

BAYESIAN BELIEF NETWORK-BASED PROJECT COMPLEXITY MEASUREMENT CONSIDERING CAUSAL RELATIONSHIPS

Lan LUO¹, Limao ZHANG^{2*}, Guangdong WU³

¹ School of Civil Engineering and Architecture, Nanchang University, Nanchang, P. R. China

² School of Civil and Environmental Engineering, Nanyang Technological University, Singapore, Singapore

³ School of Public Affairs, Chongqing University, Chongqing, P. R. China

Received 27 April 2019; accepted 11 September 2019

Abstract. This research proposes a Bayesian belief network-based approach to measure the project complexity in the construction industry. Firstly, project complexity nodes are identified for model development based on the literature review. Secondly, the project complexity measurement model is developed with 225 training samples and validated with 20 test samples. Thirdly, the developed measurement model is utilized to conduct model analytics for sequential decision making, which includes predictive, diagnostic, sensitivity, and influence chain analysis. Finally, EXPO 2010 is used to testify the effectiveness and applicability of the proposed approach. Results indicate that (1) more attention should be paid on technological complexity, information complexity, and task complexity in the process of complexity management; (2) the proposed measurement model can be applied into practice to predict the complexity level for a specific project. The uniqueness of this study lies in developing project complexity measurement model (PCMM) with the cause-effect relationships taken into account. This research contributes to (a) the state of knowledge by proposing a method that is capable of measuring the complexity level under what-if scenarios for complexity management, and (b) the state of practice by providing insights into a better understanding of causal relationships among influencing factors of complexity in construction projects.

Keywords: project complexity measurement model (PCMM), Bayesian belief network, sensitivity analysis, influence chain analysis.

Introduction

In recent years, rapid growth in the construction industry has led to an increase in size and complexity of the projects (Luo et al., 2016; Qazi et al., 2016). However, construction projects are usually beset with serious waste and cost overruns (Applegate & Tien, 2018; Thomas & Mengel, 2008; Zhu & Mostafavi, 2017). Underestimating the project complexity is the main reason, which is the state of being involved and intricate as a result of including varied interrelated parts within a subject (Gao et al., 2018; He et al., 2015; Luo et al., 2017). Therefore, with an aim to manage the complexity of construction projects efficiently, researchers and industry experts concentrate on measuring project complexity (Bakhshi et al., 2016; Coenen et al., 2018; Luo et al., 2017; Wallner, 1999).

Accordingly, numerous studies have been conducted on measuring project complexity from different perspectives (Bosch-Rekvelde, 2011; Lebcir & Choudrie, 2011;

Qazi et al., 2016). However, most studies focus on the framework of project complexity and ignore the cause-effect relationships between project complexity and its influential factors. In addition, the existing models cannot be used to model the project complexity under different scenarios. Therefore, it is necessary to propose an approach that can measure the project complexity considering the cause-effect relationships.

Bayesian Belief Network (BBN), a graphical framework for modeling uncertainty, incorporates a unique feature for capturing the interaction between elements (Wu et al., 2015; Zhang et al., 2014). BBN has been applied in various domains, including root cause analysis (Diallo et al., 2018; Wee et al., 2015), risk management (Dikmen et al., 2018; Wang & Zhang, 2018; Zhang et al., 2014), and decision making (Pan et al., 2019; Wang et al., 2018). The BBN has several advantages: (1) It can describe

*Corresponding author. E-mail: limao.zhang@ntu.edu.sg

the probability relationship (causality) between variables combining the Bayesian probability theory with the graph theory; and (2) It can compute the probabilities with given evidence under different scenarios (Zhang et al., 2016). A BBN-based project complexity measurement model (PCMM) is proposed in this study to measure the project complexity by revealing the cause-effect relationships between the project complexity and its influential variables. Thus, key factors influencing the project complexity level are identified, and the corresponding recommendations are suggested based on the research results.

The main research questions include: (i) How to build an effective PCMM, associated with the consideration of causal relationships among complexity factors? (ii) How can the developed model be used to measure the complexity level of a construction project? In this study, the proposed BBN-based method measures the level of project complexity with the causality among various factors taken into account. This novelty of this research lies in (a) the state of knowledge by proposing a method that is capable of measuring the complexity level under what-if scenarios for complexity management, and (b) the state of practice by providing insights into a better understanding of causal relationships among influencing factors of project complexity in construction projects. The proposed approach can be used as a decision tool to provide support for complexity management in construction projects.

The paper is organized as follows. Section 1 reviews recent works on measurement methods of project complexity. Section 2 proposes a novel BBN-based project complexity measurement method. Section 3 develops the project complexity measurement model, including model design and validation. Section 4 presents the model analytics including predictive analysis, diagnostic analysis, sensitivity analysis, and influence chain analysis. Section 5 discusses the model implication from theoretical and practical perspectives.

