DYNAMIC RISK ASSESSMENT OF INTERNATIONAL ENGINEERING PROJECTS FROM THE LIFE CYCLE PERSPECTIVE

Xu DUAN, Pengcheng XIANG✉, Shuai FENG

School of Management Science and Real Estate, Chongqing University, Chongqing, China

Abstract. Compared to other types of engineering projects, the development of international engineering projects (IEPs) is particularly challenging due to the uncertainties and risks posed by external environments. The risks of IEPs arise from both external threats and inherent vulnerabilities. As projects progress, these risks evolve dynamically, posing significant challenges for risk management. Existing studies on IEPs have focused mainly on the static assessment of risks at a certain stage or types of risk, but few have considered the dynamic and interconnected nature of risks. This study employs a comprehensive risk assessment framework for IEPs using dynamic Bayesian network. Specifically, the fuzzy set method and Monte Carlo simulation create the prior probabilities of root nodes and conditional probabilities of intermediate and leaf nodes. Then, propagation analysis is conducted to uncover the dynamic evolution of risks throughout the project life cycle. The proposed framework can capture the evolution of critical risks in life cycle. Internal and external risks in the three phases of construction, operation, and maintenance have been identified. Based on the findings from a case study, targeted management strategies are proposed to address critical risks, providing practical guidance for project managers to optimize risk management practices.

✉Corresponding author. E-mail: *58349781@qq.com*

1. Introduction

International engineering projects (IEPs) are characterized by their large investment scale, technological complexity, and long operating cycles. Compared to domestic engineering projects, IEPs are exposed to a more complex range of risks (Duan et al., 2023). These risks are further amplified in IEPs due to variations in institutional environments, cultural differences, and the political, legal, and socioeconomic conditions of host countries. To address these challenges, a dynamic risk assessment model is essential to effectively identify and evaluate critical risks across different stages of the project lifecycle.

Existing studies have highlighted the importance of IEPs and made significant advancements in risk identification (Moret & Einstein, 2016; Bugalia et al., 2021), risk assessment (Sun et al., 2022), and risk response (Hetemi et al., 2020). However, these studies have primarily adopted a static perspective on risk management, often overlooking more effective dynamic approaches that incorporate the dimension of time. Actually, the risks of IEPs should be analyzed within a life-cycle-based framework to enable efficient and sustainable risk management. Risks evolve over time, accumulating and interacting with proj-

ect progress. Critical risks identified in one stage of the life cycle may diminish in importance in subsequent stages or transform into more significant threats. Conversely, risks that appear insignificant in earlier stages may become critical in later stages. This dynamic nature of risk has a profound impact on the outcomes of IEPs, highlighting the need for a life-cycle perspective to reveal their inherent characteristics and evolution over time. To address this gap, this study aims to enhance the current understanding of risk management in IEPs by exploring the following research questions:

- **(i)** What risks do IEPs face at different stages of the project life cycle?
- **(ii)** How can critical risks of IEPs be dynamically assessed from a life-cycle perspective?
- **(iii)** How can stakeholders effectively address the critical risks of IEPs?

Addressing this research question necessitates incorporating the time component into the risk assessment model. Traditional quantitative risk assessment methods, such as Choquet fuzzy integral analysis (Mazher et al., 2018), multi-attribute group decision-making model (Liu

et al., 2021), and structural equation model (Wang et al., 2019), are static in nature and unable to capture the risk evolution. The dynamic Bayesian network (DBN) offers a more suitable approach for three primary reasons: (i) it facilitates the dynamic assessment of risks by accounting for temporal changes, (ii) it visually represents the interdependencies among risks, and (iii) it incorporates fuzzy set theory and Monte Carlo simulation to calculate risk probabilities with greater accuracy. However, most DBN-based risk management for IEPs have focused on risks associated with specific project stages (e.g., investment decision stage risks, construction stage risks) or specific risk types (e.g., cost overruns, technical risks, safety risks), and have not examined the dynamic evolution of IEPs' risks from a holistic project perspective (Duan et al., 2021; Bai & Zhao, 2021; Xiao et al., 2024; Zai et al., 2023; Halabi et al., 2017).

The main contributions of this study are as follows. First, this study dynamically assesses the risks of IEPs from a life-cycle perspective, enriching the field of IEP risk research and advancing more effective and sustainable risk management practices. Second, the application of a DBN introduces a novel risk management tool, providing precise and dynamic risk assessments that surpass the limitations of traditional static methods. Finally, by identifying significant risks and uncovering their intrinsic dynamic characteristics throughout the project life cycle, this research enhances the effectiveness of risk response strategies and improves the overall resilience of IEPs.

2. Literature review

2.1. Risk management of international engineering projects (IEPs)

Risk is defined as an uncertain event or condition that, if it occurs, can have a significant positive or negative impact on the strategic objectives of IEPs (Project Management Institute, 2017). However, a thorough review of the literature indicates that risk is predominantly viewed as a negative occurrence, leading most risk management frameworks to focus on minimizing potential project losses.

Risk management in IEPs encompasses three key components: risk identification, risk assessment, and risk response. Among them, risk identification is the first and most critical step, involving the recognition of potential risks and the validation of relationships among them. In terms of risk identification, existing research on IEPs has often concentrated on specific categories of risks, such as social risks (Li et al., 2020), natural disaster risks (Liu et al., 2018; Wang et al., 2021), and cost and schedule risks (Moret & Einstein, 2016). Furthermore, previous studies have explored the interrelationships among risks and stakeholder-associated risks during various stages of IEPs. However, limited attention has been given to the interactions between internal and external risks.

Risk assessment must be conducted by decision-makers to evaluate the influence of identified risks, enabling the identification of critical risks and mitigating their neg-

ative impacts (Bai et al., 2024). Wu and Xu (2021) applied unascertained measurement theory and an analytic hierarchy process-fuzzy comprehensive evaluation method to detect quantity error exploitation and unbalanced bids in IEPs. Li et al. (2019) developed a fuzzy decision analysis method for risk assessment in IEPs, considering dual interdependent effects. Additionally, Andrić et al. (2019) integrated fuzzy matrices, fuzzy logic, and probabilistic theory into a unified approach for risk assessment. However, these methods predominantly adopt a static perspective and fail to consider the importance of dynamic risk assessment for IEPs throughout their lifecycle. This limitation contrasts with the reality that risks evolve over time during the long-term service period of IEPs.

To prevent identified risks from materializing, risk response measures should be implemented proactively. Arabi et al. (2022) utilized Bayesian networks to select appropriate risk responses in IEPs. Yang et al. (2021) modeled complex networks to identify optimal risk responses. Zuo and Zhang (2018) formulated risk response strategies with consideration of secondary risks. Nevertheless, these approaches tend to overlook process-based risk response measures, which may result in risk response plans that lack specificity regarding the time dimension.

Current research on the risk management of IEPs often adopts a static approach and focuses on specific stages of the project life cycle, neglecting the dynamic characteristics of risk probability. This oversight can result in project management strategies that fail to adapt to evolving environmental conditions. In practice, as projects progress, the organizational environment and conditions continuously change, leading to variations in critical risks and their probabilities across different stages of the life cycle. Ignoring the dynamic nature of risks may result in inappropriate risk assessment, thereby diminishing the effectiveness of risk responses. This highlights a significant research gap in the literature on the risks associated with IEPs. To address this gap, risks should be assessed dynamically from a life cycle perspective. Based on such dynamic assessments, project managers can identify critical risks at each stage and understand their evolving characteristics. This approach enables more effective and adaptive risk management, ensuring better alignment with the changing project environment.

2.2. Application of dynamic Bayesian network (DBN) in risk management of IEPs

DBN has been demonstrated to be effective in dynamic risk assessment for IEPs. For example, Duan et al. (2021) applied DBN to evaluate investment environment risks at the national level, supporting investment decision-making. Bai and Zhao (2021) analyzed occupational safety risks (e.g., falls from heights during construction) and quantified the influence of risk factors on accident probabilities. Xiao et al. (2024) and Zai et al. (2023) constructed dynamic investment risk evolution models using DBN, employing forward and backward reasoning to trace risk propa-

gation across time nodes. Halabi et al. (2017) modeled technical risk management efficiency and identified critical risks through sensitivity analysis. Piao et al. (2021) developed a fall risk assessment model for construction workers, analyzing the temporal evolution of safety risks. Nwadigo et al. (2021) explored factors influencing schedule management using DBN, identifying adaptive strategies for varying scenarios. Overall, existing research primarily focuses on specific project stages or risk types, yet fails to examine the dynamic evolution of risks from a whole project perspective.

