and Wu, 2021). The lack of established standards and references on data security and protection, knowledge transfer, interoperable formats, data ownership, digital contracts, etc., as well as the lack of proper training to familiarize the professionals with digital technologies, are hindering the widespread application of industry 4.0 technologies in practice (Oesterreich and Teuteberg, 2016). However, it leaves room to integrate ethic codes and standards in writing such standards for a human-centric and ethic-aware application of technology in the sector. This subsection aims to delineate the potential harms and ethical issues that might arise during different stages of the AI application process, as well as to determine the key aspects and components of an ethics-aware technology application framework in the construction industry, which can greatly benefit the integration of the developed model with the company processes.

6.10.1 Ethics of Digital Technologies

The implementation of AI models may raise various ethical, moral, and social dilemmas that digital agents are not equipped to resolve. Ethical dilemmas occur when a decision must be made between two alternatives that are both ethically problematic and can result in unethical behaviors, not following some values, norms, and laws in the society like justice and inclusion (Arroyo, Schöttle and Christensen, 2021). On the other hand, a social dilemma happens when there is a conflict between self and collective interests (Van Lange et al., 2013). A deep understanding of ethics and morality is beneficial in addressing these dilemmas. Morality refers to internal principles and codes of conduct regarding right and wrong that are upheld by the individuals themselves and not by any law or regulation (Stanford Encyclopedia of Philosophy, 2020), while ethics are societal principles and disciplines to guide individuals on how to act in different circumstances based on what is deemed right or wrong (Kuipers, 2020; Stanford Encyclopedia of Philosophy, 2022). Both principles are influenced by various cultural, social, organizational, geographic, contextual, and historical factors and are intended to promote positive interactions and prevent negative ones (Kuipers, 2020), and to create stronger, safer, healthier, more inclusive, and more just societies.

Applied ethics defines protective boundaries alongside the autonomy and authority given to a human agent or a technology agent, like AI. AI ethics, as a set of values, principles, and techniques employing widely accepted standards of right and wrong in such dilemmas (Leslie, 2019), is developed to address ethical issues related to the AI system and its developers (Siau and Wang, 2020) that may arise when designing and developing AI (e.g., human biases that exist in data, data privacy, and transparency), and ethical issues caused by AI (e.g., unemployment, wealth distribution, and change in power dynamic).

As evident in the theoretical definition, AI ethics is directly connected to human-technology relationships and trust. Trust is a psychological state comprising the trustor's intention to accept vulnerability based on positive expectations of the intentions or behavior of the trustee (Kuipers, 2020). Trust can motivate an action or collaboration, in this context, public engagement in AI vast applications. Once the society or a part of the society, in this case, the construction industry professionals, are convinced that AI systems are human-centered and serve humankind, are reliable, are compatible with the established workflows and reinforce best practices instead of replacing them, are interactable and controllable and are inclusive and accessible to all groups of society, they will be more open to accept and promote them (Emaminejad and Akhavian, 2022).

A better knowledge of human rights laws can help AI algorithm developers eliminate or at least alleviate the potential harms, biases, discrimination, and invasion of privacy issues in AI (Siau and Wang, 2020). Therefore, it is important for the AI developers, as well as the researchers and practitioners who are going to use it, to understand existing ethical principles that need to be applied to construct ethical AI models following the same principles. Such AI models capable of translating ethical principles into practical and measurable metrics throughout the planning, development, deployment, tracing, and operation phases of the system are addressed as moral autonomous systems, ethical controllers (Trentesaux and Karnouskos, 2022), artificially intelligent autonomous systems (Russell, 2016), or responsible AI (Trentesaux and Karnouskos, 2022; Russell, 2016) in the literature. The main ethical principles that need to be addressed in developing ethical AI models for construction projects are as following (Arroyo , Schöttle and Christensen, 2021):

- Sources of Data, Biases, and Discriminations: The accuracy of AI algorithms depends on the quality and quantity of input data. Specially, in the construction industry, with inherent data scarcity and subjectivity issues, ensuring objectivity, completeness, generalizability, fairness, diversity, inclusion, and confidentiality of collected data becomes even more critical (Weber-Lewerenz, 2021; Koolen and van Cranenburgh, 2017). AI-driven technologies reflect and amplify patterns of marginalization, inequality, and discrimination in the social context (Leslie, 2019), which are critical issues to consider when choosing the input data and algorithm to use for a specific problem (Altman, Wood and Vayena, 2018; Weber-Lewerenz, 2021).
- Trust in AI Technology and Decisions: Establishing trust between the AI agents and human counterparts is determined by a) the legal environment and standards, and b) the technical aspects of the system, warranting safety, security, transparency, and explainability (Emaminejad and Akhavian, 2022), c) concerns regarding job displacement caused by AI (Gillespie, Lockey and Curtis, 2021), and d) the level of trust and reliance on decisions and predictions made by AI (Arroyo, Schöttle and Christensen, 2021). Based on a thematic analysis in Architecture, Engineering, and Construction (AEC) literature conducted by Emaminejad and Akhavian (2022), four key dimensions to build trust in the AI algorithms are a) Explainability and interpretability, b) Reliability and Safety, c) Performance and Robustness, and d) Privacy and Security; which are as following.
- Explainability and Interpretability: These concepts indicate the state where the operations of a system can be understood by a human through introspection or explanation (Haibe-Kains et al., 2020), which is of special importance in the construction industry, where the professionals are not familiar with advanced structures of AI algorithms like black-box. Therefore, the black-box to white-box transformation of AI, like the use of Probabilistic Graphical Models (PGM) over ANNs (Hvam and Mortensen, 2008; Pan and Zhang, 2021)

allows intuitive interpretation of users on how algorithms and models arrive at an output (Pillai and Matus, 2020), keeping them in their decision loop and ensuring them of model accuracy, fairness, and transparency (Gunning *et al.*, 2019).

- Reliability and Safety: They indicate the capacity of the models to avoid failures or malfunctions and exhibit the same expected behavior over time (Hoff and Bashir, 2015). Both concepts are related to trust from a performance (rather than a moral) angle and find meaning in human-technology interactions (Malle and Ullman, 2021). Overtrust and overreliance on technology may lead to ignorance of its risks, the solution to which is training and educating the users on the abilities, reliability, and failure of AI agents (Merritt et al., 2015).
- Performance and Robustness: Performance indicators offer standardized and common criteria to compare different AI models (Glikson and Woolley, 2020). Robustness refers to performance consistency in different situations, which in construction translates to the ability to successfully transfer models between different projects, sectors, and locations considering the uniqueness and context-drivenness of projects without compromising the user's trust in the system (Emaminejad and Akhavian, 2022).
- Privacy and Security: The protection of human identity and sensitive data, as well as the protection of the system against attacks that breach privacy, need to be addressed (Orr and Davis, 2020). Privacy is defined as the right not to have personal data acquired, observed, and used, while security in AI ensures the confidentiality of data and preserves information integrity. Data regarding contract information, transactions, blueprints, photos, and project personnel are considered confidential, and careful attention must be paid to guarantee data confidentiality and prevent data leaks (Emaminejad and Akhavian, 2022).
- Autonomy and Accountability: AI can have different levels of autonomy and authority (Abioye *et al.*, 2021): a) Artificial Narrow Intelligence (ANI), b) Artificial General (or "strong") Intelligence (AGI), and c) Artificial Super-Intelligence (ASI). ANI aims to automate some repetitive and learnable activities without the ambition to substitute human intelligence authority or decision-making. AGI aims to match human-level intelligence in any field and type of human activity and is capable of complex decision-making. ASI aims to exceed human intelligence and faculties, staying unbeatable by any human mind (Müller and Zalta, 2020). The stronger the AI system autonomy, the more accountability it should bear and the more serious the accountability becomes, since it is difficult to determine the accountable agent, such as the programmer, data owner, or end-user, for the mistakes or accidents (Leslie, 2019).

6.10.2 Ethical Standards, Laws, and Regulations

Codes of ethics, regulations, and standards developed by governments, companies, technical organizations, trade unions, and societies are the most influential factors in building public trust toward AI (OECD, 2019; Galindo,2021). Such regulations enforce compliance with ethical and moral values and determine human responsibility in the development and deployment of intelligent systems, filling the gap that emerges from the increased automation of decisions (Theodorou and Dignum, 2020). AI standards have been developed on national and international levels, such as the Organization for Economic Co-operation and Development (OECD) (OECD, 2019; Galindo, 2021), the Institute of Electrical and Electronics Engineers (IEEE) standardization Association (IEEE, 2021), Future of Life Institute (Future-of-Life, 2017), International organizations for standardization such as IEC and ISO standards (ISO, 2021), European Union, European Commission's High-Level Expert Group on AI (European Commission, 2019), US National Institute of Standards and Technology (NIST) (NIST, 2021), and many more. These standards and regulations need to be supported by the AI community, State administration, and Standardization bodies (Mezg´ar and V´ancza 2022). These principles aim to promote a) inclusive growth, sustainable development, and well-being through trustworthy AI, b) human-centered values and fairness throughout the AI system lifecycle, c) transparency, explainability, and responsible disclosure regarding AI systems, d) robustness, security, and safety, and systematic risk management, e) accountability of AI systems (Yueng, 2020), g) culture of awareness and alignment of AI with ethical values, h) the competitiveness of the construction industry, and i) education and awareness-raising for the potentials, opportunities and risks of AI (Weber-Lewerenz, 2021). There are two approaches for developing ethical standards (Nagel, 2021), finding a balance between which can resolve ethical dilemmas in AI systems:

a) The Consequentialist justification evaluates and weights actions in terms of their long-term impact and outcome, their implied costs and benefits.
b) The Deontological approach suggests sticking to some basic principles that embody the notion of values in a society and directly evaluating the rightness or wrongness of actions and policies without considering their direct impact explicitly.

The aim of this subsection is to develop an ethical AI implementation framework with the help of the abovementioned standards that can address the potential ethical, social, and moral dilemmas raised by AI and can facilitate the wider and harmless application of AI in the construction industry, presented in the Results section.

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Chapter 7: Case Studies

7.1. Case studies introduction

This research follows a case study approach to implement the proposed solutions and compare the results. Two case studies have been used for this purpose. The first one is the portfolio of 44 construction projects conducted by the industry partner of the study, which is of small size and has intrinsic complexities like missing values and various types of risks. It consists of 47 columns as input project variables and 65 columns as output project risks for each project. The second case study is entirely different in terms of the size of the database, number of features, and data complexity. It is an open-access database of school buildings' construction in New York, which includes data on more than 13570 projects, 12 input features, and two output features. The main objective of implementing the proposed solutions on two completely different databases was to conduct a comparative analysis between the results to delineate the importance of the database size and type of data in the performance of each ML algorithm. As a result, this research can contribute to construction companies' proper choice of ML algorithms with respect to their data availability.

7.1.1. First Case Study:

The first set of Case studies includes the building and pharmaceutical construction projects of Jacobs SPA, Italy, which are 44 projects in total. These projects are chosen among the vast portfolio of Jacobs' projects due to their ease of data acquisition, i.e., the availability of project documents and project manager for conducting interviews. Furthermore, as Jacobs Italy conducts mainly building and pharmaceutical projects, the data gathering was conducted in a way that creates a proper balance between different types of projects for future use. A general list of different types of projects and their other features like budget ranges, intervention types, and built area ranges were prepared based on the company's statistical information and was used for ease of reference by the project managers when filling in the missing values. That is, for each project, an excel spreadsheet was prepared with all the features of the projects, the state of which needed to be chosen from a dropdown menu by the corresponding project manager, and on the second page, there was a list of all possible risks identified in previous projects, from which the project manager needed to select the ones that happened in their project. Figure 7.1.a. to 7.1.i. show the statistical distribution of projects in the database.

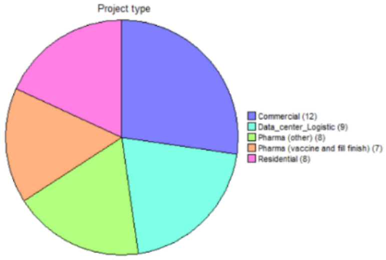


Figure 7.1.a Different project types in the database

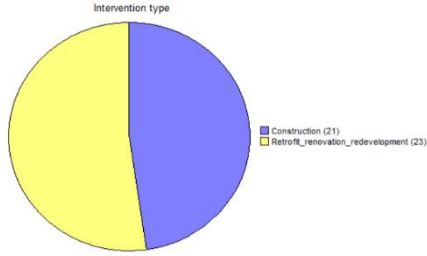


Figure 7.1.b Different intervention types in the database

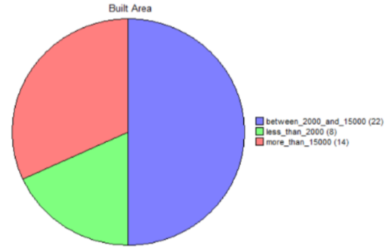


Figure 7.1.c Different project sizes in the database

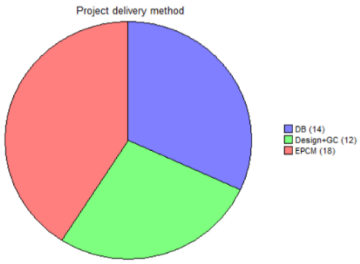


Figure 7.1.d Project delivery methods in the database

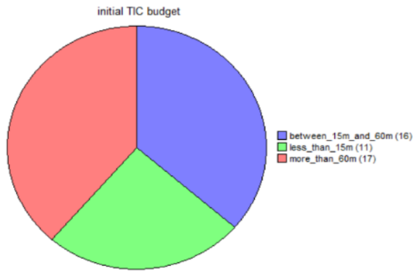


Figure 7.1.e Project TIC budget groups in the database

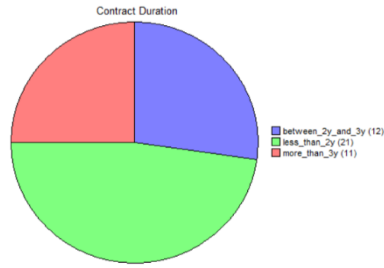


Figure 7.1.f Project durations in the database

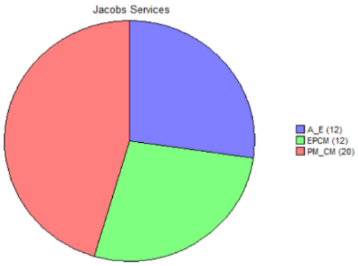


Figure 7.1.g Different Jacobs services in the database

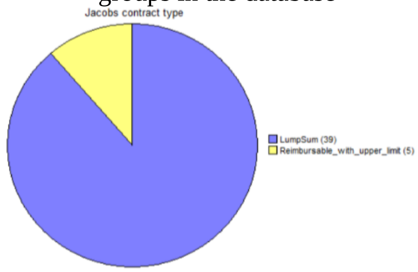


Figure 7.1.h Jacobs contract types in the database

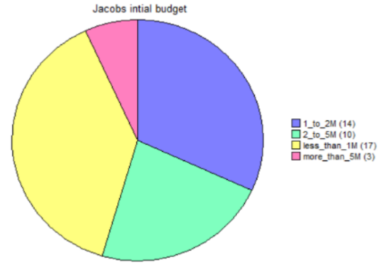


Figure 7.1.i Jacobs internal budget groups in the database

The project variables of these 44 projects are collected from their documents and through interviews with their project managers. The number of these variables is 47, which could influence specific types of risks in the projects. These variables are:

- Property/Project Type (Residential, Commercial, Pharma, Data Centers)
- Built Area (m2)
- Lot Size (m2)
- Number of Floors
- Number of End Users (for example number of residents)
- Intervention Type (new construction, renovation and development)
- Delivery Method (DB, EPC, Design+ General Contractor)
- Number of Contractors (one GC or multiple subcontractors)
- Number of Design/Eng. Companies (one or multiple)
- Initial Construction Budget (TIC budget value)
- Cost contingency in TIC budget
- Construction cost overrun
- Contractual discounts
- Initial schedule duration
- Project Start delay
- Project Closure delay
- Covid suspension
- Specific Quality standards used
- Sustainability certificates application (LEED, BREEM, WELL)

- Specific HSE standards or safety protocols used
- Other specific building permits
- Number of Accidents
- Number of near misses
- Number of site workers per day
- Project Location
- Outdoor temperature and condition
- Seismic Zone (1,2,3,4,5)
- Soil type (clay, sand and gravel, rock)
- Existence of underground waters
- Existence of water pollutants
- Structure type (concrete, steel, others)
- HVAC system (central, local)
- Energy demand amount for heating/cooling/electricity
- Jacobs Internal: Company Service Type in the project (PM_CM, A and E, EPCM)
- Jacobs Internal: Company Work Packages involved (Civil, electrical, mechanical, etc.)
- Jacobs Internal: Project phases involved (partially, completely)
- Jacobs Internal: Contract type (lump-sum, reimbursable and cost plus)
- Jacobs Internal: Contracting relationship with client (joint venture, direct to owner)
- Jacobs Internal: Collaborations with other headquarters
- Jacobs Internal: Contract value
- Jacobs Internal: Cost overrun
- Jacobs Internal: Gross Margin (revenue-cost)
- Jacobs Internal: approved change orders' amount
- Jacobs Internal: Value plus saving
- Jacobs Internal: contract duration
- Jacobs Internal: time overrun

Moreover, a comprehensive list of risks that occurred in previous projects was composed. The risks were grouped into 11 categories: 1) Technical, Scope, and Management risks, 2) Administrative risks, 3) Communication risks, 4) Environmental risks, 5) Procurement risks, 6) Resource risks, 7) Safety risks, 8) Schedule risks, 9) Stakeholders risks, 10) Quality and change risks, and 11) financial risks. Some additional risks were added from literature and interviews with project managers of the company, and some irrelevant risks were dropped from the list, aggregating to a total of 65 risks.

In order to deepen the analysis of the case study projects, a feature importance analysis and a project significance analysis were conducted using random forest and linear regression built in functions. Feature importance analysis is a technique used in various fields, including machine learning and statistical modeling, to determine the relative importance or contribution of different features or variables in predicting a target or outcome. Tree-based models, such as decision trees and random forests, provide a built-in measure of feature importance. The importance is calculated based on how much each feature contributes to reducing the impurity or variance in the model. Features that are frequently used for splitting nodes higher up in the tree are considered more important. Figure 7.2. and 7.3. present the feature importance of two of the procurement risks, “Change of procurement strategy and contract type” and “Delay due to contract awarding/ tender closing”, respectively.

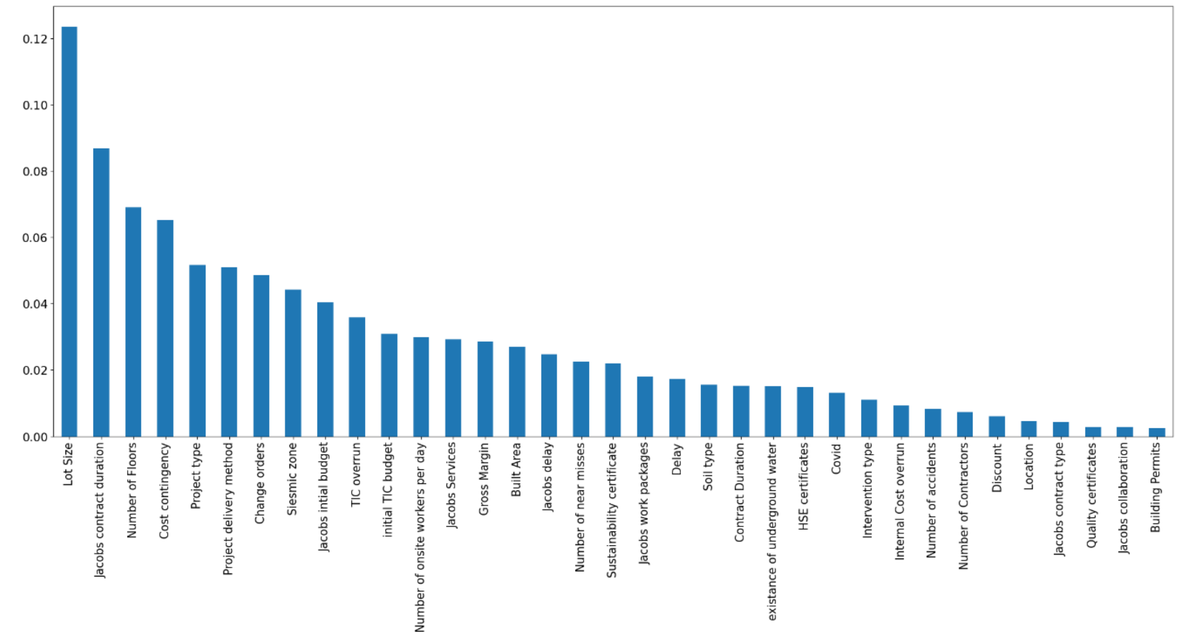


Figure 7.2. Feature importance for “Change of procurement strategy and contract type” risk prediction

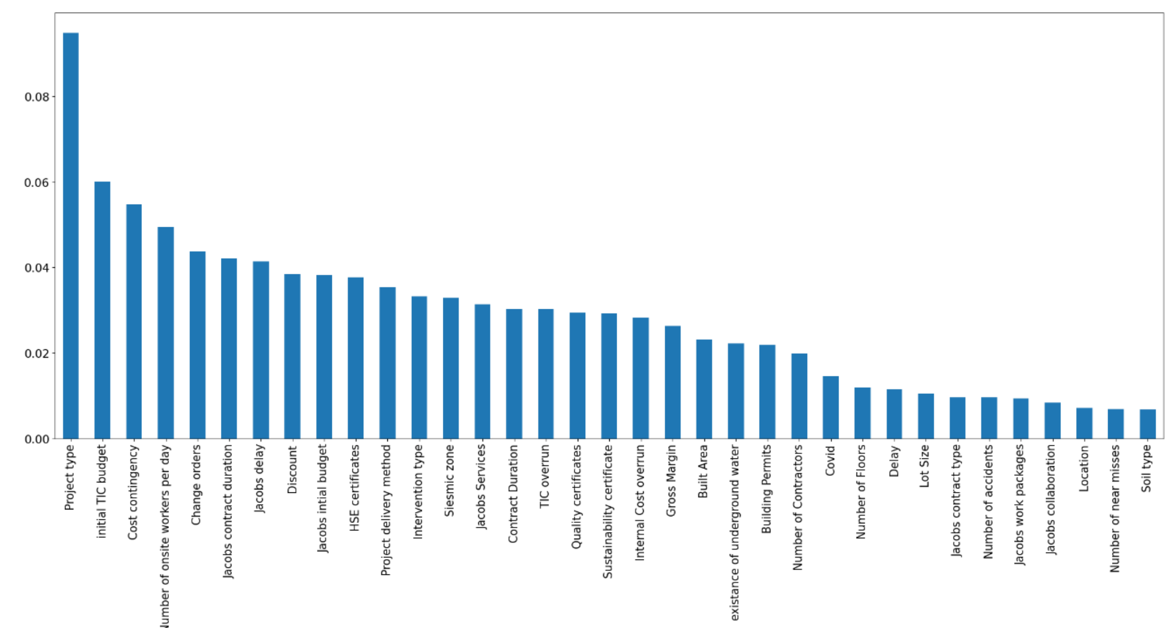


Figure 7.3. Feature importance for “Delay due to contract awarding/ tender closing” risk prediction

Furthermore, in order to determine the influence of each of the 44 projects on the final output, a sensitivity analysis was conducted. Initially, the overall mean square error (MSE) of a simple logistic regression model ran on the entire database was calculated. Then, each row of the database was excluded one by one, creating a new database of the remaining 43 projects, and the MSE of the new database was calculated and saved in a new variable called MSE_new. The difference between the overall mean square error (MSE) of the prediction and the mean squared error of the new database excluding one row or project (MSE_new) was calculated and saved in a list called influences. The greater the amount of this value, positive or negative, the more influential and significant that project was in the overall precision of the model. Figures 7.4. and 7.5. present the project influence/significance analysis for two of the procurement risks, "Change of procurement strategy and contract type" and "Delay due to contract awarding/ tender closing", respectively.