1. Literature review on project complexity measurement

The concept of project complexity has been discussed for years, but there is a lack of consensus on what constitutes project complexity since it is a term that is difficult to define and even harder to quantify (Luo et al., 2017; Vidal et al., 2011a). Baccarini (1996) defined project complexity as “consisting of many varied interrelated parts”. Williams (1999) divided project complexity into structural complexity (the number and interdependence of those components) and uncertainty in goals and means. Other researchers regard project complexity as a subjective and highly dynamic concept. For instance, Vidal et al. (2011b) proposed that project complexity is difficult to be understood, foreseen and kept under control its overall behavior, even when given reasonably complete information about the project system. Xia and Chan (2012) pointed out that it is not appropriate to use the same variables to measure project complexity since construction projects

include various categories of projects. Generally, project complexity is one of the most fundamental properties of the project, which results from the interactions of structural, dynamic, and uncertain elements (Mihm et al., 2003; Xia & Chan, 2012).

Project complexity is an emerging but critical topic in construction project management. Researchers have increasingly recognized the importance of complexity measurement in project diagnosis and sought to measure project complexity from multiple perspectives (Baccarini, 1996; Bakhshi et al., 2016). Literature review on project complexity measurement is summarized in Table 1. As the project complexity is difficult to be quantified precisely, many researchers identified complexity factors to build a framework describing the project complexity qualitatively. For instance, Sinha et al. (2006), Bosch-Rekvelde et al. (2011), Xia and Chan (2012), Lessard et al. (2014), Maylor et al. (2008), Gransberg et al. (2012), Vidal and Marle (2008), Owens et al. (2012), Jarkas (2017), and Luo et al. (2016) mainly focus on the framework of project complexity from different views. In addition, several attempts have been made to propose methods to measure the project complexity quantitatively such as Vidal et al. (2011b), Nguyen et al. (2015), He et al. (2015), Shafiei-Monfared and Jenab (2012), Lu et al. (2015), Qureshi and Kang (2015), and Ellinas et al. (2018).

In general, existing studies have addressed some frameworks of project complexity, and some scholars primarily adopted quantitative methods in measuring project complexity. However, project complexity results from interactions of numerous elements which are required to further measure the cause-effect relationships. In addition, the existing models have the limitation of measuring the complexity under what-if scenarios. For instance, the aforementioned FAHP, AHP, FANP, and SEM can measure complexity from one aspect, but cannot be used to measure the magnitude of project complexity under different scenarios. Accordingly, this study proposes a simulation model for measuring the magnitude of the project complexity considering the cause-effect relationships in construction projects.

2. Research methodology

BBN offers an effective modeling technique for uncertainty (Qazi et al., 2016), which can be used in measuring the project complexity with interdependency taken into account. Flowchart for implementing project complexity measurement model using BBN is shown in Figure 1. This approach consists of four main phases. The first phase of model development is the identification of project complexity nodes. The second phase involves the construction of the network structure, structure optimization, and determination of conditional probability table (CPT) followed by model validation in the third phase. In the fourth phase of the model analytics, the developed PCMM is utilized to conduct model reasoning which includes predictive analysis, diagnostic analysis, sensitivity analysis, and influence chain analysis.

Table 1. Literature review on project complexity measurement

| Author (year) | Measurement method | Results |
|-----------------------------------|---------------------|---|
| Sinha et al. (2006) | Qualitative method | Proposed a framework for measuring project complexity based on the Shannon information theory |
| Vidal and Marle (2008) | Qualitative method | Defined the project complexity framework as project size, project variety, project interdependence, and elements of context |
| Maylor et al. (2008) | Qualitative method | Reported a grounded model with an investigation of the perceptions of project managers |
| Bosch-Rekveltdt et al. (2011) | Qualitative method | Developed a framework for characterizing project complexity as technical, organizational and environmental complexity |
| Vidal et al. (2011b) | Quantitative method | Used the Analytic Hierarchy Process (AHP) to formulate a project complexity measure model for assisting project managers' decision making |
| Gransberg et al. (2012) | Qualitative method | Developed the "complexity footprint" based on an international research team's detailed study of eighteen complex projects |
| Owens et al. (2012) | Qualitative method | Developed a five-dimensional complexity model including cost, schedule, design, context, and finance |
| Shafiei-Monfared and Jenab (2012) | Quantitative method | Combined managerial and technical graphs and the complexity design structure matrix to measure the relative complexity of design projects |
| Xia and Chan (2012) | Qualitative method | Identified several key parameters for measuring building project complexity |
| Lessard et al. (2014) | Qualitative method | Built a house of project complexity to understand complexity in large infrastructure projects |
| He et al. (2015) | Quantitative method | Utilized a Fuzzy Analytic Network Process (FANP) approach to measure the complexity of mega construction projects |
| Lu et al. (2015) | Quantitative method | Adopted a simulation model to measure project complexity with the hidden workload |
| Nguyen et al. (2015) | Quantitative method | Employed the Fuzzy Analytic Hierarchy Process (FAHP) method to measure the overall project complexity |
| Qureshi and Kang (2015) | Quantitative method | Used a Structural Equation Modeling (SEM) technique to measure the organizational factors of project complexity |
| Luo et al. (2016) | Qualitative method | Classified six dimensions of project complexity including 26 factors |
| Jarkas (2017) | Qualitative method | Recognized uncertainty, organizational complexity, and inherent complexity as the most significant principles of the project complexity |
| Ellinas et al. (2018) | Quantitative method | Proposed a quantitative assessment with empirical activity networks to deal with one aspect of project complexity-structural complexity |