From a methodological perspective, the scarcity of objective data on project risks has led much of the existing DBN-based research to depend on small-sample-based expert judgment for input parameterization (Bai et al., 2025; Zhang et al., 2023). Given the limited number of expert assessments, the resulting prior probabilities may be subject to uncertainty, then compromising the robustness and reliability of probabilistic inference outcomes. Therefore, it is essential to adopt appropriate methods to quantify the fuzziness and randomness embedded in expert judgment. Monte Carlo simulation (MCS) is an effective method for addressing random uncertainty and solving artificial models with probabilistic conditions (Ye et al., 2021). To address the challenge of large data requirements in DBN, this study combines MCS with DBN to enhance risk assessment for IEPs. MCS has been extensively applied in risk management research to simulate risk states (Xin et al., 2021). For example, Sadeh et al. (2021) utilized MCS to prioritize construction project risks based on cost impact and probability. Similarly, Chen et al. (2022) applied MCS to quantify the probability of risk propagation within the scheduled risk network of major engineering projects, providing more reliable, risk-informed decision-making. These examples highlight the versatility and reliability of MCS in risk analysis. In this study, DBN and MCS are integrated to evaluate the probability of risk occurrence in IEPs. Specifically, the causal relationships and temporal dependencies among risks are within the DBN framework, while MCS is embedded into the parameter learning of the DBN. This integration enables the dynamic risk assessment, capturing their evolution throughout the life cycle of IEPs.

3. Methodology

This research flowchart is primarily divided into three steps (Figure 1). First, external and internal risks associated with IEPs are identified through case studies and literature analysis. Second, the probability of risk occurrence is calculated using DBN and MCS to assess the risks of IEPs. Finally, the critical risks at various project stages of the IEPs are prioritized, and the dynamic characteristics of these risks are analyzed.

3.1. Risk identification of IEPs

Risk identification distinguishes between internal risks, which are inherent to the project itself, and external risks, which arise from outside factors. According to the Project Management Body of Knowledge (Project Management Institute, 2017), project management comprises ten knowledge areas. However, to avoid content overlap, this study classifies internal risks into five categories that directly impact project objectives: organizational, schedule, cost, technical, and management risks. Meanwhile, external risks are identified across four dimensions: political and legal, social and cultural, natural environment, and economic risks. A detailed risk list is provided in Table 1.
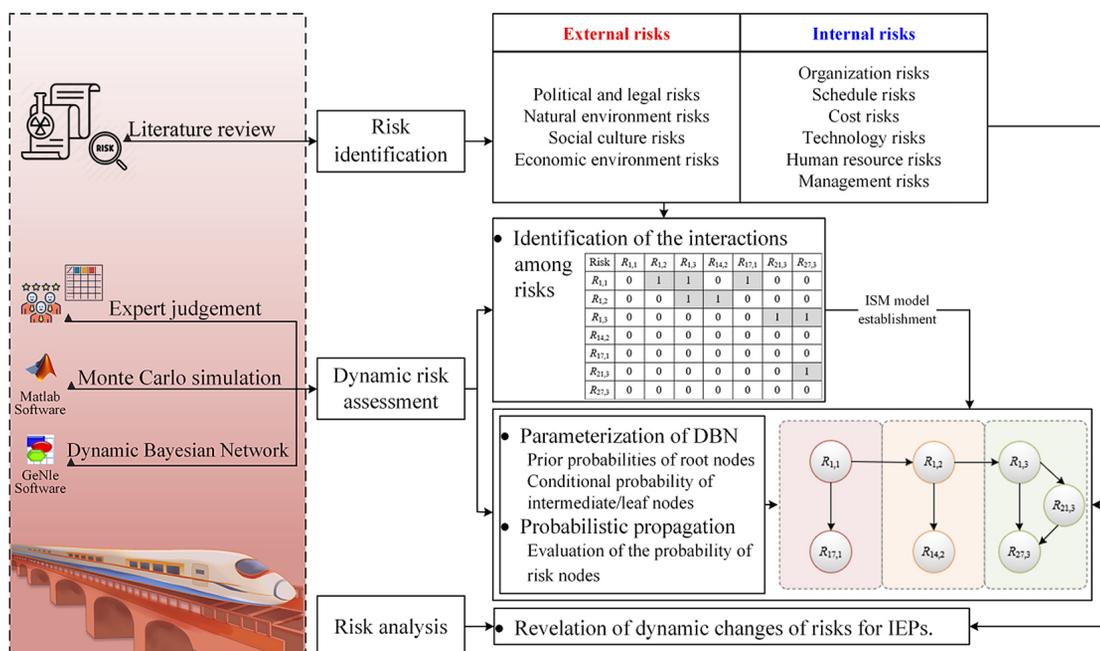

Figure 1. Research flowchart

Table 1. Risk list of IEPs

Categories	Risks	Code	Description	Project stages		
				I	II	III
External risks						
Political and legal risks	Political instability	R_1	Political unrest, such as terrorist attacks, regime changes, and civil wars, can disrupt IEPs.	√	√	√
	Excessive government intervention	R_2	Strict or frequent government supervision poses challenges for projects.	√	√	√
	Difficult legal compliance	R_3	Complex laws and regulations, including land use, environmental, and labor laws, can hinder project execution.	√	√	√
Natural environmental risks	Unstable geological conditions	R_4	Poor natural conditions, like geological instability and complex terrain, may affect project operation and construction.		√	√
	Frequent extreme weather	R_5	Extreme weather events, such as floods, blizzards, and droughts, can damage projects.		√	√
Social culture risks	Cultural conflicts	R_6	Cultural differences may cause misunderstandings, conflicts, and stakeholder issues.	√	√	√
	Public oppositions	R_7	Public opposition due to construction impacts, such as noise and traffic, may obstruct progress.	√	√	√
Economic risks	Exchange or interest rates fluctuations	R_8	Exchange rate and interest rate fluctuations can affect project feasibility.	√	√	√
	Currency inflation	R_9	Rising local prices may lead to budget overruns.	√	√	√
Internal risks						
Organizational risks	Cross-cultural communication issues	R_{10}	An unclear management structure can cause confusion and poor decisions.	√	√	√
	Decision-making misplay	R_{11}	Information asymmetry may lead to judgment errors by project managers.	√	√	√
	Unclear management structure	R_{12}	An unclear management structure causes confusion in responsibilities and ineffective decision-making.	√	√	√
Schedule risks	Delayed environmental approval	R_{13}	Delays in obtaining environmental permits and approvals hinder project initiation.	√	√	
	Construction schedule delays	R_{14}	Failure to complete construction tasks on schedule leads to delivery delays.		√	
	Supply chain disruptions	R_{15}	Disruptions in material and equipment supply slow project progress.		√	√
Cost risks	Adverse financing conditions	R_{16}	Financial activities encounter unfavorable conditions, such as high financing costs and limited financing channels.	√		
	Insufficient investment returns	R_{17}	Changes in market demand and increased costs lower the project's investment return.	√		
	Cost overruns	R_{18}	Budget overruns occur due to higher-than-expected expenditures.		√	
Technical risks	Design deficiencies	R_{19}	Design flaws, such as structural defects, reduce quality and may require rework.		√	
	Technical transfer and localization issues	R_{20}	Inconsistent technical standards hinder project localization.		√	√
	Physical and cyber security threats	R_{21}	Physical security threats (e.g., theft and destruction) and cybersecurity threats (e.g., hacker attacks and data leaks) may damage project assets.			√
Human resource risks	Frequent construction accidents	R_{22}	Frequent safety incidents during construction delay progress and affect safety.		√	
	Labor shortages	R_{23}	Labor shortages at the project site reduce quality and delay schedules.		√	√
Management risks	Insufficient feasibility studies	R_{24}	Insufficient feasibility studies fail to fully assess potential project risks.	√		
	Inadequate contract execution	R_{25}	Ineffective implementation of contract terms leads to disputes.	√	√	√
	Low operational efficiency	R_{26}	Equipment failures, poor management, and security threats reduce operational efficiency.			√
	Market demand fluctuations	R_{27}	Unstable market demand results in low returns on investment.			√

Notes: I, II, and III represent investment decision stage, planning & construction stage, and operations & maintenance stage, respectively.

Considering the dynamic nature of risks, those in IEPs evolve as the project progresses. To reveal the changing characteristics of key risks, it is necessary to determine the project stage at which each risk arises. Currently, the Integrated Investment-Construction-Operation (ICO) model has been widely adopted in IEPs, where the enterprises oversee not only the initial investment, planning and construction but also subsequent operations and maintenance. In the investment decision stage, the stakeholders assess feasibility, conduct cost-benefit analyses, and evaluate projected returns to determine whether to proceed with IEPs. The planning & construction stage involves detailed design, regulatory approvals, and physical construction. The operations & maintenance stage entails sustaining the completed IEPs through long-term maintenance. Based on this framework, this study identifies the project stage during which each risk materializes.

