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Fuzzy Bayesian Belief Networks Method on Risk Assessment of EPC Pipeline Project

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Abstract

Subsea gas pipeline projects are experiencing significant technical and managerial challenges across Engineering, Procurement, and Construction (EPC) phases. To address the challenges, effective risk management in the early project phases is essential to mitigating cascading failures that cause significant schedule delay and cost overrun. Therefore, this study aimed to apply the Fuzzy Bayesian Belief Networks (FBBNs) method to model risk assessment during EPC phases. The findings showed that FBBNs made it possible for a new way to evaluate risks, find interdependencies, and guess what would happen next, which created a strong framework for reducing risk. Based on probabilistic analysis as supported by expert elicitation, risks from the early phase of engineering and procurement showed high probabilities of occurrence, including Incompetent Personnel, Project Mismanagement, Unsupportive Stakeholder, Corruption, and Design Inaccuracies. A significant impact was also observed on Construction Rework, Material Quantity Increase, Construction Delay, and Cost Overrun. The results showed the importance of addressing systemic issues early in the EPC project lifecycle, emphasizing personnel competency, design accuracy, strategic and project management planning, procurement management, stakeholder management, and constructability preparation to reduce vulnerabilities. This integrated method aimed to enhance accuracy predictions by determining causal risk probability relationships in high-risk offshore environments of EPC subsea gas pipeline projects.

Keywords: Fuzzy Bayesian Belief Networks; Risk Management; Subsea Gas Pipeline; Cost Overrun; Risk Analysis.

1. Introduction

A global energy shift is significantly increasing to accomplish Sustainable Development Goals (SDGs) and reduce carbon emissions [1, 2]. In this context, the gas pipeline project satisfies the operational priorities under SDGs of addressing climate change, thereby enhancing environmental sustainability, and building climate as well as disaster resilience. This is achieved through the implementation of the Asian Development Bank (ADB) Strategy 2030, specifically under the headings of "affordable and clean energy" as well as "industrial innovation and infrastructure"[3]. Gas pipelines are integral to modern energy infrastructure in line with SDGs to achieve clean energy and net zero emissions as targeted in 2060 [4, 5]. Specifically, pipelines focus on providing a reliable and cost-effective method of transporting natural gas across various distances, which is incredibly effective and efficient in terms of capacity when used as a delivery system [6-10].

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Despite its significant importance, the gas pipeline project is among the most complex undertakings in the energy sector. It is characterized by high-risk factors that span Engineering, Procurement, and Construction (EPC) phases [11-14], particularly for subsea gas pipeline infrastructure projects [15-17]. Although the construction phase often gains attention due to the tangible outcomes [18], engineering [19, 20], and procurement [21, 22], the upstream phase risk factors are also essential, including poor estimating, design change, lack of professional pre-planning studies, and increased material and equipment costs [23] (Figure 1). EPC phases set the foundation for project success but are influenced by risks such as weather/site condition scope change [24], design inaccuracies, quality management [23], government approval delay, material procurement inefficiencies, competency, and stakeholder disagreement [25, 26].

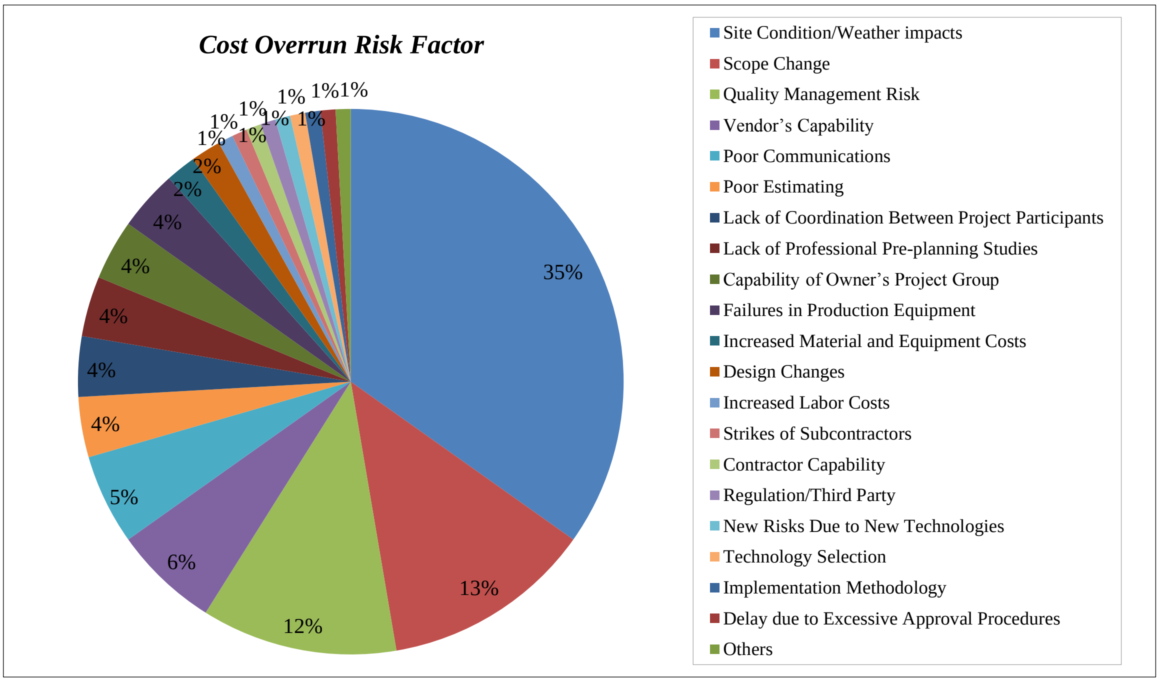

Figure 1. Cost Overrun Risk Factor [23]

Addressing these risks proactively is essential to minimizing cascading failures that can lead to significant Cost Overruns and project delays [27, 28]. Traditional risk assessment methods, including Event Tree Analysis (ETA) [29], Fault Tree Analysis (FTA) [30], Failure Modes and Effects Analysis (FMEA) [31, 32], Bow Tie [33-35], Monte Carlo simulations [15, 36, 37], Analytical Hierarchy Process (AHP) [38, 39], and qualitative risk matrices [40-43], have been widely used to address uncertainties in large-scale infrastructure projects [44-47]. Despite widespread application, traditional methods often face limitations. This is because qualitative methods depend significantly on subjective expert opinions, which can introduce biases and fail to capture the full complexity of risk interdependencies [48, 49]. Quantitative models, while more rigorous, often require extensive datasets that may be unavailable, particularly for novel or early-phase projects [27, 28, 50]. These limitations show the need for an advanced, hybrid method that combines the strengths of existing strategies and addresses their shortcomings [16, 29, 44, 51].

Based on the description, this study aimed to present a novel application of Fuzzy Bayesian Belief Networks (FBBNs) to EPC phases of subsea gas pipeline projects. Compared to traditional Bayesian that successfully models statistical dependencies [52], FBBNs integrate fuzzy set theory to handle vagueness and imprecision in risk data [53-55] as well as causal relationships between risk factors [56-59]. This integration allows for the use of both linguistic terms and probabilistic reasoning, offering a more nuanced understanding of risk dynamics [24, 60, 61]. The novelty of this method depends on the ability to integrate the fuzzy set theory model with interdependencies among risks across multiple project levels, as shown by the data analyzed for the assessment study in subsea gas pipeline EPC projects [16].

The significant contribution of this study is applying the FBBNs method on EPC phases for the subsea pipeline project, while the previous investigation only used Monte Carlo analysis [15]. Other reports predominantly concentrated on the operation phase with corrosion risks [34, 38, 61] that fail to account for the causal interrelationship uncertainties inherent in EPC phases [11, 19, 62]. In comparison, this study shows how FBBNs proactively identify and address risks before propagating to the construction phase [24]. For instance, government approval delays and material quantity issues [21], identified as high-probability risks in the dataset, can be modeled to assess their impacts on the project timeline and contingency cost estimation [17].