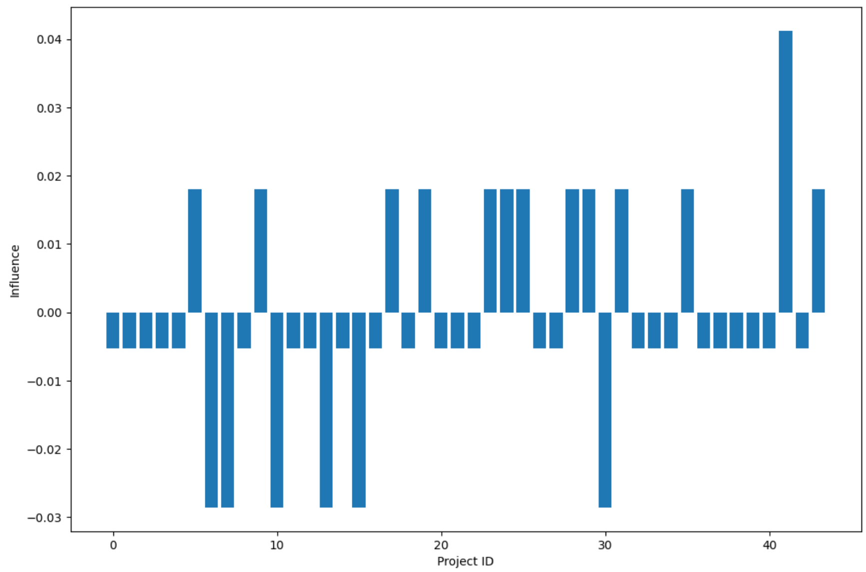


Figure 7.4. Project Significance for "Change of procurement strategy and contract type" risk prediction

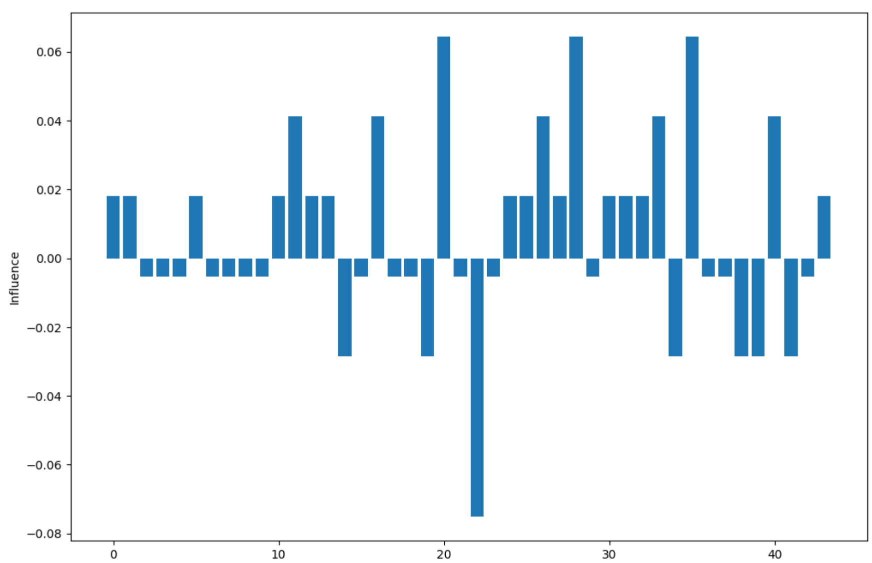


Figure 7.5. Project Significance for "Delay due to contract awarding/ tender closing" risk prediction

Additionally, in order to visualize the relationship between the value of different features in the database and the Mean Absolute Error (MAE) of the prediction of each project or row of data, an analysis was performed in python. For each row in the data frame, the script dropped the current row from the input data and target variable, trained the linear regression model on the remaining data, and then used the model to predict the target variable for the dropped row. The MAE between the predicted and actual target variable for the dropped row was calculated and stored in a list, and later, added as a new column in the data frame. The values of all the columns, including the newly added MAE column, were standardized using sklearn's StandardScaler, scaling the values to a mean of 0 and a standard deviation of 1. Figure 7.6. and 7.7 present the line plot of this analysis for predicting risk 1 and 2, respectively, where each line represents a different project. The x-axis represents the different features, and the y-axis represents the standardized values of these features.

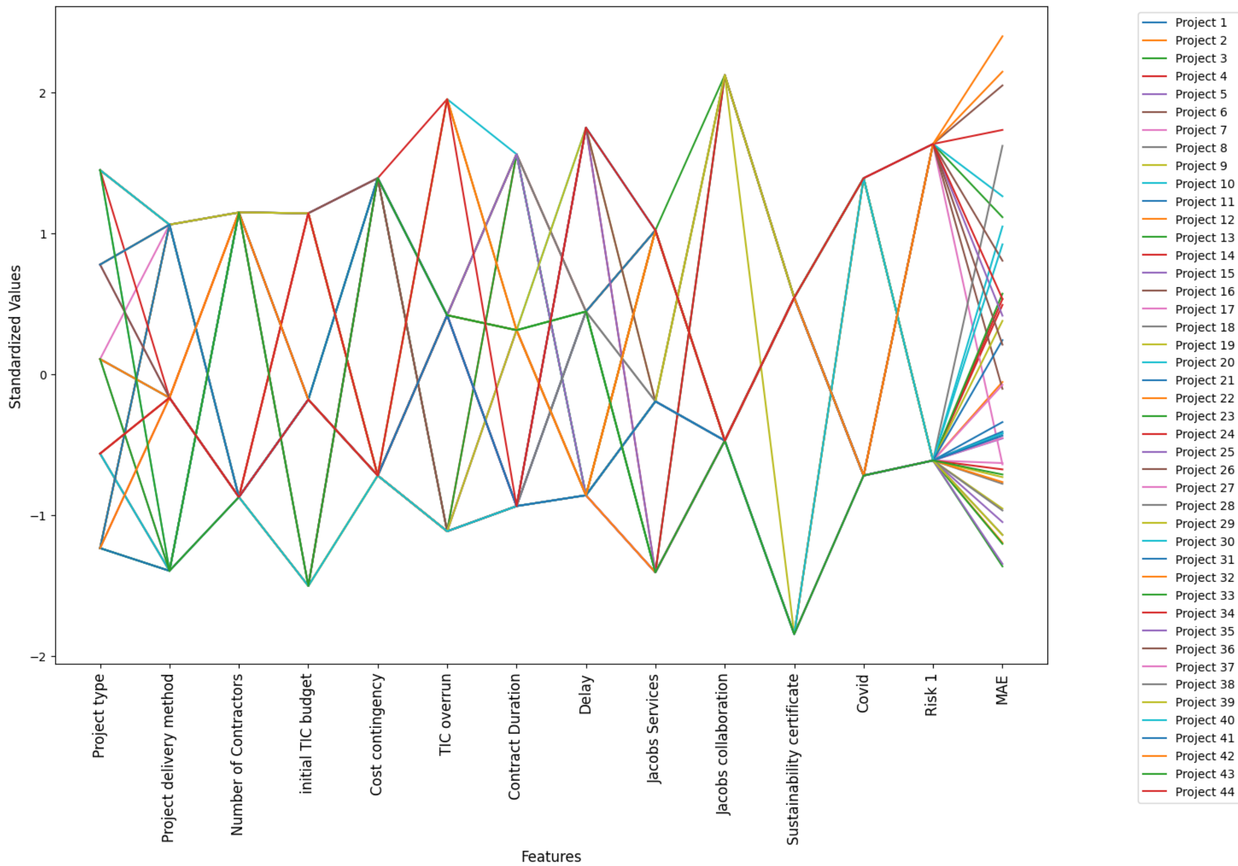


Figure 7.6. Relationship between project features and MAE value for each project for risk 1 prediction

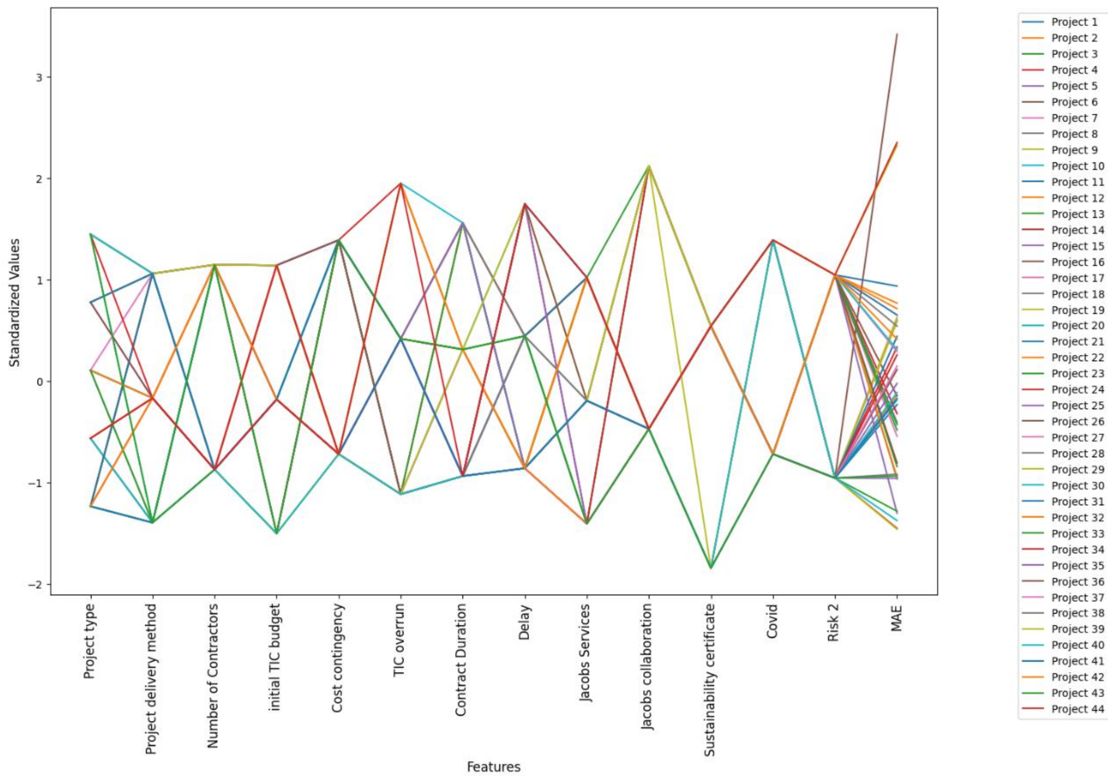


Figure 7.7. Relationship between project features and MAE value for each project for risk 2 prediction

7.1.2. Second Case Study:

The second case study is an open-access database sourced from the Capital Project Schedules and Budgets database available on the City of New York's Open Data Portal (https://data.cityofnewyork.us/Housing-Development/Capital-Project-Schedules-andBudgets/2xh6-psuq), maintained by the New York City government. The reason for choosing this case study and applying all the developed models to it was to compare the results obtained from them when the size of the database is enormous and highlight the importance of the database size in the performance of different ML models, and consequently the choice of the ML model type. Before data cleaning the database had 13570 rows or projects and 14 columns or project attributes, including Project Geographic District, Project Building Identifier, School Name, Project Type based on funding, Project Description (Description of construction/ retrofit services and work packages), Project Phase Name, Project Status (completed, ongoing), Project Phase Actual Start Date, Project Phase Planned End Date, Project Phase Actual End Date, Project Budget Amount ($), Final Estimate of Actual Costs Through End of Phase Amount ($), Total Phase Actual Spending Amount ($), DSF reference Number(s). However, after data cleaning and filtering, only 1489 completed school-building projects were selected for further analysis. Moreover, only 7 data features were selected as influential for modeling, and 10 new columns created by one hot encoder were added for the work type category. Table 7.1 presents the statistical information of the database.

Table 7.1. Statistical information of the database

Feature	Mean	Variance	Standard Deviation	Min	Max
Project Geographic District	17.67	83.96	9.16	1	32
Project Phase Name	0.68	0.55	0.74	0	3
Week Duration	36.10	1163.56	34.11	0	314.8557
Week Delays	9.53	528.422	22.98	-24	171
Project Budget Amount	453354.45	1735528285069	1317394.50	112	16096500
Final Estimate of Actual Costs through the end of the phase	373142.53	1230812537107	1109419.91	90	15120360
Total phase actual spending	335434.41	984566654594	992253.32	90	13610170

Figures 7.8.a and 7.8.b present the histogram of project geographical district and project budget amount distribution, respectively.

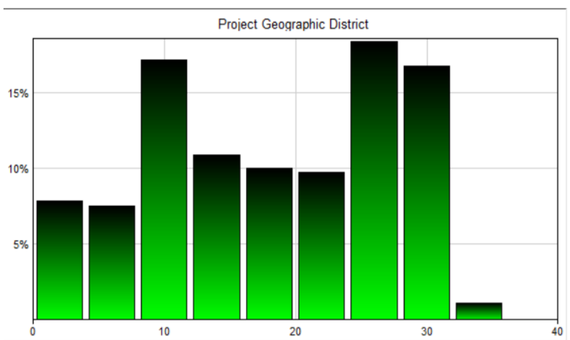


Figure 7.8.a. Histogram of project geographical district

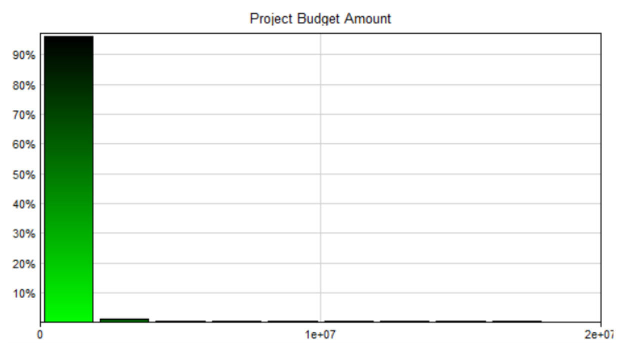


Figure 7.8.b. Histogram of project budget

Figure 7.9. shows the positive correlation between project duration (week duration) and week delay, indicating that the longer the project takes, the more prone to the risk of delay. Figures 7.10.a and 7.10.b show the positive correlation between the project budget and the final estimate of costs with the total spending amount. However, as apparent in Figure 7.11, there is no strong correlation between the project delay and total spending amount, the two target variables of the study.

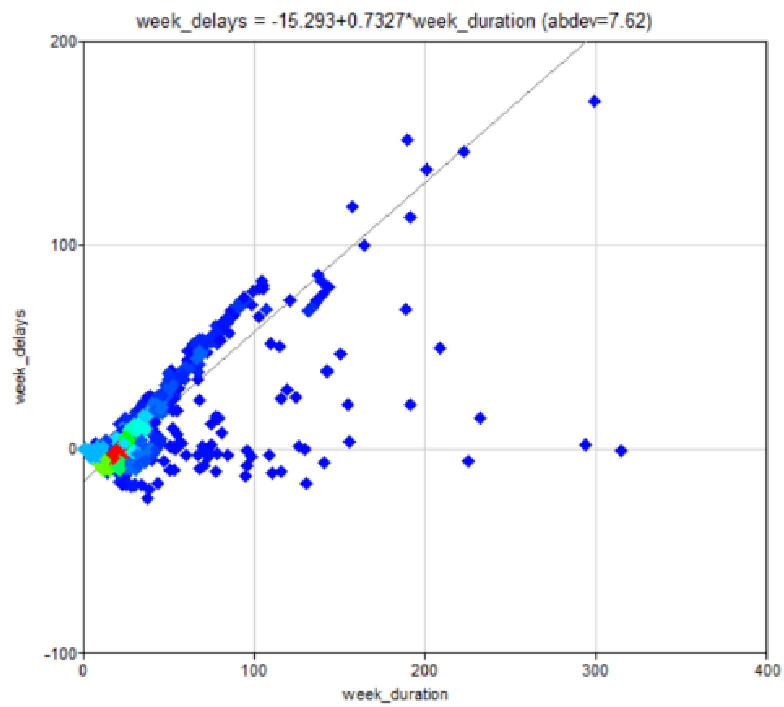


Figure 7.9. Correlation between project duration and delay

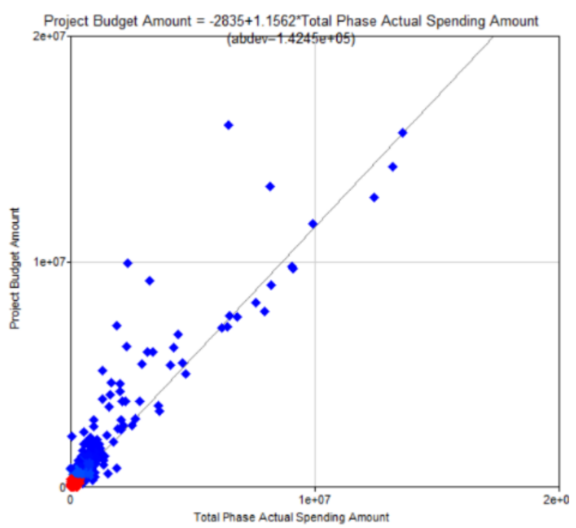


Figure 7.10.a Correlation between project budget and total phase actual spending

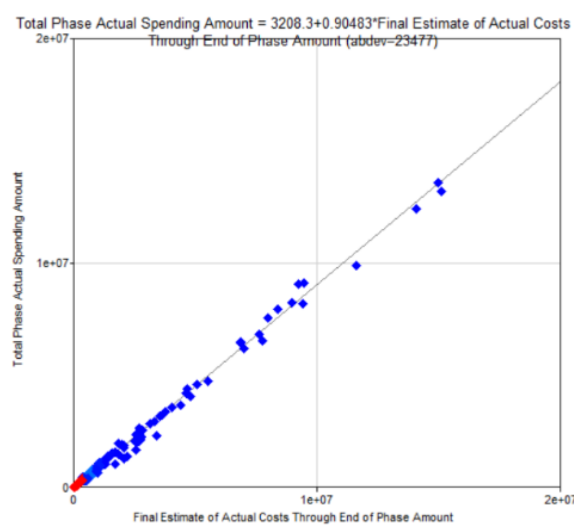


Figure 7.10.b Correlation between final estimation of costs with total phase actual spending

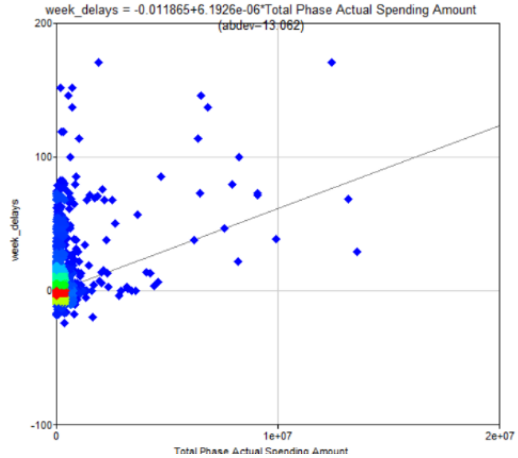


Figure 7.11. Correlation between project week delay with total phase actual spending

7.2. Experts' Backgrounds

Seventeen experts directly participated in the elicitation process for the first case study, consisting of surveys and interviews in three phases: structure learning, parameters learning, and network validation. It is noteworthy that other experts contributed to the project by providing data on their projects. Moreover, 11 of these experts contributed to the Fuzzy Logic model creation through surveys asking the probability of each risk given specific states of each project variable. Figures 7.12 to 7.15 indicate the distribution of the department the experts work at, their position in the company, their educational level, and their years of work experience in the company, respectively. Extra information on the experts and their contribution to the research cannot be shared due to data confidentiality issues.

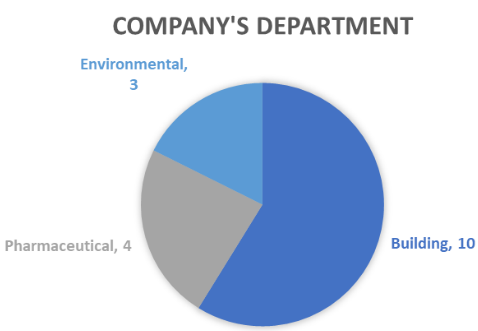


Figure 7.12. Experts' department at company

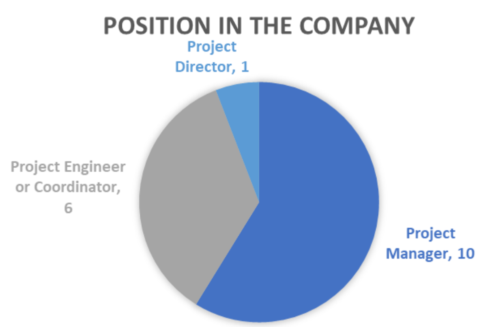


Figure 7.13. Experts' position at company

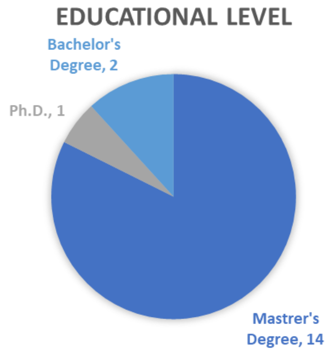


Figure 7.14. Experts’ educational level

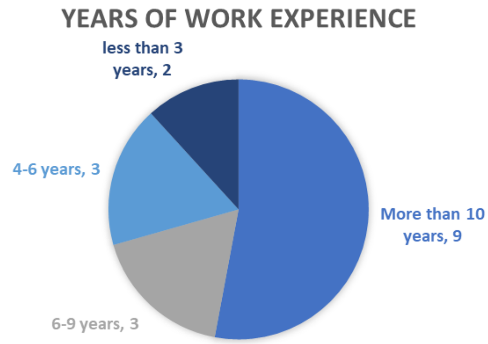


Figure 7.15. Experts’ years of work experience

Chapter 8: Results and Discussion

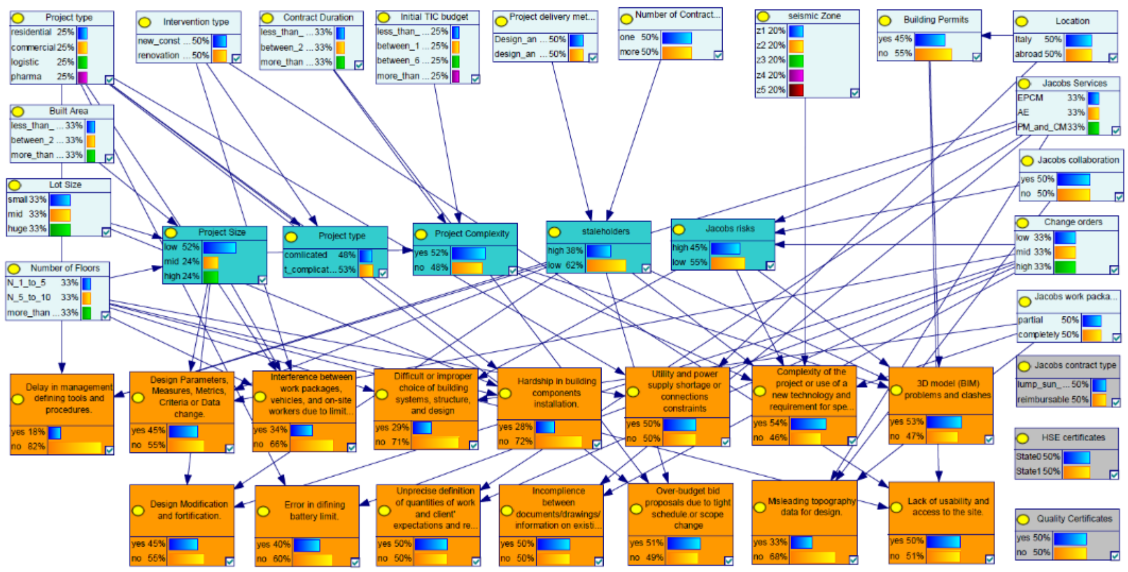
8.1 Results analysis

This subchapter presents the results retrieved in different stages of the methodology and from different models applied to both case studies:

8.1.1. Results of the first Case study

a) **Data Collection and Documents search result:** 47 main variables from 44 projects (building and pharmaceutical) were collected and listed in a database. Moreover, the risk list related to each project was collected.
b) **Data Preprocessing and Comprehensive Risk List creation:** The risks identified in all projects were listed under 11 categories: 1) Technical, Scope, and Management risks, 2) Administrative risks, 3) Communication risks, 4) Environmental risks, 5) Procurement risks, 6) Resource risks, 7) Safety risks, 8) Schedule risks, 9) Stakeholders risks, 10) Quality and change risks, and 11) financial risks, a total of 65 risks. This risk list was updated based on findings from literature and interviews with the project director, during which some insignificant risks were dropped from the lists, some were added, and some were combined to make it as clear and simple as possible for the surveys.
c) **Synthetic Data generation:** GANs were used for synthetic data generation based on the initial projects' database as a solution to overcome data scarcity and augment data. As a results, the database size has doubled, reaching 88 projects from 44 initial ones. The results obtained from both databases are compared in the next parts to indicate the positive impact of data augmentation on the model performance.
d) **First phase Survey results for Probabilistic risk network structure selection:** Systematic surveys have been conducted for feature and structure selection, i.e., 16 project managers were asked to choose if a certain project variable is affecting a certain risk category or not. If more than 60% of the answers were yes, that variable was taken into consideration in the risk network of that category. As a result, 11 general risk networks for the 11 risk categories were created and validated by the experts.
e) **Second phase survey results for Probabilistic risk network parameter selection and CPT assignment:** In this phase and through interviews, project managers were asked to evaluate the effect of each state of a project variable; for instance, for the project type variable, the states are residential, commercial, industrial and logistics, and pharmaceutical, on the occurrence of a risk of a certain risk category on a scale of 1 to 5. As a result, an interconnected network of each risk is created in GENIE software, as depicted in Figure 8.1. for technical and procurement risk categories. As evident in the network, the priors of variables are all equal for now, as the historical records have not been inserted in the model yet. Moreover, some variables were omitted from the list as experts concluded they do not have significant impact on the risks, and their existence only overcomplicates the model.

