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PROBABILISTIC RISK IDENTIFICATION AND ASSESSMENT MODEL FOR CONSTRUCTION PROJECTS USING ELICITATION BASED BAYESIAN NETWORK

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SUMMARY: *While risks in construction projects have severe consequences on the project schedule, budget, quality, and safety, the realm of Risk Management (RM) falls short in terms of efficiency, productivity, and automation. Artificial Intelligence technologies, especially Machine Learning, can address these issues and utilize risk data effectively for informed decision-making. However, due to the infrequent and unstructured data registration in projects, deterministic RM approaches with a frequentist inference are inapplicable to such small databases and cannot represent the actual risk exposure accurately. This research proposes two solutions to compensate for the data scarcity issue: a) Elicitation, which allows for the integration of subjective and experience-based expert opinions with the existing objective project database, and b) Synthetic data generation using Generative Adversarial Networks (GANs) for data augmentation. A probabilistic model based on a Bayes inference is developed, where experts' opinions are quantified and used for learning the structure and primary parameters in a Bayesian Networks (BN) representing the overall risk network of the case study. A case study of 44 construction projects in Italy is utilized for belief updates in the network, and cross-validation and elicitation methods are employed to validate the results. The results confirm the effectiveness of both solutions, as the overall model accuracy increased by 18% using GANs for synthetic generation and the collective experts' opinions served as a basis to prevent the overfitting of the model to the limited project data. These findings underscore the superiority of probabilistic ML approaches in limited databases, contributing to the body of knowledge in the construction RM field and to the enhancement of precision and productivity of RM practices in the industry.*

KEYWORDS: *Risk Assessment, Bayesian Inference, Elicitation, Construction Industry, Project Management.*

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1. INTRODUCTION

Construction projects are prone to risks and uncertainties due to their complex nature and the existence of multiple tasks and stakeholders with conflicting interests, which mostly impact the success of the projects negatively (Nyqvist, Peltokorpi and Seppänen, 2023). These risks are derived from internal (Property-based) or external (Field-based) factors happening at operational, project, portfolio, strategic, and business and enterprise levels (Wu, Chen and Olson, 2014). Uncontrolled risks negatively affect the project objectives in the form of delays, cost overruns, failure to correspond to quality standards, legal disputes and claims, and on-site accidents (Arabi, Eshtehardian and Shafiei, 2022). Risk Management (RM), the proactive approach of risk identification, analysis, assessment, mitigation planning, and control to exploit positive risks and mitigate negative risks (Project Management Institute(PMI), 2017), can decrease the probability and impact of the risks, playing a pivotal role in guaranteeing project success and on-time and on-budget delivery (Piao et al., 2021; Görsch et al., 2023). Even so, the common RM methods fail to deliver quick, precise, objective, and optimized assessment of risks and corresponding risk responses (Fitzsimmons et al., 2022). Moreover, the judgments are mostly experience-based and isolated, without considering the interdependence between risks (Arabi, Eshtehardian and Shafiei, 2022), making the conventional RM methods highly personalized and context-dependent (Li et al., 2018), and hindering automation and knowledge transfer to future projects.

The Industry 4.0 revolution is significantly altering the construction industry toward automation and digitalization thanks to the abundant production of data and the development of digital tools to document, extract, analyze, and learn from massive volumes of data (Perrier et al., 2024; Kozlovska, Klosova and Strukova, 2021). Artificial Intelligence (AI) and Machine Learning (ML) algorithms enable machines to mimic human cognition and analyze massive construction data to recognize patterns and extract knowledge for future decision-making and to automate and optimize design and construction processes (Pan and Zhang, 2021). They also contribute to the intelligent management of construction projects (Zhong et al., 2017 ; Chenya, 2022), an important part of which are RM processes. AI-based RM models are great substitutes for conventional human-based risk analysis systems that suffer from low accuracy and reliability, partial risk identification, and inconsistent risk breakdown structures (Siraj and Fayek, 2019).

Despite all the benefits of AI-based RM models, their application is limited in research and practice due to a) not frequently registration and update of risk data in project documents, b) registration mostly in unstructured text or image formats (Van Liebergen, 2017), c) existence of missing values, d) data scarcity specially on project and strategic levels where for each project only one data entry is added to the database, e) individual and isolated analysis of risks instead of inference, interrelations, and risk path analysis (Esmaeili and Hallowell, 2013; Arabi, Eshtehardian and Shafiei, 2022), and f) being affected by different individual perceptions. These reasons hinder the application of frequentist statistical approaches, like Monte Carlo and Decision Tree, which are merely based on previous project data and consider the frequency of an event in the database as its probability of occurrence. Furthermore, previous project data cannot represent the current situation and risks, as there might be differences in the current operational conditions and those during data collection (Martins and Aur, 2020), or some severe risks with low probability might not have occurred before. Therefore, the frequentist approaches and deterministic AI models are not proper candidates, as the effective application of ML greatly depends on the type of data available (El-adaway et al., 2023; Fan, 2020).

Probabilistic models and the Bayesian approach, on the other hand, seem to be the solution to the abovementioned issues, as they enable integrating 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 widely accepted as a 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. Bayesian Networks (BNs), the most applied type of Probabilistic Models (Odimabo, Oduoza and Suresh, 2017), are comprised of a graphical structure that represents the domain's variables and their qualitative relationships, also known as Directed Acyclic Graph (DAG), as well as a quantitative part that encodes causal inferences and probabilities over the variables, also known as Causal Probability Table (CPT), which are able to present the joint probability distribution and interdependence between variables (Fan, 2020; Druzdzel and van der Gaag, 2000). A great advantage of Bayesian approaches is the ability to derive inferences from multiple sources for compensating the data scarcity issue and include subjective experts' opinions through elicitation. The process of asking experts' opinions on the probabilistic data and translating the qualitative answers into quantitative probability values is called elicitation, which can be used for both structure and parameter learning in BNs (Butler, Thomas and Pintar, 2015). The historical project data records can be added to the model for beliefs and posterior updates (Mohamad and Tran, 2021), in which the machine recognizes the relationships between input and output data by constant weighting and correction. Although BNs are widely used for accidents' root cause `is and workers' safety risk assessment in construction research (Nguyen, Tran and Chandrawinata, 2016; Gerassis et al., 2017), their practical application, dynamic risk modeling, and proper network validation is still in its infancy (Nyqvist, Peltokorpi and Seppänen, 2023; Piao et al., 2021; Nguyen, Tran and Chandrawinata, 2016). Moreover, their development requires a careful trade-off between model precision and complexity and data acquisition cost.

Considering the potentials of BNs, this research aims to answer the following questions:

- What are the advantages of the probabilistic models compared to deterministic and frequentist statistical approaches in RM research?
- How can the data limitation problem be addressed and solved using BN in real-world cases?
- What other solutions can be proposed to solve the data limitation in construction risk databases?

This research proposes an elicitation-based framework for BN structure and parameter learning of construction project risks validated through case-study and cross-validation approaches using 44 construction projects of an engineering consulting firm in Italy. Besides elicitation, this research proposes synthetic data generation based on the initial project tabular database, using Generative Adversarial Networks (GANs), as another solution to overcome the risk data limitation (Fan et al., 2019; Akinosho et al., 2020). For this purpose, the following steps are taken: 1) Systematic data generation using GANs based on project risk data collected from previous and ongoing projects, 2) Finding proper structure/parameter learning algorithms of BNs to the research problem, 3) Integrating experts' opinions and judgement on risk probabilities through elicitation with previous project data, 4) generating synthetic data using Generative Adversarial Networks (GANs), 5) Comparing the results of pre and post-GAN application to assess its effectivity, 6) Validating the network through case-studies and cross-validation. This research contributes to knowledge sharing in construction projects through elicitation, as well as the application of data-driven methods for more efficient RM processes in the construction industry.

2. LITERATURE REVIEW

This study utilized a Systematic Literature Review (SLR) approach to explore scientific libraries, focusing on the intersections of RM, AI, ML, Project Management, and the Construction Industry. The SLR is a rigorous, transparent, repeatable, auditable, and structured method that aims to extract evidence from digital repositories (Tebes, et al., 2019), the biases of which are mitigated due to its systematic format (Pickering and Byrne, 2014). An SLR requires the following stages:

1) **Question formulation** – Defining the research scope, focusing on probabilistic risk modeling in construction.
2) **Localization and literature search** – Conducted across Scopus and Web of Science, ensuring comprehensive database coverage.
3) **Study selection and evaluation** – Applying inclusion and exclusion criteria to refine relevant studies.
4) **Analysis and synthesis** – Conducting bibliometric analysis, co-occurrence mapping, and categorization.
5) **Reporting and interpretation** – Structuring the findings to align with research objectives.

(Habibi Rad, Mojtahedi and Ostwald, 2021).