This study is structured as follows: Section 1: Introduction consists of study objects, the cost overrun phenomenon, novelty, and contribution. Section 2: Literature Review and Study Gap consists of an overview of existing risk management methods, fuzzy set theory in risk assessment, and study gap. Section 3: Material and Methods are described with a study flowchart, identification of risk factors (RFs), followed by the definition of fuzzy parameter criteria (probability and impact) with the construction of conditional probability tables (CPTs), data collection for probability and impact from expert elicitation, statistical testing for data validation, weightage of expert judgment, and Bayesian Belief Networks (BBNs) model development. Furthermore, Section 4: Results and Discussion, integrating the Fuzzy Bayesian Method for Risk Analysis, presents key results, focusing on critical risk factors, probabilities, impacts, and validation. The key risk insights across project phases, implications, and recommendations for risk management focus on EPC phases, combined with a robust modeling framework, showing the importance of early intervention and providing stakeholders with a powerful tool for enhancing project resilience and efficiency. The discussion emphasizes the implications of these results for project planning and risk management, particularly in the context of improving contingency cost accuracy. This study used the novel capabilities of FBBNs to integrate fuzzy logic, probabilistic reasoning, and the expert system into a fuzzy inference system for risk value and ranking decisions. The results showed a transformative method for managing risks in EPC of subsea gas pipeline projects. Section 5: Conclusion with recommendations for future studies shows the broader applicability of FBBNs in infrastructure risk management.

2. Literature Review and Study Gap

2.1. Overview of Existing Risk Management Method

Risk management is an essential component of large-scale infrastructure projects such as subsea gas pipeline, which is prone to several internal and external risks [63-67]. Traditional methods such as FTA, Monte Carlo Simulations, and qualitative matrices have been used for risk assessment [37, 49, 68]. FTA is a logical method that models potential failure pathways and the contributing factors using Boolean logic [69]. The probability of a top-level event ($P_{TopEvent}$), such as pipeline failure [30], can be calculated using:

$$P_{TopEvent} = 1 - \prod\left(1 - P_{Event_i}\right) \tag{1}$$

where P_Event_i represents the probability of independent contributing events. Although FTA is effective for deterministic systems, it is limited in the ability to model uncertainties and interdependencies between risks.

Monte Carlo Simulations depend on repeated random sampling to estimate the outcomes of uncertain processes. The expected value of a risk E[X] in this framework is given by:

$$E[X] = \int x * f(x)dx \tag{2}$$

where f(x) is the probability density function of the variable x. Although Monte Carlo Simulations are powerful, their dependence on extensive datasets hinders practical application for early project phases where data availability is limited. Qualitative methods, such as risk checklists and expert elicitation, provide useful initial insights but often lack rigor and objectivity [70, 71]. This has driven the need for hybrid models that integrate qualitative and quantitative methods while accounting for uncertainties inherent in complex projects.

2.2. Fuzzy Set Theory in Risk Assessment

Fuzzy Set Theory (FST) provides a robust framework for addressing vagueness and imprecision in risk data. As introduced by Zadeh in 1965 [68, 72-75], FST allows for the representation of linguistic variables including high probability and moderate risk as fuzzy numbers [68, 72, 74], enabling mathematical modelling of qualitative data. Fuzzy set A is defined as:

$$A = \left(x, \mu_A(x)\right)|x \in X, \mu_A(x) \in [0,1] \tag{3}$$

where $\mu_A(x)$ is the membership function that denotes the degree of membership of x in the set A. For trapezoidal fuzzy numbers (TpFNs), commonly used in risk assessments, the membership function $\mu_A(x)$ [76, 77] is expressed as:

$$\mu_A(x) = \begin{cases} 0, x \leq a_1 \; or \; x \geq a_4 \\ (x - a_1)/(a_2 - a_1), a_1 \leq x \leq a_2 \\ 1, a_2 \leq x \leq a_3 \end{cases} \tag{4}$$

where a_1 is Lower bound where the membership starts rising from 0, a_2: Lower bound of the core region where the membership is 1, a_3: Upper bound of the core region where the membership is 1, a_4: Upper bound where the membership decreases to 0, This method enables the integration of expert opinions into risk assessments, allowing for a more nuanced analysis of factors probability and impact, which are often described qualitatively [78, 79].

2.3. Overview of Existing Risk Management Methods

BBNs are a probabilistic modelling tool that uses Directed Acyclic Graphs (DAGs) to represent relationships between variables [80]. Each node in BBNs corresponds to a variable and edges indicate causal dependencies [24, 60, 61]. The joint probability distribution for a set of variables X = (X_1, X_2, ..., X_n) [80, 81] is expressed as:

$$P(X) = \prod P(Xi \mid Parents(Xi)) \tag{5}$$

where Parents (X_i) denotes the set of nodes that directly influence X_i. The power of BBNs depends on their ability to update probabilities dynamically as new evidence becomes available, using Bayes' theorem:

$$P(H|E) = [P(E|H) * P(H)]/P(E) \tag{6}$$

where P(H | E) is the posterior probability of hypothesis H given evidence E, P(E | H) is the possibility of E given H, while P(H) and P(E) are the prior probabilities of H and E, respectively. Despite their advantages, BNs face limitations in handling imprecise or vague data [55].

Defining conditional probabilities for interconnected variables is computationally intensive, and traditional Bayesian can fail to capture the full complexity of uncertain systems [82]. Therefore, BBNs are another widely recognized tool for risk assessment capable of modeling probabilistic relationships among variables. By using DAGs, BBNs provide a visual and computational framework for representing cause-and-effect relationships. These models have been applied extensively in the construction industry to predict project delay, Cost Overrun, and safety incident [53]. The primary strength is in the capacity to update probabilities dynamically as new evidence becomes available, showing suitability for dynamic and complex environments such as subsea pipeline projects.

2.4. Overview of Existing Risk Management Approaches

FBBNs integrate the probabilistic reasoning of BBNs with the flexibility of FST, addressing the limitations of each method. Furthermore, FBBNs allow for the use of fuzzy probabilities to model uncertainties, which is suitable for complex projects. These networks can be used as modularized representation [60], caused by unpredictability and elusiveness of offshore operation [81, 83], such as subsea pipeline [24, 84-86]. Fuzzy conditional probability of a child node C given its parent node P is defined as:

$$P(C|P) = \int \mu_P P(C|P) d\mu_P \tag{7}$$

where μ_P is the membership function of the parent node P. This enables the propagation of fuzzy probabilities through the network, capturing both linguistic and numerical uncertainties. In practice, FBBNs have been used to model cascading risks such as delays in engineering approvals propagating to procurement inefficiencies and affecting project schedules and costs. The integration of fuzzy logic allows decision-makers to evaluate the combined impacts of multiple interdependent risks, including when there is precise data is unavailable.

2.5. Research Gap

Although FBBNs have been applied to various domains [81, 87-91], most studies focus on the construction phase of projects or on isolated risk factors [53, 84, 92]. This shows that there is a lack of study addressing the upstream engineering and procurement phases, where risks often originate and propagate construction phases [93]. Additionally, existing applications often depend on hypothetical scenarios rather than real data, limiting their practical relevance. Current studies on subsea pipeline risk assessment mostly focus on maritime [94-97], operational cases such as corrosion [66, 98-105], and safety issues [61, 84, 85, 106-108]. This is indicated by the absence of reports analyzing the interrelated causal risk factor for EPC regarding the subsea gas pipeline project to improve cost contingency accuracy due to high risk, which can impact overall project Cost Overrun as stated in Section 1. Therefore, this study aimed to apply FBBNs to evaluate interrelated causal risks in the early EPC phases of subsea gas pipeline projects. By integrating fuzzy logic and probabilistic reasoning, the proposed framework provides a novel method for managing cascading risks, improving contingency cost accuracy, and enhancing decision-making in the complex infrastructure of subsea pipeline projects in EPC phases.

3. Material and Methods

This study applied a structured method to model and analyze risk factors in EPC phases of subsea gas pipeline projects using FBBNs.