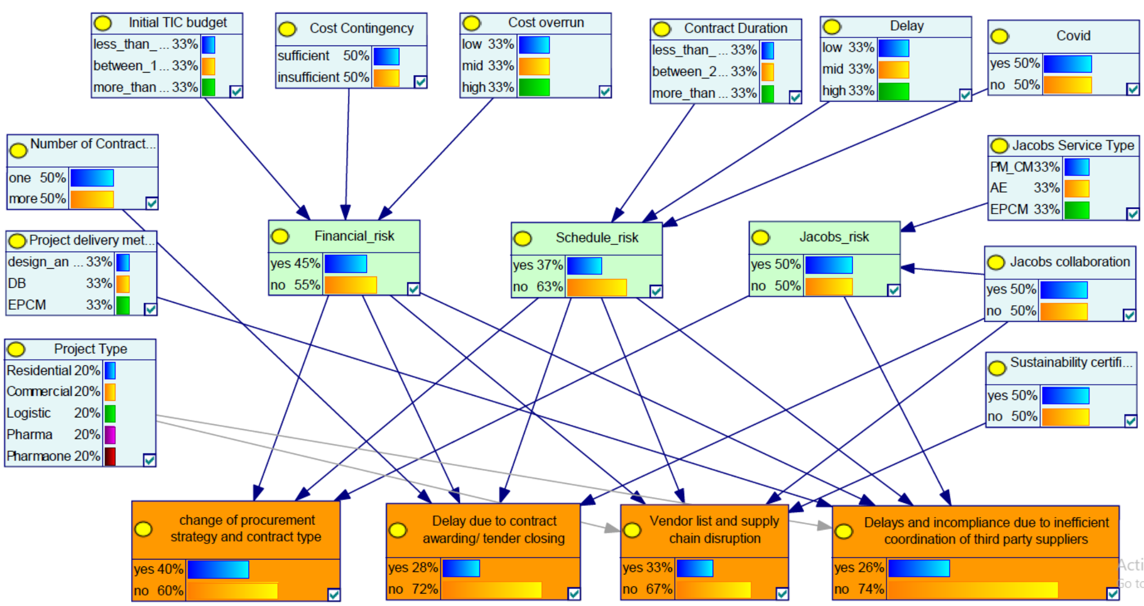
a)



Project Variables | Synthetic Variables | Omitted Variables | Risks in technical risk category | Arrows and relationships between nodes

Figure 8.1.a Structure and Parameter learning of the technical risk network by elicitation

b)

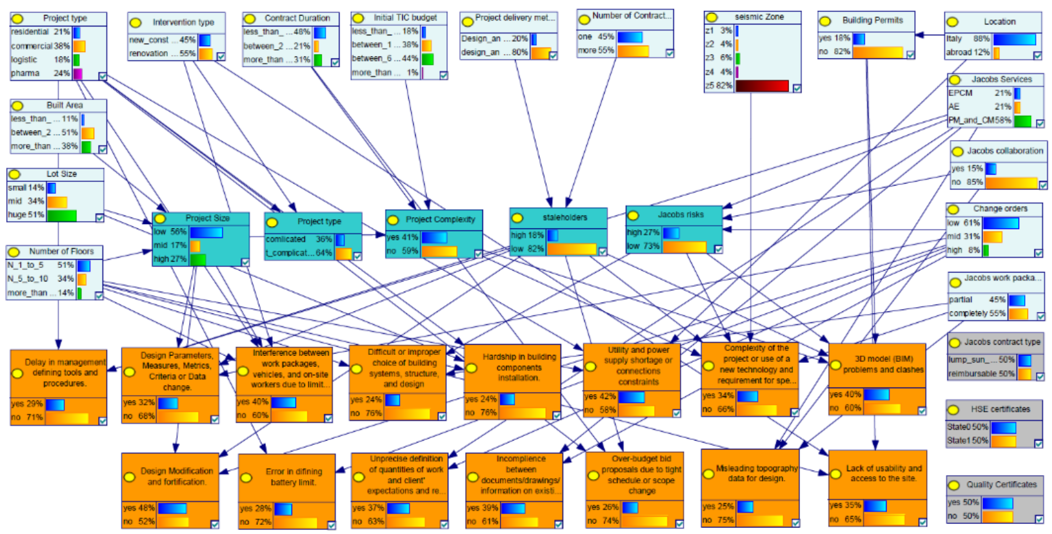


Project Variables | Synthetic Variables | Omitted Variables | Risks in technical risk category | Arrows and relationships between nodes

Figure 8.1.b Structure and Parameter learning of the procurement risk network by elicitation

f) **Parameters learning and beliefs update by project data:** In this phase, the data from the 44 projects are also added to the network and learned by the network for weights adjustment, as well as posterior probabilities adjustment or beliefs update. It is noteworthy that the result of the experts' elicitation serves as the basis of the CPT, and with new projects' data becoming available, it will be simply updated, treating the new data as evidence to update the posterior beliefs. This is a great advantage of Bayesian approaches compared to deterministic ML algorithms to be able to benefit from an experience-based judgment resulting from years of project management instead of only relying on historical records that might not be reflective enough of the actual situation. Moreover, this approach guarantees consistency between different assessments of risks for different projects, not showing extremely context-driven and overfitted results to a specific database. Figure 8.2 presents the same risk network after beliefs are updated by historical records. As seen in the figure, the priors of each variable are adjusted based on the historical data, and the final results of the risks are changed accordingly. Figure 8.3. shows an example of a case-based model prediction based on a given project's evidence for technical and procurement risks.

a)



Project Variables | Synthetic Variables | Omitted Variables | Risks in technical risk category | Arrows and relationships between nodes

Figure 8.2.a technical risk network after posterior update by historical data

b)

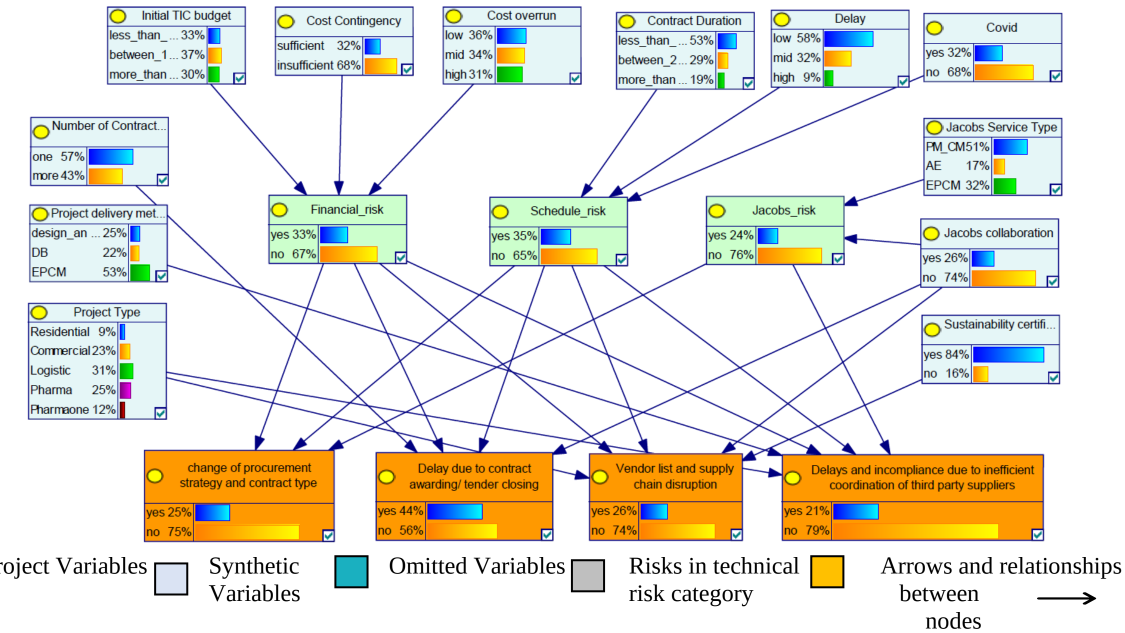


Figure 8.2.b Structure and Parameter learning of the procurement risk network by elicitation

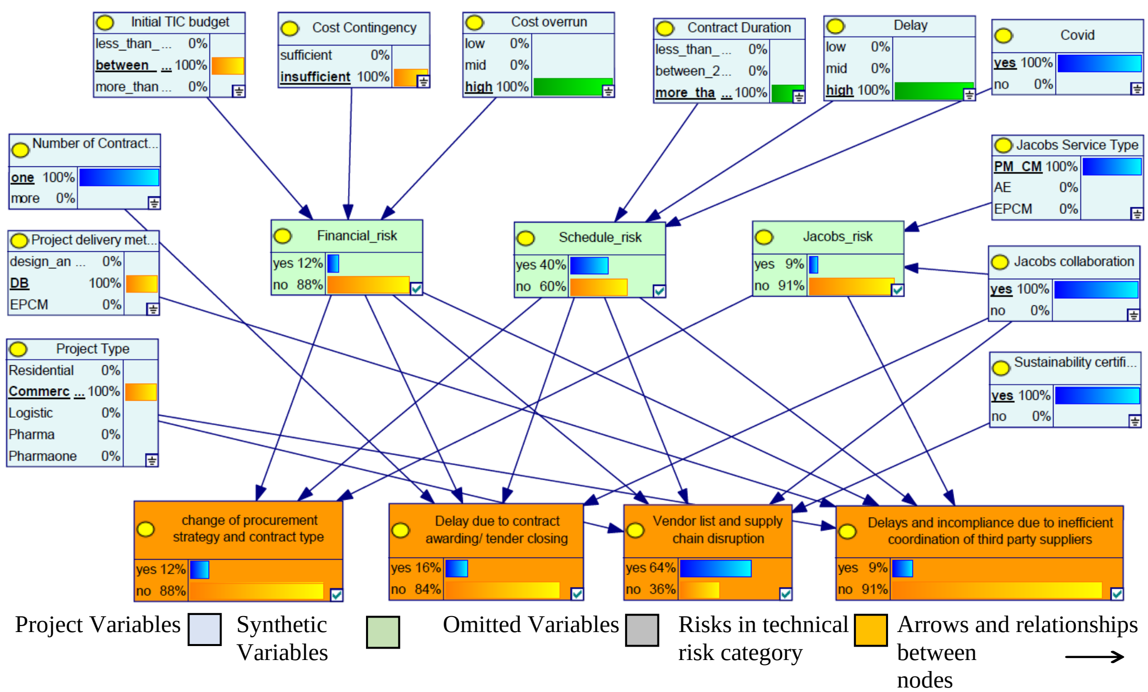


Figure 8.3. example of case-based risk assessment by the procurement risk network

g) **First round of validation:** In this phase, another set of interviews was set with the experts to show them the networks and ask their feedback about their explainability and ease of use, as well as primary validation. For the validation, they were asked to provide information on one of their ongoing projects, the data of which was not in the historical data records and was completely new to the model. Based on their provided information, the states on each node were set, the simulation was run, and the probability of each risk's occurrence was predicted. Then, the experts confirmed if those specific risks actually happened in reality or not. In most cases, the model prediction was in alignment with reality, but few changes were made in the network when the result did not correspond to reality.

h) **Second round of validation:** In this phase, the models were validated using cross-validation. For instance, the result of k-fold cross-validation of the procurement risk network before adding synthetic data to the database was 67% accuracy, which is an acceptable number given the limited database but not a promising one. However, after synthetic data generation, the accuracy reached 86% percent with 299 correct predictions out of 384 iterations for the procurement risk network, which is very remarkable compared to the initial results. Figure 8.4 presents the ROC curve of the procurement network for one the procurement risks. Table 8.1. compares the pre and post-data augmentation results for each procurement risk, which is also presented in Figure 8.5. Figures 8.6 and 8.7 present the confusion matrix and ROC curve for one of the technical risks, which returned 82% accuracy in the cross-validation process.

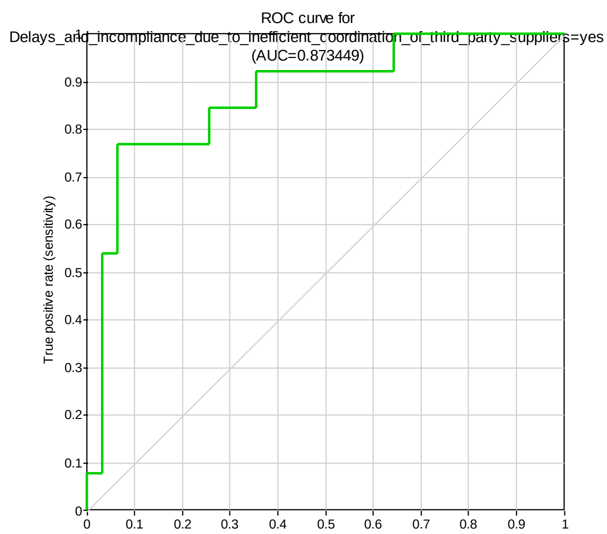


Figure 8.4. ROC curve of "Inefficient coordination of third-party suppliers" risk, after GAN

Table 8.1. comparison the pre and post data augmentation results for each procurement risk

Risk	State	Pre-Data Augmentation accuracy	Post-Data Augmentation accuracy
Change of procurement strategy and contract type	yes	0.16 (2/12)	0.44 (8/18)
	no	0.93 (30/32)	0.89 (62/69)
	overall	0.72 (32/44)	0.80 (70/87)
Delay due to contract awarding/ tender closing	yes	0.28 (6/21)	0.84 (32/38)
	no	0.43 (10/23)	0.87 (43/49)
	overall	0.36 (16/44)	0.86 (75/87)
Delays and incompliance due to inefficient coordination of third-party suppliers	yes	0.38 (5/13)	0.52 (10/19)
	no	0.96 (30/31)	0.98 (67/68)
	overall	0.79 (35/44)	0.88 (77/87)
Vendor list and supply chain disruption	yes	0.4 (4/10)	0.7 (14/20)
	no	0.94 (32/34)	0.94 (63/67)
	overall	0.81 (36/44)	0.88 (77/87)
Overall Procurement Risk		0.67 (119/176)	0.85 (299/348)

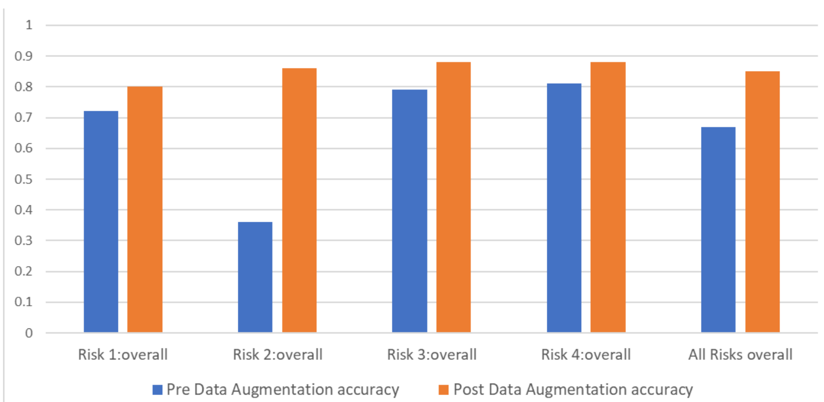


Figure 8.5. Comparison the pre and post data augmentation results precision of the procurement risks BN model

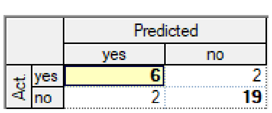


Figure 8.6 Confusion matrix of the technical risk network

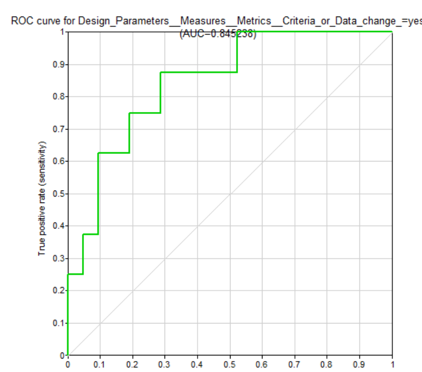
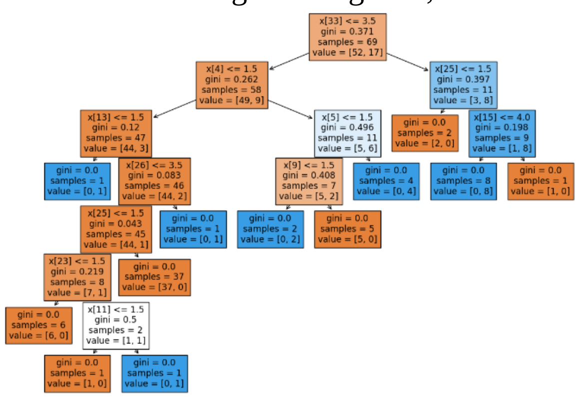


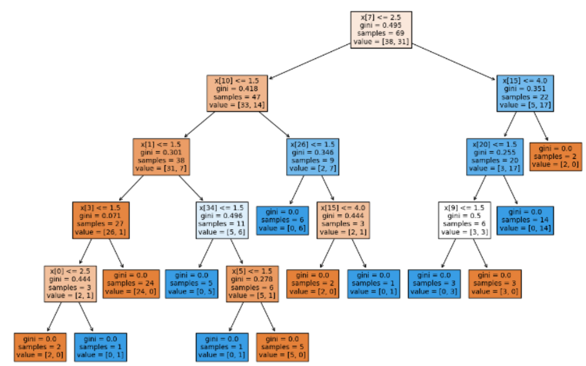
Figure 8.7 ROC curve of the technical risk network

i) **Comparison to the results obtained from other ML algorithms:** Once the data scarcity issue is partially solved through data augmentation, it is possible to implement other deterministic ML algorithms, such as ANN, DT, and SVM, for risk identification and assessment purposes. This is a supervised learning problem, more specifically a classification problem, for which several ML algorithms are suitable. Each classifier algorithm was applied for the four risks of the Procurement risks category, and results and performance metrics were registered for comparative analysis. The following figures and tables indicate the results obtained from each of the algorithms for the four risks.

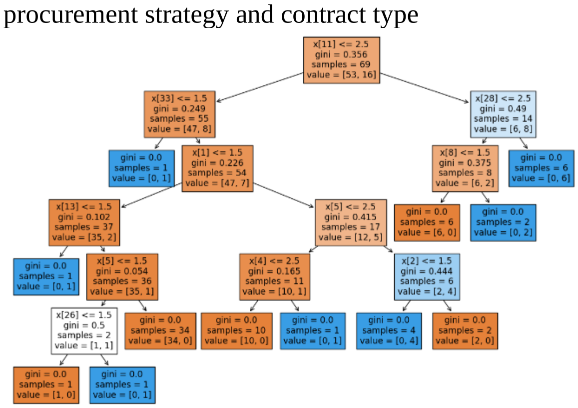
1. Decision Tree: Figures 8.8.a to 8.9.d indicate the structure of the decision trees that were trained. Each node in the tree specifies a condition on a feature that is used to split the data. The tree makes a prediction for a sample by starting at the root and following the path that corresponds to the sample's features until it reaches a leaf node. The prediction of the tree is the value associated with the leaf node. Figures 8.9.a to 8.9.d show the loss function during the learning and validation phases. Table 8.2. indicates the performance metrics for each of the risks. Unfortunately, due to the small size of the database, sometimes the algorithms are overfitted and, despite indicating good accuracy, are not generalizable to other projects. Due to the nature of decision trees, the R2 score might be negative, which indicates that the model is arbitrarily worse.



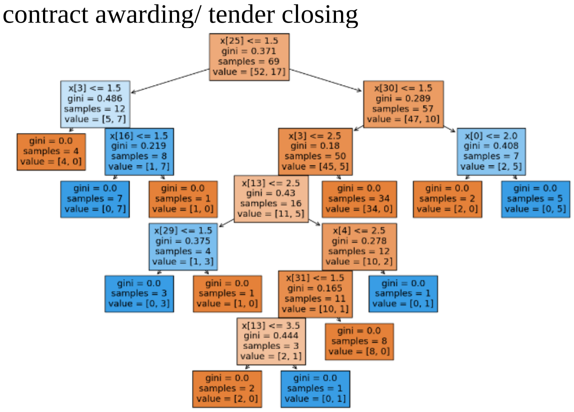
8.8.a. Decision Tree Structure of Risk 1: Change of procurement strategy and contract type



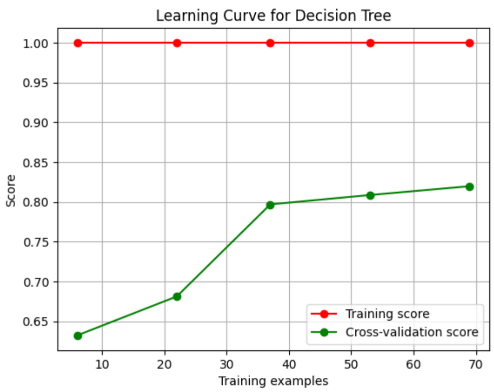
8.8.b. Decision Tree Structure of Risk 2: Delay due to contract awarding/ tender closing



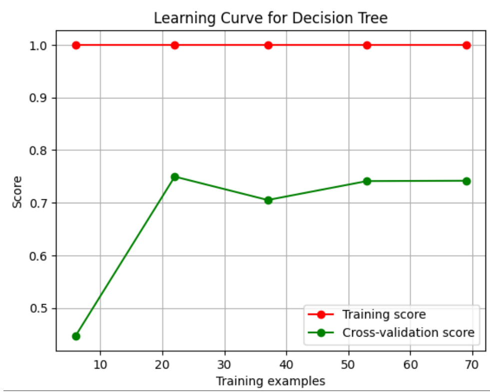
8.8.c. Decision Tree Structure of Risk 3: Vendor list and supply chain disruption



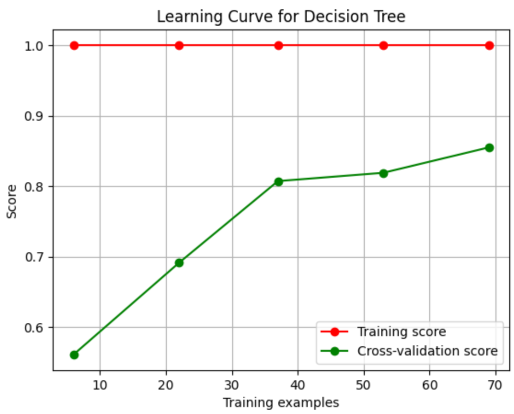
8.8.d. Decision Tree Structure of Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers



8.9.a. Learning curve of Decision Tree for Risk 1: Change of procurement strategy and contract type



8.9.b. Learning curve of Decision Tree for Risk 2: Delay due to contract awarding/ tender closing



8.9.c. Learning curve of Decision Tree for Risk 3: Vendor list and supply chain disruption

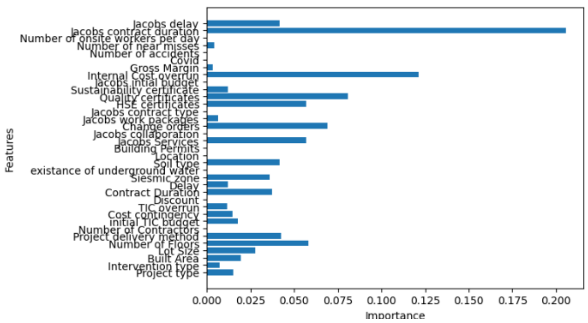
8.9.d. Learning curve of Decision Tree for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers

Table 8.2. Performance metrics of the Decision Tree model for the four procurement risks

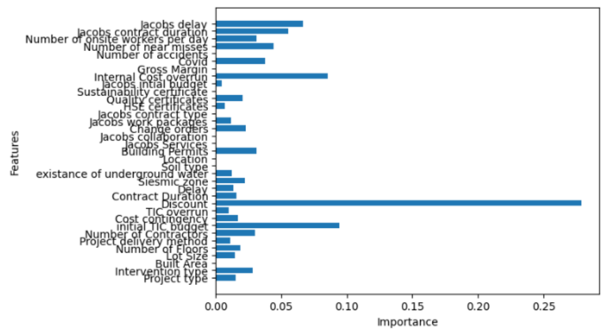
Performance Metrics	Risk 1: Change of procurement strategy and contract type	Risk 2: Delay due to contract awarding/ tender closing	Risk 3: Vendor list and supply chain disruption	Risk 4: Delays and incompliance due to inefficient coordination of third-party suppliers
Accuracy	0.88	0.77	1.0	0.88
MSE	0.11	0.22	0.0	0.11
MAE	0.11	0.22	0.0	0.11
R^2 score	-1.11	0.06	1.0	-1.11
Log loss	4.00	8.0	2.22	4.00

2. Xgboost: XGBoost initializes the model with a single leaf as the initial prediction for all instances in the dataset. This prediction could be the average of the target variable or another value, depending on the objective function. Then, it builds trees one at a time, where each new tree helps to correct the errors made by the previously trained tree. With each tree added, the model

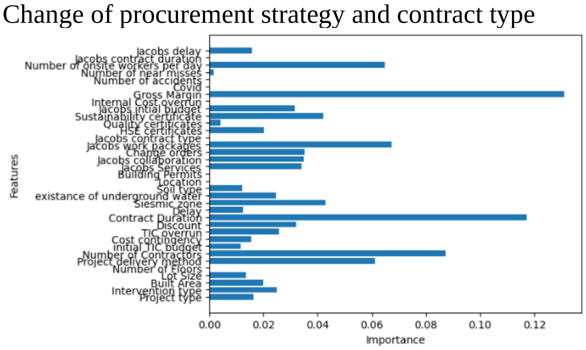
becomes even more expressive. At each iteration, XGBoost identifies the best places to split the data (the "features" to split on) by finding the split that optimizes a given "objective" or "loss" function, depending on the type of problem; for a classification problem, it could be a logistic loss if it is a binary classification or softmax loss for multi-class classification, where gradient descent is used to minimize this loss function. Figures 8.10.a to 8.10.b presents the feature importance of the four risks in XGBoost model, which indicates that the contract duration is the most influential factor. Figures 8.11.a. to 8.11.b show the loss function during the learning and validation phases. Table 8.3. indicates the performance metrics for each of the risks.