3.2. Development of the DBN model

Complex system theory presents that a complex system is composed of numerous subsystems; all components of the risk system in IEPs interact and depend on each other (as shown in Figure 2) (Li et al., 2024; Bai et al., 2025). In the context of IEPs, the project system faces external threats and internal vulnerabilities (Haimes, 2018). Due to the inherent vulnerabilities of the project system, significant changes can occur under the influence of the external environment, eventually evolving into risks (Xiang et al., 2024).

A DBN is employed to calculate the probability of risk occurrence by modeling both causal relationships and temporal dependencies. It comprises two components: a directed acyclic graph (DAG) and a conditional probability table (CPT). The DAG illustrates the correlation among factors. In this study, nodes represent risks, and edges represent relationships among risks. Interactions among nodes in the same time slice capture causal relationships, while interactions in different time slices capture temporal dependencies. Based on their inherent properties, risks are assigned two possible states: occurrence (Y) and non-occurrence (N) (Bai et al., 2025).

A DBN includes three types of nodes: (i) root nodes, which have no parent nodes; (ii) leaf nodes, which have no child nodes; and (iii) intermediate nodes, which have both parent nodes and child nodes. The CPT encompasses prior probabilities for root nodes and conditional probabilities for both leaf and intermediate nodes. The prior probabilities and conditional probabilities are derived using Monte Carlo simulation (MCS) to avoid the need for extensive data collection. The development of DBN includes two steps as follows.

Step 1. Identification of the interactions among risks

The DAG depicts causal relationships and temporal dependencies among risks in IEPs. To construct this DAG, an interpretive structure model (ISM) is first developed based on expert judgment to establish how the risks influence one another. Within the ISM, "1" signifies that an interaction exists between two risks, and "0" indicates no interaction. Specifically, the Delphi approach is employed, in which experts rated the interaction strength between each pair of risks on a 5-point Likert scale ranging from '1 = no influence' to '5 = strong influence'. A relationship between two risks is marked as "1" if the mean score across all experts exceeds a threshold of 3 (medium influence) and at least 50% of experts agree on the existence of the interaction. When two risks occur during the same project stage, any interaction between them is treated as a causal relationship. When they occur in different stages, any interaction is treated as a temporal dependency. For example, as shown in Figure 3, the risk (x) at t stage is denoted as $R_{x,t}$. If experts determine that the occurrence of $R_{x,t}$ will affect $R_{y,t}$, they record this influence as "1" to indicate a causal relationship; otherwise, it is recorded as "0".
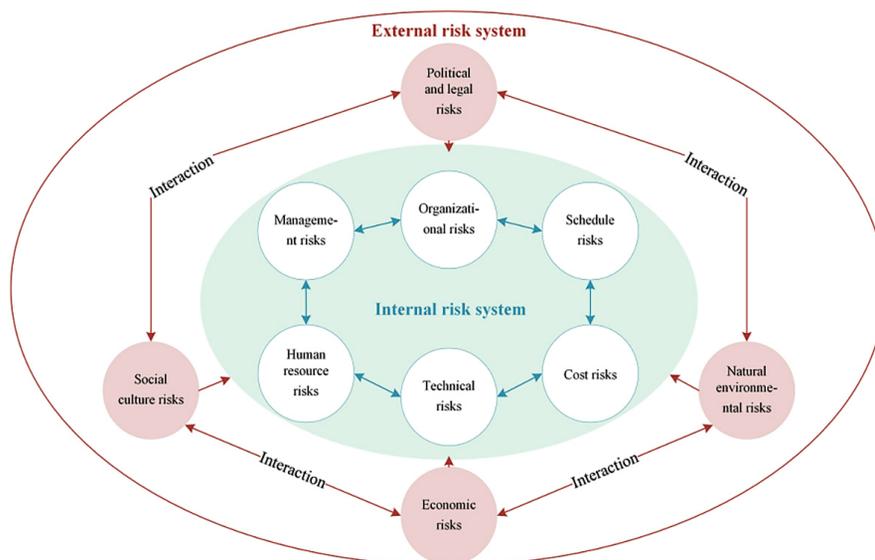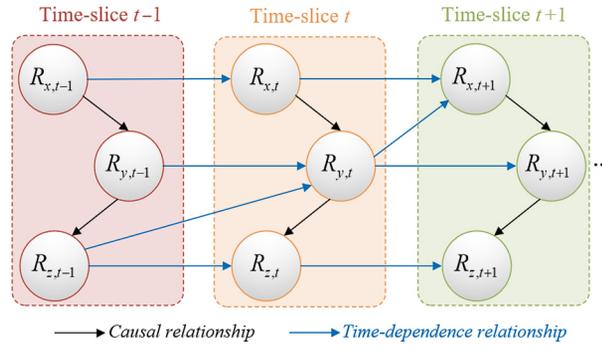

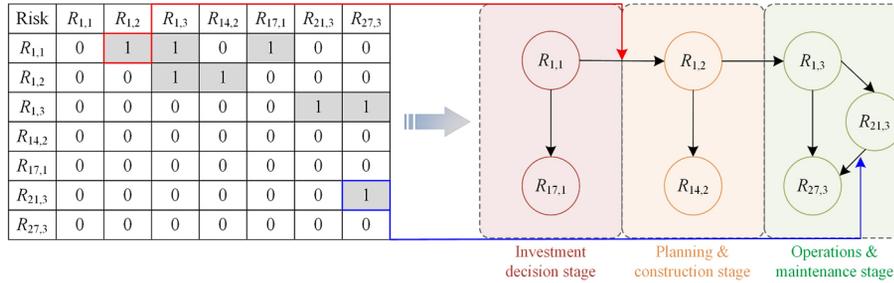**Figure 2.** Risk system of IEPs

Figure 3. Structure of DBN

Figure 4. Conversion of the ISM to DAG

Regarding temporal dependencies, a risk that occurs in an earlier stage ($t-1$) may lead to another risk in a later stage (t), which is similarly recorded as "1". The conversion of the ISM to a DAG is illustrated in Figure 4. For example, if $R_{21,3}$ affects $R_{27,3}$, it is marked as 1 in the ISM, establishing a causal relationship. Similarly, if $R_{1,1}$ at an earlier stage influences $R_{1,2}$ at a later stage, they are identified as having a temporal dependency, and a causal arc is drawn in the DAG.

Step 2. Acquisition of prior and conditional probabilities

Various experts may hold diverse perspectives on fuzzy probabilities; therefore, it is essential to consolidate their views to reach a consensus. To integrate multiple experts' judgments on the prior probability of root nodes, this research adopts a method combining trapezoidal fuzzy numbers with MCS. Referring to relevant literature (Haruna & Jiang, 2022; Singh et al., 2022; Guo et al., 2021), it found that fuzzy set theory has been used to capture and quantify the uncertainty inherent in expert judgments in the absence of sufficient empirical data. Trapezoidal fuzzy numbers are more suitable for this research than triangular fuzzy numbers because they allow a flat interval in the membership function, better capturing uncertainty in real-world scenarios where a "most likely range" rather than a single point is more appropriate (Govindan & Jepsen, 2016). This flexibility enables trapezoidal fuzzy numbers to model extreme values, but triangular fuzzy numbers can not explicitly represent them (Ruan et al., 2024). Empirical studies in risk assessment further validate that trapezoidal fuzzy numbers provide more robust results by accommodating multi-dimensional uncertainties (Sadeghi et al.,

2023; Elbarkouky et al., 2016). In this research, each expert provides a trapezoidal fuzzy number $\tilde{P} = (p, q, r, s)$ based on their professional experience to represent the prior probability of a given node. Among them, p is the lowest possible value, q and r define the most likely interval, and s is the highest possible value, with $p < q < r < s$. For example, if an expert assigns a trapezoidal fuzzy number $\tilde{P} = (0.2, 0.4, 0.5, 0.7)$, indicating that the risk probability is at least 20%, most likely between 40% and 50%, and could potentially reach up to 70%. Then, for each trapezoidal fuzzy number, random sampling is conducted using MCS across its three subintervals. Specifically, the probability of selecting each interval is proportional to its length, ensuring that the generated samples reflect the probabilistic characteristics of the original fuzzy number.

Assuming that random samples are generated from each expert's assessment, all samples from the experts are then combined into a comprehensive dataset. Finally, the average value of this dataset is calculated and used as the estimated prior probability of the node. The calculation formula is shown in Eqn (1):

$$P = \frac{1}{N} \sum_{i=1}^{N} x_i, \tag{1}$$

where x_i denotes the ith random sample, and N is the total number of samples.

MCS is used to derive the conditional probability tables for nodes that have parent nodes. MCS primarily evaluates the likelihood of risk occurrence within a specific time interval under the assumption that each simulation identifies a single occurrence state. The procedure includes the following steps:

(i) Identify the inputs for MCS. These inputs consist of each risk's independent probability of occurrence and its transmission probability when other risks are present. For example, if a risk ($R_{x,t1}$) has a 6% probability of occurring independently, its probability may increase to 9% when influenced by another risk $R_{y,t1}$.