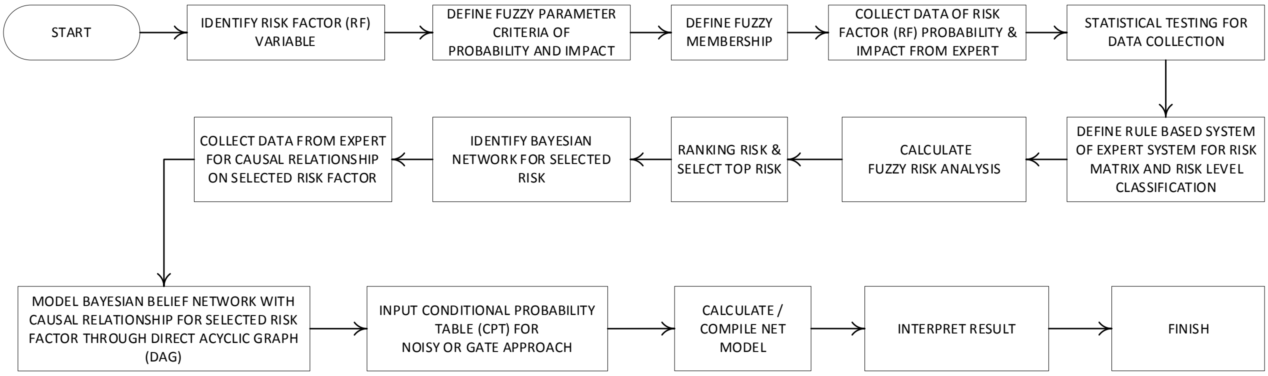

Figure 2. Methodological Flowchart for FBBNs Application

Step 1. Identification of Risk Factors (RFs)

The first phase includes identifying potential risk factors relevant to the project. These comprise 53 risks associated with project mismanagement, material procurement delays, government approval processes, and other critical elements that can affect project timelines or budgets. The risk factors are identified through a comprehensive review of existing literature, project documentation, and expert consultations with wide-ranging literature references, as shown in Table 1.

Table 1. Risk Factor Identified for Subsea Gas Pipeline

Code	Risk Factor	Code	Risk Factor	Reference
X.1	Site Condition	X1.1	Extreme Weather	[15, 109-113]
		X1.2	Free Span on Uneven Seabed	[15, 17, 109, 110, 114]
		X1.3	Unstable Pipelines on Seabed During Installation	[17, 106, 109-118]
X.2	External	X2.1	Government Approval Delay	[17, 33, 106, 110-113, 119]
		X2.2	Increase in Tax Rules	[16, 17]
		X2.3	Community Demonstration	[15, 17, 62, 110, 111]
X.3	Financial	X3.1	Payment Delay from Owner to Contractor	[16, 119, 120]
		X3.2	Payment Delay from Contractor to Subcontractor	[16, 119, 120]
		X3.3	Material Price Increase	[15, 121, 122]
		X3.4	Vessel Rate Increase	[16, 120]
		X3.5	Fuel Price Increase	[123, 124]
		X3.6	Inflation	[15, 17, 110, 119]
		X3.7	Increase in Bank Interest Rates	[15, 110, 119]
		X3.8	Currency Fluctuations	[15, 110]
X4	Management	X4.1	Project Mismanagement	[110, 113, 114, 119]
		X4.2	Unsupportive Stakeholder	[106, 110-113]
		X4.3	Inaccurate Scheduling and Budgeting	[15, 111, 113]
		X4.4	Corruption/Bribery	[16, 114]
		X4.5	Incompetent Personnel	[111, 119]
		X4.7	Tender Process Delay/Failure	[111, 119]
X5	Technical	X5.1	Linepipe Damage During Transportation	[16, 109]
		X5.2	Linepipe Damage During Lifting/Staking	[16, 109]
		X5.3	Linepipe Fabrication Delay	[15, 19, 111, 113]
		X5.4	Material/Equipment Arrival Delay	[17, 109, 111]
		X5.6	Lifting Failure Due to Crane Damage	[15, 17, 33, 114]
		X5.7	Equipment Mechanical Breakdown	[15, 17, 33]
		X5.8	Wire Damage	[15-17]
		X5.9	Tugboat Drive Engine Damage	[16, 109]
		X5.10	Accident During Working at Heights	[16, 119]
		X5.11	Fire in Firing Line (Pipeline Production Area)	[16, 17, 119]
		X5.12	Subsea Facilities Damage Due to Anchor Drag	[16, 109]
		X5.13	Pipeline Damage Caused by Shipwreck	[16, 109]
		X5.14	High Rework/Rejection Rate for Fabrication/Installation Documents	[15, 19, 111, 113]
		X5.15	Documents Approval Delay from Owner	[15, 17, 113]
		X5.16	Inaccurate Design Engineering	[15, 111, 113]
		X5.17	Material Quantity Increase	[15, 16]
		X5.18	Non-Compliant Material	[15, 17, 33, 109, 112, 125]
		X5.19	High Repair/Rejection Rate for Welding/NDT	[15, 16]
		X5.20	Approval Delay from Inspector	[15, 111]
		X5.21	Tool/Material Certificate Expired	[16, 126]
		X5.22	Riser Clamp Cannot be Installed	[109, 110]
		X5.23	Pipe Buckle/Overstress	[16, 109]
		X5.24	Flange/Gasket Installation Error	[16, 114]
		X5.25	Pig Stuck	[109, 127, 128]
		X5.26	Pipe Indicated Leaking During Pre-commissioning	[109, 127, 128]
		X5.27	Moisture Still Exists in Pipe During Pre-commissioning	[127, 128]
		X5.28	Simultaneous Operation (SIMOP) Constraints	[15, 111, 119]
		X5.29	Target Box Placement Error	[16, 109]
		X5.30	Pipe Route Deviation from the Plan Corridor	[16, 109]
		X5.31	Construction Rework	[15, 33, 111, 113]
		X5.32	Completion Delay of Construction/Installation	[15, 33, 111]

Step 2. Definition of Fuzzy Parameter Criteria

In this step, fuzzy parameter criteria are defined for both ***probability*** and ***impact*** assessments. This parameter uses a 5-point scale to account for the probability of occurrence and severity of consequences for risk events [16]. The definitions of both criteria are as follows:

Probability Assessment

The probability of events which obtain from expert consultations with literature references as shown in Table 2, Table 4 and Table 7 are adapted from [94, 129] and reference from Company "Z", which will be utilized with fuzzy membership functions as shown in Figure 4.

Table 2. Probability Assessment Criteria (P) adapted from [94, 129]

Scale	Probability Assessment	Probability Value (P)	Remarks	
1	Rarely/Almost Impossible	0% < P ≤ 20%	Not been heard in Oil and Gas Industry	<10^{-6} per year
2	Unlikely	20% < P ≤ 40%	Previously heard in Oil and Gas Industry	10^{-6} until 10^{-4} per year
3	Moderate	40% < P ≤ 60%	Has occurred in the work operation area up to 1 time since last 100 year	10^{-4} until 10^{-2} per year
4	Likely	60% < P ≤ 80%	Has occurred in work operation area up to 1 time since last year	10^{-2} until 1 time per year
5	Almost Certain	80% < P < 100%	Has occurred in working area several times since last year	>1 time per year

Impact Assessment

The severity of the consequences is based on the following Table 3, which includes key categories such as schedule delay, financial impact, and scope/quality adapted from [14, 94] and reference from Company "Z".

Table 3. Impact Assessment Criteria (I) adapted from [94, 129]

Scale	Consequence Assessment	Schedule Impact	Cost/ Financial Impact	Scope/Quality Impact
1	Insignificant	Schedule Increase < 1%, or (< 1 day)	Cost Impact < 1% Project Cost	Quality degradation almost not found
2	Minor	1% ≤ Schedule Increase < 5%, or (1 day to 1 week)	1% ≤ Cost Impact < 2% Project Cost	Some part of scope area is affected
3	Moderate	5% ≤ Schedule Increase < 10%, or (1 - 2 weeks)	2% ≤ Cost Impact < 3% Project Cost	Mostly part of scope area is affected
4	Significant	10% ≤ Schedule Increase < 20%, or (2 weeks - 1 month)	3% ≤ Cost Impact < 4% Project Cost	Quality degradation is not acceptable by Project Sponsor
5	Catastrophic	Schedule Increase ≥ 20%, or ≥ 1 month	Cost Impact ≥ 4% Project Cost	Result of project is useless

The rules, fuzzifier, inference, and output processor are the four parts of a rule-based fuzzy system. Fuzzy membership functions for probability and impact assessment are modelled using trapezoidal functions [74, 76, 77], to represent overlapping and imprecise boundaries between categories [130], as shown in Figures 3 and 4, including Table 4.