Given the vastness of the research domains, the SLR was instrumental in identifying key interdisciplinary publications (Khodabakhshian, Puolitaival and Kestle, 2023). Research sources included Scopus and Web of Science, with the PRISMA guidelines ensuring a structured review process. The search rule in these sources is as shown in Equation 1, and the SLR search process is presented in Figure 1:

("Construction Management" OR "Construction Project" OR "Construction Industry") AND ("Risk" OR "Probability") AND ("Bayesian" OR "Bayesian network" OR "Bayesian inference") (Equation 1)

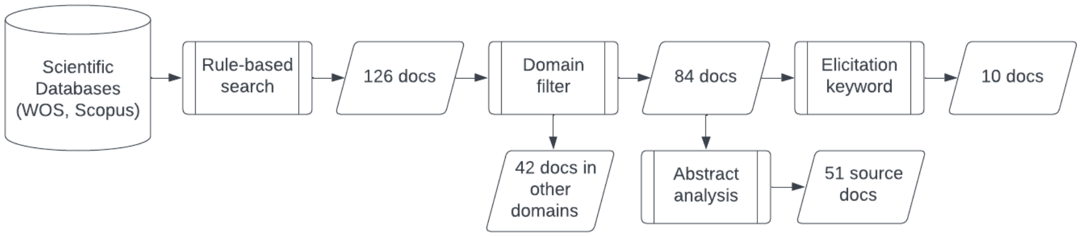

Figure 1: Systematic Literature Review Search Process.

2.1 Time Frame and Document Selection Criteria

Research papers published between 2010 and 2024 were considered to ensure recent developments in construction risk modeling. Journal articles, conference proceedings, and book chapters were prioritized, while editorials and non-peer-reviewed reports were excluded. Papers focusing on non-construction-related domains (e.g., healthcare, finance) were excluded unless they provided transferable methodologies. Only Scopus-indexed and Web of Science-indexed publications were included to ensure quality. The review was restricted to English-language publications to maintain consistency in interpretation and analysis.

As a result of these criteria, 51 papers were analyzed for their abstracts, determining relevance to Bayesian inference in construction risk management. 10 papers specifically addressed elicitation techniques, forming the theoretical foundation for expert-driven Bayesian modeling. The remaining 23 papers were used for comparative analyses, methodology validation, and benchmarking risk modeling techniques against conventional approaches.

2.2 Co-Occurrence Analysis and Thematic Clustering

After selection of the source papers, a bibliometric analysis was performed for the quantitative study, utilizing techniques like co-occurrence analysis of keywords presented in Figures 2 The keyword co-occurrence diagram, presented in Figure 2, highlights research concentrations, techniques, and topic interrelations using the Bibliometrix package in R studio. As apparent in Figure 2, three general groups of keywords that represent the papers' categories are:

a) Risk modeling techniques- Covering Bayesian networks, Monte Carlo simulation, and fuzzy logic models.
b) Project management application area- Investigating how Bayesian models integrate with cost, schedule, and resource planning. and
c) Risk factors- Exploring key risk variables influencing construction project outcomes.

The main focus of this article is on probabilistic risk modeling techniques, specifically the Bayesian Networks. Furthermore, the two solutions for compensating for the data limitation issue, namely elicitation and synthetic data generation, are thoroughly studied in the literature and are briefly presented in the next subchapters.

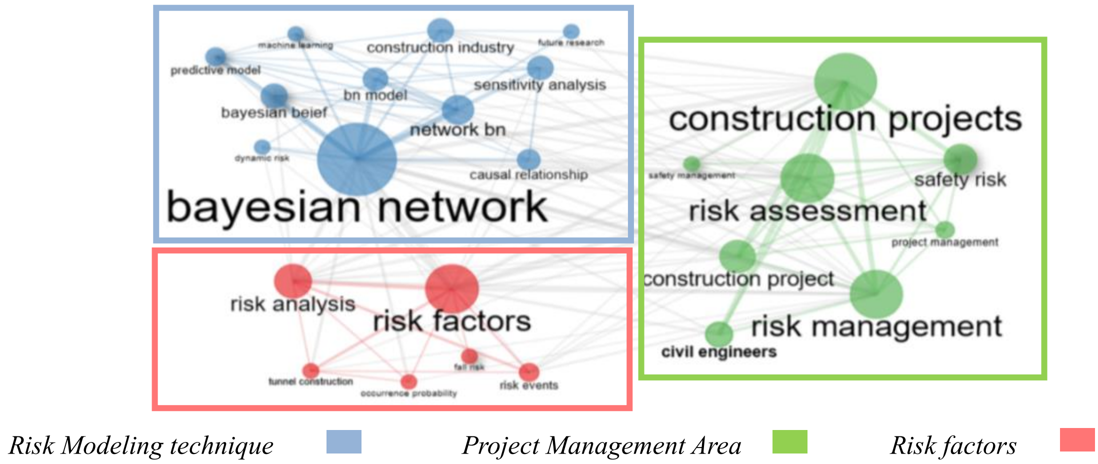

Figure 2: Co-occurrence diagram of keywords-main domains of literature review.

2.3 Comparison of Conventional Frequentist, and Probabilistic Risk Management Models

Risk management in construction projects has traditionally relied on deterministic and frequentist approaches. However, recent advancements in probabilistic modeling, such as Bayesian Networks (BNs), have introduced significant improvements in addressing uncertainty and data scarcity. Table 1 provides a comparative analysis of these models.

Table 1: Comparative Analysis between various deterministic, frequentist, conventional and probabilistic Risk management methods in construction.

Approach	Methodology	Description	Advantages	Limitations	Reference
Deterministic and conventional methods	Expert Judgment	Risk assessments are based on subjective evaluations from domain experts.	Intuitive, experience-driven, practical for qualitative risks.	Highly subjective, varies between experts, lacks reproducibility.	(Hubbard, 2020)
	Checklist Method	Uses predefined checklists to identify and manage risks.	Simple to implement, ensures consistency in risk identification.	Static, does not account for dynamic risks or interdependencies.	(PMI, 2017)
	Failure Mode and Effects Analysis (FMEA)	Identifies potential failures in processes and their impacts.	Structured, proactive approach, widely used in engineering projects.	Limited quantification of uncertainty, subjective rankings.	(Stamatis, 2003)
	Decision Trees	Models decision paths based on predefined probabilities.	Structured approach, useful for sequential decision-making.	Assumes known probabilities, difficult to scale for complex projects.	(Dikmen et al., 2018)
Frequentist Statistical Models	Monte Carlo Simulation	Uses repeated random sampling to estimate risk probabilities.	Accounts for variability, effective for large datasets.	Computationally intensive, requires historical data.	(Chou et al., 2020)
	Regression Analysis	Establishes relationships between variables to predict risks.	Provides statistical confidence, identifies key risk drivers.	Requires extensive historical data, sensitive to data quality.	(Odeyinka et al., 2012)
	Time Series Analysis	Forecasts risk trends based on historical patterns.	Effective for recurring risks, applicable to scheduling risks.	Assumes historical trends continue, may not capture new risks.	(Makridakis et al., 2020)
	Risk Matrices	Categorizes risks based on likelihood and impact.	Simple visualization, widely adopted in industry.	Subjective classification, oversimplifies complex risk interdependencies.	(ISO 31000, 2018)
Probabilistic/Bayesian Models	Bayesian Networks (BN)	Uses conditional probabilities and expert inputs to model risks dynamically.	Handles uncertainty, updates with new data, captures interdependencies.	Computationally intensive, requires expert input for priors.	(Fenton & Neil, 2013; Arabi et al., 2022)
	Markov Chains	Models state transitions over time to assess risks.	Effective for sequential risks, useful for reliability analysis.	Requires transition probabilities, computationally demanding.	(Shapiro, 2018)
	Hidden Markov Models (HMM)	Tracks unobservable risk states based on observed data.	Useful for detecting latent risks, dynamic risk assessment.	Requires training data, complex to interpret.	(Nguyen et al., 2016)
	Fuzzy Bayesian Networks	Combines fuzzy logic with Bayesian Networks to model uncertain risks.	Effective for qualitative risks, handles vague expert opinions.	Complex parameter estimation, difficult to validate.	(Zhang et al., 2023)
	Stochastic Bayesian Inference	Uses probability distributions to update risk estimations.	Adapts to new data, robust for uncertain environments.	Requires strong prior distributions, computationally heavy.	(Koller and Friedman, 2019)

2.4. Probabilistic Graphical Models and Bayesian Networks

Probabilistic Graphical Models are 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. Among these models, Bayesian Networks (BNs) are the most implemented ones for analyzing causal influences, offering several advantages, including the ability to model uncertainty and dynamic risks, handle large amounts of data, and perform sensitivity analysis and validation. 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). They consist of two main components:

- A directed acyclic graph (DAG) to qualitatively present the interdependency among variables and encode conditional independence assumptions, which is also referred to as the structure of the BN.
- Conditional Probability Tables (CPTs) or Conditional Probability Distribution (CPD) quantitatively represent the relationship between the 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.

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 AI techniques 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).

In construction projects, Bayesian approaches, and specially the BNs (Hon et al., 2022), have been applied as a tool to model and analyze project risks and complex relationships between various project factors such as project schedule, budget, quality, and safety for risk assessment, decision making, safety management, uncertainty analysis, identification of the key drivers of project risk, and assessing the impact of risks on project objectives (Nyqvist, Peltokorpi and Seppänen, 2023; Islam et al., 2019). Among the four types of BN reasoning, e.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, the 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, has been limitedly studied (Eybpoosh, Dikmen and Talat Birgonul, 2011). For depicting 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. Therefore, relying merely on the project data limits the choice of algorithms to implement, as each project serves as only on data entry in the database for project-level RM. For instance, deterministic and black-box models like Artificial Neural Networks, which have a significant performance in huge databases, are inapplicable for small datasets. Hence, this study relied on probabilistic models, which handles the data scarcity problem through integrating various sources of information and uncertainty.