(ii) Calculate the risk occurrence threshold. A random number (*RN*) represents the probability of random occurrence. Risk occurrence probabilities typically follow discrete, uniform, normal, or skewed distributions. For simplicity, this study adopts a uniform distribution in the interval [0, 1], generating using Java random function. In addition, *RN* considers only the independent probability of each risk and does not account for interactions among risks. Since upstream risks may trigger downstream risks, the overall occurrence probability is derived using Bernoulli distribution principles, as illustrated in Eqn (2):

$$ROP_{R_x,n} = 1 - \left[(1 - SP_x) \times \Pi_{z=1}^{m} (1 - TP_z^x) \right], \quad (2)$$

where $ROP_{x,n}$ represents the probability of occurrence for risk (R_x) in the *n*-th simulation. SP_x denotes the independent probability of R_x. *m* is the number of risks that have already occurred and can directly influence R_x in the *n*-th simulation. TP_z^x represents the probability of transmission to R_x when an upstream risk occurs in the *n*-th simulation.

(iii) Simulate the risk occurrence status. According to Eqn (3), if the *RN* of the risk in the *n*-th simulation is less than or equal to the $ROP_{R_x,n}$, R_x is considered to have occurred and is marked as $mc_{R_x,n} = 1$. Otherwise, R_x does not occurred and is marked as $mc_{R_x,n} = 0$.

$$mc_{R_x,n} = \begin{cases} 1, RN_{R_x,n} \leq ROP_{R_x,n} \\ 0, RN_{R_x,n} > ROP_{R_x,n} \end{cases}. \quad (3)$$

The occurrence probability represents the likelihood of a risk occurring across all valid simulations. For example, if R_x occurs 8,000 times in 10,000 valid simulations, its occurrence probability is 80% $\left(SOP_{R_x} = 8000 / 10000 = 0.8 \right)$, as calculated using Eqn (4):

$$SOP_{R_x} = nt(R_x) / NT. \quad (4)$$

The numerator $nt(R_x)$ represents the number of times the R_x occurs in all valid simulations, while the denominator *NT* is the total number of valid simulations.

3.3. Probability propagation

Once the conditional probability tables of all nodes are integrated into the constructed DBN model, the probability of risk occurrence can be examined dynamically via probability propagation. Forward propagation proceeds from root nodes to leaf nodes, evaluating the probability of each node along the way. Using these propagation results, the occurrence probabilities of various risks at different project stages can then be determined.

4. Case demonstration

4.1. Case background

To validate the effectiveness of the dynamic risk assessment framework for IEPs proposed in this study, a case study was conducted on the Addis Ababa-Djibouti railway project (AADR). The AADR project was selected as a case study for the following reasons: (i) it serves as a major trunk railway for both freight and passenger transportation, traversing Ethiopia and Djibouti; (ii) it operates under an integrated investment-construction-operation model, incorporating Chinese technology, standards, equipment, financing, construction, supervision, operation and management; and (iii) due to its substantial construction investment, extended operation cycle, and challenging geographic conditions, the project is exposed to a wide range of complex external and internal risks.

4.2. Structure construction of DBN

The ISM was first developed to define the influencing relationships between risks, which subsequently informed the construction of the DBN. Given the limited availability of empirical data, expert judgment was employed to assess risk probabilities, leveraging the insights of professionals with extensive experience in project risk management. Here, 100 experts were invited to evaluate the risk probabilities of IEPs. As presented in Table 2, 100 participants were selected from two channels: (i) 50 scholars from institutions of higher learning, identified through a review of literature related to risk management, and (ii) 50 practitioners from industrial channels, such as the Architectural Society of China and the China Chamber of Commerce for Foreign Contractors. The industrial practitioners had participated in at least one IRP and had at least five years of work experience. Researchers had advanced educational backgrounds and extensive research experience in risk management.

According to Section 3.2.1, the ISM was then converted into a DAG. Following expert judgment on these relationships, the ISM of risks for IEPs was determined. Based on this ISM, a DAG of risks for IEPs was established (Figure 5), offering a structured representation of risk interactions. Given the potential overlap of connections among nodes in Figure 5, Table 3 illustrates root, intermediate, and leaf nodes based on their respective types for clearer representation.

4.3 Determination of prior probabilities and CPTs of DBN

Prior probabilities of root nodes: According to Section 3.2.2, the prior probabilities of risk nodes were determined through expert judgment. Taking "unstable geological conditions (R_4)" as an example, 100 experts provided their assessment in the form of trapezoidal. For each expert's fuzzy number, 100 random samples were generated, resulting in a total dataset containing 10,000 samples. The prior probability of R_4 was then estimated by calculating the average of all samples.

Table 2. Experts' profile

| Characteristic	Category	Researcher (N = 50)		Industrial practitioners (N = 50)		Total (N = 100)	
		N	%	*N*	%	*N*	%
Affiliation	Institution of higher learning	50	100	/	/	50	50
	Owner	/	/	6	12.24	6	6
	Designer	/	/	7	13.5	7	7
	Contractor	/	/	12	24.32	12	12
	Consultant	/	/	5	10.2	5	5
	Supervisor	/	/	11	22.58	11	11
	Operator	/	/	9	17.16	9	9
Work experience	6–10 years	7	14.5	5	9.9	12	12
	11–15 years	13	26.6	6	12.3	19	19
	16–20 years	15	30.2	14	28.1	29	29
	≥20 years	15	28.7	25	49.7	40	40
Professional title	Professor	13	27.3	/	/	13	13
	Associate professor	17	33.6	/	/	17	17
	Assistant Professor	20	39.1	/	/	20	20
	Senior project manager	/	/	28	55.4	28	28
	Junior project manager	/	/	22	44.6	22	22
Education level	Doctoral degree	21	42.5	5	10.7	26	26
	Master degree	19	37.3	8	15.5	27	27
	Bachelor's degree	10	20.2	36	71.9	46	46
	Other	0	0	1	1.9	1	1
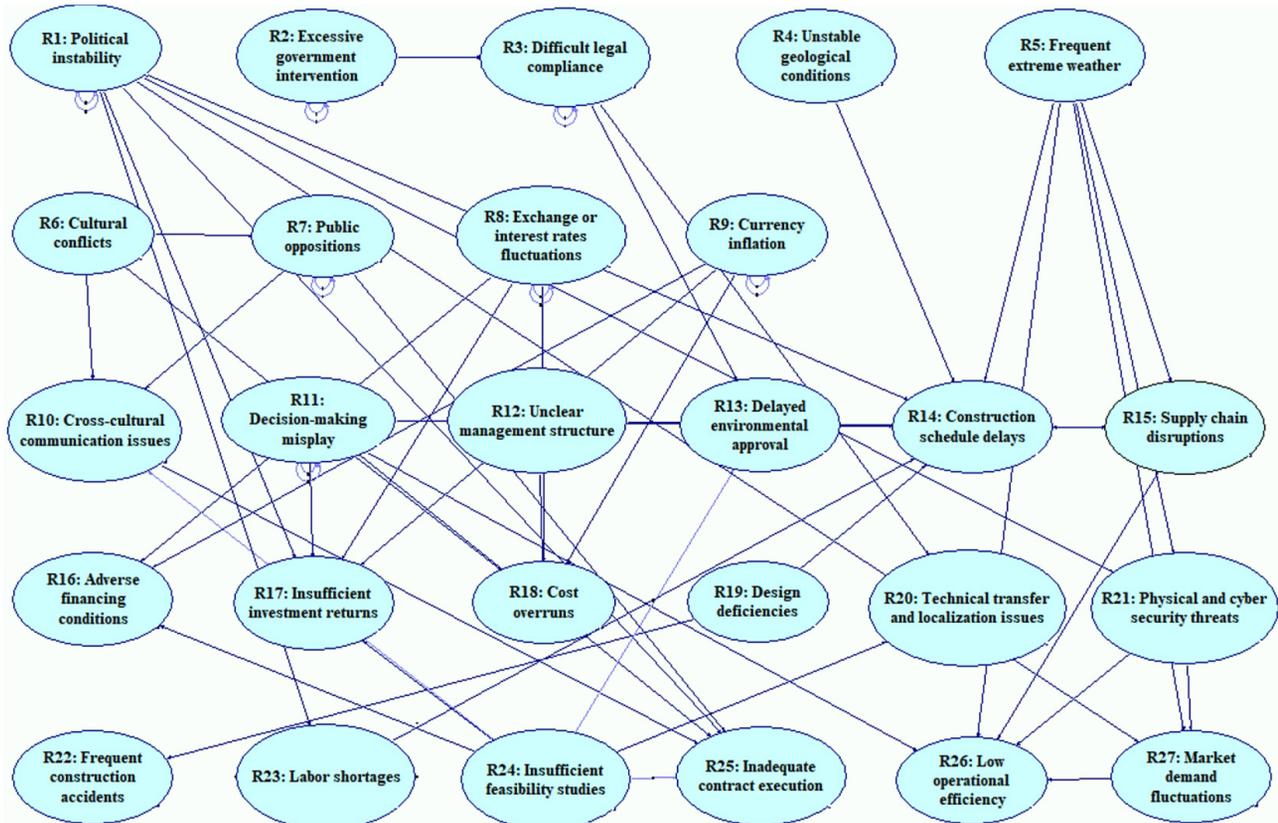
Figure 5. DBN of risks for IEPs