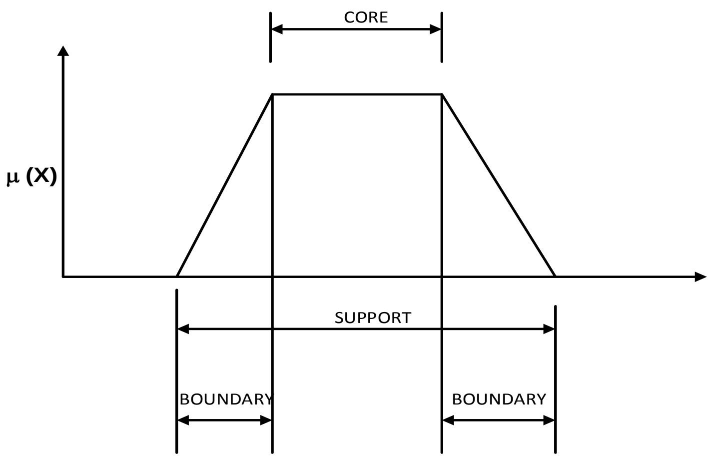

Figure 3. Fuzzy Membership Trapezoidal Function [74, 76, 77, 131]

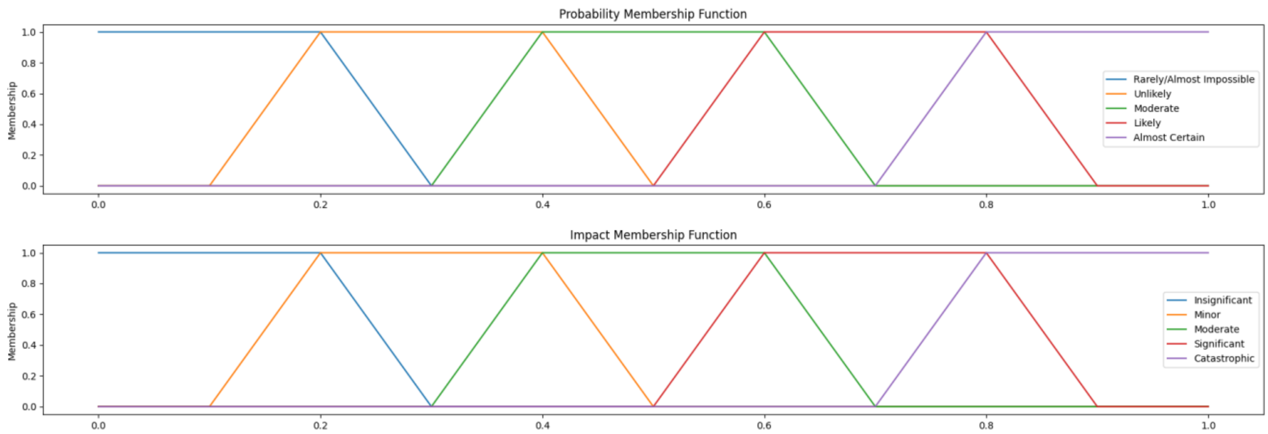

Figure 4. Fuzzy Membership for Probability and Impact

Table 4. Linguistic Variables & Corresponding Trapezoidal Membership Functions [74, 76, 77]

Scale	Probabilistic Linguistic	Impact Linguistic	Fuzzy Membership Function	Meaning
1	Rarely/Almost Impossible	Insignificant	0; 0; 0.2; 0.3	Represents an extremely low probability or negligible impact of an event occurring or its consequences.
2	Unlikely	Minor	0.1; 0.2; 0.4; 0.5	Indicates a low probability or impact, but slightly higher than "rarely/almost impossible."
3	Moderate	Moderate	0.3; 0.4; 0.6; 0.7	Represents an average level of probability or impact, where events or consequences are neither low nor high.
4	Likely	Significant	0.5; 0.6; 0.8; 0.9	Denotes a moderately high probability or significant impact, requiring attention and action to mitigate risks.
5	Almost Certain	Catastrophic	0.8; 0.9; 1; 1	Represents a very high probability or catastrophic impact, demanding immediate action and strong mitigation.

Step 3. Data Collection for Probability and Impact

Data on the probability and impact of each identified risk factor was collected from 71 respondents, consisting of experts and stakeholders in the field of subsea gas pipeline projects. The data collection process included surveys, interviews, and workshops where respondents provided qualitative judgments on the probability and impact of each risk factor from expert consultations with literature references as shown in Tables 2 and 7.

Step 4. Statistical Testing for Data Validation

To validate the reliability and coherence of the collected data, Pearson correlation analysis was used as the primary statistical testing method. Specifically, this method measured the strength and direction of the relationships between the weighted inputs across different respondents' categories (education level, years of experience, and job position) as well as their assessments of probability and impact for each risk factor.

Process of Statistical Testing

1. Weighted Input Preparation:

Respondents' inputs were first weighted based on their background:

- Education Level: Weights of 1 (bachelor's), 2 (master's), and 3 (doctorate).
- Years of Experience: Weights of 1 (1–5 years), 2 (6–10 years), 3 (11-15 years), 4 (16-20 years), 5 (>20 years)
- Job Position: Weights of 1 (Pipeline/Project Engineer), 2 (Project Manager), and 3 (Director/Advisor).

The weights were aggregated to compute a total score for each respondent, showing their expertise and influence on the overall data.

2. Interpretation of Results:

- $r > 0.7$: Strong positive correlation, indicating a high alignment between respondent background and their assessments.
- $0.3 < r \leq 0.7$: Moderate correlation, indicating a reasonable alignment.
- $r \leq 0.3$: Weak or negligible correlation, warranting further investigation.

The results of the statistical testing are attached in Appendix A.

To ensure robustness and reliability, a weighting system was implemented to account for respondents' backgrounds, allowing the input to show their level of expertise and relevance to the topic. The weighting system was structured as follows:

1. Education Level:
   - Bachelor's degree: Weight = 1
   - Master's degree: Weight = 2
   - Doctorate: Weight = 3
2. Years of Experience:
   - 1–5 years: Weight = 1
   - 6–10 years: Weight = 2
   - 11-15 years: Weight = 3
   - 16-20 years: Weight = 4
   - More than 20 years: Weight = 5
3. Job Position:
   - Pipeline/Project Engineer: Weight = 1
   - Project Manager: Weight = 2
   - Director/Advisor: Weight = 3

The weighted responses were aggregated to ensure that more experienced and qualified respondents had a proportionately higher influence on the results. This method improved the qualitative data by reducing bias and emphasizing input from highly knowledgeable respondents. Subsequently, the data collected were converted into fuzzy numbers, which allowed for the representation of imprecise judgments in a mathematically tractable form.

Moreover, the project data from real projects below are utilized for validation purposes

Table 5. Project Data for Testing

Item	Project Title	Pipeline Length (km)	Pipeline diameter (inch)	Overall Project Cost
Project-1	EPC Project for constructing transmission pipelines	130	N/A	$ 30,800,000
Project-2	Gas Distribution Pipeline Engineering Procurement & Construction Project	14.8	8	$ 5,767,667

Phase 5. Fuzzy Logic-Risk Analysis

After fuzzy data was collected, risk factors were ranked based on their relative probability and impact as fuzzy logic [79]. Fuzzy system is also referred to as fuzzy-rule-based, fuzzy expert, fuzzy model, and fuzzy logic controller [132]. A rule-based fuzzy system contains four components, namely rules, fuzzifier, inference, and de-fuzzifier [132]. For risk matrix and level, rule-based fuzzy system is inference based on Risk Matrix Criteria as shown in Tables 5 and 6, which is adapted from Taufiq et al. (2023) [129] and Adi (2014) [19] and Company "Z" reference. Subsequently, fuzzy risk analysis is applied to calculate risk based on probability and impact data as previously collected. The defuzzification based on criteria in Table 6 produces all-risk value, for the selection of high risk. This ranking helps identify the most critical risks that require immediate attention. Meanwhile, the traditional risk analysis is calculated as follows:

$$R_i = P_i \cdot I_i, \tag{8}$$

where R_i is the risk score, P_i is fuzzy probability, and I_i is fuzzy impact of the i-th risk factor. The risk matrix with the value and interpretation level for defuzzification from fuzzy and traditional risk analysis are shown in Table 6.