There are remarkable studies on BN applications in construction RM. Liu et al. (2021) proposed a BN-based construction risk assessment method for Public Private Partnership (PPP) projects of urban rail transit, using offline interviews and surveys and online questionnaires and result correction by leaky noisy-OR gate model. 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 BN-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. 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 validated by experts and cross-validation.

2.5 Synthetic data generation using Generative Adversarial Networks (GAN)

As construction companies and institutions do not document frequently and do not share their data in the form of open sources, a common issue in construction is data scarcity and missing values, which hinders the application of Machine Learning and Deep Learning algorithms requiring massive amounts of data to have proper performance. Therefore, data augmentation techniques like Generative Adversarial Networks (GANs) 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 deep learning algorithms 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. Figure 5 presents the architecture of a GAN. Although GANs have broader applications in creating synthetic images (Antoniou, Storkey and Edwards, 2019), they are recently being applied to tabular data as well (Xu and Veeramachaneni, 2018; Rajabi and Garibay, 2022), 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. However, advanced GANs’ algorithms for tabular data generation are still missing and the produced data might face overfitting problem. This study aims to use GANs for data augmentation in the risk context and compare the accuracy of the model prediction pre- and post-data augmentation to validate the proposed framework.

2.6 Elicitation-based RM Models

The probability of uncertain events or conditions like risks can be assessed based on various sources, including historical records, model simulation, analogues, theories, and physical principles (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.

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. In case of a lack of prior knowledge of the event, it will have a uniform distribution. Therefore, the prior does not limit the application of the Bayesian theorem in case an informative prior is lacking.

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, including Betting Method, Equivalent Lottery Method, and Direct Probability Assignment Using Predefined Intervals, 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. In Betting Method, the expert is asked to determine the amount of money they are willing to bet on an event occurring versus not occurring, which can introduce bias if the expert is risk-averse or lacks numerical confidence. In Equivalent Lottery Method, the expert compares two lottery-like games: one based on the uncertain event of interest and the other with a known probability, Requiring experts to think in probabilistic terms, which can be cognitively demanding. In Direct Probability Assignment Using Predefined Intervals, experts choose a discrete probability interval (e.g., "Very Low" to "Certain") from a predefined scale, which can introduce inconsistency when experts are uncertain or forced into predefined categories. Finally, the AHP, originally used for decision-making, is adapted to structure pairwise probability comparisons between variables and provides the most consistent probability values while identifying inconsistencies in expert 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.

Despite the advantages of elicitation, the main challenge is the massive amount of probability assessments needed when the model is complex and contains many nodes with multiple states or continuous values, as the CPT grows exponentially with the number of parent nodes (Laitila and Virtanen, 2016). 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). To address these challenges, this study implemented a structured elicitation framework, integrating three phases of expert elicitation with Bayesian Network (BN) modeling to systematically assess the probabilistic relationships between various risks and project variables. The elicitation method, which is detailed in the Methodology section, consists of:

a) Structured Surveys, utilizing a survey matrix to evaluate the impact of various project variables on each risk category;
b) Expert Interviews and Likert Scale Assessments, where experts assess the likelihood of each risk under specific project conditions; and
c) Collective Validation and Refinement, ensuring consistency and reliability in the elicitation results.

This approach reduces inconsistencies by structuring expert inputs across multiple elicitation phases, enhances efficiency by using surveys to identify key risk variables before detailed probability assignments, improves accuracy by integrating subjective expert knowledge with objective project data through Bayesian inference, and mitigates cognitive bias by employing Likert scales and pairwise probability comparisons instead of direct probability estimation.

3. METHODOLOGY

This research uses a case study approach (Yin, 2014) to define the risk network and probabilities for an Italian engineering consulting firm. The case study approach is particularly useful to employ when there is a need to obtain an in-depth appreciation of an issue, event, or phenomenon of interest in its natural, real-life context (Crowe et al., 2011) and can be considered a robust research method particularly when a holistic, in-depth investigation is required (Zainal, 2007). The main phases, also depicted in Figure 3, are:

- One; Data gathering from a) Previous projects' documents such as Monthly reports, Project charters, Risk registers, Cost reports, and Schedule baselines to extract a comprehensive list of effective project variables (e.g., budget, contract type, project duration, procurement methods)and a list of common risks for each project, b) state of the art, best practices, and professional standards retrieved from literature review, c) surveys and interviews with project managers, At the end of this phase 65 common risks and 46 effective project variables were extracted for the entire portfolio of studied projects. It is noteworthy that Interviews at this phase only aimed to finalize the risk and variable list and did not yet focus on their causal relationships or probability distributions among them.

- Two; Data cleaning and pre-processing, through Standardization of the extracted data by removing inconsistencies, handling missing values, and normalizing variable formats to ensure compatibility with Bayesian Network modeling, and creation of structured templates for risk variables, ensuring consistency across projects and facilitating further elicitation and probabilistic modeling.
- Three; Surveys and interviews with project managers and company representatives, These included yes/no questions to determine whether each project variable effectively triggered a given risk, as well as qualitative questions based on a Likert scale to evaluate the effect of each variable on the risk. At the end of this phase, a designated spreadsheet was prepared for each risk, containing the input of the effective variables identified for that risk across all the case study projects, along with the state of that risk (yes/no) in each project.
- Four; Bayesian Risk network creation based on experts' opinion elicitation. Experts defined parent-child relationships between project variables and risks, forming Directed Acyclic Graphs (DAGs) that capture causal dependencies. The initial BN structure was implemented using GENIE software, ensuring that the network adhered to Bayesian inference principles.
- Five; BN parameters learning, merely based on experts' elicitation. Experts assigned prior probability distributions for each risk based on historical insights and domain expertise. Conditional Probability Tables (CPTs) were structured by aggregating expert probability assessments, ensuring accurate risk propagation across the network.
- Six; Synthetic data generation based on previous projects' data (44 projects) using GAN for overcoming data scarcity problems. It resulted in doubling the dataset sizde to 88 projects and balancing it. The full code of GAN can be found here.: https://github.com/aniakh/BN-for-RM
- Seven; The updated project dataset (including both real and synthetic data) was integrated into the BN model. Belief updates and posterior probability calculations were performed dynamically using Bayesian inference. The influence of data augmentation on risk prediction accuracy by the model was analyzed.Eight; Validating the network through another round of elicitation and cross-validation. Cross-validation is a statistical technique used in ML to assess model performance by partitioning data into training and testing subsets. The k-fold variant divides the dataset into 'k' subsets, iteratively using k-1 subsets for training and 1 subset for testing, training and testing the model 'k' times to provide a comprehensive evaluation (Bates, Hastie and Tibshirani, 2022). This validation method ensured robustness and minimized overfitting, providing a statistical evaluation of model accuracy.
- Nine; The following four Bayesian Network models were compared:
    - Pure elicitation-based BN model (expert-driven risk probabilities without project data).
    - Pure data-based BN model (project data-driven risk probabilities without expert elicitation).
    - BN model before and after GAN-based data augmentation (to measure the impact of synthetic data and database size).
    - Hybrid BN model combining expert elicitation and project data (optimal balance between subjective and objective risk modeling). The comparative analysis demonstrated the superiority of the hybrid BN model, as it provided higher accuracy and better risk inference capabilities compared to other configurations.

In the next subchapters, a detailed preview of structure and parameter learning methods, in BN, as well as elicitation methods are presented.

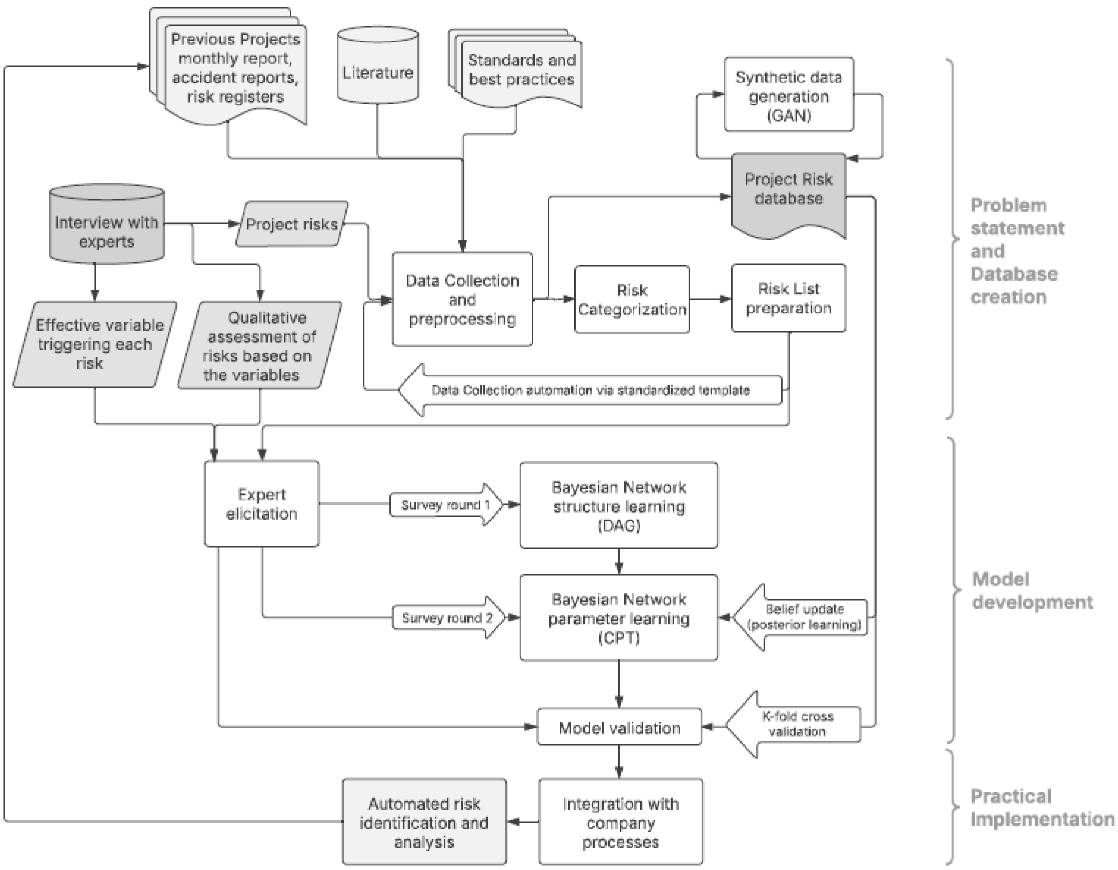

Figure 3: Research Scheme and phases.