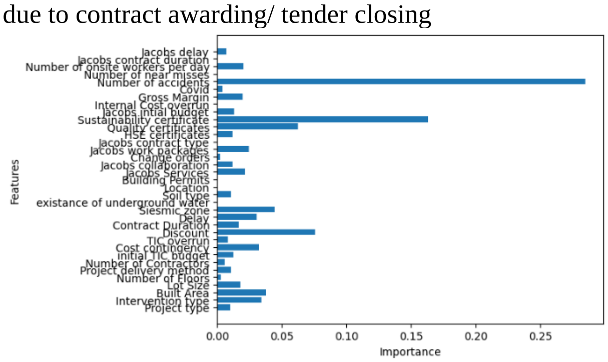
8.10.a. XGboost Feature Importance for Risk 1: Change of procurement strategy and contract type



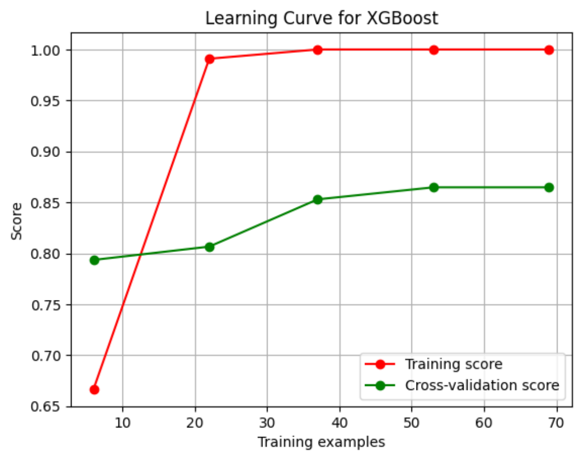
8.10.b. XGboost Feature Importance for Risk 2: Delay due to contract awarding/ tender closing



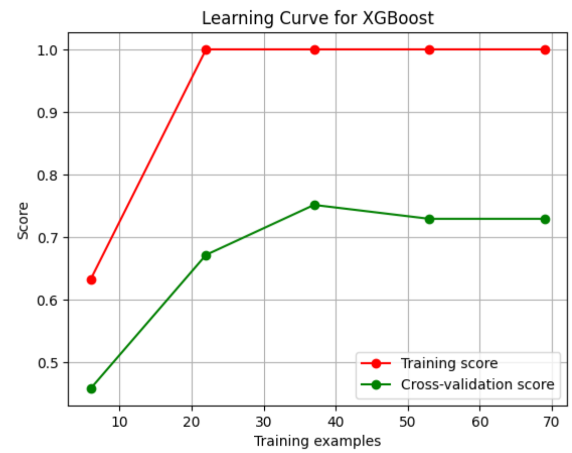
8.10.c. XGboost Feature Importance for Risk 3: Vendor list and supply chain disruption



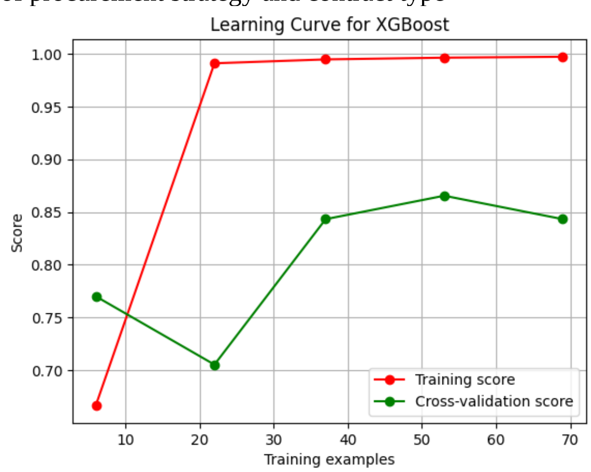
8.10.d. XGboost Feature Importance for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers



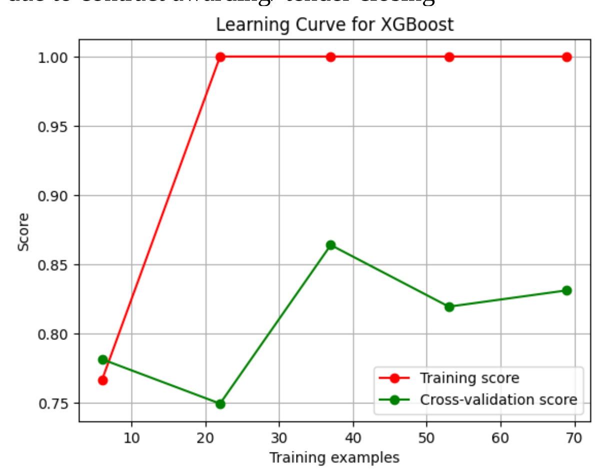
8.11.a. Learning curve of XGboost for Risk 1: Change of procurement strategy and contract type



8.11.b. Learning curve of XGboost for Risk 2: Delay due to contract awarding/ tender closing



8.11.c. Learning curve of XGBoost for Risk 3: Vendor list and supply chain disruption



8.11.d. Learning curve of XGBoost for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers

Table 8.3. Performance metrics of the XGBoost model for the four procurement risks

Performance Metrics	Risk 1: Change of procurement strategy and contract type	Risk 2: Delay due to contract awarding/ tender closing	Risk 3: Vendor list and supply chain disruption	Risk 4: Delays and incompliance due to inefficient coordination of third-party suppliers
Accuracy	0.94	0.77	1.0	0.88
MSE	0.055	0.22	0.0	0.11
MAE	0.055	0.22	0.0	0.11
R^2 score	-0.05	0.06	1.0	-1.11
Log loss	2.00	8.0	2.22	4.00

3. Logistic Regression: Logistic regression models the probability that each input belongs to a particular category. For binary classification, the output is a

probability that the given input point belongs to a certain class. The key component of the logistic regression model is the logistic function, also called the sigmoid function, which takes any real-valued number and maps it into a range between 0 and 1, giving the output a probability interpretation. The loss function used for logistic regression is the log loss, which is a suitable measure for classification. Figures 8.12.a to 8.12.d show the loss function during the learning and validation phases. Table 8.4. indicates the performance metrics for each of the risks.

Figure 8.12.a. Learning curve of Logistic Regression for Risk 1: Change of procurement strategy and contract type

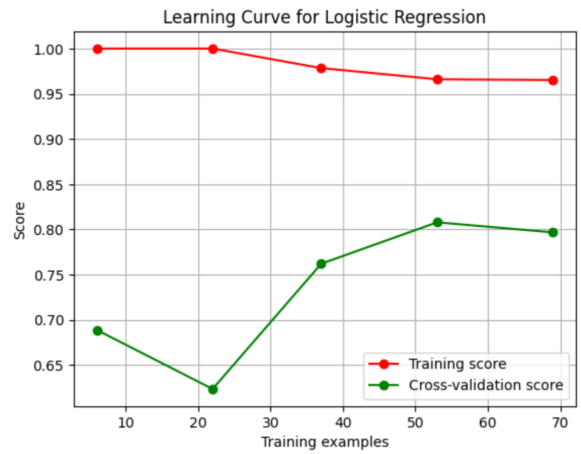


Figure 8.12.b. Learning curve of Logistic Regression for Risk 2: Delay due to contract awarding/ tender closing

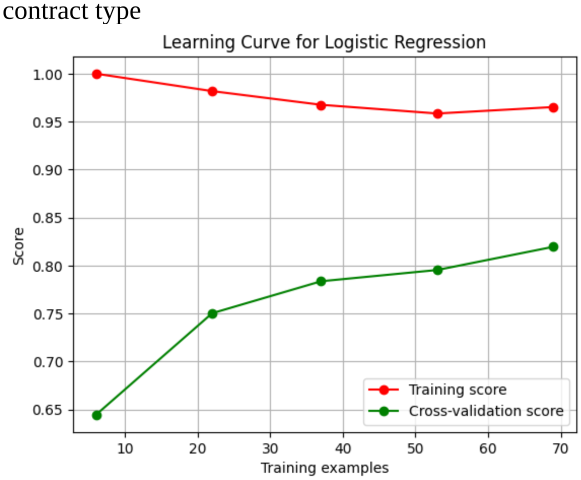


Figure 8.12.c. Learning curve of Logistic Regression for Risk 3: Vendor list and supply chain disruption

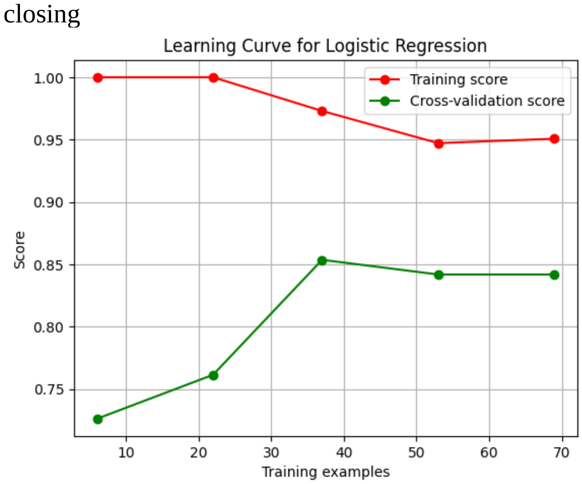


Figure 8.12.d. Learning curve of Logistic Regression for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers

Table 8.4. Performance metrics of the Logistic Regression model for the four procurement risks

Performance Metrics	Risk 1: Change of procurement strategy and contract type	Risk 2: Delay due to contract awarding/ tender closing	Risk 3: Vendor list and supply chain disruption	Risk 4: Delays and incompliance due to inefficient coordination of

				third party suppliers
Accuracy	1.0	0.83	0.83	0.94
MSE	0.0	0.16	0.16	0.05
MAE	0.0	0.16	0.16	0.05
R^2 score	1.0	0.29	0.03	0.43
Log loss	2.22	6.0	6.00	2.0

4. Support Vector Machine: SVMs construct a hyperplane or set of hyperplanes in a high- or infinite-dimensional space. In simple terms, the SVM algorithm finds the line (in 2D), plane (in 3D), or hyperplane (in more than three dimensions) that separates the data into two classes. The objective is to find the "maximum margin" hyperplane that has the largest distance to the nearest training data points of any class. The learning task is formulated as a constrained optimization problem, specifically a quadratic programming problem. This problem is solved using techniques such as Sequential Minimal Optimization. The result of the optimization process is a set of weights (or parameters) that can be used to define the hyperplane for the SVM. Figures 8.13.a. to 8.13.d. show the loss function during the learning and validation phases. Table 8.5. indicates the performance metrics for each of the risks.

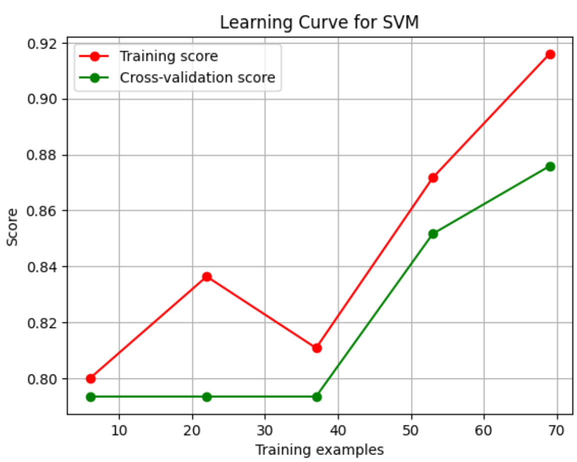


Figure 8.13.a. Learning curve of SVM for Risk 1: Change of procurement strategy and contract type

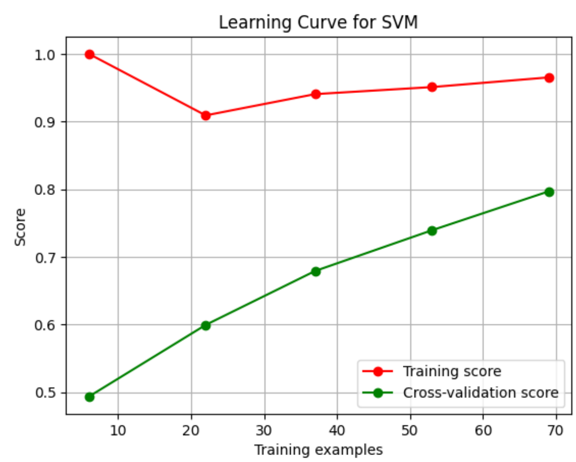


Figure 8.13.b. Learning curve of SVM for Risk 2: Delay due to contract awarding/ tender closing

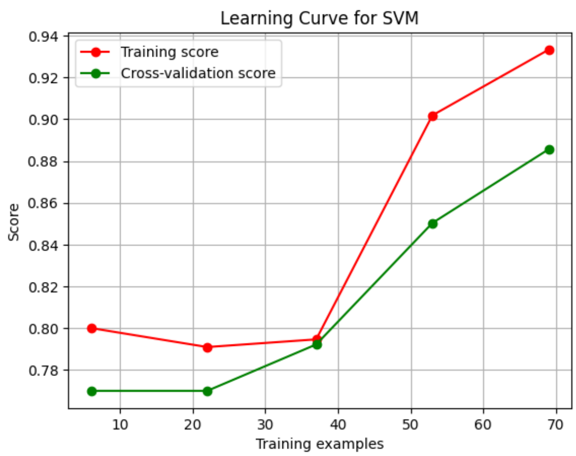


Figure 8.13.c. Learning curve of SVM for Risk 3: Vendor list and supply chain disruption

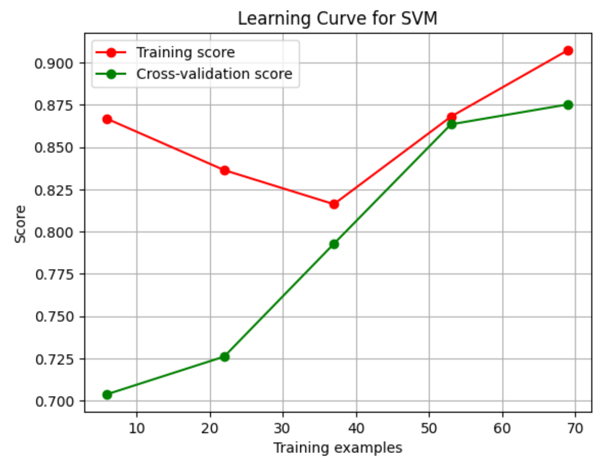


Figure 8.13.d. Learning curve of SVM for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers

Table 8.5. Performance metrics of the SVM model for the four procurement risks

Performance Metrics	Risk 1: Change of procurement strategy and contract type	Risk 2: Delay due to contract awarding/ tender closing	Risk 3: Vendor list and supply chain disruption	Risk 4: Delays and incompliance due to inefficient coordination of third-party suppliers
Accuracy	1.0	0.88	1.0	0.94
MSE	0.0	0.11	0.0	0.05
MAE	0.0	0.11	0.0	0.05
R^2 score	1.0	0.53	1.0	0.43
Log loss	2.22	4.0	2.22	2.0

5. Random Forest: Random Forest builds a set of independent decision trees. Each tree in the Random Forest gets a random subset of the training data (done by bootstrap sampling) and is built independently of the others. For each node in the decision tree, a random subset of features is chosen to decide the best split. This process of selecting random subsets of features adds an extra layer of randomness to the model beyond that introduced by the bootstrap sampling. The split that results in the greatest reduction in the impurity measure is chosen. Random Forests also provide a measure of feature importance, which can be a very handy tool for exploratory analysis to identify features that are particularly useful for prediction. This importance is calculated by looking at how much the tree nodes that use that feature reduce impurity across all trees in the forest.

Figures 8.14.a. to 8.14.d. show the loss function during the learning and validation phases. Table 8.6. indicates the performance metrics for each of the risks.

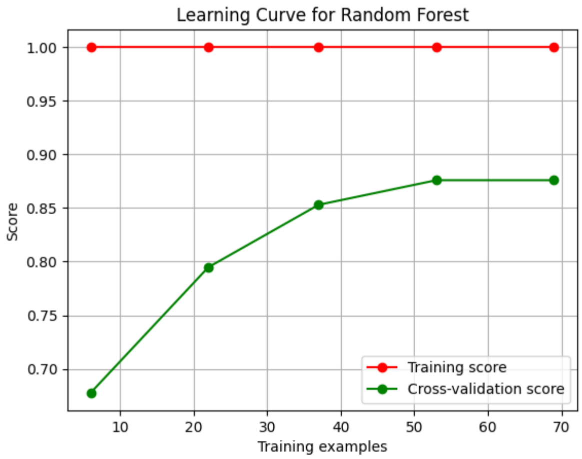


Figure 8.14.a. Learning curve of Random Forest for Risk 1: Change of procurement strategy and contract type

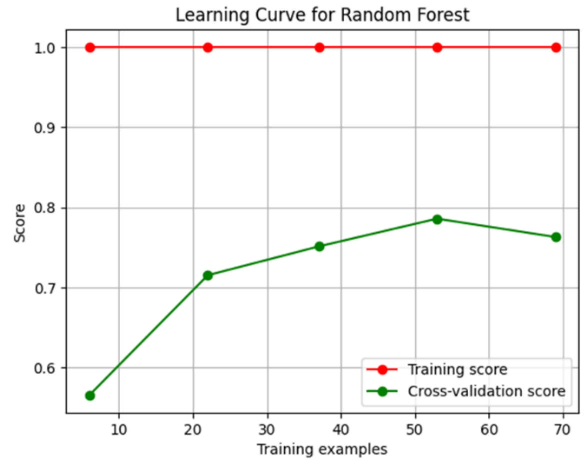


Figure 8.14.b. Learning curve of Random Forest for Risk 2: Delay due to contract awarding/ tender closing

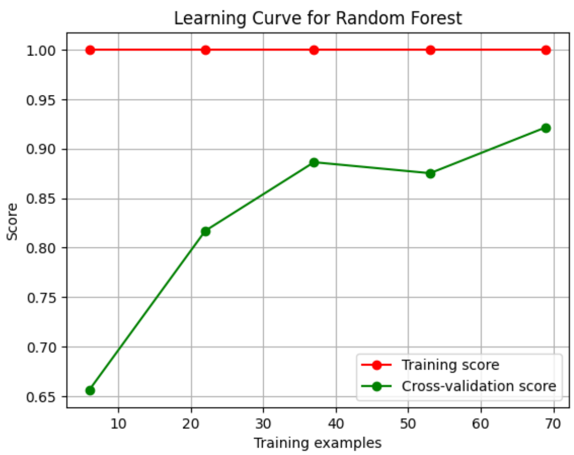


Figure 8.14.c. Learning curve of Random Forest for Risk 3: Vendor list and supply chain disruption

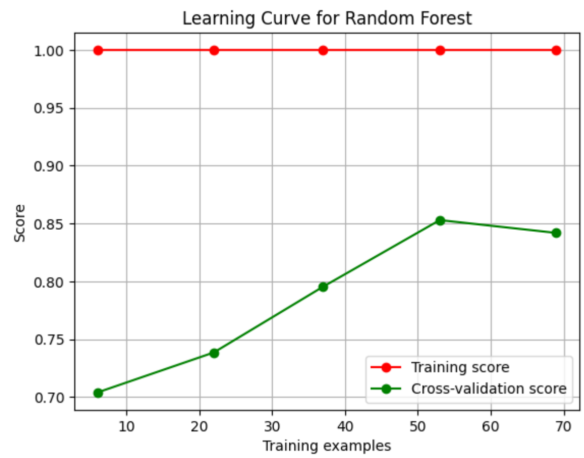


Figure 8.14.d. Learning curve of Random Forest for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers

Table 8.6. Performance metrics of the SVM model for the four procurement risks

Performance Metrics	Risk 1: Change of procurement strategy and contract type	Risk 2: Delay due to contract awarding/ tender closing	Risk 3: Vendor list and supply chain disruption	Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers
Accuracy	1.0	0.88	1.0	0.94
MSE	0.0	0.11	0.0	0.05
MAE	0.0	0.11	0.0	0.05
R^2 score	1.0	0.53	1.0	0.43

Log loss	2.22	4.0	2.22	2.0

6. KNN: The KNN algorithm operates by computing the distance between the input sample and each training instance. This distance can be any metric measure but is commonly the Euclidean distance. Unlike other methods that construct a model from the training data, KNN does not perform explicit training. It simply stores the training dataset. For classification, the most common class among the k neighbors is returned. In other words, the new instance is assigned to the class that has the majority vote among its k nearest neighbors. Figures 8.15.a to 8.15.d show the loss function during the learning and validation phases. Table 8.7. indicates the performance metrics for each of the risks.

