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DEVELOPING A COMPREHENSIVE RISK ASSESSMENT MODEL BASED ON FUZZY BAYESIAN BELIEF NETWORK (FBBN)

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Abstract. Reliable and efficient risk assessments are essential to deal effectively with potential risks in international construction projects. However, most conventional risk modeling methods are based on the hypothesis that risk factors are independent, which does not account adequately for the causal relationships among risk factors. In this study, a risk assessment model for international construction projects was developed to improve the efficacy of risk management by integrating fault tree analysis and fuzzy set theory with a Bayesian belief network. The risk rating of each risk factor, expressed as the product of risk occurrence probability and impact, was incorporated into the risk assessment model to evaluate degrees of risk. Therefore, risk factors were categorized into different risk levels taking into account their inherent causal relationships, which allowed the identification of critical risk factors. The applicability of the fuzzy Bayesian belief network-based risk assessment model was verified using a case study through a comparative analysis with the results from a fuzzy synthetic evaluation method. The comparison shows that the proposed risk assessment model is able to provide guidelines for an effective risk management process and ultimately to increase project performance in a complex environment such as international construction projects.

Keywords: international construction projects, risk assessment, causal relationships, fuzzy numbers, fuzzy Bayesian belief network, fault tree analysis, fuzzy synthetic evaluation.

Introduction

Rapid economic development and globalization have provided increasing opportunities for construction enterprises to expand their businesses to the international construction market (Bu-Qammaz et al., 2009; Kuo & Lu, 2013; Liu et al., 2016). Compared with domestic construction projects (DCPs), some major characteristics of international construction projects (ICPs) are as follows: larger contract amounts; longer return periods of investment; involvement of a higher number of contracting parties with diverging interests; and susceptibility to external environments (e.g., political, economic, social and cultural conditions). As well as different construction practices (Zhao et al., 2016) and inadequate skill and expertise (Liu et al., 2016) in ICP contractors, the implementation of ICPs generally has a higher risk exposure and greater challenges than DCPs. As a result, failure to deal with potential risks effectively in ICPs can increase the difficulties in achieving project objectives and often causes project delays, budget overruns and lower reputation for the construction company.

Risk management is a formal and fundamental process to improve project performance by mitigating or controlling the consequences of risks associated with project objectives, usually including risk identification, risk assessment, and risk treatment as well as monitoring phases throughout a project life cycle (El-Sayegh, 2008; Islam et al., 2017). Among these principal phases of the risk management process, risk identification and risk assessment are the most essential components that enable decision makers to formulate appropriate risk treatment plans in advance and to take appropriate proactive measures. Thus, there is a strong need for a reliable and efficient risk assessment (RA) framework to facilitate the effectiveness of risk management in ICPs. Since risks in complex construction projects such as ICPs are dynamic and interdependent (Islam et al., 2017), an adequate RA framework

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should account for the interrelationships among risk factors (RFs). Ignoring risk interdependencies can lead to insufficient reflection of real risk conditions of construction projects and may cause less reliable outcomes of RAs for decision making (Liu et al., 2016).

A wide range of methods have been developed for RAs in construction projects. These methods generally include qualitative, quantitative, and semi-quantitative methods (Chien et al., 2014). Additionally, the degree of risk is usually evaluated according to several criteria, such as the probability of risk occurrence and the magnitude of risk impact on project objectives. There are many existing RA frameworks or models developed for construction projects using various methods, such as the analytical hierarchy process (AHP) method (Wang et al., 2016), the technique for order preference by similarity to ideal solution (TOPSIS) and complex proportional assessment (COPRAS) (Zavadskas et al., 2010), step-wise weight assessment ratio analysis (SWARA) and COPRAS-based analysis (Valipour et al., 2017), a combination of failure mode and effect analysis (FMEA), fault trees, event trees and fuzzy logic (Abdelgawad & Fayek, 2012), fuzzy AHP and fuzzy TOPSIS-based analysis (Taylan et al., 2014), fuzzy synthetic evaluation (FSE)-based (Wu et al., 2017; Xu et al., 2010; Zhao et al., 2016), and fuzzy decision making trial and evaluation laboratory (DEMATEL)-based (Seker & Zavadskas, 2017). However, these RA frameworks do not consider the causal relationships among RFs. Thus, in order to address this issue, some researchers have proposed a few of methods that can analyze risk causal relationships when develop RA frameworks for ICPs. For example, Bu-Qammaz et al. (2009) presented an RA model for ICPs by applying analytic network process (ANP) method that can handle the interrelationships among RFs. Yildiz et al. (2014) considered the causalities among RFs that may lead to cost overrun in ICPs and proposed a knowledge-based risk mapping tool for systematic assessment of project vulnerabilities. Deng et al. (2014) investigated ICPs vulnerability to political risks and uncovered the interrelationships among variables using exploratory factor analysis. Liu et al. (2016) proposed a network of 20 significant risk paths through the structural equation modeling (SEM) technique, aiming to examine risk effects on the objectives of ICPs from the perspective of Chinese contractors. In addition, Bayesian belief network (BBN)-based methods have become increasingly popular with researches for use in risk management of offshore engineering systems (John et al., 2016; Meng et al., 2019; Ren et al., 2009), process systems (Guo et al., 2019; Yazdi & Kabir, 2017; Zarei et al., 2019), supply chain (Ojha et al., 2018; Qazi et al., 2018), and construction projects (Chen & Wang, 2017; Khanzadi et al., 2017; Leu & Chang, 2013; Wang & Chen, 2017; Zhang et al., 2014) because of their ability to model interdependencies among variables both qualitatively and quantitatively combined with the ability to incorporate knowledge representation and reasoning. In conventional BBN analysis, occurrence probabilities of root nodes are regarded as the crisp values. However, in construction engineering, it is difficult or nearly impossible to obtain exact values of occurrence probabilities due to a lack of sufficient data (Zhang et al., 2014). Fuzzy set theory (FST) can solve such engineering problems under uncertainty using fuzzy numbers, so that the integration of FST and BBN may well provide a useful means of incorporating uncertain factors in probabilistic risk analysis.

Some research has been conducted to study RA in ICPs by investigating the inherent causal relationships among RFs, however the fuzzy Bayesian belief network (FBBN) method is seldom adopted in the risk management of ICPs. Therefore, the main objective of this research is to develop a comprehensive FBBN-based RA model for ICPs by considering inherent causal relationships among RFs, so as to facilitate more effective evaluation and control of project risks. The remainder of this paper is organized as follows: the research methodology is presented in Section 1; Section 2 describes five major phases of the proposed FBBN-based RA model; Section 3 demonstrates the application of the proposed RA model using a case study and compares its results with those obtained from an FSE method; the insights of the research findings are discussed in Section 4; and finally, the conclusion section highlights the contributions from this research, existing limitations, and research directions for future study.

1. Research methodology

This section focuses on an explanation of the methods of identifying causal relationships of RFs in ICPs, risk impact assessment methods, risk occurrence probability (OP) assessment methods, and risk ranking method, which constitutes the FBBN-based method to construct an RA model for ICPs. In addition, fuzzy synthetic evaluation (FSE) method is introduced as a technique to be used to conduct a comparative analysis with FBBN-based method in regard to RAs for ICPs.

1.1. Identifying causal relationships of RFs

After identifying potential RFs in ICPs based on a comprehensive literature review and expert interviews, a hierarchical risk breakdown structure (HRBS) can be developed. Fault tree (FT) analysis and BBN, as root-cause analysis methods, are then used for further investigating causal relationships among the identified RFs. A causal relationship is also called a cause-effect relationship, denoting the relationship between a first event (the cause) and a second event (the effect), where the second event is a consequence of the first (Hu et al., 2013). A causal relationship is different from a correlation relationship which is bidirectional. The causal relationship can be represented in the form of "A influences or leads to B". In reality, risks in ICPs are interrelated and have cause-effect relationships among them and therefore, the occurrence of one RF may lead to a chain reaction of occurrence of other RFs which may then exaggerate the impact of the first risk on project objectives through risk paths.

1.1.1. FT analysis

The FT structure is a graphical deductive model including a series of basic events (BE) and intermediate events (IE) leading to the occurrence of a particular undesired event, i.e., a top event (TE) (Abdollahzadeh & Rastgoo, 2015), as illustrated in Figure 1(a). It is constructed in a top-down manner which starts with the upper events and proceeds to their causes until the basic failure components are reached; relationships among different elements are represented by logical AND/OR gates (Leu & Chang, 2013).

Conventional FT analysis method has the advantage of providing a good sketch of the root-causes of risks and analyzing defects or weaknesses of a system with imprecise information (Islam et al., 2017). However, it assumes that the state variables of events are binary and all events are statistically independent (Kabir et al., 2016). If multiple failures affect the components of a system and cause several different consequences, the state variables of events are not limited to a binary state (Weber et al., 2012), in which case the FT analysis method is inappropriate. In addition, the FT analysis method is limited in its ability to capture and demonstrate causal relationships among variables especially in complex projects.

1.1.2. BBN method

The BBN, also known as a Bayesian network or a causal network, is a probabilistic model that can visually present cause-effect relationships among a set of random variables in the form of a directed acyclic graph (Khodakarami & Abdi, 2014; Luu et al., 2009). Figure 1(b) shows a simple structure of a BBN. Nodes in the graph represent probabilistic variables: the nodes without any parent node are called root nodes (RN) while the nodes without any child node are called leaf nodes (LN), and the nodes having both parent and child nodes are called intermediate nodes (IN). Edges in the graph, directed from a parent node to a child node, denote the interdependencies or causal relationships among variables. The intensity of interdependencies can be quantified through conditional probability distributions associated with each node.

The BBN method can be suitable for risk analysis in large and complex risk networks, and when coping with risk-related problems, it is usually used in terms of a set of identified RFs (input variables) linked to potential failure events (the output variables) (Cárdenas et al., 2013). Unlike the FT analysis method, the BBN has the advantage of modeling flexibility in involving various kinds of cause-effect interdependencies using probabilistic gates instead of merely deterministic AND/OR connections. However, it is usually difficult to establish causal relationships among variables directly in a complex BBN. To solve this problem, several transformation processes from an FT structure to a BBN have been proposed, showing how the results obtained from the FT analysis can be further cast in the corresponding BBN (Kabir et al., 2016; Wilson & Huzurbazar, 2007). In this paper, FT analysis and BBN were therefore merged to determine causal relationships of RFs in ICPs.

1.2. Risk impact assessment methods

The unavailability of precise and numerical data is common in the RA of complex ICPs because of the uncertainties involved. The FST, first introduced by Zadeh (1965), solves problems characterized by uncertainties due to the imprecision, vagueness and subjectivity of human thoughts. FST is a well-recognized decision support tool that can mathematically represent the vague data from experts' judgments and can implement effective RA in a fuzzy environment (Islam et al., 2017). Therefore, FST is useful to be applied to the assessment of risk impact on ICP objectives, where fuzzy numbers and corresponding continuous membership functions can be developed to quantify linguistic variables from empirical judgments and the uncertainties involved (Cheng & Lu, 2015). A normalized fuzzy number denoted as $\tilde{A}$ is in the form of a fuzzy set, and its membership function is expressed as $F_{\tilde{A}}(x)$ with an interval $\left[0, 1\right]$ (Kuo & Lu, 2013). There are many different types of fuzzy numbers commonly used for converting linguistic variables into quantitative forms, such as triangular, trapezoidal and Gaussian fuzzy numbers (John et al., 2014; Samantra et al., 2017). Considering the conceptual and operational simplicity, trapezoidal fuzzy numbers are extensively adopted for modeling uncertainties and therefore are the most generic class of fuzzy numbers with linear membership functions (Kabir et al., 2016). As a result, normalized trapezoidal fuzzy numbers are used in this research related to fuzzy computing.