Table 3. Nodes in DBN

Root nodes (Number of nodes: 11)		Intermediate nodes (Number of nodes: 7)			Leaf nodes (Number of nodes: 9)	
Code	Child nodes	Code	Parent nodes	Child nodes	Code	Parent nodes
R_1	$R_{14}, R_{17}, R_{21}, R_{23}, R_{25}, R_{27}$	R_3	R_2	R_{13}, R_{20}	R_{13}	R_3, R_{24}
R_2	R_3	R_7	R_6	R_7, R_{10}, R_{25}	R_{14}	$R_1, R_4, R_5, R_{11}, R_{12}, R_{15}, R_{19}, R_{23}$
R_4	R_{14}	R_{10}	R_6, R_7, R_{24}	R_{25}	R_{16}	R_8, R_9, R_{24}
R_5	$R_{14}, R_{15}, R_{21}, R_{26}, R_{27}$	R_{15}	R_5, R_{12}	R_{14}, R_{26}	R_{17}	$R_1, R_8, R_9, R_{11}, R_{24}$
R_6	R_7, R_{10}, R_{25}	R_{21}	R_1, R_5	R_{26}, R_{27}	R_{18}	R_8, R_9, R_{11}, R_{12}
R_8	R_{16}, R_{17}, R_{18}	R_{23}	R_1	R_{14}	R_{20}	R_3, R_{24}
R_9	R_{16}, R_{17}, R_{18}	R_{27}	R_1, R_5, R_{21}	R_{26}	R_{22}	R_{19}
R_{11}	$R_{14}, R_{17}, R_{18}, R_{26}$				R_{25}	$R_1, R_6, R_7, R_{10}, R_{24}$
R_{12}	R_{14}, R_{15}, R_{18}				R_{26}	$R_5, R_{11}, R_{15}, R_{21}, R_{27}$
R_{19}	R_{14}, R_{22}					
R_{24}	$R_{10}, R_{13}, R_{16}, R_{17}, R_{20}, R_{25}$					

Conditional probabilities of leaf and intermediate nodes: The conditional probabilities of leaf and intermediate nodes were calculated. Taking "cost overruns (R_{18})" as an example, the calculation process was briefly demonstrated to illustrate the applicability of the MCS and DBN combination. As shown in the DAG (Figure 5), R_{18} has 4 parent nodes (i.e., $R_{12}, R_8, R_9,$ and R_{11}). The prior probability of R_{18} was determined (i.e., $P_{R_{18}} = 0.5574$). Similar to the obtain of prior probability, the propagation effects of its parent nodes were assessed (i.e., $P_{R_{12} \rightarrow R_{18}} = 0.2570$, $P_{R_8 \rightarrow R_{18}} = 0.7563$, $P_{R_9 \rightarrow R_{18}} = 0.6582$, $P_{R_{11} \rightarrow R_{18}} = 0.4630$).

Then, as shown in Table 4, if $R_{12}, R_8, R_9,$ and R_{11} occurred in a simulation, the occurrence probability of R_{18} was calculated as: $ROP_{R18} = 1 - \{(1 - 0.5574)*[(1 - 0.2570)*(1 - 0.7563)*(1 - 0.6582)*(1 - 0.4630)]\} = 0.9853$. If R_{12} occurred but $R_8, R_9,$ and R_{11} did not, the probability was: $ROP_{R18} = 1 - \{(1 - 0.5574)*[(1 - 0.7563)*(1 - 0.6582)*(1 - 0.4630)]\} = 0.9802$. Furthermore, if the *RN* generated in the simulation run was not greater than its calculated *ROP*, R_{18} was considered to have occurred in the simulation (i.e., $mc_{i,t} = 0$). Running 10,000 MCN determined its conditional prob-

ability, yielding $P(R_{18} = Y|R_{12} = N, R_8 = Y, R_9 = Y, R_{11} = Y) = 97.06\%$. Repeating this process allowed for the computation of the CPT of "cost overrun (R_{18})".

After determining the CPT for all intermediate and leaf nodes, probability propagation in the DBN was applied for quantitative analysis. This progress updates the probability of risk occurrence by propagating the influence of interconnected nodes throughout the network. In this study, probability propagation was conducted to analyze real cases (Figure 5) and gain a clearer understanding of the occurrence of each risk across the project life cycle. As illustrated in Figure 6, the probability of the same risk occurring varies across different project stages, which is effectively captured by the DBN model. For example, considering the temporal dependencies among risks, the occurrence probability of "exchange or interest rates fluctuations (R_8)" decreases from 76.58% in the investment decision stage to 39.98% in the planning & construction stage, and further declines to 12.89% in the operations & maintenance stage. This trend is primarily attributed to the investment decision stage, which involves substantial

Table 4. CPT of "cost overrun (R18)"

Node	Node status							
R_{12}	Y							
R_8	Y				N			
R_9	Y		N		Y		N	
R_{11}	Y	N	Y	N	Y	N	Y	N
Y	0.9853	0.9726	0.9570	0.9199	0.9396	0.8876	0.8234	0.6711
N	0.0147	0.0274	0.0430	0.0801	0.0604	0.1124	0.1766	0.3289
Node	Node status							
R_{12}	N							
R_8	Y				N			
R_9	Y		N		Y		N	
R_{11}	Y	N	Y	N	Y	N	Y	N
Y	0.9802	0.9631	0.9421	0.8921	0.9188	0.8487	0.7623	0.5574
N	0.0198	0.0369	0.0579	0.1079	0.0812	0.1513	0.2377	0.4426

capital allocation, financial transactions, and future cash flow estimations. These factors directly affect the success or failure of IEPs. Although exchange or interest rate fluctuations also affect the planning & construction and operations & maintenance stages, their influences appear in daily operational and maintenance costs. This finding highlights the temporal dependencies among risks. That is, DBN can effectively assess risks in IEPs by capturing their dynamic changes over time.

DBN effectively captures the causal relationships among risks. The occurrence probability of "cost overruns (R_{18})" is initially 54.63%. When considering the causal relationships in DBN, this probability increases to 95.66%. The key reason is the interaction between risks. Changes in the state of one risk can exacerbate others, creating a chain reaction. For example, during the planning & construction stage, unfavorable exchange rate fluctuations increase the cost of equipment and materials, leading to construction cost overruns. Therefore, both causality relationships and temporal dependencies should be considered when analyzing risk probabilities, as they significantly impact risk assessment results.

4.4. Dynamic analysis of risks

This study developed a dynamic risk assessment model using DBN to identify critical risks and determine risk management priorities throughout the project life cycle. As shown in Figure 6, key external risks in the investment decision stage primarily include excessive government intervention (R_2), difficult legal compliance (R_3) and exchange rate or interest rates fluctuations (R_8), while key internal risks involve delayed environmental approval (R_{13}), insufficient investment returns (R_{17}), and adverse financing conditions (R_{16}). During the planning & construction stage, key external risks include excessive government in-

tervention (R_2), difficult legal compliance (R_3) and unstable geological conditions (R_4). Meanwhile, key internal risks include delayed environmental approval (R_{13}), cost overruns (R_{18}) and technology transfer and localization issues (R_{20}). In the operations & maintenance stage, major external risks include excessive government intervention (R_2), frequent extreme weather (R_5), and public opposition (R_7). Key internal risks at this stage involve difficulties in technology transfer and localization (R_{20}), low operational efficiency (R_{26}), and physical and cyber security threats (R_{21}). As illustrated in Figure 7, the occurrence probability of the same risk may vary across project stages. Dynamically identifying key risks at each stage is crucial for project managers to develop effective risk response strategies.