3.1 Elicitation-based RM Model Development

The development of BNs includes two parts: the development of the topology or the structure, which is the qualitative part containing the nodes and arrows, and the parameterization, which is the quantitative part containing the CPT. The structure and parameters of a BN can be learned from expert knowledge, 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 Fault Tree Analysis, Event Tree Analysis, and Influence Diagrams), and the combination of two or three of them (Phan et al., 2016). The probabilities elicited from domain experts are called subjective probabilities. Elicitation-based BN models are thought to carry biases and uncertainty, while learning BN from data is considered evidence-based (Mazaheri, Kujala and Montewka, 2014), since the model is built on real accident data. There are three types of probability data or parameters in BNs:

- Prior probability, the probability distribution before taking into consideration any evidence;
- Posterior probability, calculated after observing evidence (Mohamad and Tran, 2021);
- Conditional probability, reflecting the degree of influence of the parent nodes on the child node.

To obtain the CPT represengint the prior and conditional probabilities, first, the possible combination values of the parent nodes need to be found, which are 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).

Structure-learning methods proposed in the literature are a) based on a conditional independence test such as X2 tests (Campos, 1998) or b) based on a scoring metric and a search algorithm (Lam and Bacchijs, 1994). 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). 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 et al., 2015).

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 (Cooper, Herskovits and Edu, 1992). 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 (Ji et al., 2015). Moreover, 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 (Zhang et al., 2020). 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).

The computational complexity of learning BN structures can be a major challenge, specially 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, Azzi and Ezebili, 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 if 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 (Castelo, 2003).

3.2 Elicitation Method Selection

There are several elements to consider when selecting an elicitation method, including:

- One; A proper issue and questions section, formatting, and analysis, resolvable within the assigned time, resources, and available knowledge area of the experts (Kuhnert, Martin and Griffiths, 2010).
- Two; Elicitation methods and means selection, either a loose and informal method or a structured and rigorous. Some of the common means are questionnaires, surveys, interviews, and round tables.
- Three; 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, linguistic terms are easier to comprehend and evaluate by experts (Mohamed and Tran, 2021).
- Four; Experts' selection based on their professional skills, position or role, superior knowledge or experience with the issue, preferability in terms of citations and published works, certainty in their judgements, and recommendations from respected bodies (Kuhnert, Martin and Griffiths, 2010).
- Five; 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, elicitation measures used, and judgment biases (Hora, 2018).

Some lucrative previous studies on elicitation frameworks served as the benchmark of the elicitation process of this study (Low-Choy, O'leary and Mengersen 2009; Martin et al., 2005). However, the research gap remains for a holistic and detailed elicitation process for real-world problems in the construction industry. Even though elicitation seems like a solution to many problems in BN application, the selection of the elicitation method, the determination of experts, and the training process could be daunting (Kuhnert, Martin and Griffiths, 2010). Furthermore, when the BN gets bigger and contains more nodes, the number of conditional probabilities grows exponentially, which requires a 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:

Simplifying the model structure by reducing nodes or using methods like the Noisy-OR rule and generating a full CPT from limited probability items (Fenton, Neil and Caballero, 2006), and the weighted sum algorithm, all of which could be applied to nominal variables and reduce experts' elicitation workload.

Easing probability elicitation using direct methods like the probability wheel or indirect methods like AHP.

Other common issues with the elicitation method are the aleatory and epistemic uncertainties derived from the randomness of systems and lack of knowledge of systems (Merrick, Van Dorp and Dinesh, 2005), the risk of different interpretations by various individuals and ambiguity when using linguistic scales, the risk of inconsistency between the results, and errors such as Extension Error, Conjunction Error, Disjunction Error (Bar-hillel and Neter, 1993), Judgmental Errors (Representativeness and Availabilities heuristics), Overconfidence/conservatism (Hora, 2018), Misunderstanding of conditional probabilities (Kuhnert, Martin and Griffiths, 2010), Translation of scales, and Affect error.

Structure learning of the BN in this study is done through elicitation, conducted in three phases shown in Figure 4, and parameter learning is done based on elicitation and previous projects' data. 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.

During the first round of elicitation, Experts identified the influential project variables on common risks among the extracted variables' list from previous projects' documents, which served as the network parent nodes; the risks among the list of 65 common risks in previous projects, which served as the child nodes; and their connection as the DAG, forming the BN structure. It is noteworthy that the total of 65 risks and their classification in the 11 categories were extracted from previous project documents and were validated by different experts in the company. The same process of data extraction from previous projects and validation by company experts happened for the 46 project variables to form the general inputs and outputs of the risk registery. The full list of input project variables and risks in each category is attached in Annex 1. The elicitation was conducted through a poll survey sent to all the Project Managers and directors of the company, which aggregated to thirty people. Sixteen 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 (Table 2). Experts were asked to select whether any of these project variables, such as budget and delivery method, influenced 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 .

Table 2:The survey matrix on the effect of various project variables on each risk category.

Risk Category Project Variable	Financial risks	Technical risks	Schedule risks	Safety risks	Quality risks	Administrative	Communication	Environmental	Procurement risks	Resource risks	Stakeholders risks
Property/Project Type (Residential, Commercial, Industrial, etc.)											
Built Area (m2)											
Lot Size (m2)											
Number of Floors											
Number of End Users											
Intervention Type (new construction, renovation, development, etc.)											
Delivery Method (DB, EPC, CM, PPP, etc.)											
Number of Contractors (one general contractor or multiple subcontractors)											

Number of Design/Eng. Companies (one or multiple)											
Initial Construction Budget											
Cost contingency in 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, etc.)											
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, etc.)											
Existence of underground waters											
Existence of water pollutants											
Structure type (concrete, steel, etc.)											
HVAC system (central, local) Energy demand amount for heating/cooling/electricity											
Case study company’s Service Type in the project (PM, A and E, etc.)											
Case study company’s Work Packages involved (Civil, electrical, mechanical, etc.)											
Case study company’s Project phases involved (design, construction, procurement, etc.)											
Case study company’s Contract type (lump-sum, fixed-price, cost plus, etc.)											
Case study company’s contracting relationship with client (joint venture, direct to owner, etc.)											
Case study company’s collaborations with other headquarters											
Case study company’s Contract value											
Case study company’s cost overrun											
Case study company’s Gross Margin (revenue-cost)											
Case study company’s approved change orders amount											
Case study company’s Value saving solutions											
Case study company’s contract duration											
Case study company’s time overrun											

Based on the findings, the overall structure of the risk networks was created in GENIE software. GENIE, developed by BayesFusion, is a graphical user interface for Bayesian network (BN) modeling and decision analysis. It enables intuitive construction, visualization, and inference in probabilistic models, supporting both discrete and continuous variables. GENIE's advanced inference algorithms allow real-time probability updates, making it ideal for dynamic risk assessment in construction projects. The software facilitates parameter learning, integrating historical data with expert elicitation for robust risk modeling. Its what-if analysis, causal relationship visualization, and quantitative risk assessment enhance predictive analytics and decision support. GENIE’s interoperability with third-party applications further strengthens its utility in construction risk management. In this research, the parent nodes in the BN are project variables like budget and project type, and the child nodes are other dependant project variables and project risks.

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. A sample of such survey can be found in Table 3.

Table 3: Sample of second round of elicitation survey to qualitatively assess the effect of project type of various procurement risks.

Project Type / Procurement Risk	Building: Residential	Building: Commercial	Industrial/ Data Center/ Logistic	Pharma
Change of procurement strategy and contract type	Asnwers: »Very Low« to »Very High«			
Delay due to contract awarding/ tender closing				
Vendor list and supply chain disruption				
Delays and incompliance due to inefficient coordination of third party suppliers				

Then, these numbers were turned into percentages between 0 and 100, using the formula presented in Equation 2, and were inserted into the network as the priors. Since most child nodes, in this case, the risks, have more than one parent, in this case, influential project variables (Figure 4), the joint distributions of collective posteriors are calculated by a geometric mean presented in Equation 3. These priors shape the background knowledge of the BNs derived from years of experience. Afterwards, the projects' objective data was inserted into the model, and the beliefs or posteriors were updated based on these observations. Combining two sources of data and judgment, this research succeeded in compensating for the data scarcity problem, as depicted in Figure5.