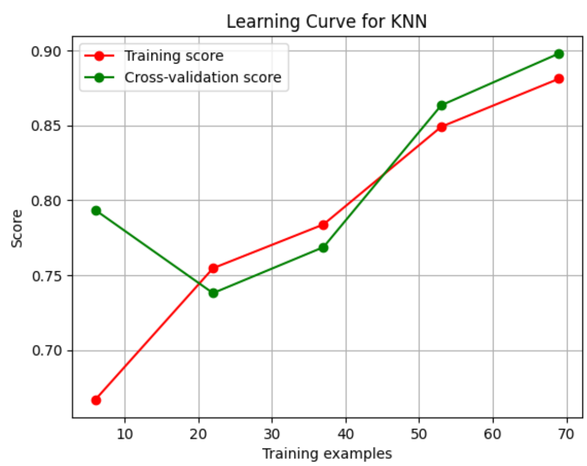


Figure 8.15.a. Learning curve of KNN for Risk 1: Change of procurement strategy and contract type

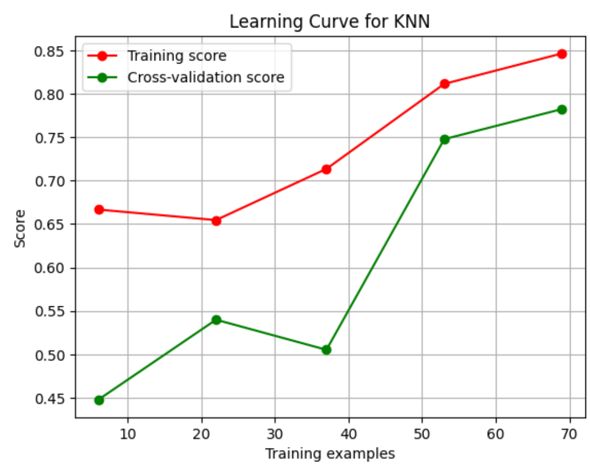


Figure 8.15.b. Learning curve of KNN for Risk 2: Delay due to contract awarding/ tender closing

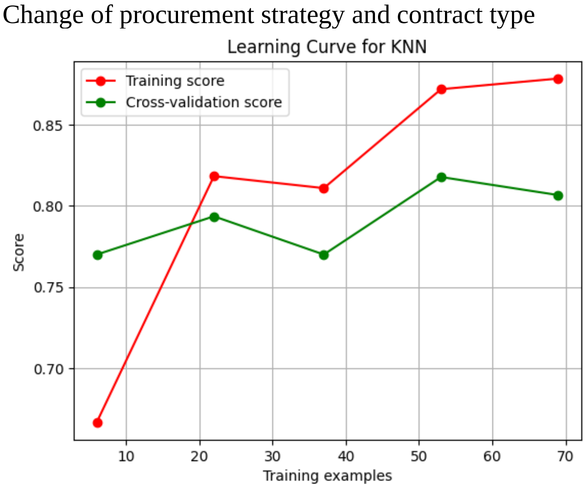


Figure 8.15.c. Learning curve of KNN for Risk 3: Vendor list and supply chain disruption

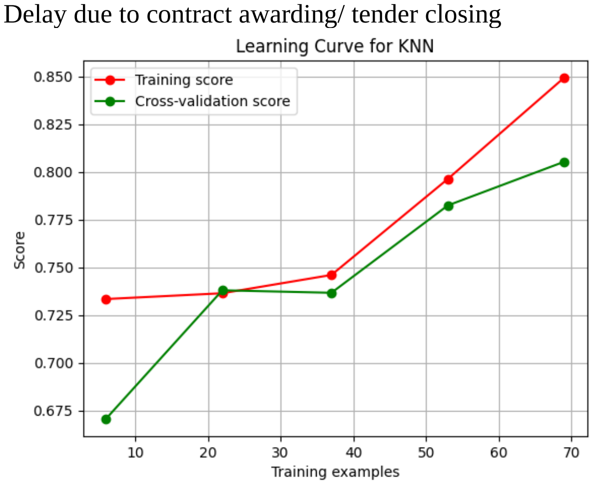


Figure 8.15.d. Learning curve of KNN for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers

Table 8.7. Performance metrics of the SVM model for the four procurement risks

Performance Metrics	Risk 1: Change of procurement strategy and contract type	Risk 2: Delay due to contract awarding/ tender closing	Risk 3: Vendor list and supply chain disruption	Risk 4: Delays and incompliance due to inefficient coordination of third-party suppliers
Accuracy	1.0	0.72	0.88	0.94
MSE	0.0	0.27	0.11	0.05
MAE	0.0	0.27	0.11	0.05
R^2 score	1.0	-0.16	0.35	0.43
Log loss	2.22	10.01	4.0	2.0

7. Naive Bayes Classifier: Naive Bayes uses Bayes' Theorem to calculate the probabilities of each class given the input features. Naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable. The parameters of a Naive Bayes model are estimated from the training data. This is typically done using maximum likelihood estimation (MLE). For each feature and each class, the MLE is used to estimate the parameters of the distribution of the feature given the class. Figures 8.16.a. to 8.16.h. show the loss function during the learning and validation phases and heatmap of correct and wrong predictions. Table 8.8. indicates the performance metrics for each of the risks.

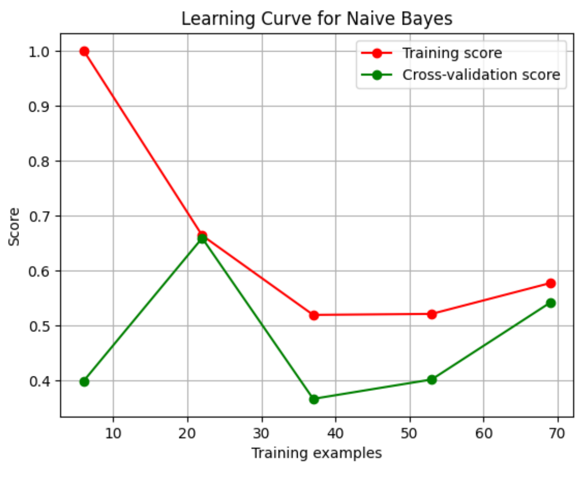
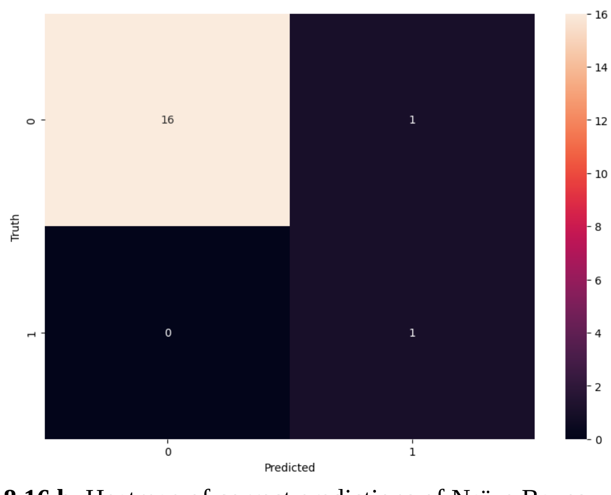


Figure 8.16.a. Learning curve of Naïve Bayes Classifier for Risk 1: Change of procurement strategy and contract type



8.16.b. Heatmap of correct predictions of Naïve Bayes Classifier for Risk 1: Change of procurement strategy and contract type

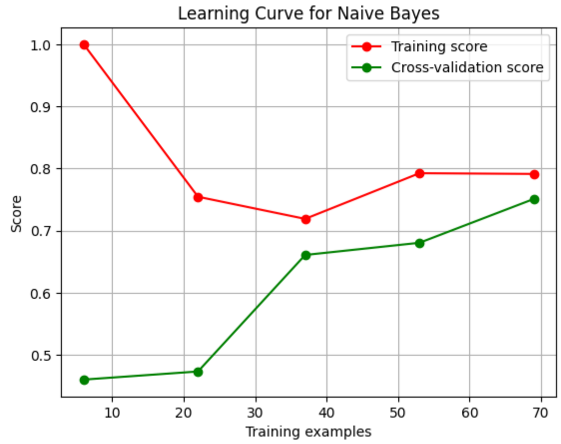


Figure 8.16.c. Learning curve of Naïve Bayes Classifier for Risk 2: Delay due to contract awarding/ tender closing

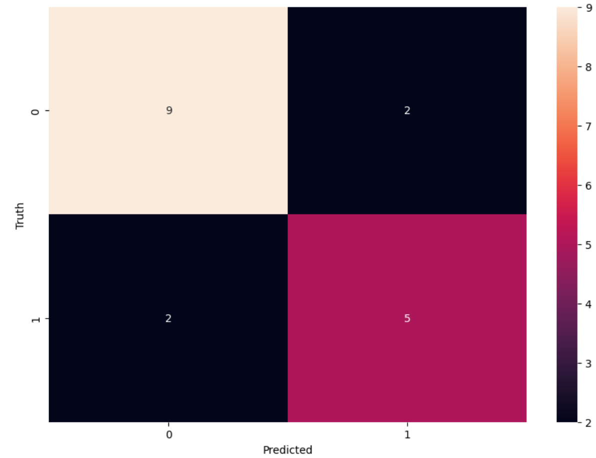


Figure 8.16.d. Heatmap of correct predictions of Naïve Bayes Classifier for Risk 2: Delay due to contract awarding/ tender closing

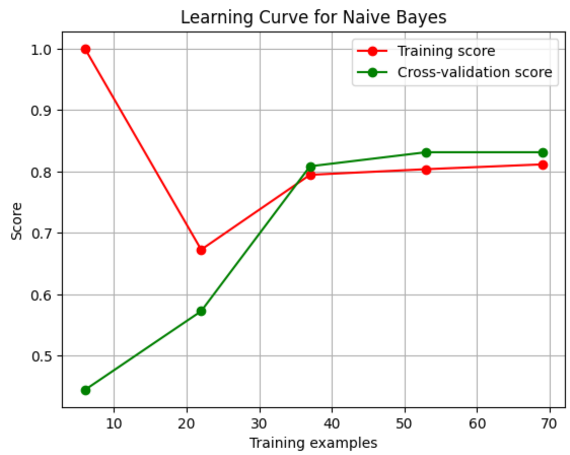


Figure 8.16.e. Learning curve of Naïve Bayes Classifier for Risk 3: Vendor list and supply chain disruption

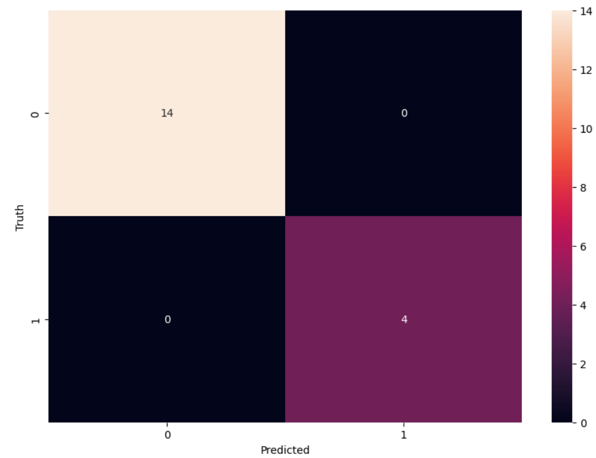


Figure 8.16.f. Heatmap of correct predictions of Naïve Bayes Classifier for Risk 3: Vendor list and supply chain disruption

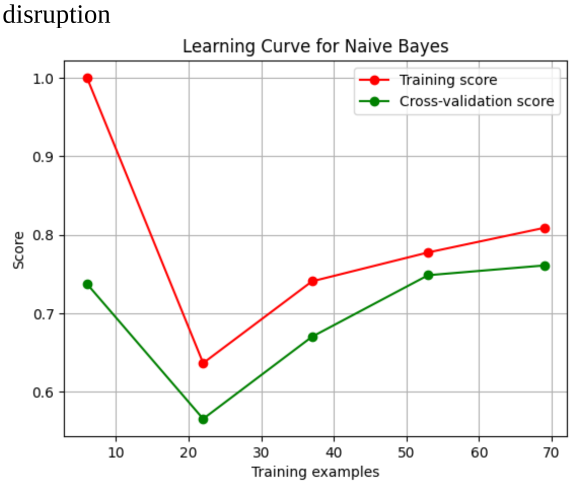


Figure 8.16.g. Learning curve of Naïve Bayes Classifier for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers

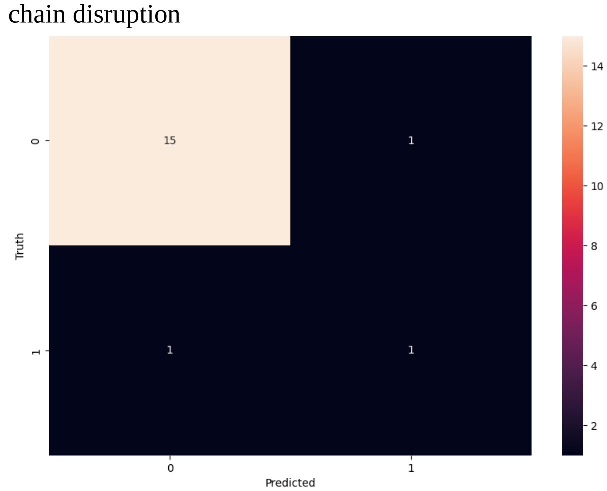


Figure 8.16.h. Heatmap of correct predictions of Naïve Bayes Classifier for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers

Table 8.8. Performance metrics of the Naïve Bayes Classifier model for the four procurement risks

Performance Metrics	Risk 1: Change of procurement strategy and contract type	Risk 2: Delay due to contract awarding/ tender closing	Risk 3: Vendor list and supply chain disruption	Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers
Accuracy	0.38	0.88	1.0	0.88
MSE	0.61	0.11	0.0	0.11
MAE	0.61	0.11	0.0	0.11
R^2 score	-10.64	0.53	1.0	-0.125
Log loss	22.02	4.00	2.22	4.00

8. Artificial Neural Network: Each connection between nodes in the network has a "weight" associated with it, which determines the influence of one node on another. These weights are usually initialized with small random values. The network makes predictions using forward propagation. Starting at the input layer, it applies a series of functions (linear combinations and activation functions) to the inputs and the weights, propagating this information through the hidden layers all the way to the output layer. The result is a predicted output. During backpropagation, the network calculates the gradient of the loss function with respect to the weights. This tells us how much a small change in each weight would help to minimize the loss. One complete pass through the entire training dataset is called an epoch. Figures 8.17.a. to 8.16.d show the loss function during the learning and validation phases. Table 8.9. indicates the performance metrics for each of the risks.

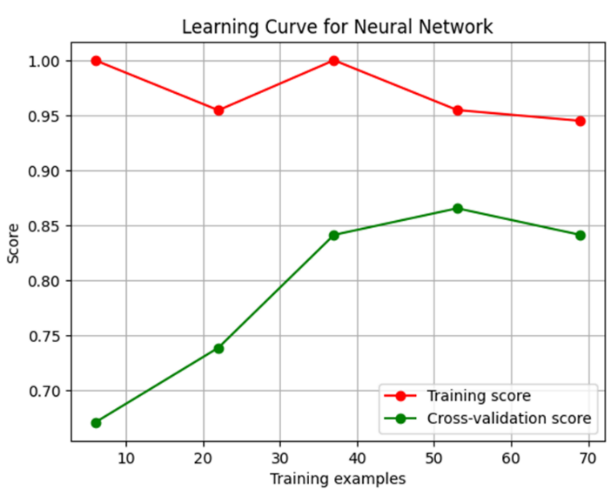


Figure 8.17.a. Learning curve of Neural Networks for Risk 1: Change of procurement strategy and contract type

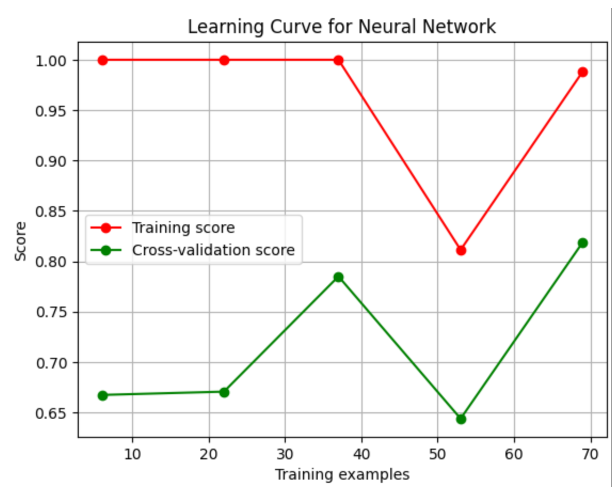


Figure 8.17.b. Learning curve of Naïve Bayes Classifier for Risk 2: Delay due to contract awarding/ tender closing

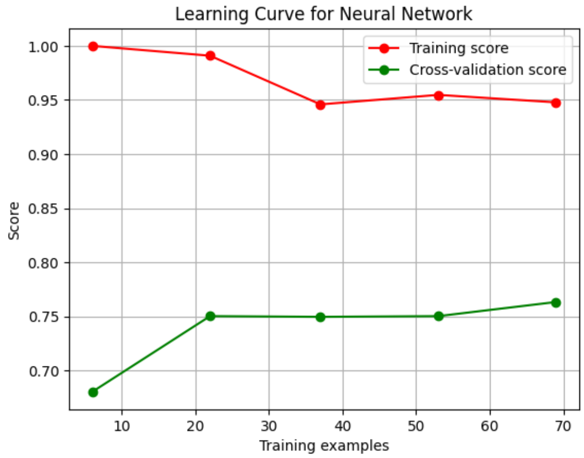


Figure 9.17.c. Learning curve of Naïve Bayes Classifier for Risk 3: Vendor list and supply chain disruption

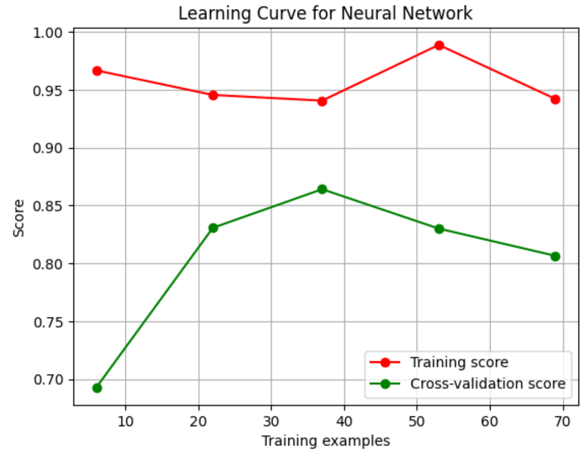


Figure 9.17.d. Learning curve of Naïve Bayes Classifier for Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers

Table 8.9. Performance metrics of the Naïve Bayes Classifier model for the four procurement risks

Performance Metrics	Risk 1: Change of procurement strategy and contract type	Risk 2: Delay due to contract awarding/ tender closing	Risk 3: Vendor list and supply chain disruption	Risk 4: Delays and incompliance due to inefficient coordination of third party suppliers
Accuracy	1.0	0.94	1.0	1.0
MSE	0.0	0.05	0.0	0.0
MAE	0.0	0.05	0.0	0.0
R^2 score	1.0	0.76	1.0	1.0
Log loss	2.22	2.00	2.22	2.22

9. Results summary and Comparison of performance metrics retrieved from each algorithm: Figures 8.18.a. to 8.21.e. indicate the comparative analysis of the eight abovementioned ML algorithms based on their performance metrics for each of the four risks.
   Overall, ANN and XGBoost indicated a better and more consistent performance for all four risks. This is due to their ability to address both linearity and non-linearity in the data. Moreover, their ever-improving and optimized structures help consider the underlying relationships and interdependencies between variables in output prediction. However, due to the small size of the database, most developed models suffer from overfitting, which, despite returning good results for the studied database, makes them ungeneralizable to other databases. Even though data augmentation made it possible to implement deterministic

ML models in the case study database, probabilistic models still outperform this problem type, producing more transparent and realistic results.

Another key point is the inability of ML algorithms to provide a probability assigned to the predictions. The predicted value in the abovementioned algorithms is a binary state, and the probability distribution of each state follows a frequentist statistic, merely considering the repetition of each state in the database. This is a non-realistic and non-accurate way of risk assessment since even though some risks might not be present often in the current database, that does not mean their probability is low. In most cases, the project databases are not representative enough of reality and cannot mimic the future behavior of projects. That is why experts' opinions and experience-based judgments need to be considered to bring the assessments closer to reality. Probabilistic models like BN and FL benefit from expert elicitation and quantify their qualitative assessments into a learnable format for the machine, and hence, can provide a probability assessment of each of the states of the output variable, in this case happening or not happening of the risk. However, deterministic ML models do not have this ability and cannot benefit from Bayesian statistics to assign a probability to the answers. Therefore, probabilistic models are more appropriate for risk assessment purposes, especially in small and incomprehensive databases like the first case study, where deterministic approaches are prone to overfitting.

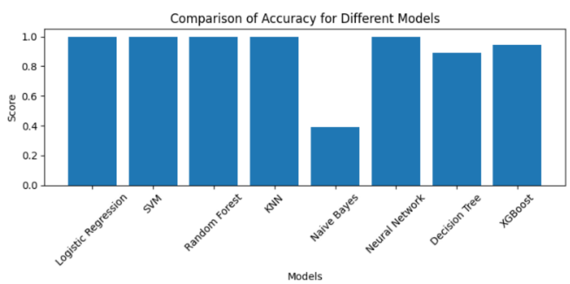


Figure 8.18.a. Comparison of accuracy metrics for different ML algorithms in predicting Risk 1.

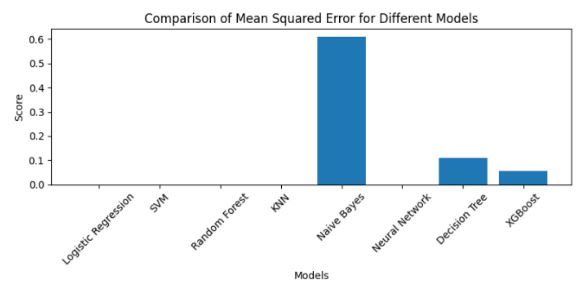


Figure 8.18.b. Comparison of MSE metrics for different ML algorithms in predicting Risk 1.

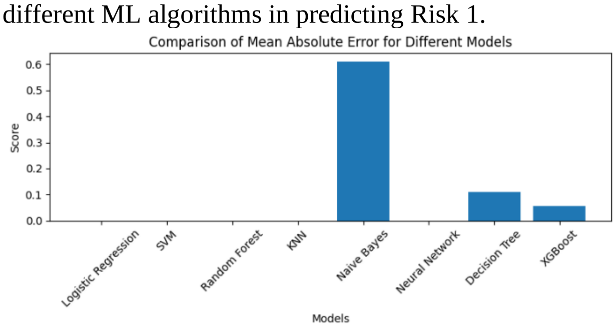


Figure 8.18.c. Comparison of MAE metrics for different ML algorithms in predicting Risk 1.

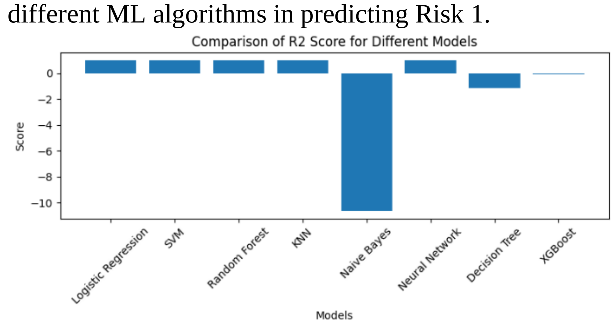


Figure 8.18.d. Comparison of R2 score for different ML algorithms in predicting Risk 1.

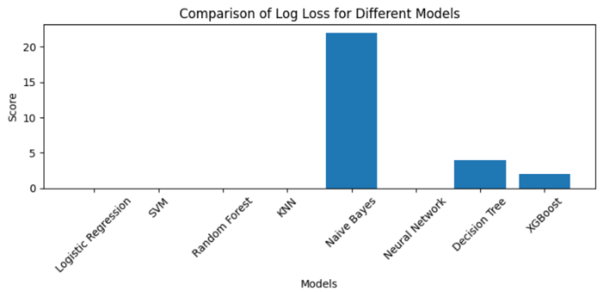


Figure 8.18.e. Comparison of Log loss for different ML algorithms in predicting Risk 1.

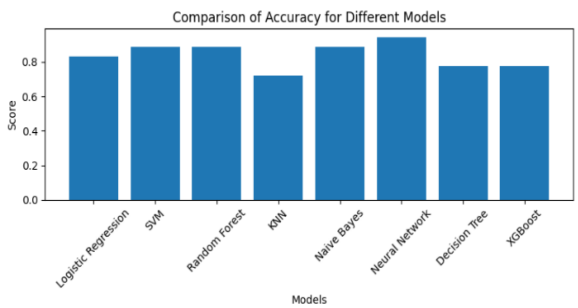


Figure 8.19.a. Comparison of accuracy metrics for different ML algorithms in predicting Risk 2.

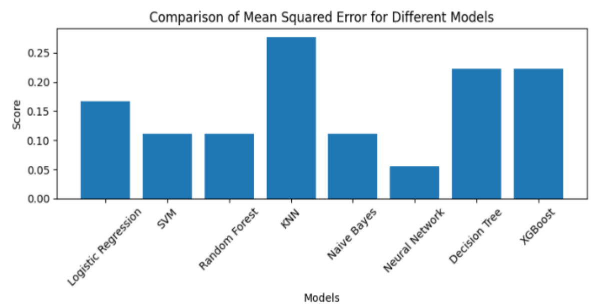


Figure 8.19.b. Comparison of MSE metrics for different ML algorithms in predicting Risk 2.