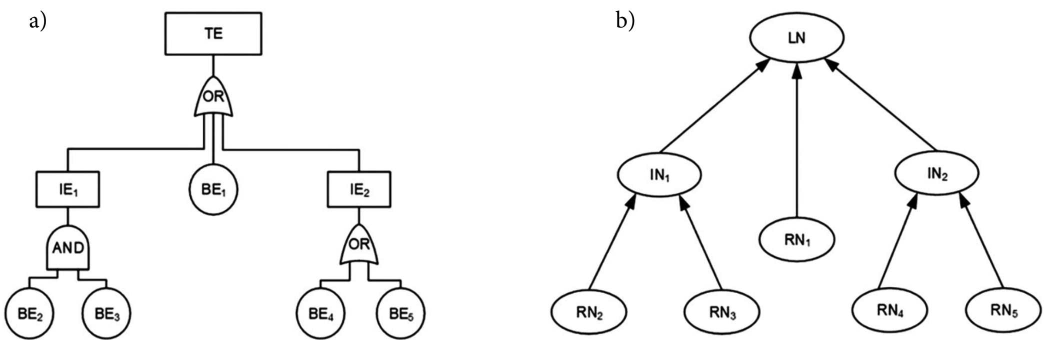

Figure 1. a) A simple structure of an FT; b) A simple structure of a BBN

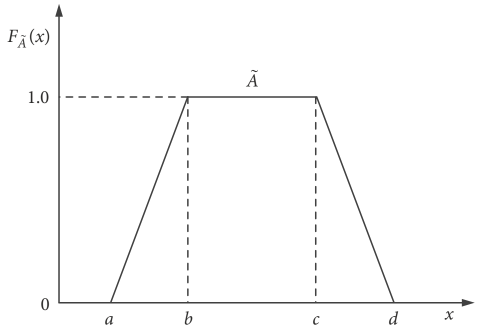

Figure 2. The normalized trapezoidal fuzzy number $\tilde{A} = (a,b,c,d)$

A normalized trapezoidal fuzzy number can be parameterized by $\tilde{A} = (a,b,c,d)$ where a, b, c and d are real numbers (Figure 2), and its trapezoidal membership function $F_{\tilde{A}}(x)$ is given by Eqn (1):

$$F_{\tilde{A}}(x) = \begin{cases} \dfrac{x-a}{b-a}, & a \le x \le b, \\ 1, & b \le x \le c, \\ \dfrac{x-d}{c-d}, & c \le x \le d, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

Let $\tilde{A}_1$ and $\tilde{A}_2$ be two trapezoidal fuzzy numbers, namely $\tilde{A}_1 = (a_1, b_1, c_1, d_1)$ and $\tilde{A}_2 = (a_2, b_2, c_2, d_2)$. Based on Zadeh's extension principle, the fuzzy-number arithmetic operations between $\tilde{A}_1$ and $\tilde{A}_2$ are defined by a series of operational laws, including addition, subtraction, multiplication and division, as presented respectively from Eqns (2) to (5); while the scalar multiplication result of $\tilde{A}$ is defined by Eqn (6) (Andrić & Lu, 2016; Chen et al., 2012).

$$\tilde{A}_1 \oplus \tilde{A}_2 = (a_1, b_1, c_1, d_1) \oplus (a_2, b_2, c_2, d_2) = (a_1 + a_2, b_1 + b_2, c_1 + c_2, d_1 + d_2); \quad (2)$$

$$\tilde{A}_1 \ominus \tilde{A}_2 = (a_1, b_1, c_1, d_1) \ominus (a_2, b_2, c_2, d_2) = (a_1 - a_2, b_1 - b_2, c_1 - c_2, d_1 - d_2); \quad (3)$$

$$\tilde{A}_1 \otimes \tilde{A}_2 \approx (a_1, b_1, c_1, d_1) \otimes (a_2, b_2, c_2, d_2) = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2, d_1 \times d_2); \quad (4)$$

$$\tilde{A}_1 \oslash \tilde{A}_2 \approx (a_1, b_1, c_1, d_1) \oslash (a_2, b_2, c_2, d_2) = (a_1 / d_2, b_1 / c_2, c_1 / b_2, d_1 / a_2); \quad (5)$$

$$k \otimes \tilde{A} \approx k \otimes (a,b,c,d) = (k \times a, k \times b, k \times c, k \times d), \text{ if } k > 0. \quad (6)$$

1.3. Risk OP assessment methods

1.3.1. FBBN

The FBBN method integrating the FST and BBN is proposed for quantifying the probability of risk occurrence in ICPs. While conducting the RA process, BBN is a suitable tool which not only illustrates the causes influencing a given event directly, but also enables probabilistic inference within a model. In a BBN structure, prior and conditional probabilities of corresponding variables are required to run a BBN computation. The quantitative analysis of interdependencies between variables relies on different states of parent nodes and a set of conditional probability tables (CPTs) assigned to each node. The CPTs contain conditional probabilities with respect to all the combinations of values of certain node associated with their parent nodes. As for root nodes, their CPTs only contain the prior probabilities (Bobbio et al., 2001).

Assuming x_i is the set of parents of node y_j in a BBN graph, then the CPT of y_j is defined by $P(y_j | x_i)$. Eqn (7) indicates the conditional independence (Li et al., 2012), and Eqn (8) shows the calculation of joint probability (Ren et al., 2009). The marginalization rule and Bayesian rule can be defined by Eqn (9) and Eqn (10), respectively (Kabir et al., 2016; Khodakarami & Abdi, 2014). Thus, an inference mechanism that permits both causal and diagnostic inference in the BBN can be conducted based on a Bayesian theorem to present the conditional probability dependencies among variables (Cárdenas et al., 2013).

$$P(U) = P(y_1, y_2, \cdots y_n) = \prod_{j=1}^{n} P(y_j \mid x_i); \quad (7)$$

$$P(Y = y_j, X = x_i) = P(X = x_i) \times P(Y = y_j \mid X = x_i); \quad (8)$$

$$P(Y = y_j) = \sum_{i=1}^{n} P(X = x_i) \times P(Y = y_j | X = x_i); \quad (9)$$

$$P(X = x_i | Y = y_j) = \frac{P(Y = y_j, X = x_i)}{P(Y = y_j)} = \frac{P(X = x_i) \times P(Y = y_j | X = x_i)}{\sum_{i=1}^{n} P(X = x_i) \times P(Y = y_j \mid X = x_i)}, \quad (10)$$

where, $P(X = x_i)$ represents the prior occurrence probability of x_i before observing any relevant evidence; $P(X = x_i | Y = y_j)$ is the posterior occurrence probability of x_i given that y_j has occurred; $P(Y = y_j | X = x_i)$ refers to the conditional occurrence probability of y_j given that x_i has occurred; and $P(Y = y_j)$ represents the marginal occurrence probability of y_j which can be viewed as a constant when evidence is found.

Using the BBN method in RA has the following principal advantages: (1) BBNs have a higher efficiency and accuracy compared to stochastic Petri networks (Weber et al., 2012) and artificial neural networks (Khodakarami & Abdi, 2014) for coping with incomplete and small number of datasets, especially in integrating different sources of knowledge in one model; (2) BBNs can conduct inference inversely and perform probability updating of variables easily when new information becomes available, which is a unique feature compared with some traditional risk-based methods such as feed-forward-like approximate reasoning approaches (Ren et al., 2009); (3) BBNs can construct large and complex risk networks using an aggregation process to take sub-networks into previous hierarchy levels (Khakzad et al., 2011); and (4) modifications to BBNs are isolated and the remainder of the network will not be affected when variables are added or removed (Luu et al., 2009). However, traditional BBN analysis only deals with crisp values of prior and conditional probabilities as input parameters, which is a major limitation in risk OP assessment. By incorporating the FST into the traditional BBN analysis, the FBBN method is further able to conduct risk OP assessment with linguistic variables and fuzzy numbers apart from expressing causal relationships among RFs and conducting inverse inference in a risk network (Zhang et al., 2016).

1.3.2. Defuzzification of fuzzy numbers in FBBN

The defuzzification of converting fuzzy numbers into their equivalent crisp values is required for the calculation of fuzzy Bayesian inference. Currently, several defuzzification methods have been developed and used, such as mean of maxima (MOM), center of maxima (COM), centroid method and α-weighted valuation method (Kabir et al., 2016; Kuo & Lu, 2013). The centroid method is efficient in minimizing information loss that leads to more reliable fuzzy Bayesian inference during a fuzzy-to-crisp transformation (Kabir et al., 2016), so it is adopted in this research for the defuzzification of fuzzy numbers in FBBN. Eqn (11) expresses the fuzzy-to-crisp transformation when a trapezoidal fuzzy number $\tilde{A} = (a,b,c,d)$ is defuzzified based on the centroid method (Ross, 2004), where $D(\tilde{A})$ is the equivalent crisp value of $\tilde{A}$. Therefore, using Bayesian computation rules together with fuzzy-number arithmetic operations and the centroid defuzzification method, FBBN-based inference can then be conducted to obtain both marginal and posterior OPs of RFs.

$$D(\tilde{A}) = \frac{\int x \cdot F(x)dx}{\int F(x)dx} = \frac{\int_a^b \left(\frac{x-a}{b-a}\right) \cdot x\,dx + \int_b^c x\,dx + \int_c^d \left(\frac{d-x}{d-c}\right) \cdot x\,dx}{\int_a^b \left(\frac{x-a}{b-a}\right) dx + \int_b^c dx + \int_c^d \left(\frac{d-x}{d-c}\right) dx} = \frac{-ab+cd+\frac{1}{3}(d-c)^2 - \frac{1}{3}(a-b)^2}{-a-b+c+d}. \quad (11)$$

1.4. Risk ranking method

During the decision making process in a fuzzy environment, ranking of fuzzy numbers is viewed as an essential aspect. Various ranking procedures have been proposed since the FST was first introduced, but some of them fail to discriminate fuzzy numbers and do not match with human intuition (Samantra et al., 2017). Rao and Shankar (2011) explored an improved ranking method using "circumcenter of centroids (CoC)" and verified its applicability. This work thus uses the CoC method to obtain crisp values of risk ratings for evaluating the risk degree of each RF. For a normalized trapezoidal fuzzy number $\tilde{A} = (a,b,c,d)$ (Figure 2), the trapezoid figure of its membership function can be split into three parts: two triangles and a rectangle. The CoC of these three parts is considered as a reference point to rank normalized fuzzy numbers. Let $S_{\tilde{A}}(\overline{x}_0, \overline{y}_0)$ be the circumcenter, and it is defined by Eqn (12). The ranking function of $\tilde{A}$ is then presented in Eqn (13), where $R(\tilde{A})$ means the Euclidean distance between the $S_{\tilde{A}}(\overline{x}_0, \overline{y}_0)$ and the origin of coordinates.