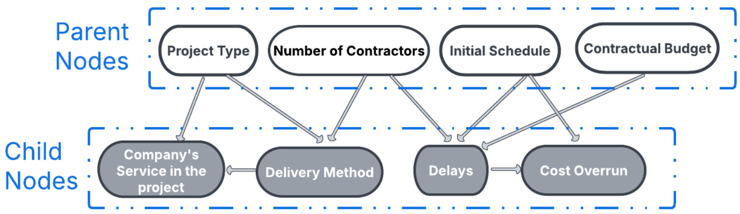

Figure 4: Sample of Parent and Child nodes relationships in construction projects.

{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}

(Equation 2)

$$\left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}} = \sqrt[n]{x_1 x_2 \dots x_n} \quad \text{(Equation 3)}$$

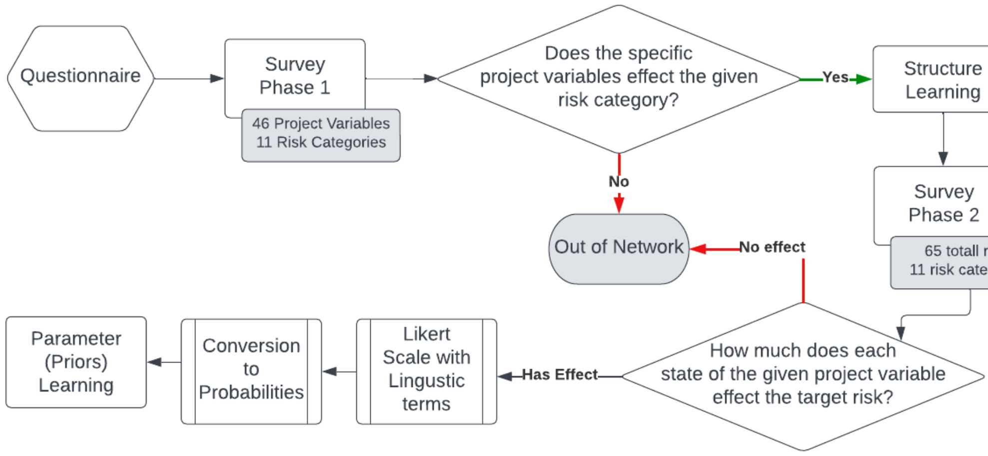

Figure 5: Elicitation-based BN structure and parameter learning process.

The third phase of elicitation was conducted after the project data insertion into the model. Experts were asked to validate the networks of each risk categoty, for instance finanical risk network or procurement risk network, which will be presented in the results section, 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.

3.3 Data Augmentation using Generative Adversarial Networks (GANs)

Another solution this research used to overcome the data scarcity problem was the use of synthetic data generated by Generative Adversarial Networks (GANs). In order to mitigate the data scarcity issue, this study used GANs to produce synthetic data from the project database, initially consisting of 44 projects; as a result, the total number of projects reached 88. Figure 6 shows the steps to implement the data augmentation technique, in which all the continuous data columns were discretized and turned into numeric values, then were inserted into the GAN model. As a result, the size of the database doubled, reaching to 88 projects. The complete code can be found here.

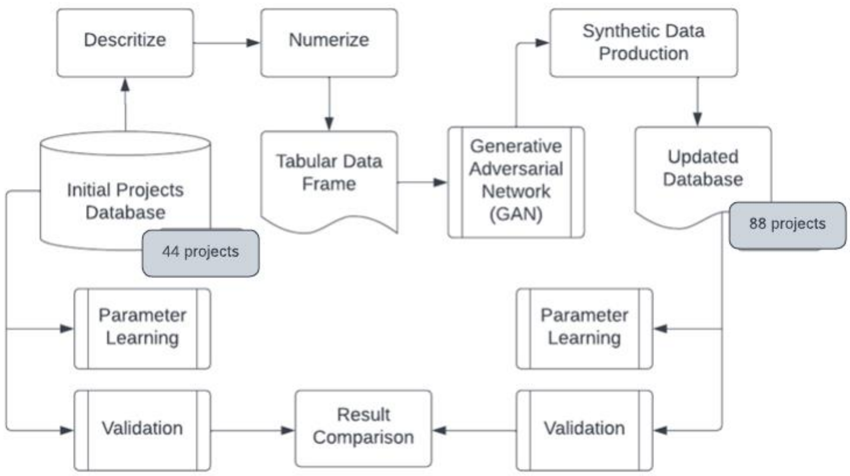

Figure 6: Steps to implement the Data Augmentation technique using GANs (Parameter learning refers to belief update and posterior probability learning by the BN after encountering the project data).

3.4 BN model development

Finally, the proposed RM model for this study was developed, as presented in Figure 7, consisting of a) input data, including the independent project variables, which are the ones not influenced by the choice of any other variable, and the dependent project variables somewhat affected by the independent ones, the number of independant and depentant variables differ in each risk category network, 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.

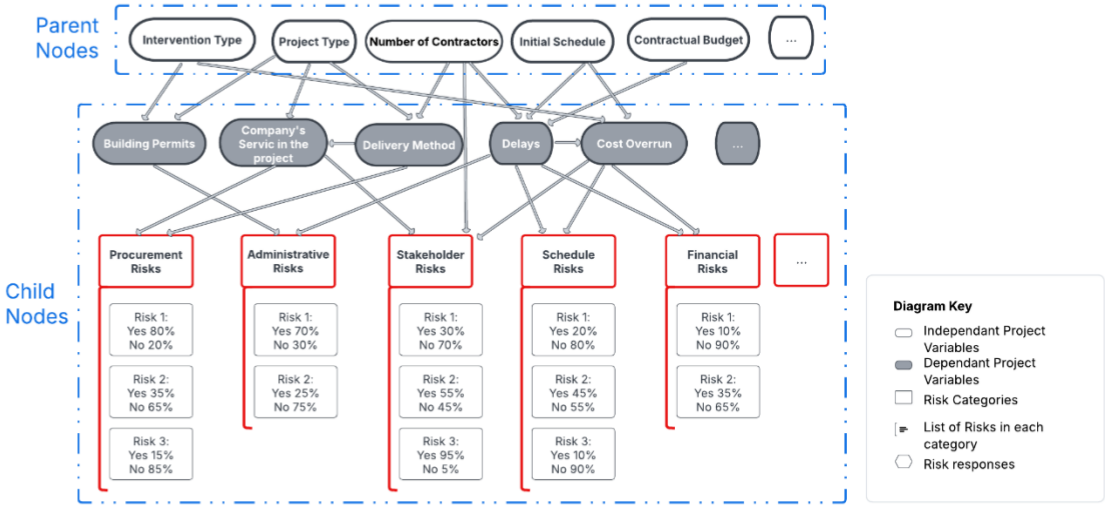

Figure 7: General Risk Network of the study using BN.

4. RESULTS AND DISCUSSION

A total number of 44 construction projects' data were gathered and analyzed, including 15 pharmaceutical, 13 commercial, 8 residential, and 8 industrial assets. The key project variables are collected from these projects' documents and through interviews with their project managers. The number of these variables is 46, which could influence specific types of risks in the projects, such as project type, built area, and type of contract. Each of these variables could have various importance in assessing each risk. For instance, the 'contract type' variable was found to significantly impact procurement risks, as lump-sum contracts often correlated with delays due to rigid pricing structures. Similarly, 'built area' was observed to have a stronger relationship with safety and scheduling risks, particularly in larger projects where logistical challenges are more complex. The full list of risks and project variables can be found in Annex 1.

Moreover, a comprehensive list of common risks in previous projects was composed. The risks were grouped in 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. These 11 risk categories were developed based on a systematic literature review and expert inputs, aligning with established construction risk taxonomies such as ISO 31000. Special attention was given to interdependencies between categories, for example, 'Procurement Risks' and 'Schedule Risks' often exhibited causal links, where delays in material delivery directly increased project schedule risk. 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. Sixteen experts directly participated in the elicitation process, consisting of surveys and interviews in three phases. Figures 8.a to 8.d indicate the distribution of the department the experts work at, their position in the company, their educational level, and their work experience in the company, respectively. Moreover, Figure 9 shows the sensitivity analysis of each of the 44 projects in "Delay due to contract awarding/ tender closing" risk prediction.