Table 6. Risk Probability Impact Matrix as adapted from [19, 129]

			Risk Value				
Probability	Almost Certain	5	5	10	15	20	25
	Likely	4	4	8	12	16	20
	Moderate	3	3	6	9	12	15
	Unlikely	2	2	4	6	8	10
	Rarely/Almost Impossible	1	1	2	3	4	5
			1	2	3	4	5
			Insignificant	Minor	Moderate	Significant	Catastrophic
			Impact				

The results of the risk value and comparison between fuzzy and traditional risk analysis with the top selected high-risk factors have been ranked and prioritized in Table 7.

Table 7. Risk Ranking

No.	Code	Risk Factor (Rf)	Probability	Impact	Fuzzy Risk Value	Traditional Risk Value	Var	Risk Category	Risk Rank
1	X1.1	Extreme Weather	Likely	Significant	18.247	16	14%	High	1
2	X1.2	Free Span on Uneven Seabed	Likely	Significant	18.247	16	14%	High	2
3	X2.1	Government Approval Delay	Moderate	Significant	12.404	12	3%	High	3
4	X3.2	Payment Delay from Contractor to Subcontractor	Moderate	Significant	12.404	12	3%	High	3
5	X3.3	Material Price Increase	Likely	Moderate	12.404	12	3%	High	3
6	X3.4	Vessel Rate Increase	Moderate	Significant	12.404	12	3%	High	3
7	X3.6	Inflation	Likely	Moderate	12.404	12	3%	High	3
8	X4.1	Project Mismanagement	Moderate	Significant	12.404	12	3%	High	3
9	X4.2	Unsupportive Stakeholder	Moderate	Significant	12.404	12	3%	High	3
10	X4.3	Inaccurate Scheduling and Budgeting	Moderate	Significant	12.404	12	3%	High	3
11	X4.4	Corruption/Bribery	Moderate	Significant	12.404	12	3%	High	3
12	X4.5	Incompetent Personnel	Moderate	Significant	12.404	12	3%	High	3
13	X4.7	Tender Process Delay/Failure	Moderate	Significant	12.404	12	3%	High	3
14	X5.4	Vessels Arrival Delay	Moderate	Significant	12.404	12	3%	High	3
15	X5.6	Lifting Failure Due to Crane Damage	Moderate	Significant	12.404	12	3%	High	3
16	X5.7	Equipment Mechanical Breakdown	Moderate	Significant	12.404	12	3%	High	3
17	X5.10	Accident During Working at Heights	Moderate	Significant	12.404	12	3%	High	3
18	X5.12	Subsea Facilities Damaged Due to Anchor Drag	Moderate	Significant	12.404	12	3%	High	3
19	X5.16	Inaccurate Design Engineering	Moderate	Significant	12.404	12	3%	High	3
20	X5.17	Material Quantity Increase	Moderate	Significant	12.404	12	3%	High	3
21	X5.18	Non-Compliant Material	Moderate	Significant	12.404	12	3%	High	3
22	X5.23	Pipe Buckle/Overstress	Moderate	Significant	12.404	12	3%	High	3
23	X5.26	Pipe Indicated Leaking During Pre-Commissioning	Moderate	Significant	12.404	12	3%	High	3
24	X5.31	Construction Rework	Moderate	Significant	12.404	12	3%	High	3
25	X5.32	Completion Delay of Construction/Installation	Moderate	Significant	12.404	12	3%	High	3

Step 6. BBNs Development

To address the complexities and interdependencies of risks across the lifecycle of subsea gas pipeline projects, BBNs will be developed for each of the three critical EPC phases [60, 61, 133]. Each network captures the causal relationships and cascading effects among selected top risk factors unique to the phase as well as maintains continuity. In Engineering phase, BBNs focus on risks such as project mismanagement, stakeholder resistance, inaccurate scheduling and budgeting, and personnel competence. Key risk factors include X4.1 (Project Mismanagement), X4.2 (Unsupportive Stakeholder), X4.3 (Inaccurate Scheduling and Budgeting), X4.5 (Incompetent Personnel), X2.1 (Government Approval Delay), and X5.16 (Inaccurate Design Engineering). This phase is foundational, as Inaccurate Design Engineering, Inaccurate Scheduling and Budgeting, and Government Approval Delay propagate through subsequent phases, affecting procurement timelines and construction execution

In Procurement phase, BBNs expand to include risks related to material procurement, price fluctuations, corruption, and payment delays. Key risk factors include X3.3 (Material Price Increase), X3.4 (Vessel Rate Increase), X3.6 (Inflation), X4.4 (Corruption/Bribery), X3.2 (Payment Delay from Contractor to Subcontractor), X5.17 (Material Quantity Increase), and X5.18 (Non-Compliant Material). This phase also incorporates risks inherited from Engineering phase, such as Inaccurate Design Engineering or Government Approval Delay, showing the interconnectedness of project risks. Material/Equipment Arrival Delay (X5.4) can trigger the impact on project timelines, which is significant to construction.

BBNs for EPC phases enable quantitative risk assessment through probabilistic analysis, dynamic updating of risk probabilities due to new data, and causal analysis for identifying critical risks with cascading effects. These networks serve as decision-support tool for project managers, providing actionable insights to prioritize risk mitigation efforts effectively. The diagrams presented show the interconnected risk factors and dependencies for each phase, forming a comprehensive framework for managing project risks across Engineering and Procurement phases. This phenomenon impacts the risk occurring during Construction phase of subsea pipeline projects. When there is only one parent node, the Delphi method of probability figure for each parent condition can be used to determine the conditional probabilities of the child nodes directly connected to the root node. To optimize the model, the Noisy-or-Gate model's process should be used by determining the value of the true condition for each specific parent [107, 134, 135].

4. Results and Discussion

4.1. Integrating Fuzzy Bayesian Method for Risk Analysis Results

The analysis of risks across Engineering and Procurement phases using BBNs has provided valuable insights into the critical factors influencing the success of subsea gas pipeline projects. This is shown by networking model and probability value result, as presented in Figures 5 to 7.