$$S_{\tilde{A}}(\overline{x}_0, \overline{y}_0) = \left(\frac{a+2b+2c+d}{6}, \frac{(2a+b-3c)\times(2d+c-3b)+5}{12}\right); \quad (12)$$

$$R(\tilde{A}) = \sqrt{\overline{x}_0^{\,2} + \overline{y}_0^{\,2}}. \quad (13)$$

1.5. Comparing RA results of the FBBN-based method and the FSE method

To validate the effectiveness of the proposed FBBN-based RA method, the FSE method was used to conduct a comparative analysis. The FSE method is a comprehensive evaluation approach based on fuzzy mathematics. As an application of FST, FSE uses multiple criteria to evaluate an object relative to an objective in a fuzzy environment (Islam et al., 2017; Zhao et al., 2016), which can deal with complicated evaluations with multiple levels and attributes, and is able to represent empirical knowledge of practitioners. Therefore, the FSE method is very practical for various types of non-deterministic problems (Wu et al., 2017) and has been widely adopted in construction management research particularly for the aspect of RAs. However, this method cannot manage the randomness and discreteness characteristics of project risks. In addition, it also fails to describe causal relationships of the risks at different hierarchy levels. Considering the wide use and availability of the FSE method in RAs, it was selected in this work to compare the results (e.g., risk ranking, critical RFs, and overall project risk rating) with those obtained from the FBBN-based method. The FSE method consists of three basic steps which are as follows:

Step 1. RAs of individual RFs

In this study, the OP and magnitude of impact (MI) of each individual RF (in the first level) were collected from a questionnaire survey, and then were represented with an 11-point linguistic scale and a nine-point linguistic scale, respectively. Trapezoidal membership functions were used to denote the OP and MI of RF i. In order to rank risks based on the FSE method, the score of risk rating (S_i) of RF i can be calculated using Eqn (14):

$$S_i = \sqrt{P_i \times I_i}, \quad (14)$$

where, P_i is the OP of RF i after defuzzification using Eqn (11); I_i is the MI of RF i after defuzzification using Eqn (11).

Step 2. RAs of risk groups

To calculate the OP, MI, and score of the risk rating of each risk group (in the second level), the weight of each

RF (in the first level) within each risk group should be first determined. The weights assigned to the OP and MI of RF i can be obtained based on Eqn (15) and Eqn (16), respectively:

$$w_i^P = \frac{P_i}{\sum_{i=1}^{k} P_i},\ 0 \le w_i^P \le 1,\ \sum w_i^P = 1; \quad (15)$$

$$w_i^I = \frac{I_i}{\sum_{i=1}^{k} I_i},\ 0 \le w_i^I \le 1,\ \sum w_i^I = 1, \quad (16)$$

where k is the number of RFs within a risk group.

The membership functions for OP and MI of risk groups were obtained by calculating the fuzzy composition of the corresponding weight vector W and the evaluation matrix M of RFs, i.e., $D = W \times M$. With the defuzzification results of both OP and MI, the score of risk rating for each risk group can be calculated based on Eqn (14).

Step 3. Evaluating overall project risk

Firstly, the weights assigned to the OP and MI of each risk group t (in the second level) can be calculated by Eqn (17) and Eqn (18), respectively:

$$w_{Gt}^P = \frac{P_{Gt}}{\sum_{t=1}^{q} P_{Gt}},\ 0 \le w_{Gt}^P \le 1,\ \sum w_{Gt}^P = 1; \quad (17)$$

$$w_{Gt}^I = \frac{I_{Gt}}{\sum_{t=1}^{q} I_{Gt}},\ 0 \le w_{Gt}^I \le 1,\ \sum w_{Gt}^I = 1, \quad (18)$$

where q is the number of risk groups in the second level; $\left(\sum_{i=1}^{k} P_i\right)_t$ denotes the sum of OP of k RFs under group t; and $\left(\sum_{i=1}^{k} I_i\right)_t$ represents the sum of MI of k RFs under group t.

If the overall project risk is in the third level, its membership functions for OP and MI are obtained by calculating the fuzzy composition of the corresponding weight vector W_G and the evaluation matrix M_G of risk groups in the second level. Then, the score of overall project risk rating can be derived based on the rationale of Eqn (14). Similarly, if there are more levels of risk groups, their risk evaluation results can be determined in the same way.

2. The proposed FBBN-based RA model

This study aims to propose a systematic FBBN-based RA model in relation to ICPs for risk ratings and categorization which can provide guidelines for decision making. Figure 3 demonstrates the phases of the proposed RA model, which is explained in detail in the remainder of this section.

2.1. RFs identification (P1)

This phase identifies potential RFs from the perspective of ICPs contractors, aiming to recognize and classify the RFs that are likely to affect successful completion of ICPs. A HRBS that classifies and organizes RFs explicitly can be constructed based on an extensive literature review and expert interviews. In the HRBS, a key problem (e.g., project failure) that needs to be solved is in the first level, which will then be decomposed into risk groups and more detailed RFs.

2.2. Identifying causal relationships of RFs (P2)

RFs usually interact with each other in complex ICPs, and this phase aims to explore causal relationships among identified RFs. Firstly, an FT structure can be set up in a top-down fashion based on the established HRBS and reviewed by domain experts through exploratory interviews. Other RFs and RFs' interrelationships can be further added. The considered causal relationships only involve strong

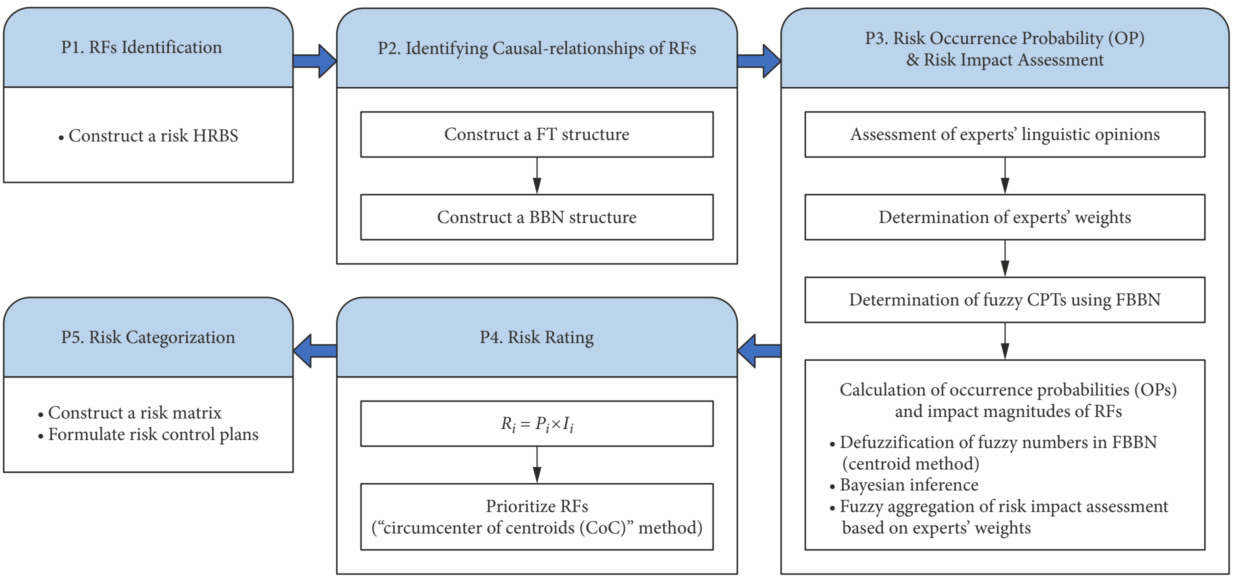

Figure 3. The FBBN-based RA model phases

links among RFs. Furthermore, a BBN structure will be constructed based on the FT transformation for fully presenting cause-effect relationships among identified RFs. The events and vertical links in an FT structure should be directly transformed into corresponding nodes and fundamental links of a BBN structure according to conversion algorithms (basic, intermediate and top events of an FT are mapped into root, intermediate and leaf nodes of a BBN, respectively). Further, overlapping nodes are combined into one node, and supplementary links are inserted into the BBN structure according to experts' opinions.

2.3. Risk OP and risk impact assessment (P3)

In this phase, RFs' OPs and MIs on project objectives will be evaluated. To quantify experts' linguistic variables on the OPs of RFs, the centroid method is used to convert the fuzzy prior and conditional occurrence probabilities of RFs into equivalent crisp values which will then be used to conduct Bayesian inference (causal and diagnostic inference).

2.3.1. Assessment of experts' linguistic opinions

Experts estimate RFs' OPs and MIs in form of fuzzy linguistic scales. When experts are making judgments based on their knowledge and experience, it is much easier for them to use qualitative descriptors than to provide crisp numerical values directly. The concept of linguistic variables is very useful in dealing with the situation that is too complex or too vague to be reasonably described in quantitative expressions, which allows for ambiguities, uncertainties or incomplete information of experts' judgments (John et al., 2014). Fuzzy linguistic scales can be designed with a set of linguistic variables, and each linguistic variable is represented by a fuzzy number and a corresponding fuzzy membership function that covers the universe of discourse (Samantra et al., 2017).

2.3.2. Determination of experts' weights

This step evaluates and weights experts on their judgments' confidence to conduct fuzzy aggregation of their judgments, which can increase the reliability of data acquired from questionnaire surveys. In most cases, experts may have different confidence levels with regard to their own judgments due to differences in their educational backgrounds, working experience and risk attitudes, resulting in deviations among the judgments of different experts (Kabir et al., 2016). Zhang et al. (2014) proposed an expert confidence indicator (θ) to reveal the credibility of collected data based on two aspects, namely, expert ability (ζ) and expert subjectivity reliability (ψ). The value of ζ increases along with the accumulation of educational backgrounds and working experience of experts. The value of ψ towards individual judgments is evaluated according to risk attitudes of different experts. In this study, the judgment weight of each expert (ω_t) is expressed in Eqn (19).

$$\omega_t = \frac{\theta_t}{\sum_{t=1}\theta_t} = \frac{\zeta_t \times \psi_t}{\sum_{t=1}\zeta_t \times \psi_t},\ t = 1,2,3,\cdots. \quad (19)$$

After the determination of experts' weights, fuzzy aggregation of individual judgments on OPs and MIs of RFs can be conducted respectively. Such an aggregation is a process in fuzzy logic, combining fuzzy numbers in order to obtain an average preference fuzzy set (Andrić & Lu, 2016). The aggregated preference fuzzy set of each RF (i.e., weighted RF–*WRF*) can be computed as in Eqn (20), where RF_{i1}, for example, denotes the individual judgments of the first expert on the OP or MI of the *i*th RF.

$$WRF_i = \omega_1 \otimes RF_{i1} \oplus \omega_2 \otimes RF_{i2} \oplus \omega_3 \otimes RF_{i3} \oplus \cdots. \quad (20)$$

2.3.3. Determination of fuzzy CPTs using FBBN

The link between any two connecting nodes in a BBN structure is developed by means of a conditional probability distribution. Before the determination of fuzzy CPTs, fuzzy prior and conditional probabilities of RFs should be estimated at first based on experts' judgments.