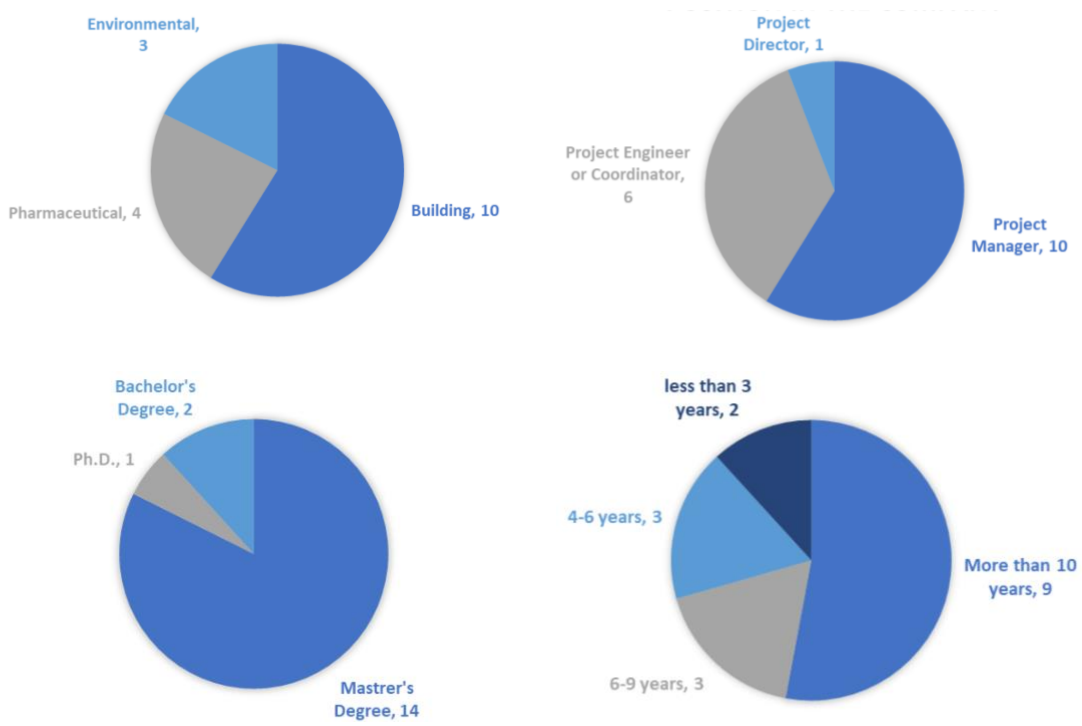

Figure 8.a: Experts' department at company; 8.b: Experts' position at company; 8.c: Experts' educational level; 8.d: Experts' years of work experience.

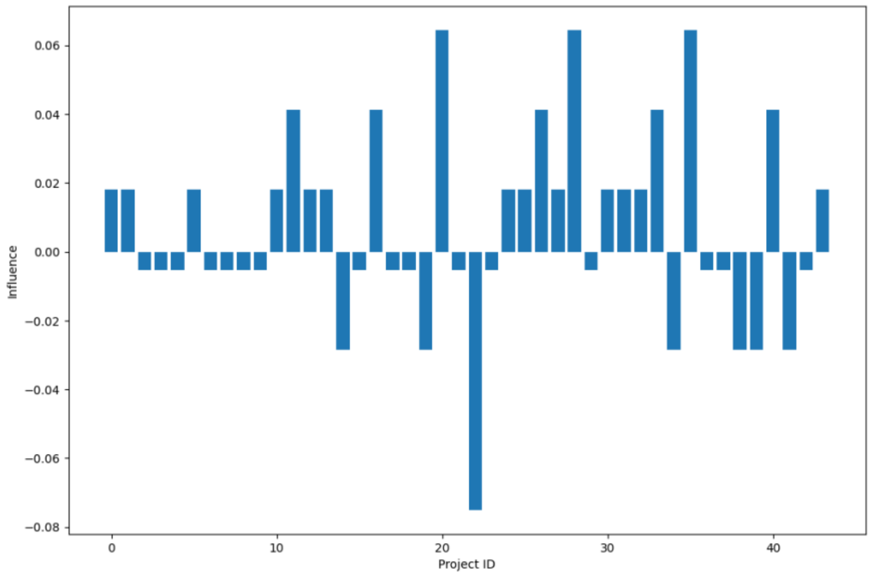

Figure 9: Project Significance for "Delay due to contract awarding/ tender closing" risk prediction.

The main results achieved in each stage are listed below:

4.1 Synthetic data generation

As a result of using GANs for synthetic data generation based on the initial projects' database, 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.

GANs were selected due to their ability to generate high-dimensional data that preserves real-world dependencies between risk variables. The synthetic data was validated using statistical tests, ensuring it maintained similar distributions to real project data. Additionally, domain experts reviewed synthetic risks to confirm logical coherence.

4.2 Elicitation through surveys, and BN structure and parameter selection

Due to the limited size of the database and the uncertain nature of the risk domain, probabilistic models have better performance; hence, the Bayesian Network was selected for this study. It utilizes Bayesian statistics and can integrate two types of data: objective project data and subjective expert opinion. Each Bayesian Network (BN) consists of three parts: a) the nodes, which represent the variables; b) the Directed Acyclic Graph (DAG), representing the structure and interrelationships between the nodes; and c) the Conditional Probability Table (CPT) or the Conditional Probability Distribution (CPD), which quantifies the strength of these interrelationships.

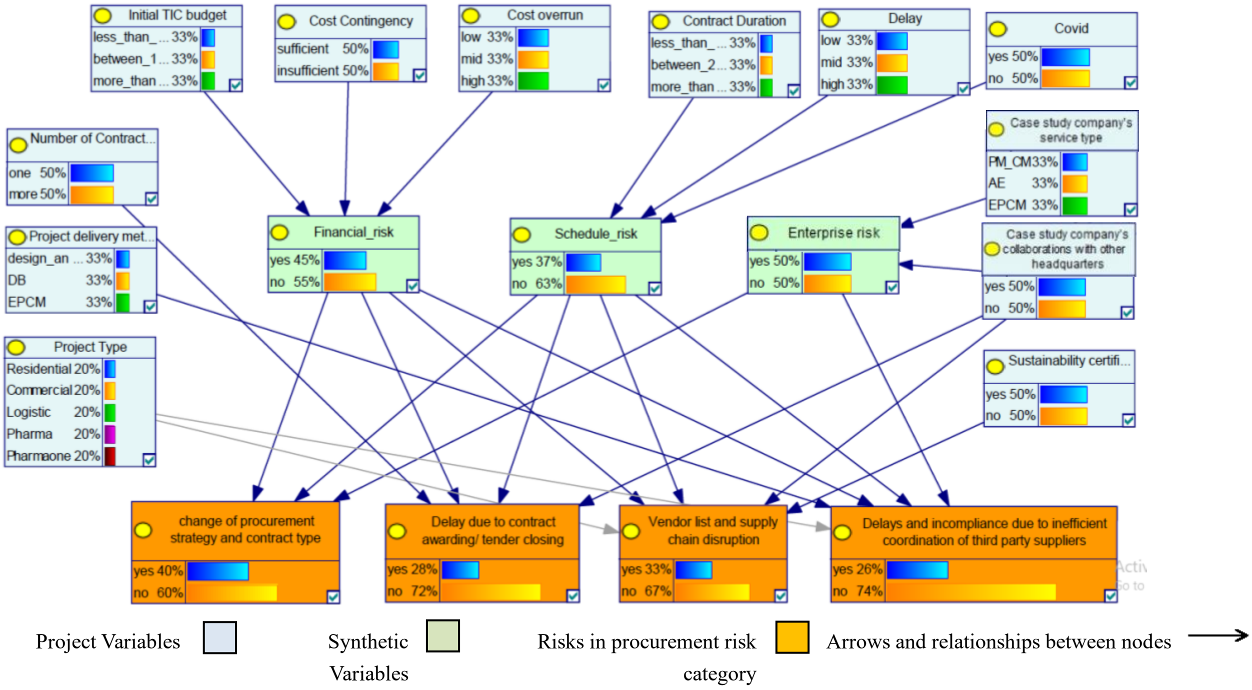

Figure 10: Structure and Parameter learning of the procurement risk network by elicitation.

Based on the first round of elicitation through surveys conducted with 17 experts, 11 general risk networks were developed, each corresponding to a specific risk category. These initial networks were structured in GENIE software using expert assessments on the qualitative impact of various project variables on risks within their respective categories. The development of Bayesian Networks (BNs) followed a two-phase process: first, constructing the topology or structure (qualitative phase) and then parameterizing the model (quantitative phase). The structure was primarily derived from the first round of interviews, where key project variables were identified as parent nodes, while associated risks were assigned as child nodes, significantly simplifying model complexity and computational requirements. Each node represented discrete states; for example, the project delivery method node could have three possible states—DB, EPCM, or Design with General Contractors—while risk nodes had binary states: "yes" (risk occurs) or "no" (risk does not occur).

Conditional probabilities between parent and child nodes were calculated based on the second round of expert interviews and integrated into the model's Conditional Probability Tables (CPTs). At this stage, prior probabilities for all parent node states were assumed to be uniformly distributed, meaning each state was considered equally probable. For instance, in the procurement risk network, the likelihood of having one general contractor versus multiple contractors was initially assumed to be equal, even though real-world data suggests otherwise. This uniform assumption persisted until the model was exposed to project-specific datasets to refine the priors.

The Bayesian Network structure was implemented in GENIE, facilitating automated parameter learning and dynamic inference updates. Expert assessments played a crucial role in defining initial priors, particularly for categories with limited historical data, such as Stakeholder Risks. However, to mitigate subjective biases, expert inputs were cross-validated against project records. Figure 10 illustrates the procurement risks network, where all priors are equal due to the absence of historical records in the model at this stage. Similar networks were developed for the remaining risk categories, ensuring a structured and systematic representation of project risks.