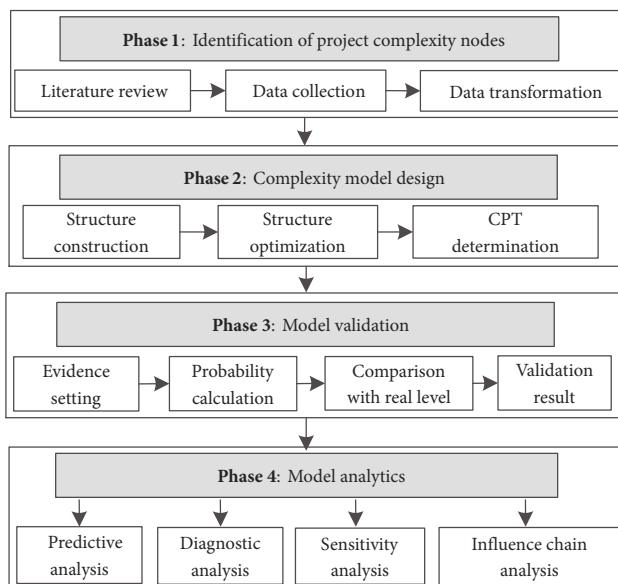


Figure 1. Flowchart for implementing project complexity measurement using BBN

2.1. Identification of project complexity nodes

The first phase of model development is to identify the complexity nodes, which can be obtained in three steps: literature review, data collection, and data transformation. Based on the literature review, 26 complexity factors are chosen as the nodes of PCMM in this study (Table 2). These complexity factors were verified through literature review, Delphi questionnaires, correlation analyses, and exploratory factor analysis considering the characteristics of complex construction in China in the study of Luo et al. (2016). The questionnaire survey is then conducted including 26 complexity factors and project complexity with a 5-point Likert scale as "1 = simple, 2 = mildly complex, 3 = moderately complex, 4 = highly complex, and 5 = extremely complex". The Likert scale has been adopted in some research. For instances, Santana (1990) used 0 to 10-point Likert scale to quantify the variable of complexity category. Vidal et al. (2011a) asked participants to evaluate the contribution of each factor to project complexity on 5-level Likert scales. He et al. (2015) measured the complexity of mega construc-

tion projects with a 5-point Likert rating scale. It can be concluded that the Likert scale is suitable for collecting data regarding the project complexity.

To ensure the representativeness and objectivity of the opinions collected from the experts, the choices of respondents were also controlled. The experts have at least two years of work experience, and they are asked to report about their most recently completed complex construction project (Luo et al., 2016). Finally, a total of 314 question-

naires were handed out and 245 valid questionnaires were collected with a 78% effective recovery rate. Demographic details are demonstrated in Figure 2. In this sample, the main respondents are male (76.7%), project manager (29.8%), and have less than five years of work experience (44.5%). The data are mainly collected from residential projects (49.8%), projects with a size of 100~500 million RMB (40%), and projects with a duration between 25 and 36 months (37.6%).