Determining the fuzzy CPT for each RF (as a node in FBBN) is an important step towards quantitative analysis of OPs based on RFs' causal relationships. The values of fuzzy CPTs (including fuzzy prior and conditional probabilities of root and child nodes respectively) are assessed by experts using linguistic variables. Trapezoidal fuzzy numbers and membership functions are determined to describe these linguistic variables and then, experts' judgments can be subsequently aggregated into weighted values (i.e., *WRF*) by incorporating experts' weights.

2.3.4. Calculation of OPs and MIs of RFs

In this step, the OPs of RFs are assessed by the FBBN-based method, and the MIs of RFs are calculated by means of the FST. Through the Bayesian inference, different types of OPs (i.e., prior and marginal OP, posterior OP) can be calculated and the final results are in the form of crisp values. Causal inference aims to predict the OPs of child nodes with regard to the combinations of all their parent nodes. The fuzzy CPTs are then converted into crisp values based on centroid defuzzification method, which are treated as evidence inputs of the causal inference. Thus, marginal OPs of intermediate and leaf nodes can be calculated using Bayesian Eqns (7)–(9). From the causal inference, OPs of RFs are predicted considering existing cause-effect relationships. However, the objective of the diagnostic inference of FBBN is to obtain the posterior OP of each node that can provide reliable references for fault diagnosis and to perform probability updating analysis when new observations are added to certain nodes. In this paper, Eqns (7)–(10) are used to calculate posterior OPs of all RFs in the FBBN when a project failure occurs. The closer the posterior OP of a RF is to 1, the greater the contribution of the RF to overall project risk.

In terms of calculating each RF's MI on project objectives, the experts' judgments represented by linguistic variables are transformed into trapezoidal fuzzy numbers according to a presumed fuzzy scale and then, a fuzzy aggregation of the judgments of all experts considering experts' weights is conducted using Eqn (20). Therefore, an average preference fuzzy set (i.e., *WRF*) is obtained representing the MI of each RF.

2.4. Risk rating (P4)

Risk rating is a process for assessing severities of undesired events, which helps developing control and mitigation strategies for potential project risks. This phase rates RFs by multiplying their OPs and MIs (i.e., $R_i = P_i \times I_i$). Due to the application of FBBN to OP assessment of RFs, different types of risk ratings can be obtained. As a result, corresponding fuzzy risk ratings are calculated by multiplying the fuzzy MIs of RFs with different types of risk occurrence probabilities using Eqn (6). Finally, critical RFs having a significant effect on project objectives will be identified by prioritizing RFs based on crisp values of risk ratings which are calculated by the CoC method (Eqn (12) and Eqn (13)).

2.5. Risk categorization (P5)

This phase categorizes RFs based on the concept of risk matrix, in which the horizontal axis and vertical axis represent the OP and MI, respectively. The referential risk matrix can be constructed through the product of the linguistic scale of OP and that of MI (Samantra et al., 2017). Every RF will be distributed in the referential risk matrix with a certain value of risk rating from the FBBN method, and different risk levels of the identified RFs will also be divided. On the basis of the results of risk categorization in terms of risk rating values, decision makers can propose appropriate risk control plans to maximize project success.

3. Case study

In this section, a case study was used to demonstrate and verify the application of the proposed FBBN-based RA model for ICPs, where risk degrees of potential RFs considering causal relationships were assessed and critical RFs were therefore determined. In addition, the FSE method was also applied to the same case in order to compare the results with findings obtained from the FBBN-based RA model.

The investigated ICP is a high-speed railway project in Turkey: the Ankara-Istanbul high-speed railway project. This infrastructure project was commenced in 2008 by a consortium of four companies (two from China and two local) through the EPC (Engineering, Procurement and Construction) agreement and it was into operation in 2014. The total length of the railway is about 158 kilometers. The project scope mainly includes railway beds and tracks, bridges, tunnels, electrification and communication engineering.

3.1. Applying the proposed FBBN-based RA model to an ICP

3.1.1. Identification of RFs and their causal relationships

A generic network structure of potential RFs for the investigated ICP was built from the perspective of contractors, presenting causal relationships among RFs at different hierarchy levels. Some important potential RFs were preliminarily summarized according to a thorough literature review. Then, these identified RFs were organized hierarchically and a four-level HRBS (Appendix A, Figure A1) enabling detailed risk analysis was developed. The highest level of the HRBS, the "ICP failure", was decomposed into "country risk", "international market risk", "project implementation risk", and "decision making behavior risk". More detailed RFs were arranged under lower levels.

In order to develop a BBN structure illustrating causal relationships among RFs, an FT structure was constructed first as a transition. A group of domain experts (see in Table 1) were invited to take part in separately organized exploratory interviews and gave their opinions on the interrelationships among RFs according to the established HRBS, which also led to the addition of 19 new RFs (i.e., R_9, R_{19}, R_{22}, R_{23}, R_{27}, R_{29}, R_{35}, R_{36}, and R_{38}–R_{48}) to the root-cause relationship of the "ICP failure". All of these identified RFs for ICPs are expressed specifically in Table 2. Thus, an FT risk structure was developed after reaching a consensus among these experts. Only strong links among RFs were considered in the FT structure, while non-significant causal relationships were ignored. While developing the BBN risk structure, basic, intermediate and top events in the FT structure were mapped into root, intermediate and leaf nodes of a BBN structure accordingly; overlapping nodes (e.g., R_{20} and R_{37}) were combined into one node; and supplementary links between RFs were inserted into the BBN structure based on experts' opinions. As an example, a directed link from "contract risk (I_9)" to "construction risk (I_{12})" in the BBN structure is added to show cause-effect relationship between these two RFs, namely, I_9 has an influence to I_{12}. The BBN structure with 91 nodes and 111 links is illustrated in Figure 4. The probabilistic gates representing causal relationships in the BBN risk structure were calculated quantitatively in Section 3.1.2.

Table 1. A profile of selected experts in the decision making group

Abbreviation	Position/Title	Work experience in ICPs field (yrs.)
E_1	Senior manager	24
E_2	Project manager	21
E_3	Academic expert	19
E_4	Operation manager	17
E_5	Estimating manager	13
E_6	Senior design engineer	9
E_7	Site engineer	8

Table 2. The RFs of ICPs based on literature review and experts' judgments

No.	RF	No.	RF
L	ICP failure	R_{11}	Changes in laws/regulations (Ls/Rs)
I_1	Country risk	R_{12}	Inadequate legal framework
I_2	International market risk	R_{13}	Unfair construction Ls/Rs
I_3	Project implementation risk	R_{14}	Invalid construction Ls/Rs
I_4	Political / government policy risk	R_{15}	Public protest / interference
I_5	Legal risk	R_{16}	Language barrier
I_6	Social risk	R_{17}	Differences in religious/cultural tradition
I_7	Resource procurement risk	R_{18}	Public insecurity / crime problems
I_8	Insufficient revenue	R_{19}	Resource demand changes
I_9	Contract risk	R_{20}	Import-export restrictions
I_{10}	Financing risk	R_{21}	Intense market competition of similar projects in host country
I_{11}	Design risk	R_{22}	Unclear contract clauses and conditions
I_{12}	Construction risk	R_{23}	Advantageous risk allocation to owner
I_{13}	Operation risk	R_{24}	Delay in payment
I_{14}	Decision making behavior risk	R_{25}	Excessive contract variation
I_{15}	Macroeconomic risk	R_{26}	Delay in solving dispute problems
I_{16}	Intervention of government	R_{27}	Insufficient financing capability
I_{17}	Unstable political situation	R_{28}	Insufficient debt repayment capability
I_{18}	Immature legal system	R_{29}	Unattractive financing to investors
I_{19}	Labor/material/equipment (L/M/E) price fluctuation	R_{30}	High financing costs
I_{20}	Unavailability of L/M/E	R_{31}	Designers' inadequate capability
I_{21}	Project demand changes in host country	R_{32}	Conflicting interfaces of work items
I_{22}	Improper contract	R_{33}	Unclear specifications for design
I_{23}	Difficulties in dispute resolution	R_{34}	Variations in design
I_{24}	Unavailability of enough financing	R_{35}	Adverse relationships among project participants
I_{25}	Inappropriate design	R_{36}	Unstable supply of L/M/E
I_{26}	Managerial problems in construction	R_{37}	Insufficient experience / skill in construction works
I_{27}	Technological problems in construction	R_{38}	Complexity in construction technologies
I_{28}	Safety-related problems in construction	R_{39}	Lack of proper construction technologies
I_{29}	Construction specification and standard problems	R_{40}	Insufficient protection of adjacent buildings and facilities
I_{30}	Adverse site conditions	R_{41}	Incomplete safety and health regulations
I_{31}	Operation cost overrun	R_{42}	Different construction standards and measurement system
I_{32}	Maintenance problems	R_{43}	Unclear construction specifications
I_{33}	Insufficient capability of decision makers (DMs)	R_{44}	Natural hazards
I_{34}	Unreasonable rent-seeking behavior	R_{45}	Uncertainty in subsurface condition
I_{35}	Irrational decision making behavior	R_{46}	Poor infrastructure on site
R_1	Interest rate fluctuation	R_{47}	Higher maintenance costs than expected
R_2	Exchange rate fluctuation	R_{48}	More frequent maintenance than expected
R_3	High inflation	R_{49}	Insufficient capability in emergency response
R_4	Corruption/bribery	R_{50}	Insufficient expertise knowledge of DMs
R_5	Expropriation/nationalization of assets	R_{51}	Poor moral/psychological quality of DMs
R_6	Bureaucracy	R_{52}	DMs' improper behavior of pursuing political interests
R_7	Protectionism	R_{53}	DMs' improper behavior of pursuing economic benefits
R_8	Strong political opposition	R_{54}	Information asymmetry
R_9	Revolutions/wars/riots	R_{55}	Unreasonable decision making methods
R_{10}	Poor international relationships	/	/

3.1.2. Risk OP and risk impact assessment

A questionnaire survey for the collection of risk data (e.g., CPTs of potential RFs for OP assessment, and the magnitudes of risk impacts for impact assessment) was conducted. Appendix B shows a sample questionnaire. All the distributed questionnaires were retrieved from the experts who ensured that valid and high-quality data were provided within their knowledge and experience. The results of returned questionnaires were then compiled for analysis.

Normalized trapezoidal fuzzy numbers and corresponding membership functions were used to represent different linguistic variables of experts' judgments from the questionnaire. OPs of RFs were quantified by an 11-point fuzzy linguistic scale, as described in Figure 5(a), and a nine-point fuzzy linguistic scale illustrated in Figure 5(b) was developed to assess the MIs of RFs. Additionally, experts' weights towards each RF were carried out using Eqn (19). Relevant information of expert ability (ζ) and expert subjectivity reliability (ψ) for each expert were obtained from the questionnaire survey (Section 1 and Section 3 in Appendix B, respectively). The value of ζ is divided into four levels with scores of "1.0, 0.9, 0.8, and 0.7", meaning experts' working experience: 20, 10–20, 5–10, and less than 5 years, respectively. The value of ψ is classified into five levels with scores of "1.0, 0.9, 0.8, 0.7 and 0.6", respectively, and the higher the score, the more reliable the expert judgment.