This study employs the elicitation method for manual structure learning and uses the Expectation-Maximization (EM) algorithm for parameter learning, drawing on data from previous projects. The EM algorithm is an iterative parameter learning method that alternates between estimating the expected sufficient statistics of the data, given the current parameter estimates, and then updating the parameters based on these statistics. The model is developed using GENIE software. Equations 4 to 6 present the formulas used for the Maximum Likelihood Estimate, Expectation, and Maximization steps, respectively. These steps are automatically executed on the input data in GENIE.

$$L\ (\theta; X) = p\ (X|\theta) = \int p\ (X, Z|\theta) dZ = \int p(X|Z, \theta) p(Z|\theta) dZ \quad \text{(Equation 4)}$$

$$Q\left(\theta \middle| \theta^{(t)}\right) = E_{Z \sim p(.|X,\ \theta^{(t)})}[\log p(X, Z|\theta)] \quad \text{(Equation 5}$$

$$\theta^{(t+1)} = arg\ _{\theta} \max\ Q\left(\theta|\theta^{(t)}\right) \quad \text{(Equation 6)}$$

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.

As a result, for every new project, given the known states of each parent node, the Bayesian Network (BN) can automatically calculate the probability of each risk occurring, as shown in Figure 12. Therefore, risks (child nodes) with a high probability of occurring (the "yes" state) will be identified and documented in the project's monitoring and mitigation planning.As a result, for every new project, given the known states of each parent node, the Bayesian Network (BN) can automatically calculate the probability of each risk occurring. Therefore, risks (child nodes) with a high probability of occurring (the "yes" state) will be identified and documented in the project's monitoring and mitigation planning

4.3 Parameters learning and beliefs update by project data

In this phase, the data from the 44 projects were 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 11 presents the same risk network after beliefs are updated by historical records and the priors of each variable and the risks' probability are changed accordingly. Figure 11 shows an example of model prediction based on inserted evidence for a given project, where the model automatically evaluates the probability of risks. After incorporating real project data, posterior probabilities of certain risks exhibited substantial shifts. For example, 'procurement delay risk' increased from 35% to 52% after integrating actual project histories. Notably, in some cases, expert assessments diverged from observed data trends, necessitating recalibration of CPT values. Hence, the main difference of Figure 11 and 12 lies in the actual values of initial probabilities of different parent nodes states (in this case the posteriors), which are learned based on the actual project data, and which effect the final probability of each risk. Finally, in figure 12, the evidences are set, in other words, actual states of a given projects are inserted in the model. For instance, this project has one general contractor, the offerd service was Project Management and Construction Management, and the delivery method was Design Build. When the evidences are set, the model automatically and based on predifiend causal probabilities between the nodes, predicts the probability of each of the four procurement risks happening (the probability of the Yes state), which reflects the existance and intensity of the risk in that given project.

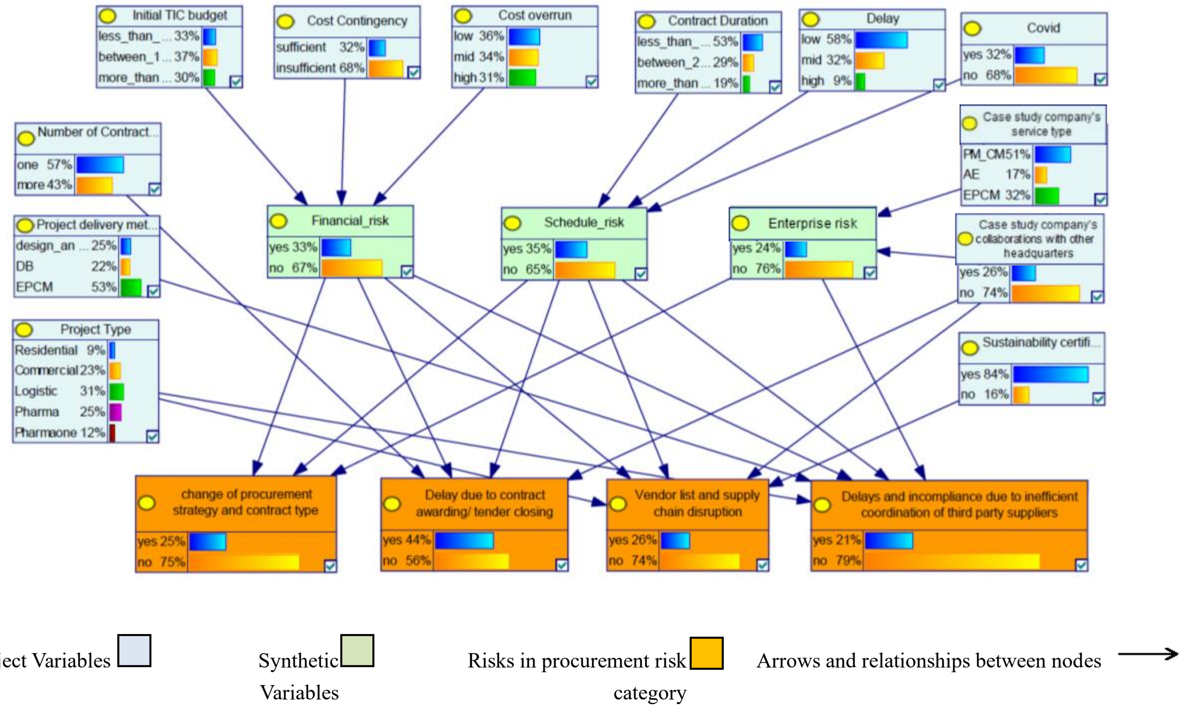

Figure 11: Procurement risk network after posterior updates by historical data.

4.4. BN model validation

Based on the information provided by experts on their ongoing projects, 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.

For the data-driven validation, the k-fold cross-validation method was used by the software. K-fold cross-validation is a statistical method used in machine learning to evaluate model performance by dividing the dataset into k subsets, iteratively using k-1 subsets for training and one for testing, ensuring robust validation and reducing overfitting; this method is a built-in function in Genie software, allowing automated separation of training and testing data while validating the network accuracy.The accuracy is measured as the ratio of the total of correct predictions of the network (in this case the correct prediction of the Yes or No state of each risk based on the actual state of the risk) to the total predictions (correct and non correct). The accuracy is measured one for the network trained with the initial 44 project data (referred to as pre data augmentation data), and later with the new database of 88 projects including the initial 44 projects and the new 44 synthetic data (referred to as post augmentation data).

The result of k-fold cross-validation of the procurement risk network before and after adding synthetic data to the database were registered and compared, as presented in Table 4. K-fold cross-validation was chosen for its ability to maximize training data utilization while minimizing overfitting. The model's accuracy improved significantly from 72% (pre-GAN) to 85% (post-GAN), demonstrating the effectiveness of synthetic data augmentation. The results indicated a great increase in prediction accuracy after data augmentation and proved the effectiveness of this solution for compensating the data scarcity issue.

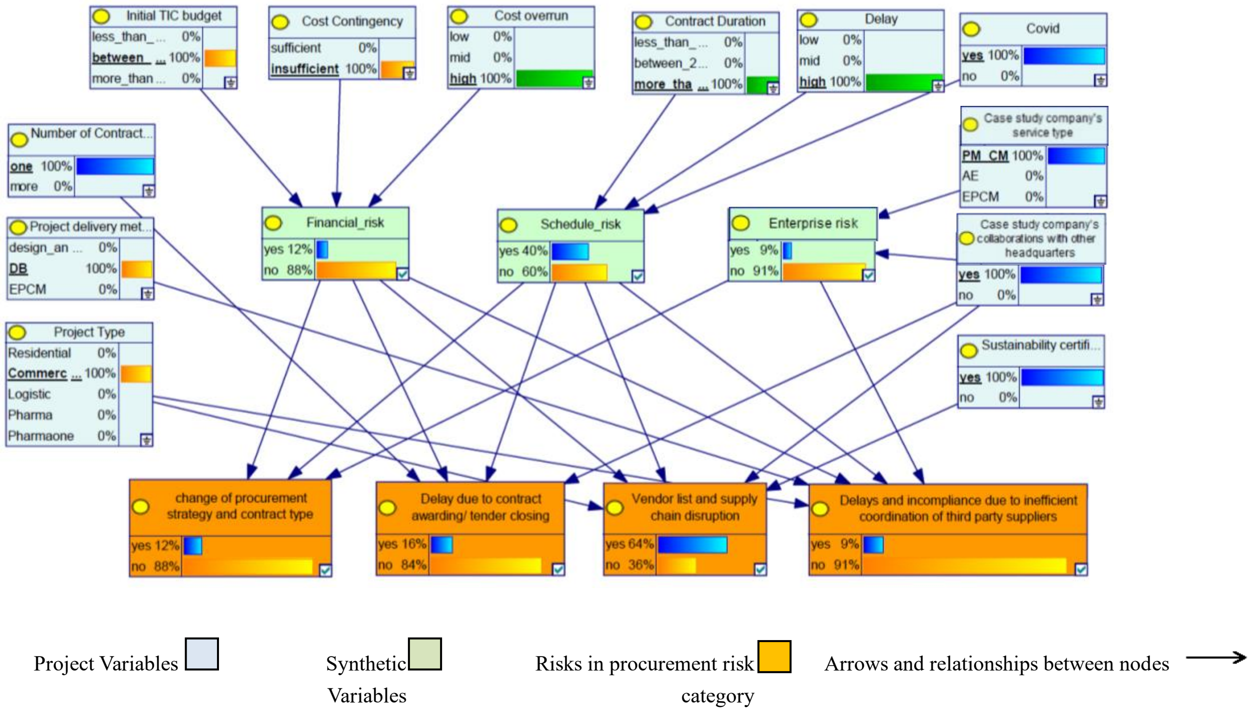

Figure 12: An example of model prediction based on inserted evidence for a given project.