5. Discussion and implications

5.1. Discussion of key findings

The key external risks in the investment decision stage primarily include excessive government intervention (R_2), difficult legal compliance (R_3), and exchange rate or interest rate fluctuations (R_8), while key internal risks involve delayed environmental approval (R_{13}), insufficient investment returns (R_{17}), and adverse financing conditions (R_{16}). These external risks largely fall under political, legal, and economic risks. The results indicate that under the Belt and Road initiative, Chinese enterprises have prioritized IEPs in underdeveloped regions like Ethiopia and Djibouti –agriculture-dependent nations with limited economic capacity. The AADR faced significant financial strain due to the Ethiopian birr's volatility against the USD, compounding risks from fluctuating interest rates and inflationary pressures in Ethiopia. The investment decision stage involves extensive financing activities (e.g., project bidding and contract negotiations), which are highly sensitive to capital flow risks.
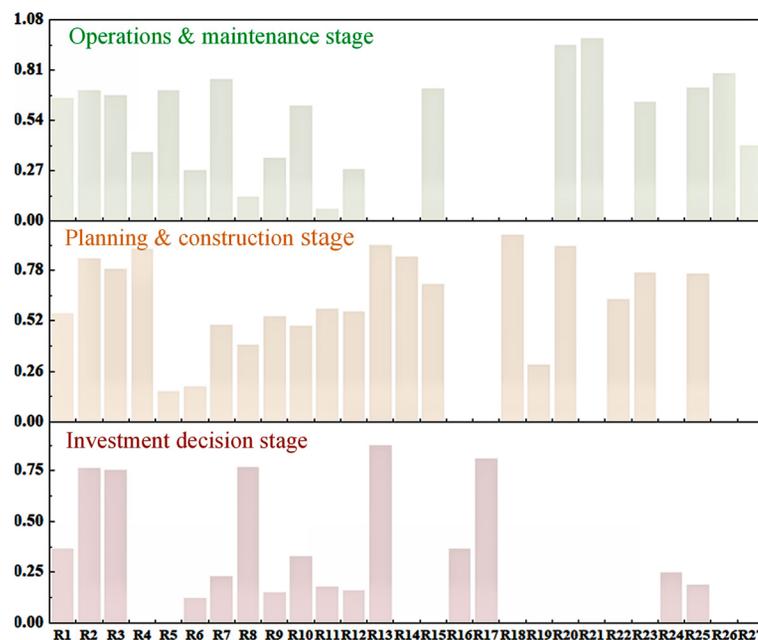

Figure 6. Occurrence probability of risks at different project stages
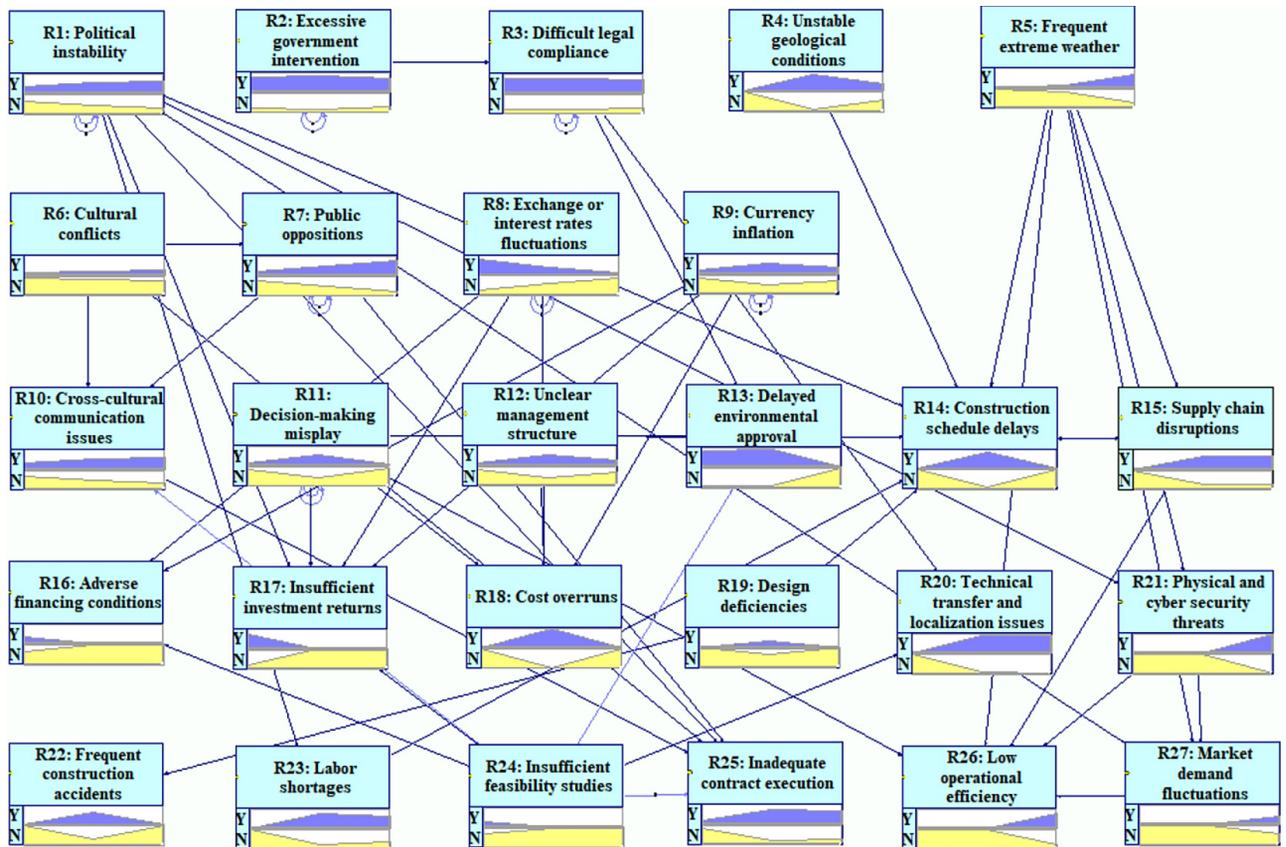
Figure 7. Results of probabilistic propagation

Besides, host governments or political organizations may implement policies or discriminatory measures that negatively impact project execution (Chang et al., 2018). Legal compliance issues and trade protectionism serve as significant barriers to IEPs implementation.

During the planning & construction stage, the key external risks for IEPs include excessive government intervention (R_2), difficult legal compliance (R_3), and unstable geological conditions (R_4), while key internal risks involve delayed environmental approval (R_{13}), cost overruns (R_{18}) and technology transfer and localization issues (R_{20}). Given that IEPs are often located in areas with complex terrain and variable geological structures, the primary risks at this stage are closely related to the contractor's construction activities. Local opposition may arise from concerns over ecological damage or employment inequities (Bouraima et al., 2023). The AADR faced harsh climatic conditions, including prolonged rainy seasons and tornadoes, which disrupted progress and endangered personnel and equipment. Regarding internal risks, due to differences in technical standards between the host and home countries, standard compatibility issues may arise. Ethiopia's lacke of a dedicated railway law further hindered the implementation of systematic Chinese project management practices. Cost overruns might emerge due to a design upgrade from China's Class III to Class II railway standards, as the original low-cost EPC contract failed to meet operational and safety requirements.

During the operations & maintenance stage, key external risks include excessive government intervention (R_2), frequent extreme weather (R_5), and public opposition (R_7), while key internal risks involve technology transfer and localization issues (R_{20}), low operational efficiency (R_{26}), and physical and cyber security threats (R_{21}). Compared to the planning & construction stage, the occurrence probability of R_{20} is lower during operation, but mitigation strategies from the planning & construction stage remain applicable. A more pressing concern is ensuring stable operations and preventing security threats (e.g., theft, terrorist attacks, and cyber attacks), which can lead to economic losses and reputational damage (Thron et al., 2024). This aligns with on-the-ground reality: local residents' lack of project understanding and safety awareness created hazardous conditions, including pedestrians on tracks, stolen/damaged components, and frequent collisions with livestock/wildlife. Additionally, the operational efficiency of certain IEPs, particularly international railway projects, is highly sensitive to environmental changes. Extreme weather events and geological disasters can cause infrastructure damage or service interruptions, further impacting project performance (Liu et al., 2018). In Ethiopia, heavy seasonal rains might cause slope failures and flooded embankments, compromising train safety and freight efficiency. The 2020 global pandemic further exacerbated operational declines.

5.2. Practical implications

To mitigate key risks in the investment decision stage, owners should engage in public diplomacy with host countries, such as developing monthly policy reviews. Blockchain smart contracts can be adapted to automatically enforce contract terms, reduce human intervention, and disclose contract performance. Additionally, the home government should expand multi-channel financing options to ease financial constraints for enterprises. Measures such as increasing loan quotas for qualified overseas investment institutions, innovating secured mortgage systems, and relaxing restrictions on overseas asset realization can help address financing challenges and enhance the success of IEPs. To ensure investment returns, the owners should conduct rigorous feasibility studies and phase-wise investment approvals to ensure alignment with market demand and profitability thresholds. Besides, regarding the risk of delays in environmental approvals, proactive engagement with local environmental agencies should be initiated while conducting the pre-feasibility. This includes submitting phased approval requests aligned with regulatory timelines to ensure compliance.