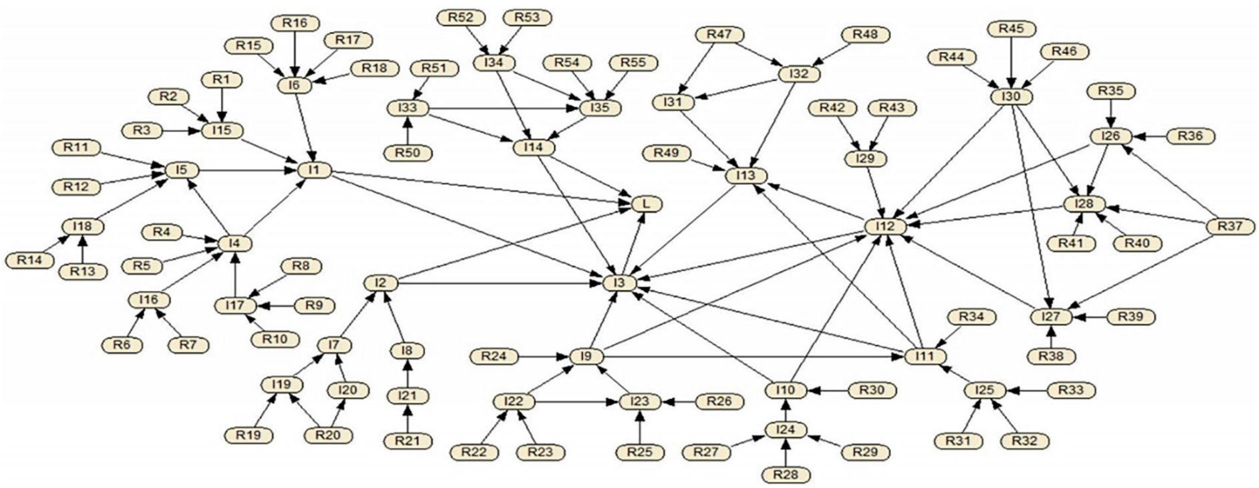

Figure 4. A BBN structure of the identified RFs for ICPs (with 91 nodes and 111 links)

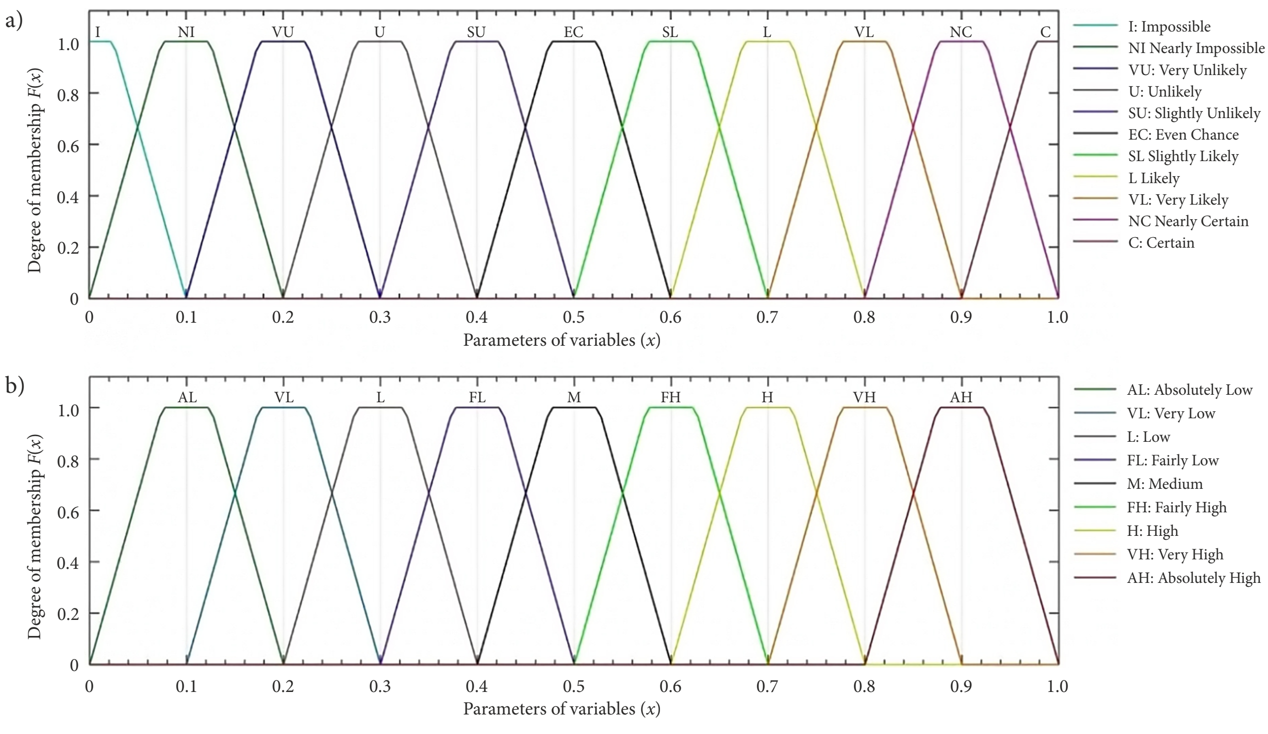

Figure 5. a) The 11-point linguistic scale and corresponding fuzzy membership functions for assessing occurrence probabilities (OPs) of RFs; b) The nine-point linguistic scale and corresponding fuzzy membership functions for assessing magnitudes of impact (MIs) of RFs

Each node in the BBN structure has two states: "*Yes*" and "*No*", reflecting whether the RF represented by the node will take place or not. To determine fuzzy CPTs of the FBBN, fuzzy prior probabilities of root nodes and fuzzy conditional probabilities of child nodes were obtained based on experts' judgments and then formulated using the 11-point fuzzy linguistic scale. In order to assess OPs of RFs for this ICP, crisp values of fuzzy CPTs were treated as the evidence inputs for Bayesian inference in FBBN. Marginal OPs of intermediate and leaf nodes were computed by Eqns (7)–(9) in the process of causal inference. When supposing the ICP failure occurred, the diagnostic inference then reasoned out to what extent the ICP failure was caused by other RFs. The posterior OPs of root and intermediate nodes conditioned to the ICP failure were computed by Eqn (10). *Netica*, a powerful and easy-to-use software package was used to implement Bayesian inference in FBBN analysis. The results of OPs of some example RFs from Bayesian inference are explained in Table 3. To verify the effectiveness of the established FBBN model, four hypothetical scenarios on ten nodes were analyzed. Table 4 shows when the number of nodes in unfavorable state increased, the marginal OP of the "ICP failure (L)" grew accordingly. Obviously, the results of these four scenarios fit with the logic of general inference and can validate the feasibility of the FBBN model applied to risk OP assessment.

Table 3. FBBN-based RA results of the nodes (i.e., leaf, intermediate and root nodes) in the risk network for the Ankara-Istanbul high-speed railway project (samples)

Node	Occurrence probabilities		Magnitude of impact	Fuzzy risk ratings		Crisp risk ratings	
	Prior/ Marginal	Posterior		Prior/Marginal	Posterior	Prior/Marginal	Posterior
L	0.65727	1.00000	(0.7610, 0.8360, 0.8860, 0.9610)	(0.5002, 0.5495, 0.5824, 0.6317)	(0.7610, 0.8360, 0.8860, 0.9610)	0.70086	0.95331
I_3	0.67449	0.72029	(0.7166, 0.7916, 0.8416, 0.9166)	(0.4833, 0.5339, 0.5676, 0.6182)	(0.5162, 0.5702, 0.6062, 0.6602)	0.68858	0.71857
I_{29}	0.67881	0.67896	(0.7017, 0.7767, 0.8267, 0.9017)	(0.4763, 0.5272, 0.5612, 0.6121)	(0.4764, 0.5273, 0.5613, 0.6122)	0.68328	0.68338
I_{22}	0.71448	0.71500	(0.6546, 0.7296, 0.7796, 0.8547)	(0.4677, 0.5213, 0.5570, 0.6106)	(0.4681, 0.5217, 0.5574, 0.6111)	0.67908	0.67938
I_9	0.69832	0.70084	(0.6328, 0.7078, 0.7578, 0.8328)	(0.4419, 0.4943, 0.5292, 0.5816)	(0.4435, 0.4961, 0.5311, 0.5837)	0.65762	0.65904
I_{11}	0.69975	0.70276	(0.6285, 0.7035, 0.7535, 0.8286)	(0.4398, 0.4923, 0.5273, 0.5798)	(0.4417, 0.4944, 0.5296, 0.5823)	0.65609	0.65778
R_{42}	0.80140	0.80144	(0.6998, 0.7748, 0.8248, 0.8997)	(0.5608, 0.6209, 0.6610, 0.7210)	(0.5608, 0.6209, 0.6610, 0.7211)	0.76185	0.76187
R_{34}	0.78775	0.78807	(0.6439, 0.7189, 0.7689, 0.8439)	(0.5072, 0.5663, 0.6057, 0.6648)	(0.5074, 0.5665, 0.6060, 0.6651)	0.71636	0.71655
R_{16}	0.80664	0.80688	(0.6015, 0.6764, 0.7264, 0.8014)	(0.4852, 0.5456, 0.5860, 0.6464)	(0.4853, 0.5458, 0.5861, 0.6466)	0.69979	0.69992
R_{54}	0.66500	0.66627	(0.7300, 0.8050, 0.8550, 0.9300)	(0.4855, 0.5353, 0.5686, 0.6185)	(0.4864, 0.5363, 0.5697, 0.6196)	0.68957	0.69041
R_{22}	0.71695	0.71704	(0.6102, 0.6852, 0.7352, 0.8102)	(0.4375, 0.4912, 0.5271, 0.5809)	(0.4375, 0.4913, 0.5271, 0.5809)	0.65548	0.65553
R_{25}	0.60170	0.60176	(0.7439, 0.8189, 0.8689, 0.9439)	(0.4476, 0.4927, 0.5228, 0.5679)	(0.4476, 0.4928, 0.5228, 0.5680)	0.65511	0.65515

Table 4. The results of four hypothetical scenarios of the FBBN-based RA model for the Ankara-Istanbul high-speed railway project

Node	Scenario 1	Scenario 2	Scenario 3	Scenario 4
I_2	*No*	*Yes*	*Yes*	*Yes*
I_{11}	*No*	*No*	*Yes*	*Yes*
I_{12}	*No*	*Yes*	*Yes*	*Yes*
I_{17}	*No*	*No*	*No*	*Yes*
I_{22}	*No*	*No*	*No*	*Yes*
I_{24}	*No*	*No*	*Yes*	*Yes*
I_{35}	*No*	*Yes*	*Yes*	*Yes*
R_2	*No*	*No*	*No*	*Yes*
R_{17}	*No*	*No*	*No*	*Yes*
R_{51}	*No*	*No*	*No*	*Yes*
L	$P(L = Yes) = 0.56748$	$P(L = Yes) = 0.67818$	$P(L = Yes) = 0.68664$	$P(L = Yes) = 0.69533$

The MI regarding each RF on project success was evaluated by the selected seven experts in light of the nine-point fuzzy linguistic scale. Afterwards, aggregated fuzzy impact preference of each RF was obtained by Eqn (20). The MIs of some example RFs are also presented in Table 3.

3.1.3. Risk rating

Different types of fuzzy risk ratings of all identified RFs were calculated by multiplying crisp values of OPs with fuzzy values of MIs. To compare risk ratings more directly, the CoC method expressed in Eqn (12) and Eqn (13) was employed for obtaining equivalent crisp values of risk ratings. The risk rating results of some samples are shown in Table 3.