Table 4: Pre and Post Data Augmentation Accuracy of the BN Model.

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 13 shows a comparative analysis between the BN prediction accuracy obtained in each risk category using k-fold cross validation. As seen in the figure, the model's accuracy is higher than 85% in all risk categories, which is a great accuracy given the limited database.

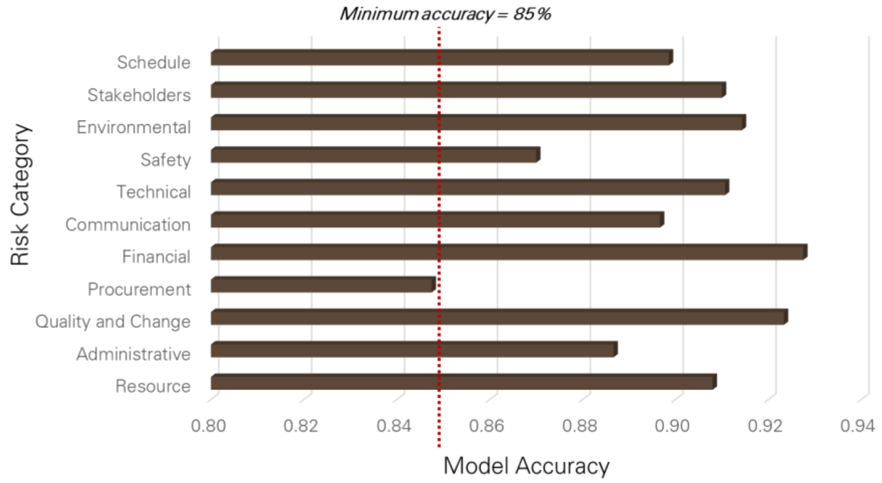

Figure 13: The average accuracy of BN for each of the eleven risk categories.

5. CONCLUSION

The Construction RM process is expected to witness significant advancements with the integration of AI, enhancing automation, optimization, and decision-making processes. Machine Learning and Deep Learning algorithms have been pivotal in RM research. However, their practical application demands extensive experience, prior knowledge, and historical data, often not easily accessible and limited. This study harnesses AI's analytical prowess, synthetic data generation using GANs, and expert judgment quantification using elicitation methods to address these challenges, aiming to refine the RM process and make the risk prediction less subjective. The study's findings demonstrate that Bayesian Network (BN)-based risk modeling, when integrated with expert elicitation and synthetic data augmentation, can significantly improve the precision and adaptability of risk assessments in construction projects. Notably, this research spotlights project management, an area less delved into than design and engineering domains for digitalization, underscoring AI's potential to elevate RM processes' performance and projects' success rate.

The proposed model is a Bayesian Network, the parent nodes of which are influential project variables, the child nodes are the project risks, and the arcs and the CPT indicate the causal probabilities and interdependencies between the variables and risks. This model is developed based on a real database of projects and benefits from a graphical representation to show relationships among project variables and risks for easier understanding, facilitating its practical application. The BN model was tested and validated on a dataset of 44 construction projects, with results indicating an 85% alignment between predicted and actual risk occurrences, underscoring the model's predictive reliability.

The promising results obtained from this research support the assertion that probabilistic ML models, specially BNs, can be the perfect solution for RM automation and optimization in limited construction databases and stand out in the RM domain due to their capacity to model intricate problems, manage high uncertainty, amalgamate diverse information sources, and handle incomplete data. This is due to their ability to integrate subjective and objective sources of data and make judgments based on various sources, which compensates for the data scarcity issue. Furthermore, the Bayesian model demonstrated an 18% improvement in accuracy following the integration of GAN-generated synthetic data, proving the effectiveness of data augmentation in compensating for sparse datasets.

Moreover, the model prediction accuracy increased significantly after data augmentation using GANs. This was the study's second important contribution and innovative aspect, as it is one of the first examples of applying GANs for tabular data augmentation. Before augmentation, the BN model exhibited an overall accuracy of 72%, which increased to 85% post-augmentation, reinforcing the viability of synthetic data generation in RM. Therefore, the two proposed solutions, namely elicitation and synthetic data generation, can be used by construction companies to increase the quantity and quality of their data and obtain more accurate results from the BN-based RM model.

A primary limitation of this research was the data scarcity and unstructured format of data registration, a common issue in construction firms. This made data acquisition arduous. While many studies target operation-level risks, this research zeroes in on project-level data, which is scarcer. While most of the previous studies conducted in the RM realm focused on operation-level risks, the data of which is produced on a daily basis, this study focuses on project-level data, which is one entry per project. This limitation affected the diversity of risk scenarios available for modeling, potentially restricting the generalizability of findings across different project types and scales. Therefore, another limitation of the study is the lack of similar previous studies that could serve as a benchmark for result comparison. BN overfitting to the portfolio of projects analyzed by this study is another concern, as the location and scope of the majority of them are similar, although the model can be easily adjusted based on various attributes of projects. The solution to this is that the experts' elicitation serves as a fixed basis of the model, the beliefs of which can be updated when new data on projects becomes available.

Future studies may focus on the AI-based RM model merging with other project management domains, like schedule and cost management, as well as expanding its application scope to operation-level risks, offering richer data and enabling a more sophisticated and dynamic modeling process. Another promising direction is the integration of Natural Language Processing (NLP) techniques to extract risk-related insights from unstructured textual project documentation, further enhancing the automation of risk identification and assessment. Moreover, the obtained results of this study can be compared with results obtained from deterministic ML models to indicate the importance of the database size and in the model performance. Lastly, automating project documentation, such as monthly report regulation and change order control, could be pivotal in risk monitoring and control phases. The findings of this study provide a foundation for future research on hybrid AI frameworks that combine probabilistic inference, deep learning, and real-time project monitoring to achieve more dynamic and adaptive risk management systems.

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APPENDIX

The full list of the **risks** in each category can be found below:

Technical Risks:

- 3D model (BIM) problems and clashes
- Complexity of the project or use of a new technology and requirement for specific expertise
- Utility and power supply shortage or connections constraints
- Hardship in building components installation.
- Difficult or improper choice of building systems, structure, and design
- Interference between work packages, vehicles, and on-site workers due to limited space and existence of confined spaces in construction site
- Lack of usability and access to the site.
- Misleading topography data for design.
- Over-budget bid proposals due to tight schedule or scope change
- Incompliance between documents/drawings/information on existing properties and demolition activities.
- Unprecise definition of quantities of work and client' expectations and requirements.
- Error in defining battery limit.
- Design Parameters, Measures, Metrics, Criteria or Data change.
- Design Modification and fortification.
- Delay in management defining tools and procedures.

Administrative Risks:

- Problems in authorization procedure and building permit from municipality or other legislative bodies.
- Modification in constructed area or lot size
- Unclear definition of authority and land use on construction site

Resource Risks:

- Contractors' scarcity or poor performance
- Delay in the issuance of the organization chart by client.
- Lack of on-site workers and personnel
- Company's human resources scarcity or improper allocation to activities
- Resources and materials price inflation

Safety Risks:

- Coronavirus / implementation of health protocols on site and in office
- Neighbor's complaints and claims
- Lack of HSE protocols, safety equipment and insurance plans

Financial Risks:

- Insufficient cost contingency
- Payment problems and invoicing delays
- Budget Cost overrun / Excessive construction cost
- Wrong Cost Estimation and Budget

Stakeholder Risks:

- Claims due to incorrect project management
- Stakeholders weak commitment to project procedures
- Incorrect attribution of responsibility for possible damage to individual companies
- Lack of coordination between subcontractors
- Problems with neighbors

Quality and Change Risks:

- Cost overrun due to changes
- Insufficient change remuneration in agreement
- Change orders not well managed

Procurement Risks:

- Delay and Change of procurement strategy and contract type
- Delay due to contract awarding/ tender closing
- Vendor list and supply chain disruption
- Delays and incompliance due to inefficient coordination of third party suppliers

Communication Risks:

- High Bureaucracy in decision making process
- Inefficient and unreactive communication strategies between stakeholders
- International communication difficulty

Schedule Risks

- Project suspension
- Delays in the documents preparation or project budget control
- Incorrect and improper schedule baseline and activities' time estimate
- Insufficient time contingency
- Fast tracking approach Delay in construction activities
- Delay in design activities

Environmental Risks:

- Construction site environmental issues like under grand water dangerous products or permeable polluted and unfortified soil
- Costly process to attenuate the noise
- Delay due to asbestos removal
- Difficulty in the authorization and obtaining sustainability certificates

- Severe climatic conditions
- Project incompliance with environmental standards and emission limits
- Waste management issues

The full list of the project 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
- Case study company’s Service Type in the project (PM_CM, A and E, EPCM)
- Case study company’s Work Packages involved (Civil, electrical, mechanical, etc.)
- Case study company’s Project phases involved (partially, completely)
- Case study company’s Contract type (lump-sum, reimbursable and cost plus)
- Case study company’s Contracting relationship with client (joint venture, direct to owner)
- Case study company’s Collaborations with other headquarters
- Case study company’s Contract value
- Case study company’s Cost overrun
- Case study company’s Gross Margin (revenue-cost)
- Case study company’s approved change orders’ amount
- Case study company’s Value plus saving
- Case study company’s contract duration
- Case study company’s time overrun