To mitigate key risks in the planning & construction stage, owners should provide the host country with detailed information regarding site selection, potential environmental impacts, and safety risks. Host governments should collaborate with owners and contractors to conduct face-to-face interviews with local communities to better understand their concerns. Owners and contractors should actively assess political and social risks in the host country. Establishing a risk control team to maintain direct communication with host country consulates can help acquire timely first-hand information. To monitor the en-

vironmental impact of project construction, virtual reality (VR) technology can be utilized to develop three-dimensional environmental models, enabling simulations of various construction scenarios and their potential environmental consequences. Additionally, safety training programs should be conducted to minimize workplace accidents. Given the discrepancies in construction standards across countries, efforts should be made to promote mutual recognition of standards at an international level. A mutual recognition framework can help establish a common technical foundation for engineering projects, facilitating smoother cross-border collaboration and standard compliance. Regarding cost control, digital dashboards may be used to track actual and projected costs, enabling real-time monitoring of financial conditions.

To enhance operational safety, operators should establish a geological and meteorological disaster early warning platform to dynamically monitor natural disaster risks. To enhance public satisfaction with IEPs, collaboration between operators, local non-governmental organizations, and the media can facilitate regular public forums and the publication of operational performance reports (e.g., service reliability and emissions), thereby addressing concerns related to safety and environmental impact. Implementing routine maintenance programs can also help improve system safety and reliability. Regarding technology transfer and localization, establishing joint R&D centers with host countries can support the adaptation of technologies to local conditions, while dedicated technical teams can be assigned to assist in the localization process. In addition, to further enhance operational efficiency, the adoption of AI-driven predictive maintenance systems can effectively reduce downtime. Overall, Figure 8 presents a risk management guidance for IEPs.

	Investment decision stage	Planning & construction stage	Operations & maintenance stage
External Risks	**Excessive government intervention (R_2)** Engage in public diplomacy with host countries (e.g., developing monthly policy reviews); Establish a risk control team to maintain direct communication with host country consulates can help acquire timely first-hand information.		
	Difficult legal compliance (R_3) Use blockchain smart contracts to automatically enforce contract terms and reduce human intervention; Disclose contract performance to demonstrate project compliance; Promote mutual recognition of construction standards at an international level.		
	Exchange rate or interest rate fluctuations (R_8) Expand multi-channel financing options to ease financial constraints; Increase loan quotas for qualified overseas investment institutions; Innovate secured mortgage systems; Relax restrictions on overseas asset realization.	**Unstable geological conditions (R_4)** Monitor the environmental impact of project construction using VR technology; Conduct safety training programs to minimize workplace accidents.	**Frequent extreme weather (R_5)** Establish a geological and meteorological disaster early warning platform to dynamically monitor natural disaster risks. **Public opposition (R_7)** Facilitate regular public forums; Publish operational performance reports (e.g., service reliability and emissions).
Internal Risks	**Delayed environmental approval (R_{13})** Engage with local environmental agencies; Submit phased approval requests; Provide the host country with detailed information regarding site selection, potential environmental impacts, and safety risks.		**Low operational efficiency (R_{26})** Adopt AI-driven predictive maintenance systems to effectively reduce downtime.
	Insufficient investment returns (R_{17}) & Adverse financing conditions (R_{16}) Conduct rigorous feasibility studies and phase-wise investment approvals.	**Cost overruns (R_{18})** Use digital dashboards to track actual and projected costs.	**Physical and cyber security threats (R_{21})** Establish a geological and meteorological disaster early warning platform to dynamically monitor natural disaster risks.
		Technology transfer and localization issues (R_{20}) Establish joint R&D centers with host countries; Assign technical teams to assist in the localization process.	

Figure 8. Risk management guidance

6. Conclusions

IEPs present significant challenges for project managers, who must navigate complex external risks and internal risks. This study examines the dynamic nature of these risks by considering both causality and temporal dependency. First, external and internal risks were identified through a literature review and case study. Second, DBN and MCS were applied to dynamically evaluate key risks across the project life cycle by calculating risk occurrence probabilities. Third, the dynamic risk assessment model was validated through a case study, allowing for the determination of risk management priorities at different project stages. Based on the research findings, risk management strategies were proposed to help project managers mitigate critical risks effectively.

Despite its contributions, this study has certain limitations that future research can address. First, given the complexity of risks, many risk factors were not included in this study. Future research can enhance dynamic risk assessment indicators by incorporating a stakeholder-based perspective to identify additional risks. Second, due to data collection constraints, this study classified risk node states as binary (occurrence vs. non-occurrence). Future research could refine risk classification by collecting more expert data, enabling a multi-level risk assessment that considers both probability and impact. A more granular risk categorization could lead to more precise risk mitigation strategies, improving overall risk management effectiveness in IEPs. Third, the current analysis relies on trapezoidal fuzzy numbers to define root node prior probabilities. Future work should validate this choice by comparing simulation results across different fuzzy number types (e.g., triangular vs. trapezoidal) using statistical tests (e.g., K-S test) to ensure optimal model fit.

Acknowledgements

Disclosure statement

The authors declare no conflict of interests.

References

Andrić, J. M., Wang, J., Zou, P. X., Zhang, J., & Zhong, R. (2019). Fuzzy logic–based method for risk assessment of belt and road infrastructure projects. *Journal of Construction Engineering and Management*, *145*(12), Article 04019082. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001721

Arabi, S., Eshtehardian, E., & Shafiei, I. (2022). Using Bayesian networks for selecting risk-response strategies in construction projects. *Journal of Construction Engineering and Management*, *148*(8), Article 04022067. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002310

Bai, X. P., & Zhao, Y. H. (2021). A novel method for occupational safety risk analysis of high-altitude fall accident in architecture construction engineering. *Journal of Asian Architecture and Building Engineering*, *20*(3), 314–325. https://doi.org/10.1080/13467581.2020.1796675

Bai, L., Kang, S., Zhang, K., Zhang, B., & Pan, T. (2024). Modeling for external stakeholder risk assessment of project portfolios. *Engineering, Construction and Architectural Management*, *31*(2), 737–766. https://doi.org/10.1108/ECAM-01-2022-0010

Bai, L., Zhao, X., Kang, S., Ma, Y., & Zhang, B. (2025). Dynamic assessment of stakeholder conflict risk for R&D project portfolios. *Engineering, Construction and Architectural Management*, *32*(4), 2342–2368. https://doi.org/10.1108/ECAM-03-2023-0301

Bouraima, M. B., Alimo, P. K., Agyeman, S., Sumo, P. D., Lartey-Young, G., Ehebrecht, D., & Qiu, Y. (2023). Africa's railway renaissance and sustainability: Current knowledge, challenges, and prospects. *Journal of Transport Geography*, *106*, Article 103487. https://doi.org/10.1016/j.jtrangeo.2022.103487

Bugalia, N., Maemura, Y., & Ozawa, K. (2021). Characteristics of enhanced safety coordination between high-speed rail operators and manufacturers. *Reliability Engineering & System Safety*, *216*, Article 107995. https://doi.org/10.1016/j.ress.2021.107995

Chang, T., Deng, X., Zuo, J., & Yuan, J. (2018). Political risks in Central Asian countries: Factors and strategies. *Journal of Management in Engineering*, *34*(2), Article 04017059. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000588

Chen, Y., Zhu, L., Hu, Z., Chen, S., & Zheng, X. (2022). Risk propagation in multilayer heterogeneous network of coupled system of large engineering project. *Journal of Management in Engineering*, *38*(3), Article 04022003. https://doi.org/10.1061/(ASCE)ME.1943-5479.0001022

Duan, X., Zhao, X., Liu, J., Zhang, S., & Luo, D. (2021). Dynamic risk assessment of the overseas oil and gas investment environment in the big data era. *Frontiers in Energy Research*, *9*, Article 638437. https://doi.org/10.3389/fenrg.2021.638437

Duan, X., Hao, J., & Niu, Y. (2023). Research on intelligent decision-making method of investment scheme of high-speed railway construction project. *IEIE Transactions on Smart Processing & Computing*, *12*(6), 483–494. https://doi.org/10.5573/IEIESPC.2023.12.6.483

Elbarkouky, M. M., Fayek, A. R., Siraj, N. B., & Sadeghi, N. (2016). Fuzzy arithmetic risk analysis approach to determine construction project contingency. *Journal of Construction Engineering and Management*, *142*(12), Article 04016070. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001191

Govindan, K., & Jepsen, M. B. (2016). Supplier risk assessment based on trapezoidal intuitionistic fuzzy numbers and ELECTRE TRI-C: a case illustration involving service suppliers. *Journal of the Operational Research Society*, *67*(2), 339–376. https://doi.org/10.1057/jors.2015.51