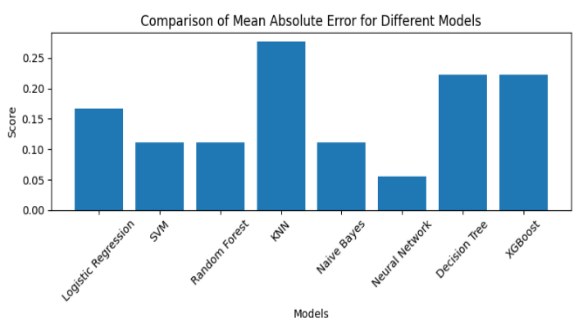


Figure 8.19.c. Comparison of MAE metrics for different ML algorithms in predicting Risk 2.

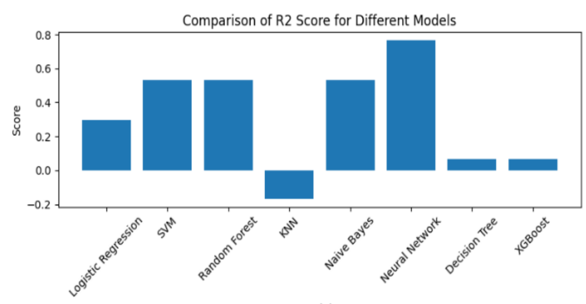


Figure 8.19.d. Comparison of R2 score for different ML algorithms in predicting Risk 2.

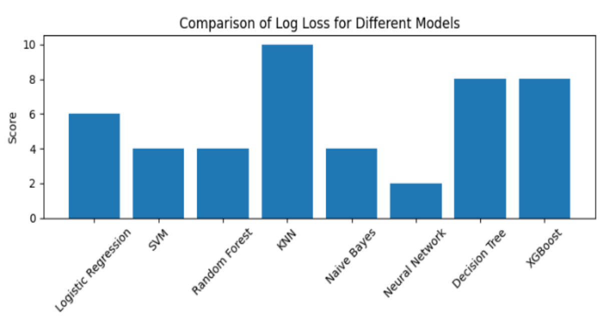


Figure 8.19.e. Comparison of Log loss for different ML algorithms in predicting Risk 2.

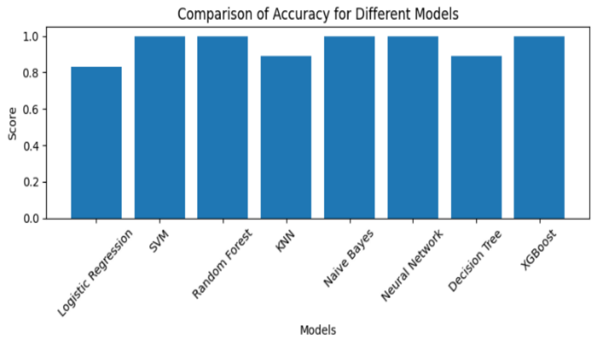


Figure 8.20.a. Comparison of accuracy metrics for different ML algorithms in predicting Risk 3.

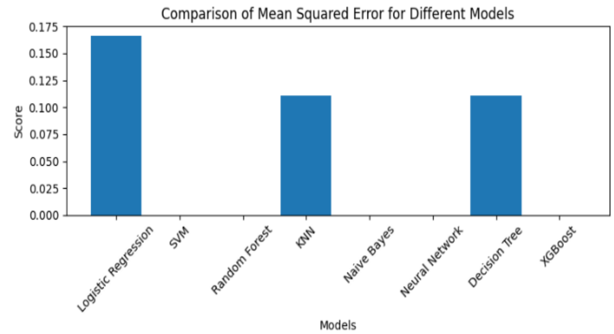


Figure 8.20.b. Comparison of MSE metrics for different ML algorithms in predicting Risk 3.

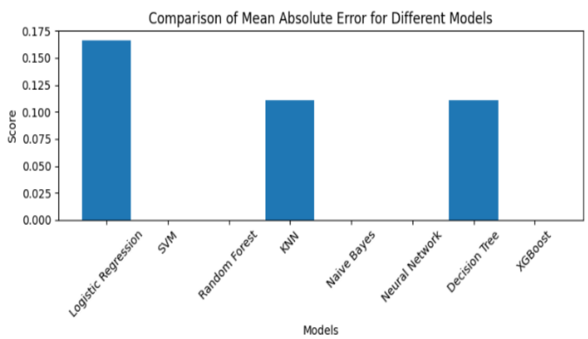


Figure 8.20.c. Comparison of MAE metrics for different ML algorithms in predicting Risk 3.

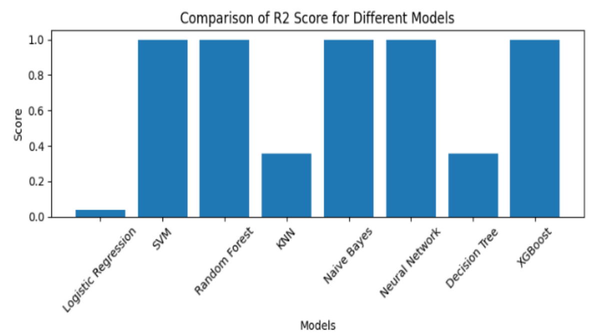


Figure 8.20.d. Comparison of R2 score for different ML algorithms in predicting Risk 3.

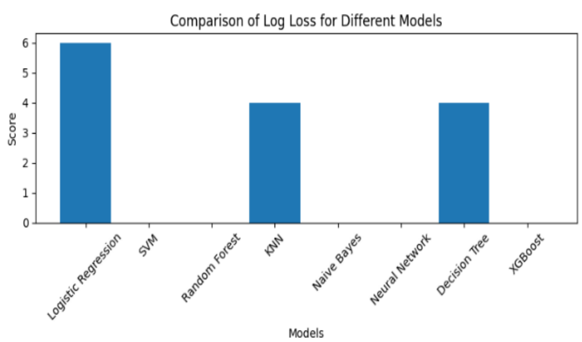


Figure 8.20.e. Comparison of Log loss for different ML algorithms in predicting Risk 3.

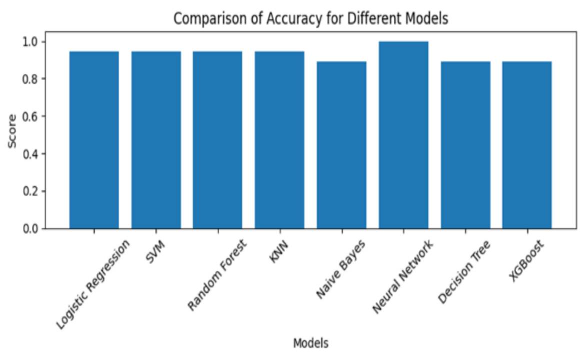


Figure 8.21.a. Comparison of accuracy metrics for different ML algorithms in predicting Risk 4.

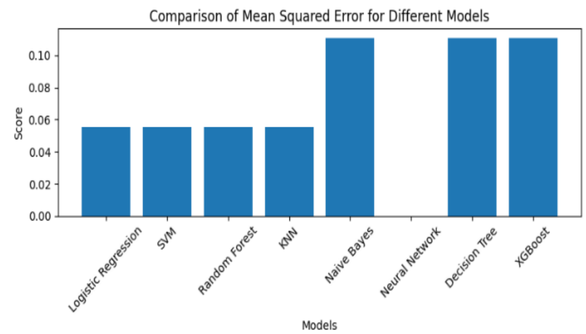


Figure 8.21.b. Comparison of MSE metrics for different ML algorithms in predicting Risk 4.

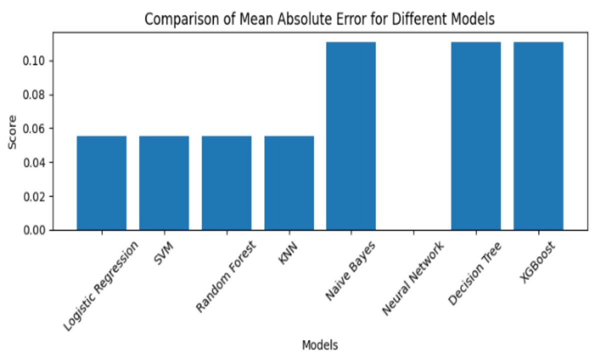


Figure 8.21.c. Comparison of MAE metrics for different ML algorithms in predicting Risk 4.

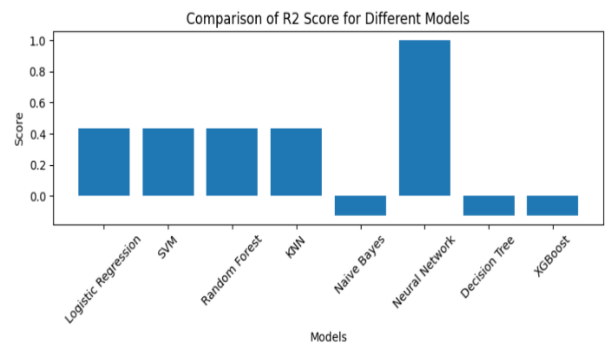


Figure 8.21.d. Comparison of R2 score for different ML algorithms in predicting Risk 4.

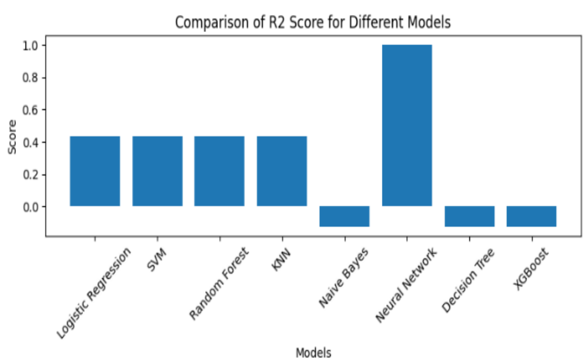


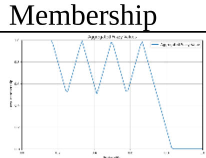
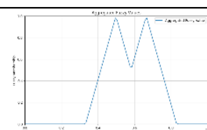
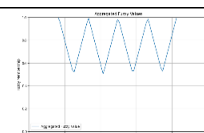
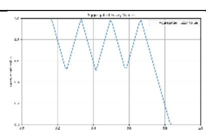
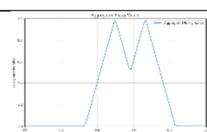
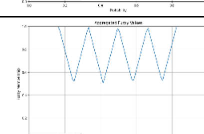
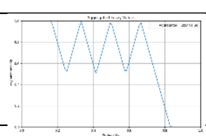
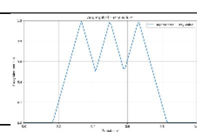
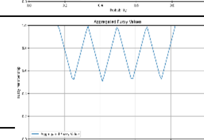
Figure 8.21.e. Comparison of Log loss for different ML algorithms in predicting Risk 4.

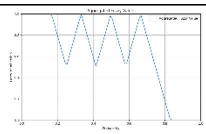
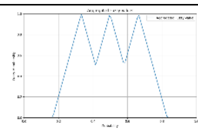
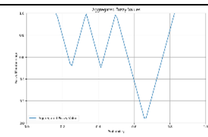
j) **Fuzzy Logic Model:** The fuzzy logic model was developed based on the eleven experts' opinions about the four procurement risks. Table 9.10. indicates the assessment of experts on the risk probability given project cost overrun using linguistic terms and Table 8.11. presents the fuzzy aggregation of experts' opinions and the deffuzified crisp value using the weighted average method.

Table 8.10. Experts' linguistic assessment of procurement risks given different states of project cost overrun

Risk	Cost overrun	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11
Change of procurement strategy and contract type	**Low**	Low	Low	Mid	Mid	Low	Very Low	NA	Low	High	Very Low	High
	Mid	Mid	Mid	Mid	Mid	Mid	Mid	Na	High	Mid	High	Mid
	High	Very High	High	Mid	Low	Mid	Very High	Very High	Very High	Mid	Very Low	Low
Delay due to contract awarding/ tender closing	**Low**	Low	Low	Mid	Mid	Mid	Very Low	NA	Low	High	Very Low	High
	Mid	Mid	Mid	Mid	Mid	Mid	Mid	Na	High	Mid	High	Mid
	High	Very High	High	Mid	Low	Mid	Very High	Low	Very High	Low	Very Low	Low
Vendor list and supply chain disruption	**Low**	Low	Low	Mid	High	Low	Very Low	NA	Low	Mid	Very Low	High
	Mid	Mid	Mid	Mid	Mid	Low	Mid	Na	Mid	High	High	Mid
	High	Very High	Very High	Mid	Low	Low	Very High	Mid	High	Mid	Very Low	Low
Delays and incompliance due to inefficient coordination of third party suppliers	**Low**	Low	Low	Mid	Low	Low	Very Low	NA	Low	Mid	Very Low	High
	Mid	High	Mid	Mid	Mid	Low	Mid	Na	High	High	High	Mid
	High	Very High	Very High	Mid	Low	Low	Very High	Very High	Very High	Mid	Very Low	Low

Table 8.11. Deffuzification of Experts assessments fuzzy aggregation for cost overrun

Risk	low	Aggregated Fuzzy Membership	mid	Aggregated Fuzzy Membership	high	Aggregated Fuzzy Membership
Change of procurement strategy and contract type	0.39		0.53		0.57	
Delay due to contract awarding/ tender closing	0.41		0.53		0.51	
Vendor list and supply chain disruption	0.39		0.49		0.53	

Delays and incompliance due to inefficient coordination of third-party suppliers	0.36		0.54		0.57	

This process is repeated for all the twelve project variables that are affecting the procurement risks. The crisp values calculated represent the collective probability assessment of the risks given each condition of the project features. The next step is the rule-based analysis of the risks given different scenarios for projects, which is modeled in Mathlab. Since the number of variables is high and considering all will require more than 11000 rules, the structure developed by BN is used, presented in Figure 8.22. For instance, the three variables of “Cost Contingency”, “Initial TIC budget”, and “Cost Overrun” influence an intermediate node called “financial risk”, which eventually influences the Procurement risks. This scenario, which includes three input variables and an output variable with fuzzy distribution and assigned fuzzy sets for each of their states, is modeled in Mathlab. Figures 8.23.a. to 8.23.d. indicate the fuzzy membership function of each of the input and output variables. Figures 8.24.a. to 8.24.d. present the fuzzy rules between input and output variables and two case-based analyses for average and risky options.

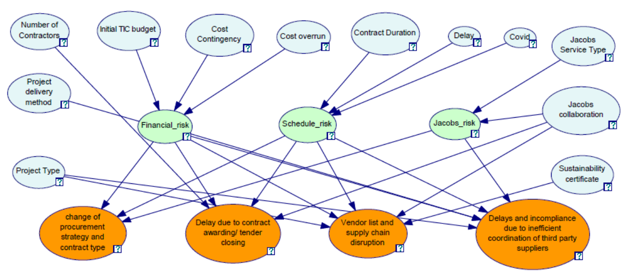


Figure 8.22. graph structure for the procurement risks

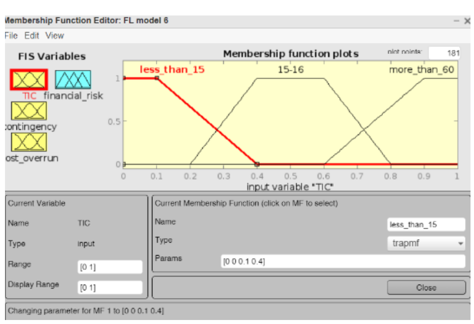


Figure 8.23.a. Fuzzy membership function of TIC budget

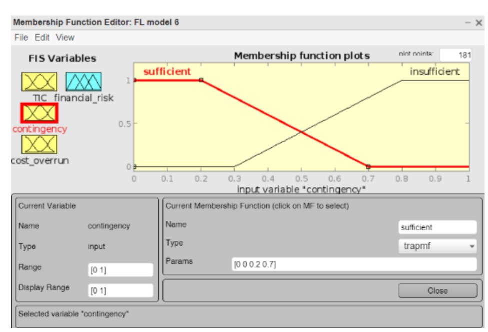
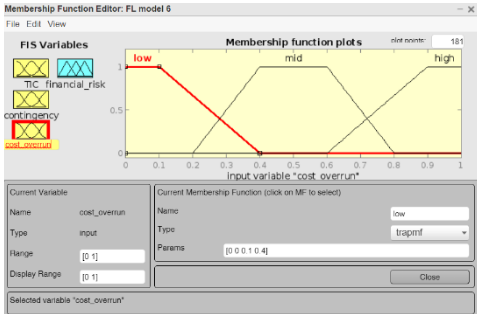


Figure 8.23.b. Fuzzy membership function of cost contingency



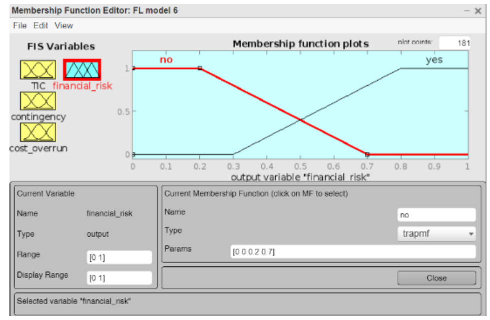


Figure 8.23.c. Fuzzy membership function of cost overrun

Figure 8.23.d. Fuzzy membership function of final output

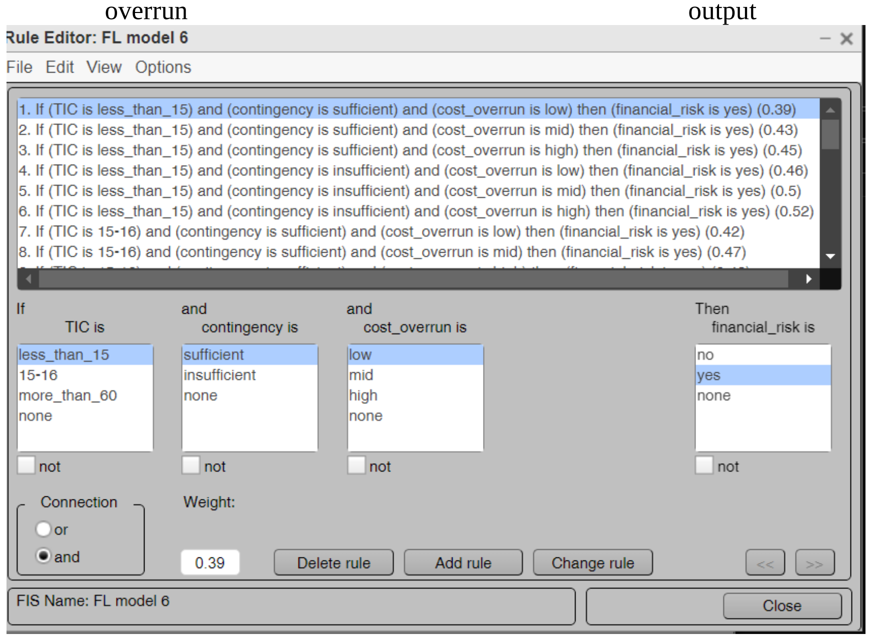
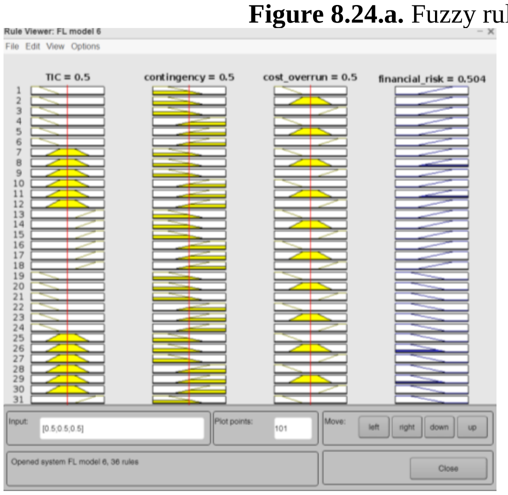


Figure 8.24.a. Fuzzy rules to connect inputs and the output



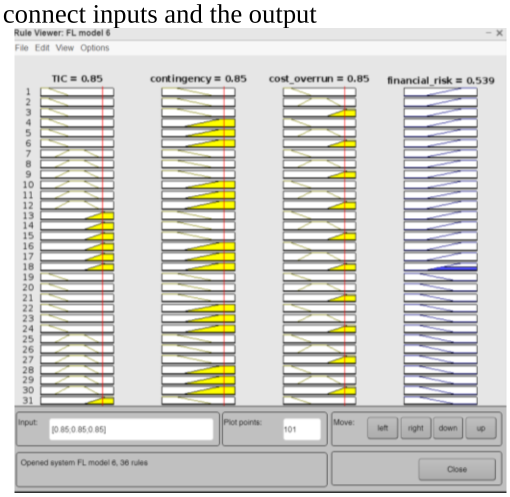


Figure 8.24.b. Case based analysis for an average project

Figure 8.24.c. Case based analysis for a more risky project

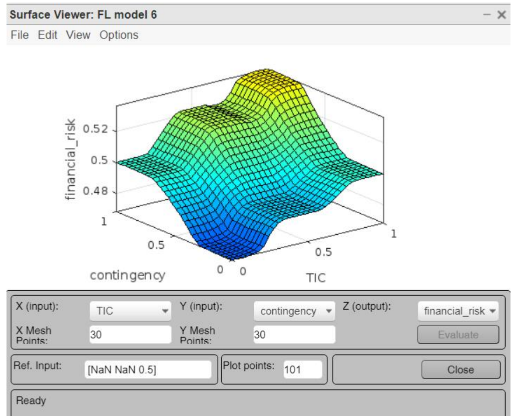


Figure 8.24.d. Surface analysis between TIC, cost contingency, and final output

Now that the algorithm can run a case-based analysis, it is important to simulate all the scenarios possible and create a probability distribution to evaluate the overall probability of each risk given all the possible scenarios. It is noteworthy that since this model is merely based on experts' opinions and not projects' data, the probabilities of all scenarios are considered equal, assigning the same prior distribution to all scenarios, which is not accurate in reality.

For running this simulation and finding the joint probability distribution of posteriors, the Scikit Fuzzy library in Python was used, the code of which can be found here. All the if rules created in MATLAB are imported in Python with the prior aggregated experts, opinions as the probability of each rule happening, like the one depicted in Table 8.11. Then, all the possible scenarios with their probabilities are run, and the integral of their probability distributions is calculated, the average of which presents the overall possibility of "yes" and "no" states or the probability of the risk happening considering all the possible scenarios. The probability of the financial risk being calculated from the FL method is 44%, which is about 11% more than the calculation of the BN model. Figures 8.25.a and 8.25.b show the probability distribution of "yes" state given two of the scenarios for the financial risk, and Figure 8.26 shows the overall probability of the "yes" and "no" states happening considering all the scenarios.

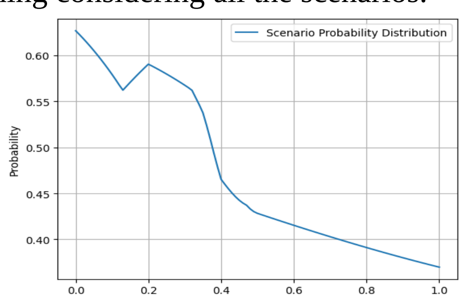


Figure 8.25.a. Probability distribution for the financial risk given this scenario:

- Initial TIC budget: less than 15
- Cost Contigency: sufficient
- Cost Overrun: low

Where the Financial risk output sum equals to 0.44

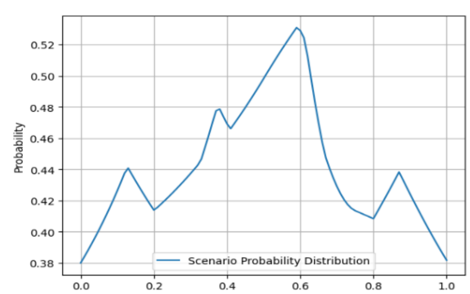


Figure 8.25.b. Probability distribution for the financial risk given this scenario:

- Initial TIC budget: 15 to 60
- Cost Contingency: insufficient
- Cost Overrun: low

Where the Financial risk output sum equals to 0.5

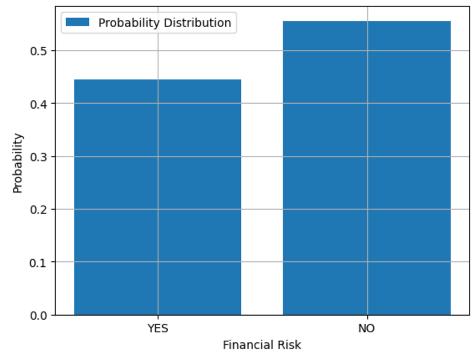


Figure 8.26. The final probability of each of the states of financial risk considering all the possible scenarios

The same scenario modeling process was repeated for all the intermediate nodes and finally the child nodes or the 4 procurement risks, as a result of which, the probability of each of the risks calculated by the FL model are as following:

- Probability of Risk 1: “Change of procurement strategy and contract types” happening is 33%, which is 8% more than the BN model calculation,
- Probability of Risk 2: “Delay due to contract awarding/ tender closing” happening is 48%, which is 4% more than the BN model calculation,
- Probability of Risk 3: “Vendor list and supply chain disruption” happening is 31%, which is 5% more than the BN model calculation,
- Probability of Risk 4: “Delays and incompliance due to inefficient coordination of third-party suppliers” happening is 24%, which is 3% more than the BN model calculation,

In conclusion, the results obtained from the FL model had higher probability estimations for each of the risks compared to the BN model, which combines two sources of data. Therefore, the results indicated that the experts assess the risk probability as higher than what happens and has happened in projects. On the other hand, if the judgment is merely based on historical project data, it might not be accurate and realistic since the database is so small and cannot properly represent the actual conditions of projects. Therefore, combining the subjective experts’ opinions with the objective project data obtained, like the process in the BN model, can balance the assessments and provide more realistic probabilities for risks. Accurate and fact-based risk assessments can greatly help project managers in their decision-making process for mitigating risks and allocating resources to overcome them.