3.1.4. Risk categorization

A six-level referential risk matrix was developed to categorize the identified RFs and to map the different risk levels to which they belonged, where 0.96028 was the highest possible value of the risk rating and 0.41667 was the lowest. In Table 5, RFs of the ICP were categorized into four risk levels (Categories 2–5) within corresponding sub-ranges of risk ratings from the FBBN method. Category 5 represents the highest risk level and Category 0 is the lowest risk level.

In addition, some rational risk response strategies directing at each risk level were formulated, which can provide a general action plan to cope with the identified RFs more effectively. For RFs in Category 0, particular risk response actions are not required but these RFs should be placed on a risk list in order to be tracked. For RFs in Category 1, general risk control measures should be defined and implemented within a reasonable timeframe (2–4 weeks) to minimize risks within acceptable ranges, and these RFs should be monitored and reviewed monthly. For RFs in Category 2, timely investigation is required and particular risk control measures should be determined and implemented within a week. The RFs need to be monitored and reviewed frequently. For RFs in Category 3, timely investigation is necessary and more detailed risk control measures should be designed and implemented within a week. These RFs need to be monitored and reviewed continuously. For RFs in Category 4, immediate investigation is needed and more detailed risk control measures should be determined and implemented quickly (within one or two days). The RFs should be monitored and reviewed continuously, and risk control measures can be revised according to real-time risk status. For RFs in Category 5, immediate investigation is essential and proper documentation that specifies current risk status should be immediately reported to the project decision team. More specific risk control measures need to be implemented immediately. The RFs should be monitored and reviewed all the time, and risk control measures are supposed to be revised in a timely manner based on current risk status.

3.2. RA results of an ICP using the FSE method

In the FSE method analysis, the RFs of ICPs in Table 2 were divided into four levels based on the HRBS (Appendix A, Figure A1). The fourth level was defined as the overall project risk; the second and third level were risk groups which were similar to the structure of the HRBS; the first level included individual detailed RFs, and compared with the lowest level of the HRBS, 19 RFs were added (i.e., R_9 was under the risk group of "political/government policy risk", R_{19} was under "resource procurement risk", R_{22} and R_{23} were in the risk group of "contract risk", R_{27} and R_{29} were under "financing risk", R_{35}, R_{36}, and R_{38}–R_{46} were in the risk group of "construction risk", and R_{47} and R_{48} were under "operation risk"). The trapezoidal membership functions of an 11-point linguistic scale (Figure 5a) and a nine-point linguistic scale (Figure 5b) were used to evaluate the OP and MI of risks, respectively.

Table 5. Risk categorization for the Ankara-Istanbul high-speed railway project based on FBBN-based RA model

Risk level	RFs	
	Causal inference	Diagnostic inference
Category 5 (Risk rating: 0.70929–0.96028)	R_{34}, R_{42}	R_{34}, R_{42}; I_3, L
Category 4 (Risk rating: 0.54975–0.70928)	R_{41}, R_7, R_2, R_{11}, R_{23}, R_6, R_{33}, R_{13}, R_{20}, R_{45}, R_{25}, R_{22}, R_{54}, R_{16}; I_{26}, I_2, I_{24}, I_8, I_{25}, I_5, I_4, I_{30}, I_{28}, I_{10}, I_{16}, I_{14}, I_7, I_1, I_{12}, I_{35}, I_{11}, I_9, I_{22}, I_{29}, I_3, L	R_{41}, R_7, R_2, R_{11}, R_{23}, R_6, R_{33}, R_{13}, R_{20}, R_{45}, R_{25}, R_{22}, R_{54}, R_{16}; I_{26}, I_{24}, I_2, I_{25}, I_8, I_5, I_4, I_{30}, I_{28}, I_{10}, I_{16}, I_7, I_{14}, I_{12}, I_1, I_{11}, I_9, I_{35}, I_{22}, I_{29}
Category 3 (Risk rating: 0.46600–0.54974)	R_{53}, R_9, R_{39}, R_{35}, R_4, R_{36}, R_{19}, R_{21}, R_{52}, R_5, R_{15}, R_{30}, R_{28}, R_{12}, R_{43}, R_{55}, R_{26}, R_{51}, R_{17}, R_{14}, R_{27}, R_{38}, R_{18}, R_{37}, R_3; I_{19}, I_{27}, I_{32}, I_{13}, I_{15}, I_{34}, I_{18}, I_{21}, I_{17}, I_{23}, I_{31}, I_{33}, I_6, I_{20}	R_{53}, R_9, R_{39}, R_{35}, R_4, R_{36}, R_{19}, R_{21}, R_{52}, R_5, R_{15}, R_{30}, R_{28}, R_{12}, R_{43}, R_{55}, R_{26}, R_{51}, R_{17}, R_{14}, R_{27}, R_{38}, R_{18}, R_{37}, R_3; I_{19}, I_{27}, I_{32}, I_{13}, I_{15}, I_{34}, I_{18}, I_{21}, I_{17}, I_{23}, I_{31}, I_{33}, I_{20}, I_6
Category 2 (Risk rating: 0.42399–0.46599)	R_{48}, R_{31}, R_{10}, R_{47}, R_8, R_1, R_{40}, R_{44}, R_{50}, R_{29}, R_{24}, R_{46}, R_{49}, R_{32}	R_{48}, R_{31}, R_{10}, R_{47}, R_8, R_1, R_{40}, R_{44}, R_{50}, R_{29}, R_{24}, R_{46}, R_{49}, R_{32}
Category 1 (Risk rating: 0.41708–0.42398)	Not identified	Not identified
Category 0 (Risk rating: 0.00000–0.41707)	Not identified	Not identified

The data needed for the application of the FSE method (i.e., OP and MI membership functions of RFs in the first level) are also available from the previous questionnaire survey. The values of OP and MI of risks were calculated based on the defuzzification of their membership functions using Eq. (11).

Firstly, the RA of RFs in the first level were calculated. For example, the OP membership function of "interest rate fluctuation (R_1)" was (0.5682, 0.6432, 0.6932, 0.7682), and its MI membership function was (0.1676, 0.2426, 0.2926, 0.3676). Based on the Eqn (11), the value of OP and MI for R_1 were obtained, which were 0.66817 and 0.26762, respectively. Then, the risk rating score of R_1 was derived based on Eqn (14):

$$S_1 = \sqrt{P_1 \times I_1} = \sqrt{0.66817 \times 0.26762} \approx 0.42287.$$

The top ten RFs in the first level in terms of risk rating scores – that is, the critical RFs – are listed in Table 6.

Then, to assess each risk group in the second level, the OP and MI weights of each RF in the first level within each risk group were calculated using Eqn (15) and Eqn (16), respectively. For example, the weight assigned to the OP of R_1 which was one of the three RFs (k = 3) within the risk group "macroeconomic risk (I_{15})" was obtained using Eqn (15):

$$w_1^P = \frac{P_1}{\sum_{i=1}^{3} P_i} =$$
$$0.66817 \ / \ (0.66817 + 0.71615 + 0.53648) \approx 0.348.$$

Taking the risk group I_{15} for example, its OP membership function D_{G1}^P was obtained as follows:

$$D_{G1}^P = W_1^P \times M_1^P = (0.348 \quad 0.373 \quad 0.279) \times$$
$$\begin{pmatrix} 0.5682 & 0.6432 & 0.6932 & 0.7682 \\ 0.6162 & 0.6912 & 0.7412 & 0.8162 \\ 0.4365 & 0.5115 & 0.5615 & 0.6365 \end{pmatrix} =$$
$$(0.5494 \quad 0.6244 \quad 0.6744 \quad 0.7494),$$

where W_1^P is the OP weight matrix related to the risk group I_{15}, consisting of the OP weights of the three RFs within this group; and M_1^P is the OP membership function matrix, consisting of the OP membership functions of the three RFs within this group.

Similarly, the MI membership function and risk rating score of risk group I_{15} were also calculated. The RA results of risk groups in the second level (i.e., I_4–I_{13}, I_{15}, and I_{33}–I_{35}) are shown in Table 7. In addition, the OP and MI weights of these risk groups are also presented in Table 7. For example, the weights assigned to the OP and MI of I_{15} (which was one of the four risk groups (q = 4) within the group "country risk (I_1)" in the third level) were obtained using Eqn (17) and Eqn (18), respectively:

$$w_{G1}^P = \frac{P_{G1}}{\sum_{t=1}^{4} P_{Gt}} =$$
$$0.64940 \ / \ (0.64940 + 0.49959 + 0.57240 + 0.70557) \approx 0.268;$$

$$w_{G1}^I = \frac{I_{G1}}{\sum_{t=1}^{4} I_{Gt}} =$$
$$0.53640 \ / \ (0.53640 + 0.72480 + 0.63255 + 0.59870) \approx 0.215.$$

Furthermore, the RA results of risk groups in the third level (i.e., I_1–I_3, and I_{14}) and the overall project risk (i.e., L) in the fourth level were obtained by running the similar calculation process, as shown in Table 8. Finally, the score of risk rating of the overall project risk is calculated as 0.59500 based on the FSE method.

A six-level referential risk matrix was also developed to categorize RFs, risk groups, and overall project risk into different risk levels, where 0.86850 was the highest possible value of the referential risk rating while 0.00350 was the lowest. As shown in Table 9, the overall project risk, most RFs, and all risk groups are located in Category 4 using FSE method.

3.3. Results analyses

The RA results from the FBBN-based method in Table 3 and Table 5 show that the crisp marginal risk rating of the leaf node "ICP failure (L)" after the causal inference was 0.70086, located in the risk level of Category 4.

Table 6. RA results of top ten RFs in the first level for the Ankara-Istanbul high-speed railway project

Node	Occurrence probability		Magnitude of impact		Risk rating	Rank
	Membership function	Value	Membership function	Value		
R_{42}	(0.7014, 0.7764, 0.8264, 0.9014)	0.80140	(0.6998, 0.7748, 0.8248, 0.8997)	0.79976	0.80058	1
R_{34}	(0.6877, 0.7627, 0.8128, 0.8878)	0.78775	(0.6439, 0.7189, 0.7689, 0.8439)	0.74391	0.76552	2
R_{16}	(0.7113, 0.7862, 0.8329, 0.8981)	0.80664	(0.6015, 0.6764, 0.7264, 0.8014)	0.70143	0.75220	3
R_{54}	(0.5650, 0.6400, 0.6900, 0.7650)	0.66500	(0.7300, 0.8050, 0.8550, 0.9300)	0.83000	0.74293	4
R_{22}	(0.6170, 0.6920, 0.7420, 0.8170)	0.71695	(0.6102, 0.6852, 0.7352, 0.8102)	0.71017	0.71355	5
R_{25}	(0.5017, 0.5767, 0.6267, 0.7017)	0.6017 0	(0.7439, 0.8189, 0.8689, 0.9439)	0.84386	0.71257	6
R_{45}	(0.6047, 0.6797, 0.7297, 0.8047)	0.70471	(0.6129, 0.6879, 0.7379, 0.8129)	0.71290	0.70879	7
I_{29}	(0.5008, 0.5758, 0.6258, 0.7008)	0.60084	(0.7017, 0.7767, 0.8267, 0.9017)	0.80167	0.69403	8
I_{17}	(0.5214, 0.5964, 0.6460, 0.7199)	0.62088	(0.6569, 0.7319, 0.7819, 0.8569)	0.75687	0.68551	9
I_{25}	(0.5037, 0.5787, 0.6287, 0.7037)	0.60369	(0.6720, 0.7470, 0.7970, 0.8720)	0.77204	0.68269	10