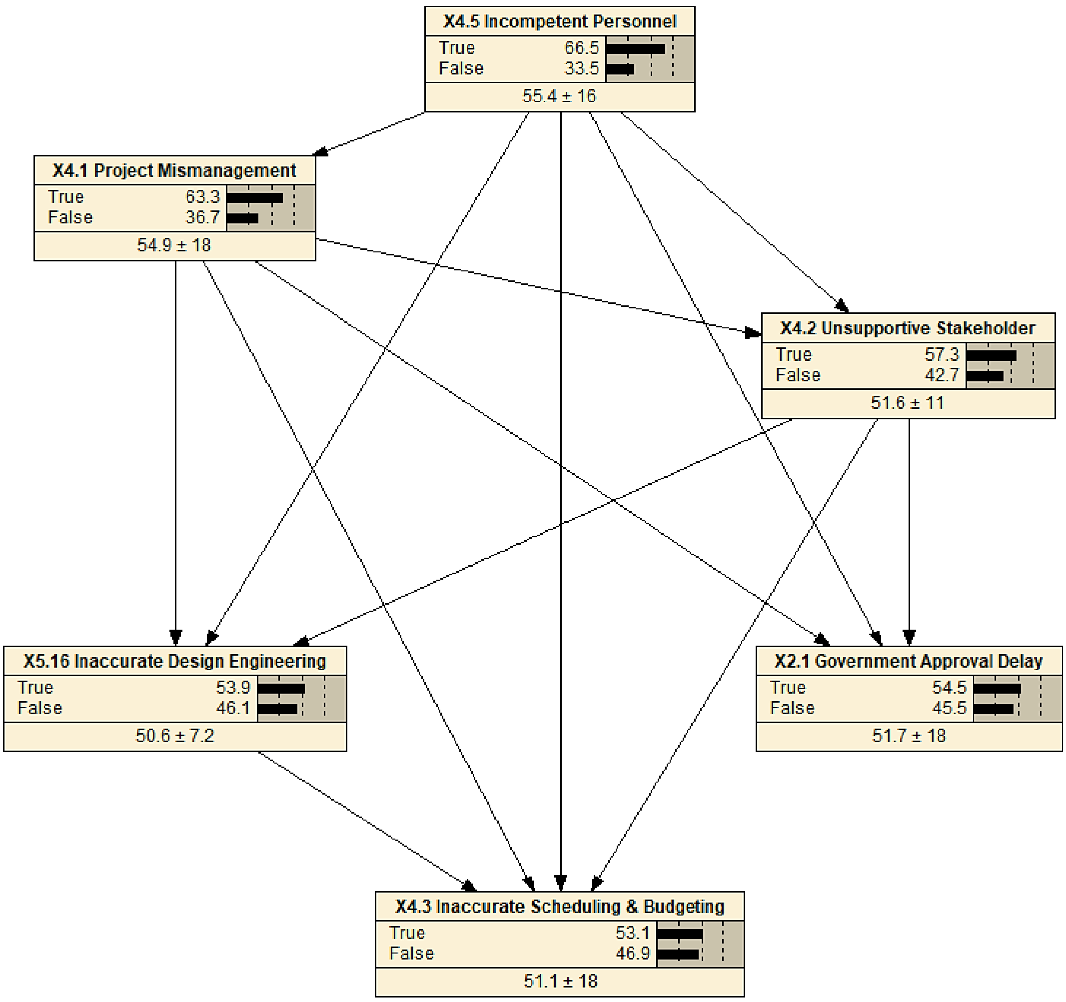

Figure 5. FBBNs for Engineering Phase

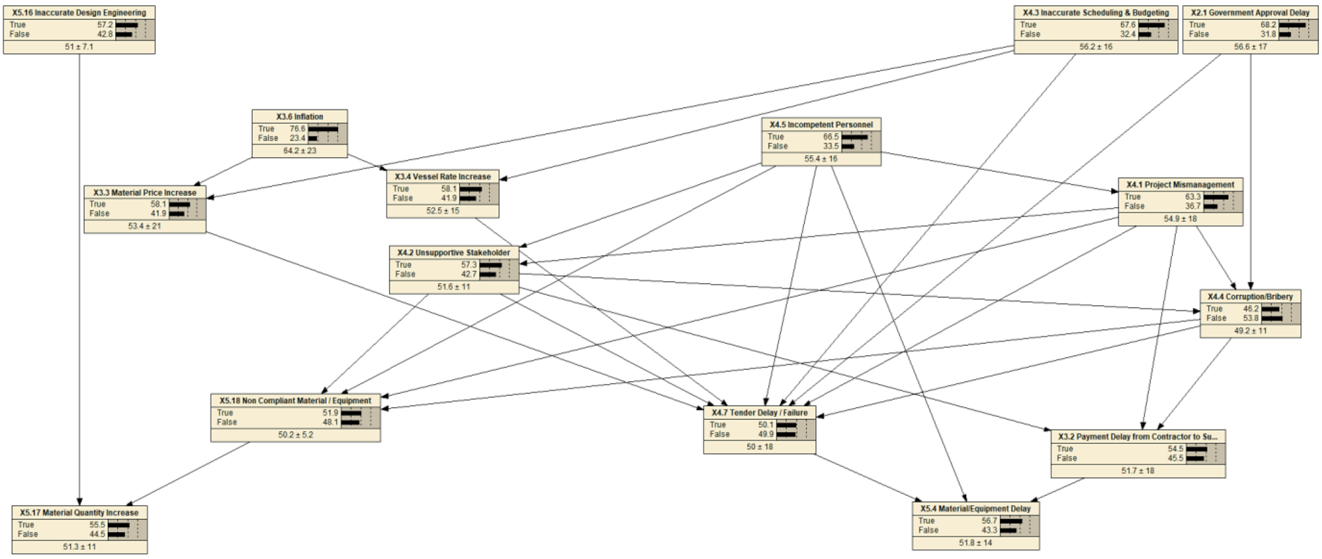

Figure 6. FBBNs for Procurement Phase

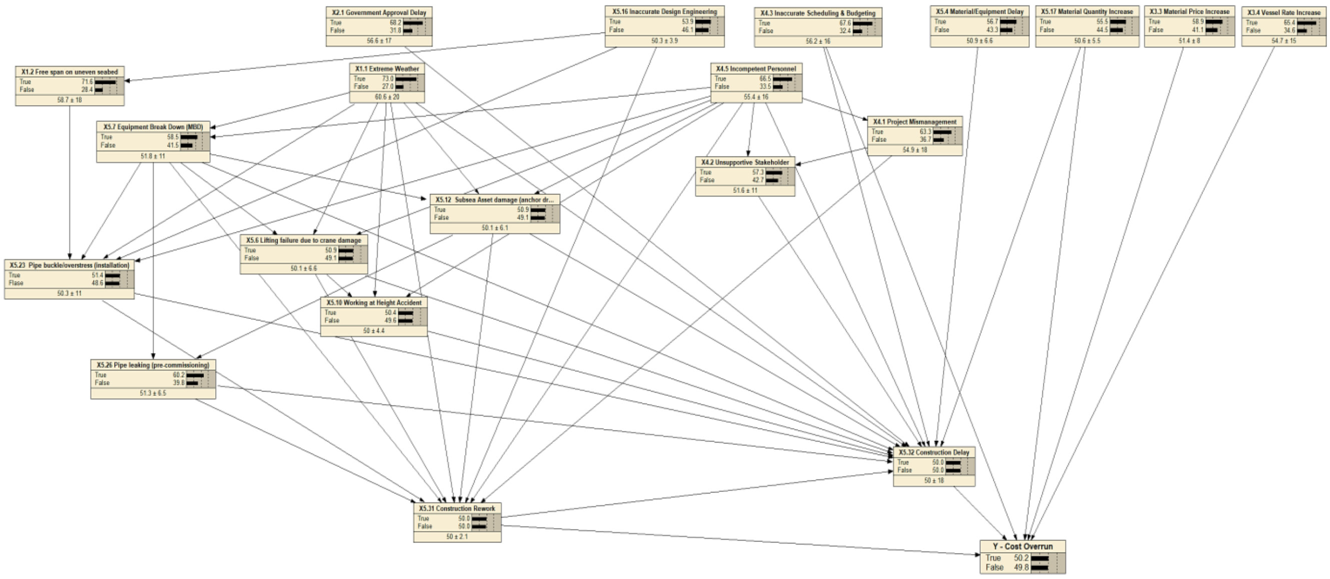

Figure 7. FBBNs for Construction Phase

4.2. Key Risk Insights Across Project Phases

The analysis of risks across EPC phases using BBNs has provided valuable insights into the critical factors influencing the success of subsea gas pipeline projects. These insights, derived from the interdependencies modeled in Netica, show the cascading nature of risks across project phases and the importance of addressing upstream issues proactively.

Engineering Phase as shown in FBBNs in Figure 5 forms the foundation of the project, and its associated risks have significant downstream impacts. Key risks identified in this phase include:

- Incompetent Personnel: This risk represents the probability of personnel incompetency as the main causal risk to others in the Preparation and Engineering phase, Government Approval Delay, Project Mismanagement, Unsupportive Stakeholder, and Inaccurate Schedule and Budgeting, as well as Inaccurate Design Engineering.
- Project Mismanagement: This risk represents the probability of inadequate planning or coordination in the project team. BBNs show centrality, indicating the direct effect of Government Approval Delay, Unsupportive Stakeholder, Inaccurate Scheduling, and Budgeting, on downstream risks such as Inaccurate Design Engineering.
- Government Approval Delay is caused by Project Mismanagement, Unsupportive Stakeholder, and Incompetent Personnel. Government Approval Delay propagates delays into Procurement phase.
- Inaccurate Scheduling and Budgeting: Scheduling and budgeting errors have a high probability and impact, as shown

in the posterior probabilities derived from Netica software. These errors propagate delays into Procurement phase, increasing the probability of Cost Overrun and material delay.

- Inaccurate Design Engineering: Design inaccuracies are identified as critical risks, with cascading effects on procurement timelines and material compliance. These inaccuracies are often rooted in Unsupportive Stakeholder and personnel incompetence.