8.1.2. Results of Second Case Study

The database of the second case initially had 13570 rows, 1489 of which remained after the data cleaning and preprocessing phases. Even after these phases, it had a massively bigger database compared to the first one, which affected the results and accuracy obtained from each algorithm. In order to compare the results, the same ML algorithms, including XGBoost, ANN, Ridge and Linear Regression, Decision Tree, and BN, were applied. However, the problem type, in contrast to the first case study, was regression. The algorithms had to predict the final delay and spending of each project. Below, the comparative results analysis for each of the two target variables is presented.

- **Delay Prediction:** Table 8.12. presents the results obtained from each ML algorithm when predicting the delay. The performance of each algorithm is assessed using the four tests of R2, Mean of Cross-Validation (CV), MSE, and MAE. Based on the obtained results, XGBoost model outperforms the other algorithms due to its robust gradient-boosting framework that combines multiple decision trees, enhancing accuracy and reducing overfitting. This results in the highest R-squared value (0.91), indicating a strong correlation between the predicted and observed values, as well as the lowest Mean Squared Error (45.77) and Mean Absolute Error (3.5 weeks), signifying superior prediction accuracy. The Decision Tree model follows with a slightly lower performance, which can be attributed to its single-tree structure, making it more prone to overfitting than the XGBoost model. It is worth noting that the ANN model does exhibit a good mean of CV scores, indicating an acceptable level of generalizability. However, when considering other performance metrics, such as R-squared, MSE, and MAE, the XGBoost model still outperforms the ANN model. Linear and Ridge Regression models have the lowest performance since these models assume a linear relationship between the predictors and the target variable, which is not the case for complex datasets. Consequently, they do not effectively capture the underlying patterns in the data, leading to reduced prediction accuracy. Notably, the Bayesian Network Model (Tree augmented Naïve Bayes Model) has poor performance compared to the other deterministic ML models, as in the database, most of the variables are independent, and there are no strong interdependencies or causal inferences to make the BN model suitable. Moreover, due to the huge size of the database, the black box ML models based on frequentist statistics and with more advanced structure compared to the white box probabilistic models outperform. Therefore, the hypothesis that the size of the database has a huge effect on the developed models' performance is approved. Figures 8.27.a to 8.27.c present the BN structure developed in GENIE, a case-based analysis for one of the projects in the database and the strength of influence of each of the arcs. As evident in this figure, there is a weak influence between variables, indicating their little interconnectedness and interdependencies, making probabilistic models like BN improper for this database. Figures 8.28.a and 8.28.b. present the ROC curve of two of the delay states, indicating the learning process.

Table 8.12. Comparison of the ML algorithms results for delay prediction

Variable	Algorithms					
Evaluation	DT	ANN	LR	RR	XGBoost	BN
R2	0.86	0.73	0.71	0.71	**0.91**	
Mean of CV	0.68	**0.78**	0.53	0.53	0.75	0.66
MSE	68.1	128.9	145.61	145.3	**45.77**	
MAE	3.68	5.32	8.36	8.34	**3.50**	

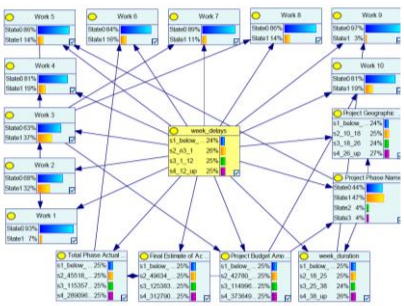


Figure 8.27.a. BN structure developed for the Delay risk prediction

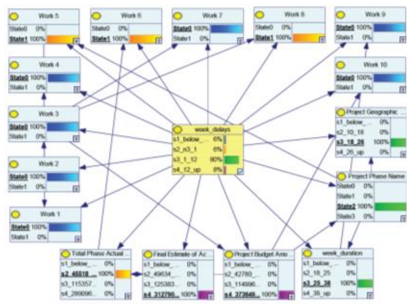


Figure 8.27.b. Case based analysis of the BN structure developed for the Delay risk prediction

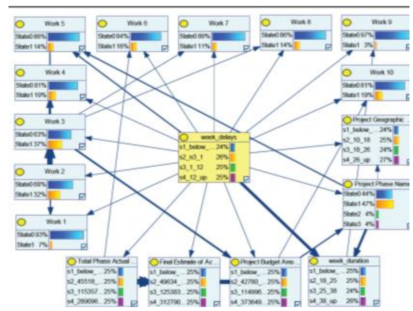


Figure 8.27.c. Influence strength of the Delay risk network

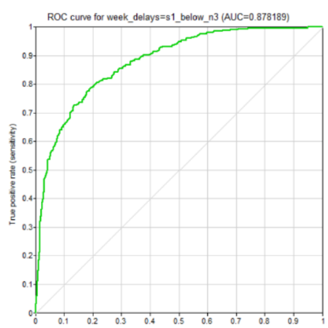


Figure 8.28.a. ROC curve for the first state of delay risk during the learning process

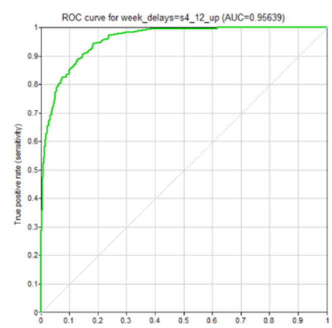


Figure 8.28.b. ROC curve for the second state of delay risk during the learning process

- **Total Cost Prediction.** In the case of total cost prediction, the XGBoost model again demonstrates the best performance, as presented in Table 8.13., achieving the highest R-squared value and the lowest error rates. The DT model's lower MSE compared to XGBoost, despite the latter's better MAE, can be explained by the unique characteristics of these error metrics. The MSE focuses on more significant errors by squaring the differences between predicted and observed values. In this case, the Decision Tree model may have a few significant errors that are heavily penalized by the MSE metric. In contrast, the MAE calculates the average of the absolute differences between predicted and observed values, treating all errors equally. The better MAE for the XGBoost model indicates that, on average, its predictions are closer to the actual values, making it a more accurate model overall for this variable. The Linear and Ridge Regression models yielded better results for predicting total costs than delays. Given that Linear and Ridge Regression models assume a linear relationship between variables and considering that the underlying relationship between the input variables and the "Total Phase Actual Spending Amount ($)" is predominantly linear, it allowed the models to capture the patterns in the data more effectively than the ANN model. The probabilistic BN model had a much better performance for total cost prediction compared to the delay prediction model, with a mean of cross-validation equal to 0.90. The main reason is a stronger influence of arcs and greater interdependencies between cost-related variables. Figures 8.29.a. to 8.29.c. present the BN structure developed in GENIE, a case-based analysis for one of the same projects in the database, and the strength of influence of each of the arcs. However, due to the huge size of the database, the deterministic approaches still outperform the probabilistic ones. Figures 8.30.a. and 8.30.b. present the ROC curve of two of the delay states indicating the learning process.

Table 8.13. Comparison of the ML algorithms results for total cost prediction

Attribute			Algorithms			
Evaluation	DT	ANN	LR	RR	XGBoost	BN
R2	0.88	0.83	0.97	0.97	0.98	
Mean of CV	0.83	0.97	0.84	0.84	0.97	0.90
MSE	30238740540	42462464672	6103773414	6102901345	3465322264	
MAE	36972	75820	38064	38127	22166	

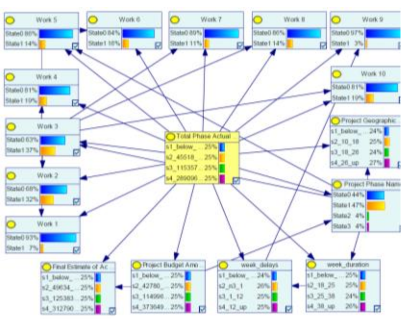


Figure 8.29.a. BN structure developed for the total cost prediction

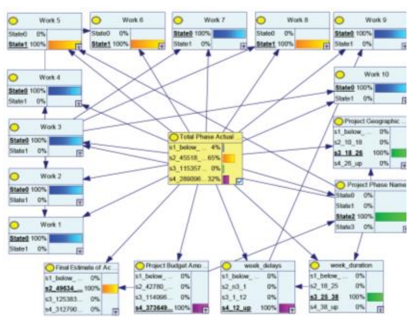


Figure 8.29.b. Case based analysis of the BN structure developed for the total cost prediction

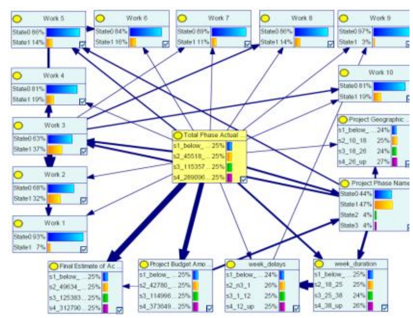


Figure 8.29.c. Influence strength of the total cost network

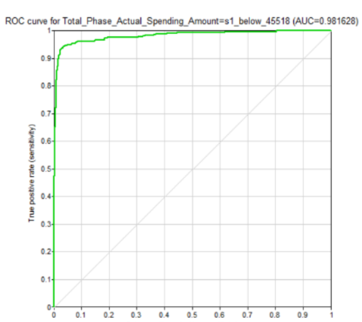


Figure 8.30.a. ROC curve for the first state of total cost during the learning process

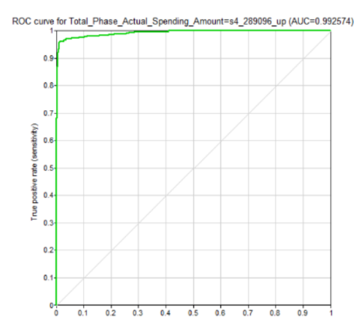


Figure 8.30.b. ROC curve for the second state of total cost during the learning process

As a result, the XGBoost model emerges as the most accurate algorithm for predicting delays and total costs, owing to its robust gradient-boosting framework and ability to handle complex datasets effectively. Figures 8.31.a to 8.33.c. present the delay and cost overrun prediction precision and feature importance for Decision Tree, ANN, and XGBoost algorithms, respectively. An important point is the significant importance and influence of project duration on final delay and total cost in all three algorithms.

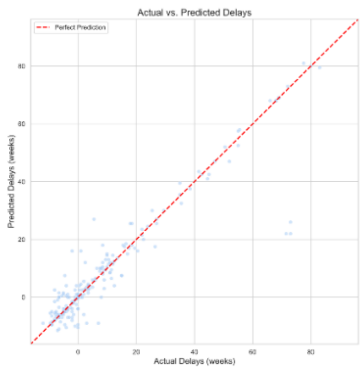


Figure 8.31.a. DT prediction accuracy for Delays

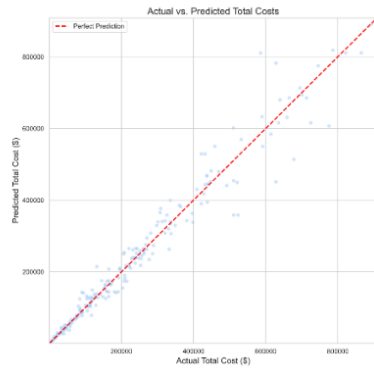


Figure 8.31.b. DT prediction accuracy for Total costs

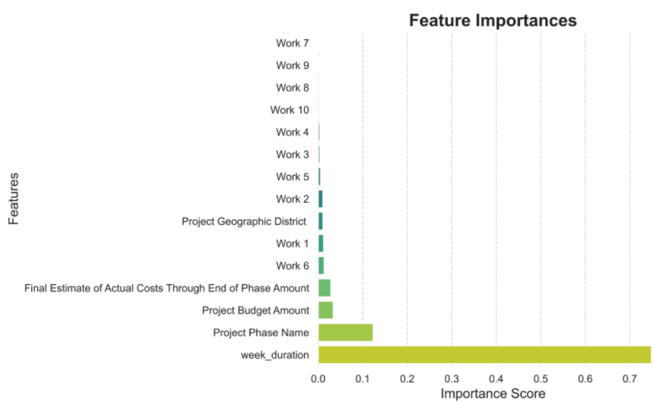


Figure 8.31.c. Feature Importance for DT model

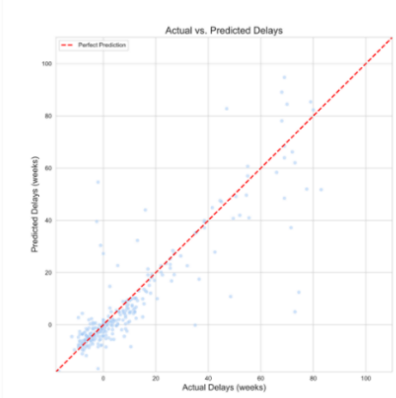


Figure 8.32.a. ANN prediction accuracy for Delays

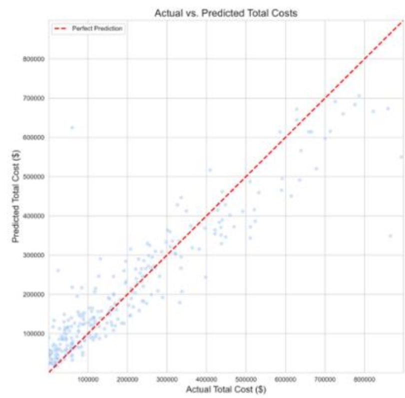


Figure 8.32.b. ANN prediction accuracy for Total costs

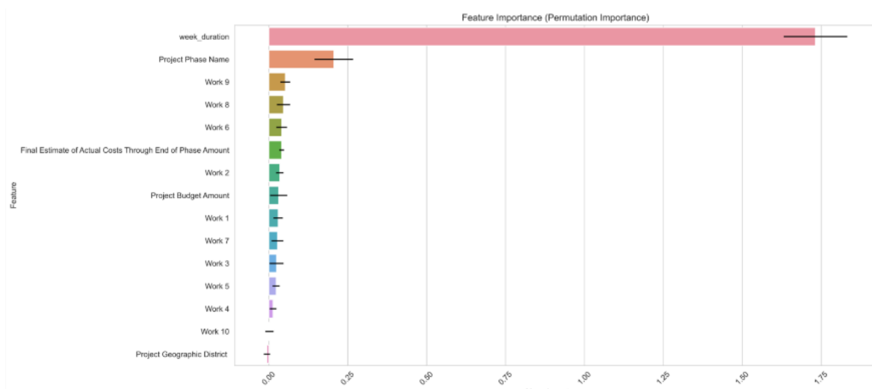


Figure 8.32.c. Feature Importance for ANN model

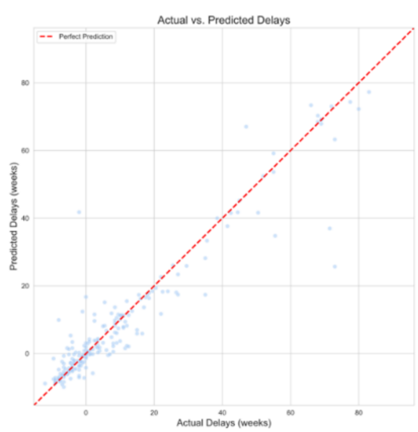


Figure 8.33.a. XGBoost prediction accuracy for Delays

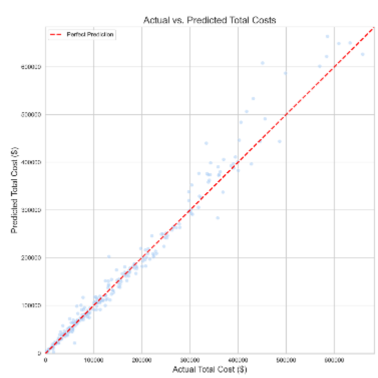


Figure 8.33.b. XGBoost prediction accuracy for Total costs

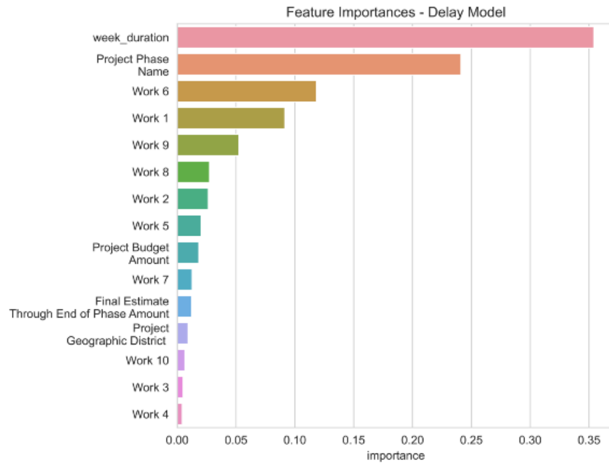


Figure 8.33.c. Feature Importance for XGBoost model

In conclusion, the XGBoost model consistently demonstrated superior performance in predicting delays and total costs, followed by Decision Tree and ANN. The linear and ridge regression models exhibited lower performance compared to the non-linear models, as they assumed linear relationships between predictors and target variables, which did not correspond to reality. The outstanding performance of XGBoost can be attributed to several factors, including:

- Model complexity: The MLPRegressor uses a fixed architecture with a predefined number of layers and nodes. This architecture might not be optimal for the specific problem at hand, whereas the XGBoost model can better adapt to complex data patterns due to its gradient boosting framework, which combines multiple decision trees, allowing it to capture non-linear relationships more effectively.
- Training process: The ANN model relies on gradient-based optimization techniques, such as backpropagation, which are sensitive to the choice of hyperparameters, including learning rate, activation functions, and the number of hidden layers. In contrast, the XGBoost model uses a more robust tree-based boosting method, which is less sensitive to hyperparameter choices, and generally converges more efficiently.
- Interpretability and Explainability: The ANN model is often considered a "black box" due to its complex structure, making it difficult to understand and interpret its internal decision-making process. This lack of interpretability may hamper the ability to diagnose and improve the model's performance. On the other hand, the XGBoost model is built upon decision trees, which are inherently more interpretable and allow for a better understanding of the relationships between the input attributes and the target variable.
- Regularization: The XGBoost model incorporates regularization techniques that penalize overly complex models, reducing overfitting and improving generalization.

As proved by the results, the choice of an appropriate ML algorithm depends on the nature and availability of data, the complexity of the problem to be solved, and the relationships between the input and target variables. The database used in this study was specifically focused on school construction projects in New York, influenced by its unique characteristics, such as building codes, construction technologies, and regulations. Consequently, the results and the performance of the selected algorithms may not be directly applicable to other types of constructions. This limitation arises due to the context-drivenness of risks and construction projects, making the developed model inapplicable in other contexts or locations.

8.1.3. Results Summary Obtained from the two Case Studies

The application of the three different models on two different case studies had two main objectives: a) highlighting the importance of integrating multiple sources of data and judgments in accurate risk prediction and data scarcity compensation, and b) highlighting the critical role of database size on the performance of each probabilistic and deterministic ML model.

To find answers to the first objective, a comparative analysis between the three proposed models was conducted with respect to their prediction accuracy and assigned probability to each risk. The comparison of prediction accuracy between the BN model and the deterministic ML models indicated that for small databases like the first case study, ML algorithms suffered from overfitting, while BN had an acceptable performance, with a minimum of 85% accuracy among the eleven risk categories. Figure 8.34 indicates the average accuracy of each of the deterministic ML models for the first case study, and Figure 8.35 indicates the average accuracy of BN for each of the eleven risk categories.

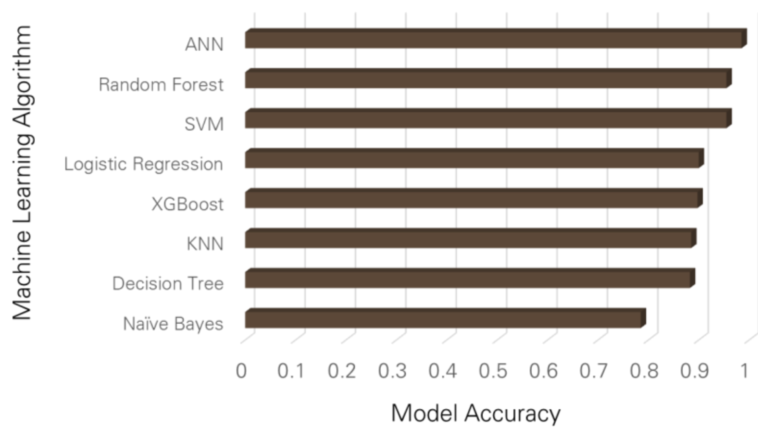


Figure 8.34. The average accuracy of each of the deterministic ML models for the first case study

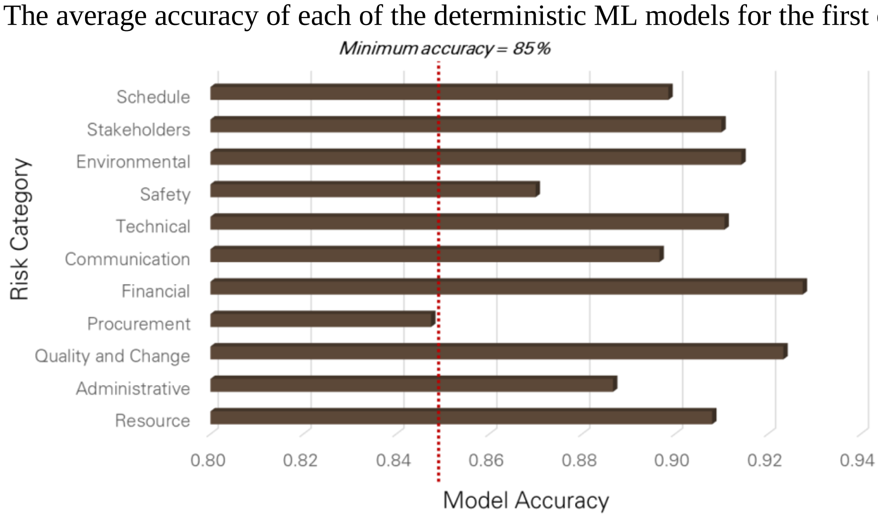


Figure 8.35. The average accuracy of BN for each of the eleven risk categories

Moreover, the comparison of the risk probability assigned by each of the models indicated that:

a) Judgment based on merely expert data in FL is over-conservative, estimating higher probabilities for risks.
b) Judgment based merely on project data in deterministic ML models is not reflective of the actual situation due to the small size of the database and can underestimate the probabilities of risks. The deterministic ML models use the frequentist approach to estimate the probabilities of risks, that is, the frequency of the occurrence of risk in the database. However, if a certain risk was not repeated much in previous projects, there is no guarantee it will not be frequent in upcoming ones.
c) Combining the two sources of judgments in BNs balances the estimates. Therefore, BNs offer the most realistic probability estimates of the risks, as evident in Figure 8.36.