Table 7. RA results of risk groups in the second level for the Ankara-Istanbul high-speed railway project

Node	Occurrence probability			Magnitude of impact			Risk rating	Rank
	Membership function	Value	Weight	Membership function	Value	Weight		
I_{15}	(0.5494, 0.6244, 0.6744, 0.7494)	0.64940	0.268	(0.4364, 0.5114, 0.5614, 0.6364)	0.53640	0.215	0.59020	8
I_4	(0.4000, 0.4746, 0.5244, 0.5993)	0.49959	0.206	(0.6248, 0.6998, 0.7498, 0.8248)	0.72480	0.291	0.60175	6
I_5	(0.4729, 0.5479, 0.5975, 0.6715)	0.57240	0.236	(0.5325, 0.6075, 0.6576, 0.7326)	0.63255	0.254	0.60172	7
I_6	(0.6070, 0.6820, 0.7310, 0.8029)	0.70557	0.291	(0.4987, 0.5737, 0.6237, 0.6987)	0.59870	0.240	0.64994	3
I_7	(0.5181, 0.5931, 0.6431, 0.7181)	0.61810	0.569	(0.4280, 0.5029, 0.5528, 0.6277)	0.52785	0.463	0.57120	9
I_8	(0.3678, 0.4428, 0.4928, 0.5678)	0.46780	0.431	(0.5114, 0.5864, 0.6364, 0.7114)	0.61140	0.537	0.53480	11
I_9	(0.5414, 0.6164, 0.6664, 0.7414)	0.64140	0.233	(0.5515, 0.6265, 0.6765, 0.7515)	0.65150	0.201	0.64643	4
I_{10}	(0.3749, 0.4499, 0.5000, 0.5751)	0.47498	0.173	(0.5368, 0.6118, 0.6618, 0.7368)	0.63680	0.196	0.54997	10
I_{11}	(0.4801, 0.5551, 0.6052, 0.6802)	0.58015	0.211	(0.6421, 0.7170, 0.7670, 0.8419)	0.74200	0.229	0.65610	1
I_{12}	(0.4936, 0.5686, 0.6187, 0.6938)	0.59368	0.216	(0.5401, 0.6149, 0.6647, 0.7395)	0.63980	0.197	0.61631	5
I_{13}	(0.3582, 0.4333, 0.4833, 0.5584)	0.45830	0.167	(0.4753, 0.5503, 0.6003, 0.6753)	0.57530	0.177	0.51348	12
I_{33}	(0.2275, 0.3025, 0.3525, 0.4275)	0.32750	0.236	(0.6325, 0.7075, 0.7576, 0.8326)	0.73255	0.377	0.48981	13
I_{34}	(0.3751, 0.4501, 0.5001, 0.5751)	0.47510	0.342	(0.3803, 0.4553, 0.5053, 0.5803)	0.48030	0.247	0.47769	14
I_{35}	(0.4855, 0.5605, 0.6105, 0.6855)	0.58550	0.422	(0.6279, 0.7029, 0.7529, 0.8279)	0.72790	0.375	0.65283	2

Table 8. RA results of risk groups in the third level and the overall project risk for the Ankara-Istanbul high-speed railway project

Node	Occurrence probability			Magnitude of impact			Risk rating	Rank
	Membership function	Value	Weight	Membership function	Value	Weight		
I_1	(0.5179, 0.5929, 0.6425, 0.7164)	0.61737	0.279	(0.5306, 0.6056, 0.6556, 0.7306)	0.63060	0.250	0.62395	1
I_2	(0.4533, 0.5283, 0.5783, 0.6533)	0.55330	0.250	(0.4728, 0.5477, 0.5977, 0.6726)	0.57270	0.227	0.56292	4
I_3	(0.4587, 0.5338, 0.5838, 0.6589)	0.55880	0.252	(0.5536, 0.6286, 0.6785, 0.7535)	0.65355	0.259	0.60432	2
I_{14}	(0.3869, 0.4619, 0.5119, 0.5869)	0.48690	0.220	(0.5678, 0.6428, 0.6928, 0.7677)	0.66777	0.265	0.57021	3
L	(0.4585, 0.5336, 0.5836, 0.6584)	0.55851	/	(0.5338, 0.6089, 0.6589, 0.7339)	0.63387	/	0.59500	/

Table 9. Risk categorization for the Ankara-Istanbul high-speed railway project based on FSE method

Risk level	RFs
Category 5 (Risk rating: 0.67551–0.86850)	I_{22}, I_{25}, I_{17}, I_{29}, R_{45}, R_{25}, R_{22}, R_{54}, R_{16}, R_{34}, R_{42}
Category 4 (Risk rating: 0.45001–0.67550)	R_{49}, R_{32}, R_{53}, R_9, R_{39}, R_{35}, R_4, I_{19}, R_{36}, R_{21}, R_{19}, R_5, R_{52}, R_{15}, R_{30}, I_{27}, R_{28}, R_{12}, R_{43}, R_{55}, R_{26}, R_{51}, I_{23}, I_{20}, R_{17}, R_{14}, I_{18}, R_{27}, R_{38}, R_{18}, I_{32}, I_{21}, R_{37}, R_3, R_{41}, I_{31}, R_7, I_{26}, R_2, I_{30}, R_{11}, I_{24}, R_{23}, R_6, I_{16}, I_{28}, R_{33}, R_{13}, R_{20}; I_{34}, I_{33}, I_{13}, I_8, I_{10}, I_7, I_{15}, I_5, I_4, I_{12}, I_9, I_6, I_{35}, I_{11}; I_2, I_{14}, I_3, I_1; L
Category 3 (Risk rating: 0.21001–0.45000)	R_{48}, R_{31}, R_{10}, R_{47}, R_8, R_{40}, R_1, R_{44}, R_{50}, R_{29}, R_{46}, R_{24}
Category 2 (Risk rating: 0.08001–0.21000)	Not identified
Category 1 (Risk rating: 0.02101–0.08000)	Not identified
Category 0 (Risk rating: 0.00000–0.02100)	Not identified

From the perspective of root nodes, "different construction standards and measurement system (R_{42})", "variations in design (R_{34})", "language barrier (R_{16})", "information asymmetry (R_{54})", "unclear contract clauses and conditions (R_{22})" and "excessive contract variation (R_{25})" possessed relatively high risk ratings both related to causal inference and diagnostic inference, while the intermediate nodes such as "project implementation risk (I_3)", "construction specification and standard problems (I_{29})", "improper contract (I_{22})", "contract risk (I_9)" and "design risk (I_{11})" weighed more heavily in the risk rating calculation. Such RFs with high values of risk ratings should be viewed as critical and treated particularly. While in the results obtained from FSE method (Tables 6–9), the top ten critical RFs were R_{42}, R_{34}, R_{16}, R_{54}, R_{22}, R_{25}, "uncertainty in subsurface condition (R_{45})", I_{29}, "unstable political situation (I_{17})", and "inappropriate design (I_{25})", where the top seven RFs were the same with root node RFs from the FBBN-based method. I_{11}, "irrational decision making behavior (I_{35})", and "social risk (I_6)" were top three critical risk groups in the second level; and the rank of risk groups in the third level from the highest risk rating score to the lowest was: "country risk (I_1)", I_3, "decision making behavior risk (I_{14})", and "international market risk (I_2)". Compared with the risk ratings of the overall project risk L, the result from FBBN-based method (i.e., 0.70086) was higher than that based on FSE method (i.e., 0.59500), which can demonstrate that causal relationships among RFs would amplify the project risk degree. From the comparative analysis between the FBBN-based method and the FSE method, the FBBN-based approach proved to be effective in RA of an ICP. In addition, from the distribution of RFs in risk matrix, it is more appropriate in categorizing RFs into different risk levels compared with the FSE method.

When compared with the real risk situations of the investigated project, many RFs during the implementation of the project were present and mostly complied with the critical RFs that were summarized from the proposed FBBN-based RA model. Among the detailed RFs that occurred, variation in design was one of the most serious problems due to the project owner's multiple requirements and inaccurate geological prospecting documents. Contractors had a higher pressure to master the required standards and specifications of the implementation process of the project. Contract risk, including unclear contract clauses and excessive contract variations, caused difficulties in coordination among project participants. Apart from that, language barrier and information asymmetry also raised challenges to achieve project objectives successfully. Given the above analyses, the proposed FBBN-based RA model for ICPs manifests its reasonability and effectiveness to be applied in practice.

4. Discussion

The unique contribution of this study is the establishment of an effective FBBN-based RA model for ICPs. In this model, the risk rating regarding each RF can be evaluated based on OP and MI assessment, where the CoC method is applied to perform risk ranking. The proposed FBBN-based RA model is able to capture the uncertainties involved, and more importantly, is able to handle complex causal relationships among RFs and assess the real-time risk status of projects. Risk levels of certain RFs may vary at various stages throughout a project life cycle (Xu et al., 2010), however, based on the proposed FBBN-based RA model, critical RFs with high risk ratings can be identified by Bayesian inference (i.e., causal inference and diagnostic inference) before the very first stage of a project, and the risk rating corresponding to each RF can be updated when new risk information is available. Compared with the existing proven FSE method, the FBBN-based approach is potentially efficient and reliable in modeling interdependent risks and updating probabilistic information (Islam et al., 2017).

In general, risk rating and risk categorization obtained from the FBBN-based RA model can provide useful risk management guidelines for decision makers. In the study of Qazi and Dikmen (2019), they have substantiated the importance of utilizing an interdependency-based risk management process. The introduction of the developed FBBN-based RA model would be helpful to refine the existing RA systems of construction projects. Specifically, when conducting causal inference, the results of risk rating and categorization of identified RFs can indicate significant RFs that have a strong influence on the success of construction projects. Risk rating and risk categorization from the diagnostic inference, on the other hand, are able to prioritize potential RFs based on new observations, which helps decision makers manage the RFs with high risk levels before or during the project implementation process. The FBBN-based RA model also has the ability to analyze updated risk ratings of intermediate or leaf nodes through causal inference if the evidences of other nodes are observed; and inversely, if a certain node is assigned with new observations, those nodes with high risk ratings leading to the given node can be identified by diagnostic inference. Moreover, fundamental causes of an undesired event can be distinguished directly in light of the root nodes in a BBN structure. Zhang et al. (2014) also verified that the FBBN method can substitute the posteriors for priors repetitively in a failure re-analysis considering risk causal relationships when a new set of failure-related information is observed. This substitution not only continuously reduces data uncertainty, but it also provides accident scenarios with real-time and up-to-date analysis.

The proposed FBBN-based RA model also has some limitations. For one thing, its application mainly relies on the knowledge of experts, especially in the process of constructing causal relationships among RFs as well as in the determination of CPTs and MIs towards RFs. The information provided by experts' judgments may affect the quality of RAs. To increase the reliability of the risk data collected from experts' judgments, experts' weights are emphasized in the proposed RA model. Some suitable uncertainty measurement methods, such as Spearman correlation coefficient analysis and Pearson correlation coefficient analysis (Islam et al., 2017), can be also applied to reduce discrepancies in experts' judgments, which will be addressed in a follow-up study. For another, risk control measures will be further extended to formulate more specific risk treatment strategies towards individual RF. Nevertheless, the established FBBN-based RA model is effective and has potential in practical usage for ICPs and even other types of construction projects with minor changes given its capabilities of handling uncertainties, presenting risk causal relationships and updating risk ratings.