The network analysis shows the requirement for robust management practices and accurate resource estimation during Engineering phase to mitigate downstream risks in Procurement and Construction Phases.

Procurement Phase is significantly influenced by risks inherited from Engineering phase as shown in Figure 6. The additional complexities are introduced by market dynamics and operational inefficiencies, with key risks as follows:

- Key risk factors from the previous phase such as Inaccurate Design Engineering will cause Material Quantity Increase as one of the main causes of Material Quantity Increase. Meanwhile, another key risk derived from Engineering phase is Government Approval Delay impact on Tender Process Delay/Failure and can trigger Corruption/Bribery due to Schedule Delay rectification issues.
- Inaccurate Scheduling and Budgeting have a high probability impact on Material Price Increase, Vessel Rate Increase, and ultimately Tender Process Delay/Failure (X4.7).
- Material Price Increase, Inflation, and Vessel Rate Increase: These risks, associated with external economic conditions, are highly probable, particularly in projects with long procurement cycles such as Tender Process Delay/Failure and Material/Equipment Arrival Delay.
- Corruption/Bribery: Although less frequent, this risk has severe consequences, affecting procurement issues such as Non-Compliant Material, Tender Process Delay/Failure, and Contractor financial health in context of Payment Delay from Contractor to Subcontractor.
- Another main causal such as Incompetent Personnel, Project Mismanagement, and Unsupportive Stakeholder also have a significant probability of Tender Process Delay/Failure.

The results emphasize the importance of financial discipline and efficient supply chain management to mitigate risks during procurement [21].

Construction Phase is significantly influenced by risks inherited from Engineering and Procurement phases. As shown in Figure 7, the additional complexities are introduced by market dynamics and technical factor inefficiencies, with key risks as follows:

- Key risk factors from the previous phase, such as Inaccurate Design Engineering will cause Installation Failure. These include Free Span on Uneven Seabed (X1.2) and Pipe Buckle/Overstress during installation (X5.23) which will cause Construction Rework (X.31) to mitigate the problem. Another key risk from Engineering phase is Government Approval Delay impact on risk event of Completion Delay of Construction/Installation (X5.32). Additionally, Inaccurate Scheduling and Budgeting have high probability impact on the occurrence of Completion Delay of Construction/Installation and affect the overall project Cost Overrun (Y).
- Key risk factors from Procurement phase such as Material/Equipment Arrival Delay, and Material Quantity Increase have impact on Completion Delay of Construction/Installation. Furthermore, Material Price Increase, Vessel Rate Increase, and Material Quantity Increase contribute to the probability of Cost Overrun risk occurrence.
- Several main causal risks such as Extreme Weather (X1.1), Incompetent Personnel during Construction, and Equipment Mechanical Breakdown (X5.7) cause various impact on Construction Rework (X5.31) and Completion Delay of Construction/Installation.
- Construction Rework and Completion Delay of Construction/Installation are caused by several interrelated causal risks, which influence project Cost Overrun.

The results emphasize the importance of competency from Engineering phase and the efficient supply chain management process during Procurement. This has triggered Construction Rework and Completion Delay of Construction/Installation, which impacted project Cost Overrun [15, 19].

4.3. Validation

The accuracy was tested using real case project data after the analysis of risks across EPC phases using BBNs, as shown in Table 8. The evaluation included mapping 25 theoretical risk factors to actual risk events, leading to the identification of 16 true positives. This led to an impressive accuracy rate of 80%, and 96% for projects 1, and 2 respectively. The results showed that the model was effective in accurately predicting potential risks associated with project management [136, 137], as presented in Equation 8.

$$Accuracy\ rate\ =\ \frac{\mathrm{TP + TN}}{\mathrm{Total\ Risk\ Factor}} = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}} \tag{8}$$

- True Positives (TP) is true risks prediction and actual.
- False Positives (FP) are false risks in actuality and true in prediction.
- True Negatives (TN) is False risks prediction and actual.
- False Negatives (FN) are false risks in prediction and true risks happening in actual.

Table 8. Risk Accuracy

Code Risk	Risk Factor	Average Belief Probability	Project-1			Project-2		
		True	Prediction	Actual	Categorize TP/FP/ TN/FN	Prediction	Actual	Categorize TP/FP/ TN/FN
X1.1	Extreme Weather	73%	True	False	FP	True	False	FP
X1.2	Free Span on Uneven Seabed	73%	False	False	TN	False	False	TN
X2.1	Government Approval Delay	68%	True	True	TP	False	False	TN
X3.2	Payment Delay from Contractor to Subcontractor	55%	False	False	TN	False	False	TN
X3.3	Material Price Increase	58%	True	True	TP	True	True	TP
X3.4	Vessel Rate Increase	65%	False	False	TN	False	False	TN
X3.6	Inflation	77%	True	False	FP	False	False	TN
X4.1	Project Mismanagement	63%	True	False	FP	False	False	TN
X4.2	Unsupportive Stakeholder	57%	True	True	TP	True	True	TP
X4.3	Inaccurate Scheduling and Budgeting	53%	True	False	FP	True	True	TP
X4.4	Corruption/Bribery	46%	False	False	TN	False	False	TN
X4.5	Incompetent Personnel	67%	True	False	FP	True	True	TP
X4.7	Tender Process Delay/Failure	50%	False	False	TN	False	False	TN
X5.4	Material/ Equipment Arrival Delay	57%	True	True	TP	True	True	TP
X5.6	Lifting Failure Due to Crane Damage	52%	False	False	TN	False	False	TN
X5.7	Equipment Mechanical Breakdown	59%	True	True	TP	False	False	TN
X5.10	Accident During Working at Heights	51%	False	False	TN	False	False	TN
X5.12	Subsea Facilities Damage Due to Anchor Drag	52%	False	False	TN	False	False	TN
X5.16	Inaccurate Design Engineering	54%	True	True	TP	True	True	TP
X5.17	Material Quantity Increase	61%	True	True	TP	True	True	TP
X5.18	Non-Compliant Material	55%	True	True	TP	True	True	TP
X5.23	Pipe Buckle/Overstress	51%	False	False	TN	False	False	TN
X5.26	Pipe Indicated Leaking During Pre-commissioning	60%	False	False	TN	False	False	TN
X5.31	Construction Rework	50%	True	True	TP	True	True	TP
X5.32	Completion Delay of Construction/ Installation	50%	True	True	TP	True	True	TP

The results showed FBBNs strong predictive capabilities, which successfully identified a significant number of risk events while maintaining zero false positives. This showed that the model not only recognized true risks but also avoided misclassifying any non-risk events as risks. FBBNs showed potential to serve as a valuable tool for project managers, enabling the ability to proactively address potential issues and improve overall project outcomes.

Receiving Operating Characteristics (ROC) curve presented in this study served as an essential tool for evaluating the performance of FBBNs model in predicting project-related risks. The x-axis of the curve represents False Positive Rate (FPR), indicating the proportion of actual negatives that are incorrectly classified as positives. Meanwhile, the y-axis shows True Positive Rate (TPR), or sensitivity, which measures the proportion of actual positives accurately identified by the model. The curve's trajectory towards the top left corner signifies that the model effectively balances high sensitivity with a low rate of false positives, showing the capability to identify true risks while minimizing erroneous alerts. With an Area Under the Curve (AUC) value of 0.83 and 0.97 respectively as shown in Figure 8, the model shows a good level of accuracy in distinguishing between true risks and non-risks. This AUC falls in the acceptable range of above 0.7 [136, 137], showing that FBBNs model performs effectively but requires further enhancement. ROC curve shows the model's strengths in risk prediction, suggesting areas where refinements can lead to improved performance.