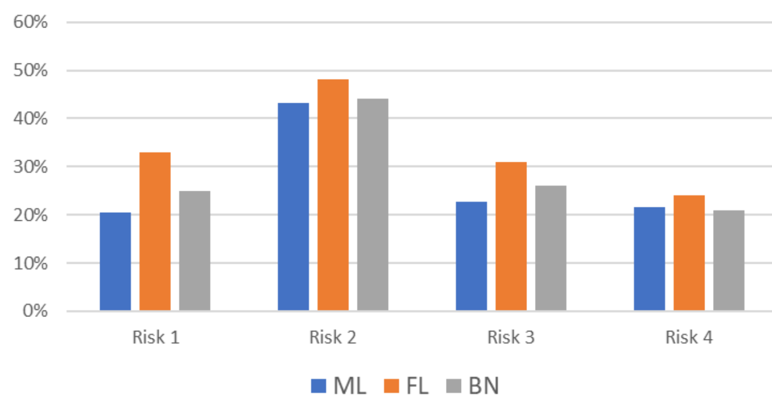


Figure 8.36. Comparison of Risk Probabilities assigned by each of the three ML, FL, and BN models

To find answers to the second objective, all three models were applied to another case study of a much larger size. As anticipated, deterministic ML models outperformed BN when the data was abundant. Among different ML algorithms, XGBoost had the best performance due to its ability to capture both linearity and nonlinearity existing in the data. Figures 8.37.1 and 8.37.2. present the mean of cross-validation and R2 score for the total cost prediction in the second case study, and Figures 8.38.1 and 8.38.2 present the mean of cross-validation and R2 score for the delay prediction in the case study. It is worth noting that BNs had a weaker performance than XGBoost as there was enough data available for the deterministic models to learn from and predict accurately, and the data was representative enough of the actual situation to rely on frequentist inference. Therefore, the advantage of Bayesian inference was not a game changer in the case of a large database.

In conclusion, when working with small databases with a great number of missing values, probabilistic approaches like BNs are recommended, as they can integrate various sources of judgments to compensate for the data scarcity and benefit from the Bayesian inference for a more realistic risk probability assessment. However, when working with large databases, the deterministic ML algorithms outperform the probabilistic ones due to their advanced structure and ability to capture both linearity and nonlinearity in the data. Furthermore, the existence of abundant data makes the frequentist inference of such models closer to reality.

8.2. Practical Implementation of the model

8.2.1. Integration of the model with the company's processes:

The proposed models should fit into the company's cycle of RM processes and should be authorized by the company. The input and output results, as well as the compatibility of the project reports' data formats with algorithm data, should be determined. Moreover, the data and model ownership, copyright, confidentiality, and operability need to be discussed with the company management. Moreover, training and guidelines on the use of the model will be provided to the project managers. The final product is aimed to be in the form of an Excel add-in that can be run on projects' documents for automated risk identification and assessment of new projects. However, it is out of the scope of this research and is considered a future research direction.

8.2.2. Ethic-aware implementation framework:

With the purpose of making it a moral, ethical, and harmless model, the areas of potential biases would be identified and addressed. Moreover, the data privacy and confidentiality issues should be discussed and compared to the company's policies. Figure 8.37. presents a holistic list of harms, biases, and challenges in three steps of AI application in construction companies, i.e., Database collection, AI model development, and Implementation for Decision Making, that need to be considered and addressed for an ethical and just AI application, which is specific to this study.

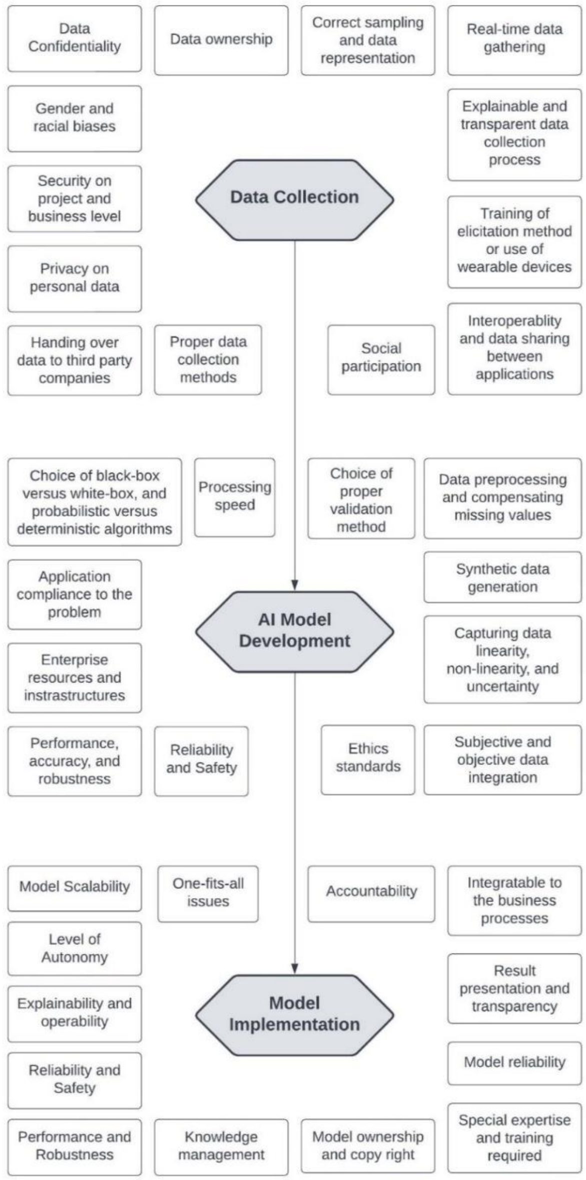


Figure 8.37. Proposed Application Framework of the developed model to address and solve the Ethical harms, biases, and challenges of AI application in construction companies

Transforming AI ethics and standards into a practical framework applicable to construction projects is difficult, where various components and processes need to be considered and assessed in terms of compliance with both the ethical standards and the enterprise processes to guarantee the system's capability of making ethical and moral decisions. There are various ways to educate AI systems and transform them into ethical agents, including a) implicit ethical agents, when a machine's actions are constrained to avoid unethical outcomes, which could significantly limit AI application, b) explicit ethical agents, stating explicitly allowed and forbidden actions, and c) full ethical agents, when machines have consciousness and free will like humans and can make their own decisions, although it is still in the research phase (Anderson and Anderson, 2007). However, measuring ethics metrics is challenging compared to hard performance metrics, leading to companies often prioritizing project budget and quality over ethical considerations. Therefore, companies face a tradeoff between focusing on AI advancement to realize profit maximization or focusing on AI ethics to ensure societal benefits derived from AI (Siau and Wang, 2020). Another challenge to face is the shift of risks in the construction industry from known space, like financial or delay risks, to unknown space, like the liability of contractors if an accident was caused by a robot or a wrong design generated by AI (Pillai and Matus, 2020). Therefore, developing an ethical AI implementation framework requires systematic analysis on various levels mentioned below:

- Ethics-Aware Design and Implementation of AI: Design engineers must be fully aware of the ethical challenges, biases, and cyber security risks, and inspect the potential flaws in the system design (Bostrom and Yudkowsky, 2014). The AI system itself should be able to reflect on the ethical and social principles and standards embedded by developers to make socially significant decisions and avoid unethical behaviors (Wallach and Allen, 2009). Finally, in order to implement a responsible and ethics-aware AI system, the ethical mindset and culture in the organization and among employees need to be promoted. Furthermore, fairness should be addressed at different levels: a) Data Fairness, when the input data is representative, relevant, accurate, and generalizable to the entire study sample, b) Design Fairness, when used target variables, features, processes, or analytical structures are not unreasonable, morally objectionable, or unjustifiable, c) Outcome Fairness, when the outcomes are not discriminatory or inequitable impacting on the lives of the people, and d) Implementation Fairness, when users are trained to implement them responsibly and without bias (Leslie, 2019).
- Integration of AI in Project Team and Processes: The project team requires motivation to accept AI in their engineering and management processes and change the usual way of doing their activities. Autonomous motivation is based on the fulfillment of the three psychological needs: autonomy, competence, and relatedness (Deci, Olafsen and Ryan, 2017), all of which will be impacted by AI. While AI automates repetitive tasks and facilitates decision-making by team members to allow them to focus on creative thinking, it can hinder the team's ability to learn from mistakes and limit productive conflicts, affecting team dynamics and collaboration (Schöttle, 2020). Therefore, there is a dilemma between team motivation and performance when AI comes into the picture.
- Education and Training on AI: Education and training have been introduced by previous researchers as the most straightforward solutions to solve the ethical, moral, and social issues of technology application in the industry (Leslie, 2019). Education has different target populations: a) AI applications developers need to be educated about ethics codes and standards, b) the AI algorithms need to be educated in embedding these standards, c) management-level policymakers need to be educated on the pros and cons and ethical considerations on AI, and d) end users, in this case, engineers, architects, and project managers, need to be educated with basic knowledge and hands-on experience on AI algorithms and codes of ethics. This way, a bilateral human-centric relationship will be shaped between the technology and human agents, and the change-resistant culture of the industry will change, giving more exposure and space for AI implementation on a vast scope.

Figure 8.38. indicates the ethics-aware and responsible AI framework with respect to proposed solutions.

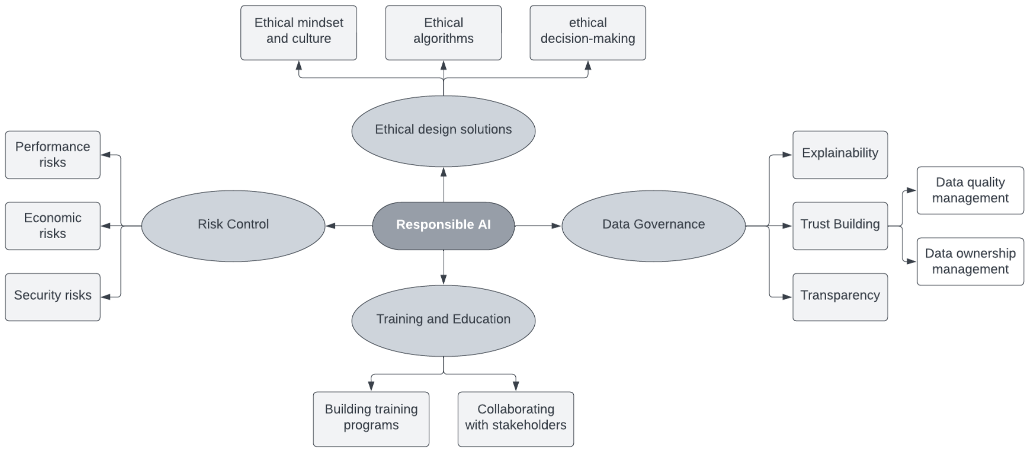


Figure 8.38. Responsible AI framework, components, and solutions (Wang, Xiong and Olya, 2020)

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Chapter 9: Conclusion

9.1. Conclusion Key Points

The construction industry, often viewed as traditional and resistant to change, is on the cusp of a technological revolution. With the advent of Artificial Intelligence (AI) and Machine Learning (ML), the construction Risk Management (RM) processes are undergoing a significant transformation. This dissertation aims to analyze the advantages, challenges, and future prospects of integrating AI and ML into construction RM in order to develop a comprehensive and efficient ML-based RM tool that can address and solve the shortcomings of traditional RM methods in the industry. A comprehensive literature review was conducted on the ML-based solutions and methods discussed by other researchers, which served as the theoretical foundation of the research. As a result, a number of probabilistic and deterministic ML algorithms were selected for the implementation phase. Searching for an optimum ML-based solution based on the specific requirements of the industry partner, the selected algorithms were implemented on the case study of their project, and results were recorded and compared; as a result, Bayesian Networks (BNs) combining experts' subjective opinions with objective project data indicated the best, most realistic, and most understandable results. Parallel to BNs, eight other deterministic ML models based on merely project data and a fuzzy logic model based on experts' opinions were developed, and their results were compared with the BN's results. Moreover, almost the same algorithms were applied to a second case study with a much bigger database, where deterministic models outperformed as expected. This finding highlights the importance of data quantity in the performance of the ML models.

Moreover, two solutions were proposed for compensating the data scarcity in the first case study: a) synthetic data generation using GANs and b) elicitation-based risk network structure and parameter learning, which made it possible to integrate two sources of data and judgment experts' experience-based opinions with historical project records. Both solutions helped largely overcome the data scarcity and increased the BN prediction precisions. Another key point in the results was the comparison between the FL and BN models' prediction of risk probability, which was higher in the FL model, meaning that experts evaluate the probability of risks higher than they actually are, and if a model is merely based on expert opinion, like most conventional RM models, the assessment of risks would not be accurate. On the other hand, the limited project database might not be comprehensive and reflective enough of the actual situation to form the entire judgment. Therefore, combining the two sources of information can balance the risk assessments and foster informed and factual decision-making in the industry.

9.1.1. The application of AI and ML in Construction RM

The integration of AI in the construction sector is not a mere trend but a necessity. With projects becoming more complex and the stakes higher than ever, there is an urgent need for tools that can predict, analyze, and mitigate risks efficiently. AI and ML, given their advanced processing capabilities, ease of implementation, and automated learning, can significantly benefit the construction RM domain by extracting insights from already completed projects' databases. Moreover, probabilistic ML models like FL and BNs provide the opportunity to translate the experience-based tacit knowledge of experts in the field into quantified and understandable formats, which can be merged with objective historical data to create augmented, comprehensive, and balanced training sets. This is a huge advantage of probabilistic models, especially in the construction domain, where data is scarce and unstructured, and historical records are unable to represent the actual risk conditions realistically.

9.1.2. Key Drivers for AI Adoption

The key drivers of AI and ML adoption in construction projects are identified as the following:

a) he complexity of modern construction projects brings with it a myriad of risks that need advanced tools for on-time and optimum identification, assessment, and mitigation.
b) Demand for efficiency, where ML-based RM tools can optimize processes, ensuring projects stay on track, on budget, and in compliance with quality and safety standards.
c) Massive data production, which enables AI and ML algorithms to go through this data, extracting valuable insights for efficient decision-making.

9.1.3. Advantages of AI-driven Risk Management

a) Automation and Optimization of RM processes, from data collection to risk analysis, AI can handle repetitive tasks efficiently, ensuring that human resources are utilized for more critical decision-making processes.
b) Fostering informed and strategic decision-making for risk mitigation and resource allocation by providing data-driven insights derived from analyzing vast amounts of data.
c) Standardization of the RM process stages, as AI-driven processes are consistent regardless of the project's scale or location, ensures the quality and predictability of the risk assessments.
d) Experience-based judgment quantification brings in a level of objectivity that was lacking in previously applied RM methods.
e) Focus on the role of intelligent project management in the construction sector, which is an area often overlooked in construction literature. However, due to the complex and unique nature of construction projects, intelligent and strategic project management can play a key role in ensuring project success, for which AI can be an instrumental tool.
f) ML models continuous learning and improvement over time. As they are exposed to more data and different scenarios, their accuracy and reliability increase. This means that the longer they are in use, the better they become at identifying and mitigating risks.
g) Optimized resource allocation, based on an ML-based analysis of project requirements against available resources, ensures optimal allocation; that is, the right personnel,

machinery, and materials are always in the right place at the right time, leading to increased efficiency and reduced risks.

h) Enhanced safety protocols, as AI can be used to monitor construction sites in real-time, identifying potential safety hazards and ensuring compliance with safety standards, preventing accidents, ensuring the well-being of the site workers, and avoiding costly legal complications.
i) Customized solutions for clients, as ML algorithms can analyze client preferences and requirements to offer tailored solutions to their specific portfolio of projects.
j) Efficient Supply Chain Management by real-time risk assessment, predicting demand, managing inventory, and ensuring timely delivery of materials. An efficient supply chain reduces project delays and cost overruns and keeps the project on track.

9.1.4. Challenges of AI-driven Risk Management

a) Data Scarcity and lack of open access databases in the construction sector, especially at the project level, which hinder the application of most ML methods.
b) Overfitting, that is, tailoring models too closely to a specific dataset, like a client's database, can lead to overfitting.
c) Reliability and trust issues; that is, for many in the construction industry, trusting an algorithm over years of experience can be challenging. Building trust in AI-driven processes is crucial for their widespread adoption.
d) Specific and Technical knowledge requirement to understand the ML processes and use it efficiently, which is lacking among construction professionals.
e) Improper choice of ML models. Most of the time, the developed models do not comply with the studied problem regarding the available data, specific requirements, complexity of the problem, role of uncertainty, and application scope, which leads to poor performance of the model.
f) Complexity and difficulty in interpreting the ML models, especially deep learning models, which make it challenging for construction professionals to interpret and understand the model's predictions. Therefore, the engagement rate and usability of the models decrease.
g) Change-resistant and traditional culture of the construction industry, its professionals, and its processes, which slows down the adoption and integration rate of ML. Moreover, Integrating AI and ML solutions with existing systems can be challenging and might require significant changes to current workflows and processes, which requires great effort and capital investment.

9.2. Research Limitations, Solutions, and Future Prospects

9.2.1. Research limitations

a) Data scarcity and existence of missing values in project-level risks of the case study. This is a common issue with most construction companies, as construction projects take a long time to complete, and data registration is not done frequently and in a standardized manner.
b) The context-driven nature of the risk analysis domain, which hindered the integration of other construction projects with the project portfolio conducted by the research industry

partner. It was not even possible to add the projects' construction by other branches of the corporation in other countries, as the scope and type of projects varied drastically, resulting in poor performance of the model predictions.

c) Lack of open access databases on construction projects that could be used for model validation.
d) Lack of similar studies that could serve as a benchmark.

9.2.2. Research Solutions

The data scarcity issue was addressed with two solutions. First, synthetic data generation using GANs, which is one of the first of its kind on tabular data. Usually, GANs are used for image data augmentation, and this research contributed to the GAN body of knowledge for tabular data. Second, the integration of subjective expert opinions, based on their experience, using elicitation, with objective project data, which was made possible by the BN application. As BNs benefit from the Bayes inference and can use multiple sources of data and judgments, they significantly solve data scarcity issues and perform well in small databases, like the research's first case study. Using white-box models like BN or FL over Blackbox models increases the model explainability and transparency, which makes it easier to comprehend for industry professionals.

While the study was developed for a specific client, and the model cannot be automatically scaled to other types of projects due to the context-drivenness of the risk realm, it has high adaptability and can be tailored to other companies with unique project portfolios with minor modifications. That is, the general framework and application steps remain unchanged, while the variables in the developed BN or deterministic ML models can easily be updated and modified when new data is inserted, making them applicable to different databases. However, the scalability of the FL model is lower since it completely relies on the tacit knowledge and experience of specific experts, which is highly subjective and differs significantly from one company to another or in different countries.

Finally, to build trust toward the ML-based model, this research conducted a vast review of literature on all possible harms, biases, discriminations, and moral/ ethical/ social issues caused by digital technologies applications. Based on the findings, a generic framework addressing all the possible threats toward trust-building that could occur during data collection, model development, and implementation phases was listed with their designated solutions, which will serve as a basis for the practical implementation strategy of the proposed model. It is expected that by addressing these issues, the acceptance rate and engagement of the industry professionals would increase. Figure 9.1. graphically presents the research solutions to each of the initial issues and limitations, proposing BN as the final solution of the research.

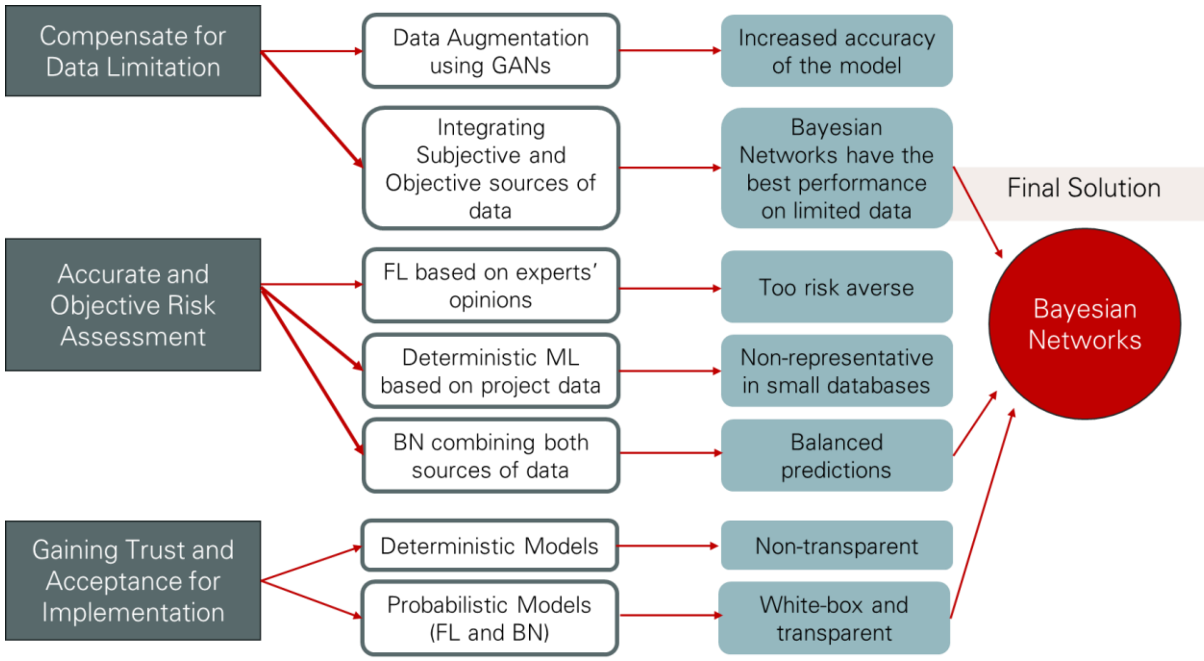

Figure 9.1. Proposed research solutions to each of the initial issues and limitation, and the final solution

9.2.3. Bayesian Approaches in Construction RM

Given the unique conditions of construction projects, which often involve a mix of quantitative data, expert judgment, and evolving scenarios, Bayesian Networks might offer the most tailored approach. Their ability to continuously update risk assessments based on new data and prior knowledge aligns well with the dynamic nature of construction projects. However, the choice of algorithm should also consider the available data, expertise, and specific project requirements. In many cases, a hybrid approach, combining the strengths of multiple algorithms, might be the most effective strategy.

In the realm of construction RM, Bayesian methods provide a dynamic way to assess and manage risks based on both prior knowledge and project data. The structure and parameter learning can be done using both expert opinions and project data, and the beliefs can be updated once new data is available. BNs graphically represent probabilistic relationships among a set of variables and can be used to model complex interdependencies between different risks in construction projects, which makes them a perfect solution to address the shortcomings of conventional methods. Moreover, with their graphical representation, they can model complex environments, like construction projects, and offer a transparent view of the interdependencies between different risks, making it easier for stakeholders to understand the risk landscape. However, the downside is the exponential growth of the model complexities as more features and variables are added to the model, making the risk modeling process complicated and requiring specialized knowledge. Additionally, while Bayesian methods can work with limited data, their accuracy and reliability improve with more data, the gathering of which is not easy in construction projects. In conclusion, Bayesian approaches offer a robust and dynamic framework for construction risk management. While they come with their set of challenges, their ability to provide real-time, data-driven risk assessments makes them invaluable in the ever-evolving landscape of construction projects. Proper training and the integration of Bayesian tools can help construction firms harness the full potential of these methods.

9.2.4. Future Research Prospects

a) Integration with other project management areas, like scheduling and cost management, offering a holistic approach to more efficient and intelligent project management in construction projects.
b) Scaling the model to operation-level risks. While this research focuses on project-level risks, the potential of AI in operation-level risk is even greater, due to the daily production of data. With more data available at this level, there's scope for more advanced risk analysis and mitigation strategies.
c) Automated and frequent documentation using AI, ensuring that reports, change orders, and other essential documents are generated, updated, and maintained, with active consideration of the risks identified by the proposed model.
d) Active supervision of risks and their consequences, linking the proposed model with progress reports and accident reports.
e) Automated intervention planning, based on historical data, to mitigate the risks and post-intervention risk modeling to assess the residual risks after taking preventive or corrective actions. This is a very new and understudied area, even in engineering RM. However, it can bring huge advantages to informed decision making on risk mitigation plans.

9.3. Summary

In conclusion, while the integration of AI and ML in construction RM presents numerous advantages and holds immense potential to revolutionize the construction industry, it's essential to be cognizant of the challenges. With continued research and collaboration between experts and technologists, the construction industry can harness the full potential of digital technologies. Proper training, collaboration, and continuous evaluation can ensure that ML models serve as valuable tools in the ever-evolving landscape of construction RM. From enhanced efficiency and safety to improved quality and client satisfaction are the contributions of an intelligent and automated RM framework with the help of ML-based models. This dissertation tried to delineate a portion of the numerous advantages of ML-based RM methods with a practical and problem-driven approach. Moreover, the extensive literature review and comparative analysis between deterministic and probabilistic ML models contribute to the AI in construction body of knowledge.