Conclusions

Conducting comprehensive and effective RAs for ICPs is pivotal to the risk management process and to provide decision makers with guidelines for mitigating and controlling critical RFs proactively. RFs in complex construction projects are potentially interrelated, which is often ignored or ineffectively addressed in most previous studies on RA for ICPs. Additionally, the implementation of ICPs is a dynamic process and therefore, an RA framework that is capable of updating to the new information is required, whereas few studies attempted to address this issue. As a result, this research has developed a comprehensive RA model for ICPs from the perspective of contractors using a FBBN-based method.

In this study, the proposed methodology combines FT analysis, BBN and FST into an integrated FBBN approach that makes it possible to incorporate RFs' causal relationships and uncertainties in an RA model. The MI assessment of RFs is included in the FBBN-based RA model other than the OP assessment, which helps to evaluate risk ratings in a systematic manner. The proposed FBBN-based method is able to perform pre-accident and post-accident analysis quantitatively by means of causal and diagnostic inference techniques, respectively. A six-level risk matrix is also inserted into the model to categorize RFs more explicitly. The critical RFs and overall project risk level can be determined for helping risk response. In addition, suspected RFs can be detected in real time when an accident occurs, assisting project risk managers to carry out fault diagnosis. The Ankara-Istanbul high-speed railway project is used as a case study to demonstrate the application of the proposed RA model, and through the comparison of results from the FSE method, it reveals the importance of exploring the underlying mechanism of a risk interdependency modeling process and verifies the feasibility of the FBBN-based RA model in practice use.

There are a few limitations of the work presented in this paper. The RF list may not be always valid throughout the life cycle of ICPs since risks tend to change during the implementation of a project. One limitation of this paper is the assumption that the identified RF list is static at the start of the ICP. A dynamic Bayesian network approach has a capacity to model the evolution over time of the probabilistic interdependencies within a complex system. It uses the preciously accumulated information for the present reasoning process in present conditions, while a BBN approach lacks such ability and only depends on the present states of RFs. Therefore, future research can further study the dynamic nature of ICP risks over the project's life cycle using regularly updated RF list and a fuzzy dynamic Bayesian network method. Risks in ICPs could also be modeled using other features of risk apart from risk OP and MI, including risk detectability and project mitigation capacity, to quantify the project risk level.

In conclusion, this study confirms that the established FBBN-based RA model can be used as a flexible decision support tool for decision makers to manage critical RFs and develop effective risk treatment measures. This model can also be applied, after minor modification, to the RA of more specific construction work items or other types of projects in different engineering areas. It is anticipated that this research will contribute to the development of RA methods and promote the capacity of existing RA systems for ICPs.

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Author contributions

Li GUAN conceived the study and was responsible for the design and development of the methodology and data analysis. Professor Qiang LIU was in charge of funding acquisition and responsible for data collection. Li GUAN and Professor Qiang LIU were responsible for data interpretation. Li GUAN wrote the first draft of the article and revised it based on reviewers' comments, and Dr. Alireza ABBASI reviewed and validated the article. Associate Professor Michael J. RYAN reviewed the article and refined the language quality.

Disclosure statement

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APPENDIX A

Some of important RFs for ICPs were summarized based on a thorough literature review, and a four-level HRBS of ICPs was formulated (Figure A1).

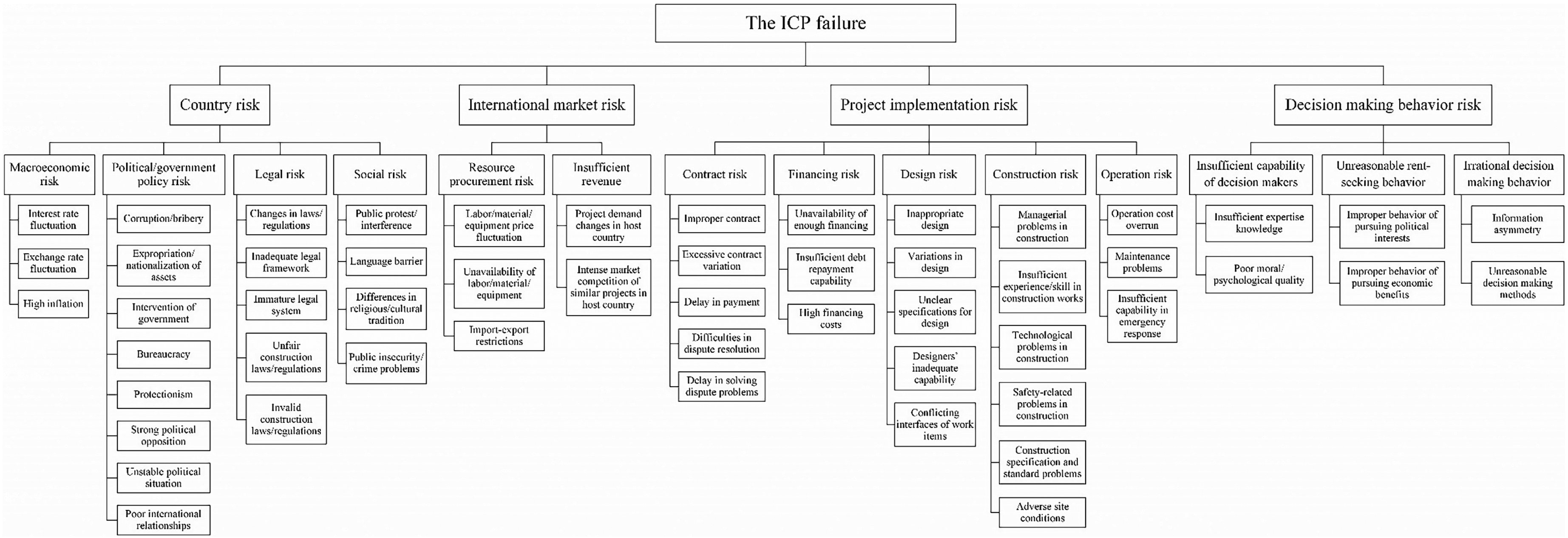

Figure A1. A four-level HRBS of ICPs based on the RFs from literature review

APPENDIX B

Sample questionnaires for the case study.

Dear Expert,

We are conducting a questionnaire survey to assess the risk factors of an international construction project, namely, the Ankara-Istanbul high-speed railway project (the second phase). We focus on two aspects: (1) the occurrence probabilities of risk factors, and (2) the impacts of risk factors influencing the project performance. The questionnaire includes three major sections and is estimated to be completed in around 1.5 hours. The results of this questionnaire survey will only be used for our academic work. Your warm participation will provide enormous help for achieving the objectives of our research work. We sincerely appreciate your valuable time for this questionnaire survey and we ensure that your personal information will be kept strictly confidential.

Section 1. Personal Information

Name: ....

Phone number: ....

E-mail: ....

Position/Title: ....

Years of work experience in international
construction projects: ....

Section 2. Occurrence Probability Assessment of Risk Factors

The occurrence probability assessment of risk factors in this questionnaire survey involves two contents: (1) prior occurrence probability assessment, and (2) conditional occurrence probability assessment. Table B1 gives the linguistic scale for assessing occurrence probabilities of risk factors.

Table B1. The 11-point linguistic scale for assessing occurrence probability of each risk factor.

Occurrence probability	Description
Impossible (I)	Events never occur
Nearly Impossible (NI)	Events are extremely impossible to occur
Very Unlikely (VU)	Events are highly unlikely to occur
Unlikely (U)	Events are unlikely but possible to occur
Slightly Unlikely (SU)	The occurrence likelihood of possible events is between unlikely and even chance
Even Chance (EC)	The occurrence likelihood of possible events is even chance (i.e., events are likely to occur on rare occasions)
Slightly Likely (SL)	The occurrence likelihood of possible events is between even chance and likely
Likely (L)	Events are likely to occur
Very Likely (VL)	Events are highly likely to occur
Nearly Certain (NC)	Events will always occur
Certain (C)	Events are expected to occur with absolute certainty

(1) Please tick [√] in any rating that you consider appropriate for each of the following risk factors (R_1–R_{55}) with respect to its prior occurrence probability. (Sample questionnaires)

No.	Risk factor	Prior occurrence probability of risk factor										
		I	NI	VU	U	SU	EC	SL	L	VL	NC	C
R_1	Interest rate fluctuation											
R_2	Exchange rate fluctuation											
R_3	High inflation											
…	…											
R_{55}	Unreasonable decision making methods											

(2) Please tick [√] in any rating that you consider appropriate for each risk factor (I_1– I_{35} and L) with respect to its conditional occurrence probability (“*Yes*” means that the risk factor will occur during the project implementation, while “*No*” means that the risk factor will not occur). (Sample questionnaires)

Interest rate fluctuation (R_1)	Exchange rate fluctuation (R_2)	High inflation (R_3)	Conditional occurrence probability of “Macroeconomic risk (I_{15})”										
			I	NI	VU	U	SU	EC	SL	L	VL	NC	C
Yes	*Yes*	*Yes*											
		No											
	No	*Yes*											
		No											
No	*Yes*	*Yes*											
		No											
	No	*Yes*											
		No											

Section 3. Impact Assessment of Risk Factors and Evaluation of Expert Subjectivity Reliability

Table B2 gives the linguistic scale for assessing magnitudes of impact of risk factors. The evaluation of the indicator “Expert subjectivity reliability” aims to obtain the reliability level towards your judgments for each risk factor (both on the aspects of occurrence probability and impact). The degree of “Expert subjectivity reliability” is classified into five levels with scores of 1.0, 0.9, 0.8, 0.7 and 0.6, respectively, and the higher the score, the more reliable the expert judgments.

Table B2. The nine-point linguistic scale for assessing magnitudes of impact of each risk factor

Magnitude of impact	Description
Absolutely Low (AL)	Impacts on project performance can be nearly ignored
Very Low (VL)	Potential for causing slight impacts on project performance
Low (L)	Potential for causing minor impacts on project performance
Fairly Low (FL)	Potential for causing fairly low impacts on project performance
Medium (M)	Potential for causing moderate impacts on project performance
Fairly High (FH)	Potential for causing fairly high impacts on project performance
High (H)	Potential for causing substantial impacts on project performance
Very High (VH)	Potential for causing critical impacts on project performance
Absolutely High (AH)	Impacts on project performance are catastrophic

Please tick [√] in any rating that you consider appropriate for each of the following risk factors (R_1–R_{55}, I_1– I_{35} and L) in terms of its impact on the project performance and expert subjectivity reliability. (Sample questionnaires)

No.	Risk factor	Impact of risk factor									Expert subjectivity reliability				
		AL	VL	L	FL	M	FH	H	VH	AH	0.6	0.7	0.8	0.9	1.0
R_1	Interest rate fluctuation														
R_2	Exchange rate fluctuation														
…	…														
R_{55}	Unreasonable decision making methods														
I_1	Country risk														
I_2	International market risk														
…	…														
I_{35}	Irrational decision making behavior														
L	International construction project failure														

The questionnaire survey is finished. Thanks a lot for your cooperation!