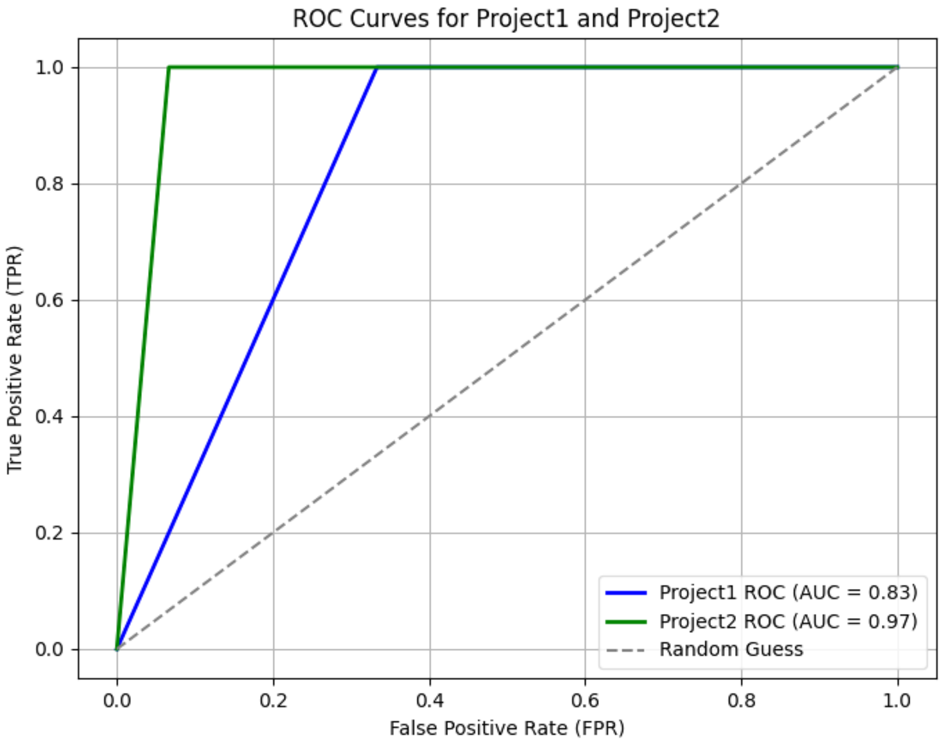

Figure 8. Receiving Operating Characteristic (ROC)

In addition to the predictive capabilities, ROC analysis also serves as a basis for conducting sensitivity analysis. By examining how variations in the model's input parameters affect TPR and FPR, stakeholders can identify which risk factors are most influential in determining outcomes. This understanding allows for targeted adjustments and improvements, thereby enhancing the model's robustness and reliability. ROC analysis shows FBBNs model's potential as a risk assessment tool in the project context, providing a framework for continuous improvements and more effective risk management strategies.

4.4. Implications and Recommendations for Risk Management

The integration of Fuzzy Bayesian method for risk analysis provides a quantitative understanding of the risks and offers actionable insights for enhancing risk management practices across the lifecycle of subsea gas pipeline projects. The results derived from BBNs and the associated probabilities of occurrence show several implications that can inform decision-making and risk mitigation strategies.

1. Addressing Critical Risks of Engineering Phase in the Overall Project Lifecycle

The results show that the most critical risks, such as Incompetent Personnel, Project Mismanagement, Inaccurate Scheduling and Budgeting, Government Approval Delay, and Inaccurate Design Engineering, originate in Engineering Phase with cascading effects throughout the project. Addressing these risks early is essential to minimize their impacts on other phases as follows:

- Implementing robust project management frameworks, with competent personnel and ensuring stakeholder cooperation can reduce the likelihood of Non-Compliant Material, Tender Process Delay/Failure, and Fabrication/Construction Delay.
- Accurate scheduling and budgeting tools, combined with expert validation, can mitigate the risk of delay and Cost Overrun in procurement phase caused by Inaccurate Scheduling and Budgeting.

2. Strengthening Procurement Strategies

Procurement phase is characterized by risks such as Material Price Increase and Payment Delay from Contractor to Subcontractor, which are driven by external market forces and internal inefficiencies. Effective risk management strategies for this phase include:

- The establishment of proper tender preparation with support from relevant stakeholders, competent personnel, and proper project management, as well as accurate schedule and budgeting to reduce potential tender problems. This can be caused by inflation, material price increase, vessel rate increase, and material/equipment arrival delay which leads to fabrication/construction delay and procurement Cost Overrun.

3. Leveraging Dynamic Risk Updates with BBNs to mitigate Construction Rework and Completion Delay of Construction/Installation in Construction Phase

A major advantage of using BBNs is the ability to dynamically update risk probabilities as new data becomes available. This feature allows for real-time decision-making and resource allocation, particularly in risks during Procurement and Construction phases as follows:

- Updating probabilities for Material/Equipment Arrival Delay, Material Quantity Increase, Material Price Increase, and Vessel Rate Increase contribute to the probability of Cost Overrun risk occurrence.
- Mitigation of several main causal risks such as Extreme Weather and incompetent Personnel during Construction, will assist project managers in avoiding deviation from the project objective which is Cost Overrun.
- Cost Overrun is mainly triggered by Construction Rework and Completion Delay of Construction/Installation, due to several interrelated causal risks. These include Equipment Mechanical Breakdown, Lifting Failure due to Crane Damage (X5.6), Subsea Facilities damage due to anchor drag (X5.12), and Pipe Buckle/Overstress during Pipeline Installation. Additionally, Construction Rework and Construction Delay are caused by other intermediate causal risks such as Unsupportive Stakeholder, Project Mismanagement during Construction, and Accident during working at height (X5.10).

The insights gained from Fuzzy Bayesian method underscore the importance of addressing interdependent risks across all project phases. By proactively managing risks during Engineering phase, strengthening Procurement processes, and adapting to dynamic conditions in Construction phase, project managers can significantly improve project outcomes [11, 13-15, 18, 19, 21, 62, 111]. The integration of real-time updates into FBBNs further enhances the ability to respond to risks, ensuring that subsea pipeline projects are executed efficiently and effectively [34, 35, 38, 39, 61, 86, 108, 138-141].

5. Conclusion

In conclusion, this study applied an integrated fuzzy Bayesian method to analyze and quantify risks across the lifecycle of subsea gas pipeline projects, focusing on EPC phases. The results showed that there were interconnected and cascading natures of risks, suggesting the need for systematic and proactive risk management strategies. Several critical risks were identified, including project mismanagement with a probability of 63%, inaccurate scheduling and budgeting at 53%, and incompetent personnel at 67%. These risks significantly affected EPC phases, showing the importance of addressing upstream challenges during the engineering phase to mitigate their downstream effects.

Phase-specific risks showed unique challenges, with the procurement phase being significantly influenced by financial and supply chain risks, such as material price increase at 58% probability. This could lead to material delays (57%) and non-compliant material (50%). In the construction phase, risks such as completion delay of construction/installation, with probabilities of 50%, were direct consequences of upstream inaccuracies and material-related issues. These results showed how risks propagate across phases, amplifying their impact. The dynamic capabilities of BBNs allowed for real-time updates of risk probabilities, enabling project managers to adapt their strategies based on evolving data. For instance, risks such as inflation material price increase, vessel rate increase, and government approval delay could be continuously monitored and reassessed to refine mitigation efforts. This feature enhanced decision-making and ensured resources were allocated effectively to address high-priority risks.

Based on the results, the integration of the Fuzzy Bayesian Belief Network method provided a comprehensive framework for quantifying and prioritizing risks across project phases. Addressing high-probability risks such as project mismanagement, inaccurate scheduling and budgeting, incompetent personnel, inaccurate design engineering, and government approval. Delays early in the project lifecycle could significantly reduce cascading effects and improve overall project outcomes. By implementing robust risk management practices and leveraging real-time updates, the probability of delay, cost overrun, and quality issues could be minimized. Moreover, the recommendation for future research development is related to a contingency reserve that can be estimated based on the above probability and estimated quantitative impact cost, with validation from experts based on cost estimation for the response impact strategies, if the risk occurs and becomes an issue.

6. Declarations

6.1. Author Contributions

Conceptualization, M.Y. and Y.L.; methodology, M.Y. and N.B.; software, M.Y.; validation, M.Y., N.B., Y.L., and B.T.; formal analysis, N.B.; investigation, N.B. and A.D.; resources, N.B.; data curation, N.B.; writing—original draft preparation, N.B.; writing—review and editing, N.B., M.Y., and Y.L.; visualization, N.B. and A.D.; supervision, Y.L.; project administration, Y.L.; funding acquisition, Y.L. All authors have read and agreed to the published version of the manuscript

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.4. Conflicts of Interest

The authors declare no conflict of interest.

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