Guo, X., Ji, J., Khan, F., Ding, L., & Tong, Q. (2021). A novel fuzzy dynamic Bayesian network for dynamic risk assessment and uncertainty propagation quantification in uncertainty environment. *Safety Science*, *141*, Article 105285. https://doi.org/10.1016/j.ssci.2021.105285

Haimes, Y. Y. (2018). Risk modeling of interdependent complex systems of systems: Theory and practice. *Risk Analysis*, *38*(1), 84–98. https://doi.org/10.1111/risa.12804

Halabi, A., Kenett, R. S., & Sacerdote, L. (2017). Using dynamic Bayesian networks to model technical risk management effi-

ciency. *Quality and Reliability Engineering International*, *33*(6), 1179–1196. https://doi.org/10.1002/qre.2186

Haruna, A., & Jiang, P. (2022). Adaptability analysis of design for additive manufacturing by using fuzzy Bayesian network approach. *Advanced Engineering Informatics*, *52*, Article 101613. https://doi.org/10.1016/j.aei.2022.101613

Hetemi, E., Gemünden, H. G., & Meré, J. O. (2020). Embeddedness and actors' behaviors in large-scale project life cycle: Lessons learned from a high-speed rail project in Spain. *Journal of Management in Engineering*, *36*(6), Article 05020014. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000849

Li, J., Zhang, J., & Suo, W. (2019). Risk assessment in cross-border transport infrastructure projects: A fuzzy hybrid method considering dual interdependent effects. *Information Sciences*, *488*, 140–157. https://doi.org/10.1016/j.ins.2019.03.028

Li, H., Zhong, Y., & Fan, C. (2020). Reducing the social risks of transnational railway construction: A discussion on the formation mechanism of host country people's coping behaviors. *Engineering, Construction and Architectural Management*, *28*(6), 1657–1682. https://doi.org/10.1108/ECAM-04-2020-0232

Li, J., Yang, Z., He, H., Guo, C., Chen, Y., & Zhang, Y. (2024). Risk causation analysis and prevention strategy of working fluid systems based on accident data and complex network theory. *Reliability Engineering & System Safety*, *252*, Article 110445. https://doi.org/10.1016/j.ress.2024.110445

Liu, K., Wang, M., Cao, Y., Zhu, W., Wu, J., & Yan, X. (2018). A comprehensive risk analysis of transportation networks affected by rainfall-induced multihazards. *Risk Analysis*, *38*(8), 1618–1633. https://doi.org/10.1111/risa.12968

Liu, B., Liu, S., Xue, B., Lu, S., & Yang, Y. (2021). Formalizing an integrated decision-making model for the risk assessment of carbon capture, utilization, and storage projects: From a sustainability perspective. *Applied Energy*, *303*, Article 117624. https://doi.org/10.1016/j.apenergy.2021.117624

Mazher, K. M., Chan, A. P., Zahoor, H., Khan, M. I., & Ameyaw, E. E. (2018). Fuzzy integral–based risk-assessment approach for public–private partnership infrastructure projects. *Journal of Construction Engineering and Management*, *144*(12), Article 04018111. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001573

Moret, Y., & Einstein, H. H. (2016). Construction cost and duration uncertainty model: Application to high-speed rail line project. *Journal of Construction Engineering and Management*, *142*(10), Article 05016010. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001161

Nwadigo, O., Naismith, N. N., Ghaffarianhoseini, A., Ghaffarian Hoseini, A., & Tookey, J. (2021). Dynamic Bayesian network modelling for predicting adaptability of time performance during time influencing factors disruptions in construction enterprise. *Engineering, Construction and Architectural Management*, *28*(10), 2994–3013. https://doi.org/10.1108/ECAM-05-2020-0371

Piao, Y., Xu, W., Wang, T. K., & Chen, J. H. (2021). Dynamic fall risk assessment framework for construction workers based on dynamic Bayesian network and computer vision. *Journal of Construction Engineering and Management*, *147*(12), Article 04021171. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002200

Project Management Institute. (2017). *The standard for portfolio management* (4th ed.). Newtown Square, Pennsylvania, USA.

Ruan, D., Bian, J., Wang, Y., Wu, J., & Gu, Z. (2024). Identification of groundwater pollution sources and health risk assessment in the Songnen Plain based on PCA-APCS-MLR and trapezoidal fuzzy number-Monte Carlo stochastic simulation model. *Journal of Hydrology*, *632*, Article 130897. https://doi.org/10.1016/j.jhydrol.2024.130897

Sadeghi, M., Mahmoudi, A., & Deng, X. (2023). Blockchain technology in construction organizations: risk assessment using trapezoidal fuzzy ordinal priority approach. *Engineering, Construction and Architectural Management*, *30*(7), 2767–2793. https://doi.org/10.1108/ECAM-01-2022-0014

Sadeh, H., Mirarchi, C., & Pavan, A. (2021). Integrated approach to construction risk management: Cost implications. *Journal of Construction Engineering and Management*, *147*(10), Article 04021113. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002140

Singh, K., Kaushik, M., & Kumar, M. (2022). Integrating α-cut interval based fuzzy fault tree analysis with Bayesian network for criticality analysis of submarine pipeline leakage: A novel approach. *Process Safety and Environmental Protection*, *166*, 189–201. https://doi.org/10.1016/j.psep.2022.07.058

Sun, S., Gao, G., Li, Y., Zhou, X., Huang, D., Chen, D., & Li, Y. (2022). A comprehensive risk assessment of Chinese high-speed railways affected by multiple meteorological hazards. *Weather and Climate Extremes*, *38*, Article 100519. https://doi.org/10.1016/j.wace.2022.100519

Thron, E., Faily, S., Dogan, H., & Freer, M. (2024). Human factors and cyber-security risks on the railway–the critical role played by signalling operations. *Information & Computer Security*, *32*(2), 236–263. https://doi.org/10.1108/ICS-05-2023-0078

Wang, C., Loo, S. C., Yap, J. B. H., & Abdul-Rahman, H. (2019). Novel capability-based risk assessment calculator for construction contractors venturing overseas. *Journal of Construction Engineering and Management*, *145*(10), Article 04019059. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001696

Wang, Q., Liu, K., Wang, M., & Koks, E. E. (2021). A river flood and earthquake risk assessment of railway assets along the belt and road. *International Journal of Disaster Risk Science*, *12*, 553–567. https://doi.org/10.1007/s13753-021-00358-2

Wu, X., & Xu, F. (2021). Detection model for unbalanced bidding in railway construction projects: Considering the risk of quantity variation. *Journal of Construction Engineering and Management*, *147*(7), Article 04021055. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002058

Xiang, P., Xia, X., & Pang, X. (2024). An integrated risk assessment method for cross-regional mega construction projects. *Engineering, Construction and Architectural Management*, *31*(6), 2369–2391. https://doi.org/10.1108/ECAM-06-2022-0534

Xiao, Y., Wan, A., Li, Y., Elahi, E., & Peng, B. (2024). Evaluating the evolution of investment risks in belt and road energy projects: A case study of Belarus' M5 thermal power station. *International Journal of Energy Research*, *2024*, Article 9322649. https://doi.org/10.1155/er/9322649

Xin, X., Liu, K., Yang, Z., Zhang, J., & Wu, X. (2021). A probabilistic risk approach for the collision detection of multi-ships under spatiotemporal movement uncertainty. *Reliability Engineering & System Safety*, *215*, Article 107772. https://doi.org/10.1016/j.ress.2021.107772

Yang, L., Lou, J., & Zhao, X. (2021). Risk response of complex projects: Risk association network method. *Journal of Management in Engineering*, *37*(4), Article 05021004. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000916

Ye, J., Koopialipoor, M., Zhou, J., Armaghani, D. J., & He, X. (2021). A novel combination of tree-based modeling and Monte Carlo simulation for assessing risk levels of flyrock induced by mine blasting. *Natural Resources Research*, *30*, 225–243. https://doi.org/10.1007/s11053-020-09730-3

Zai, W., He, Y., & Wang, H. (2023). Risk prediction method for renewable energy investments abroad based on Cloud-DBN. *Sustainability*, *15*(14), Article 11297. https://doi.org/10.3390/su151411297

Zhang, B., Bai, L., Zhang, K., Kang, S., & Zhou, X. (2023). Dynamic assessment of project portfolio risks from the life cycle perspective. *Computers & Industrial Engineering*, *176*, Article 108922. https://doi.org/10.1016/j.cie.2022.108922

Zuo, F., & Zhang, K. (2018). Selection of risk response actions with consideration of secondary risks. *International Journal of Project Management*, *36*(2), 241–254. https://doi.org/10.1016/j.ijproman.2017.11.002