Table 2. 26 complexity factors based on the literature review

| Classification | Factors | Description | References |
|--------------------------------|---|--|---|
| Information complexity (IC) | Trust among project organization (IC1) | Complexity in developing trust among organizations | Girmscheid and Brockmann (2008), Maylor et al. (2008), Bosch-Rekveltdt et al. (2011) |
| | Sense of cooperation (IC2) | Complexity in improving the sense of cooperation | Vidal et al. (2011a), Maylor et al. (2008), Vidal and Marle (2008) |
| | Capacity of transferring information (IC3) | Complexity in transferring the information | Maylor et al. (2008) |
| | Degree of obtaining information (IC4) | Complexity in obtaining the information | Maylor et al. (2008), Vidal and Marle (2008) |
| | Cultural differences (IC5) | Complexity associated with the cultural differences | Vidal et al. (2011a), Maylor et al. (2008), Remington et al. (2009), Vidal and Marle (2008) |
| | Level of processing information (IC6) | Complexity in processing the information | Maylor et al. (2008) |
| | Experience of participants (IC7) | Complexity due to insufficient experience of participants | Baccarini (1996), Maylor et al. (2008), Remington et al. (2009), Vidal and Marle (2008) |
| | Information uncertainty (IC8) | Complexity involved with the information uncertainty | Xia and Chan (2012) |
| | Uncertainty of project management methods and tools (IC9) | Complexity involving the uncertainty in the project management methods and tools | Vidal et al. (2011a), Maylor et al. (2008), Bosch-Rekveltdt et al. (2011), Remington and Pollack (2016), Vidal and Marle (2008), Williams (1999) |
| Task complexity (TAC) | Dependence of relationship among tasks (TAC1) | Complexity in the dependency among tasks | Baccarini (1996), Vidal et al. (2011a), Bosch-Rekveltdt et al. (2011), Remington and Pollack (2016), Vidal and Marle (2008) |
| | Diversity of technology in the project (TAC2) | Complexity in the diversity of technology | Baccarini (1996), Vidal et al. (2011a), Maylor et al. (2008), Remington and Pollack (2016), Vidal and Marle (2008), Williams (1999) |
| | Diversity of tasks (TAC3) | Complexity in the diversity of tasks | Baccarini (1996), Vidal et al. (2011a), Maylor et al. (2008), Bosch-Rekveltdt et al. (2011), Remington and Pollack (2016), Vidal and Marle (2008) |
| Technological complexity (TEC) | Novelty of construction products (TEC1) | Complexity in implementing the novel technology in construction products | Luo et al. (2016), Puddicombe (2011), Tatikonda and Rosenthal (2000) |
| | Risk of using highly difficult technology (TEC2) | Complexity in adopting highly difficult technology | Maylor et al. (2008), Bosch-Rekveltdt et al. (2011), Remington and Pollack (2016), Remington et al. (2009), Vidal and Marle (2008), Xia and Chan (2012) |
| | Knowledge of new technology (TEC3) | Complexity in gaining knowledge about new technology | Luo et al. (2016) |
| | Availability of resources and skills (TEC4) | Complexity in attaining the resources and skills | Vidal et al. (2011a), Maylor et al. (2008), Bosch-Rekveltdt et al. (2011), Vidal and Marle (2008), Xia and Chan (2012) |
| Organizational complexity (OC) | Number of organizational structure hierarchies (OC1) | Complexity linked to organizational structure hierarchies | Baccarini (1996), Vidal et al. (2011a), Maylor et al. (2008), Remington et al. (2009), Vidal and Marle (2008), Williams (1999) |
| | Number of organizational units and departments (OC2) | Complexity linked with organizational units and departments | Baccarini (1996), Vidal et al. (2011a), Maylor et al. (2008), Remington et al. (2009), Vidal and Marle (2008), Williams (1999) |

End of Table 2

| Classification | Factors | Description | References |
|-------------------------------|---|--|--|
| Environmental complexity (EC) | Environment of changing policy and regulation (EC1) | Complexity related to changing policy and regulation | Vidal et al. (2011a), Bosch-Rekvelde et al. (2011), Remington and Pollack (2016), Remington et al. (2009), Vidal and Marle (2008), Xia and Chan (2012) |
| | Environment of changing economy (EC2) | Complexity related to changing economy | Vidal et al. (2011a), Bosch-Rekvelde et al. (2011), Remington and Pollack (2016), Remington et al. (2009), Vidal and Marle (2008), Xia and Chan (2012) |
| | Changes in the project construction environment (EC3) | Complexity related to changes in the construction site | Remington and Pollack (2016), Remington et al. (2009), Vidal et al. (2011a), Bosch-Rekvelde et al. (2011), Vidal and Marle (2008), Xia and Chan (2012) |
| | The influence of external stakeholders (EC4) | Complexity due to the impact of external stakeholders | Luo et al. (2016) |
| Goal complexity (GC) | Number of stakeholder requirements change (GC1) | Complexity related to the change in the stakeholders' requirements | Luo et al. (2016) |
| | Change of project organization (GC2) | Complexity due to the change in project organization | Luo et al. (2016) |
| | Uncertainty of goals (GC3) | Complexity associated with the uncertain goals | Maylor et al. (2008), Remington and Pollack (2016), Remington et al. (2009), Williams (1999), Xia and Chan (2012) |
| | Complexity of the contractual relationship (GC4) | Complexity involved with the contractual relationship | Luo et al. (2016) |

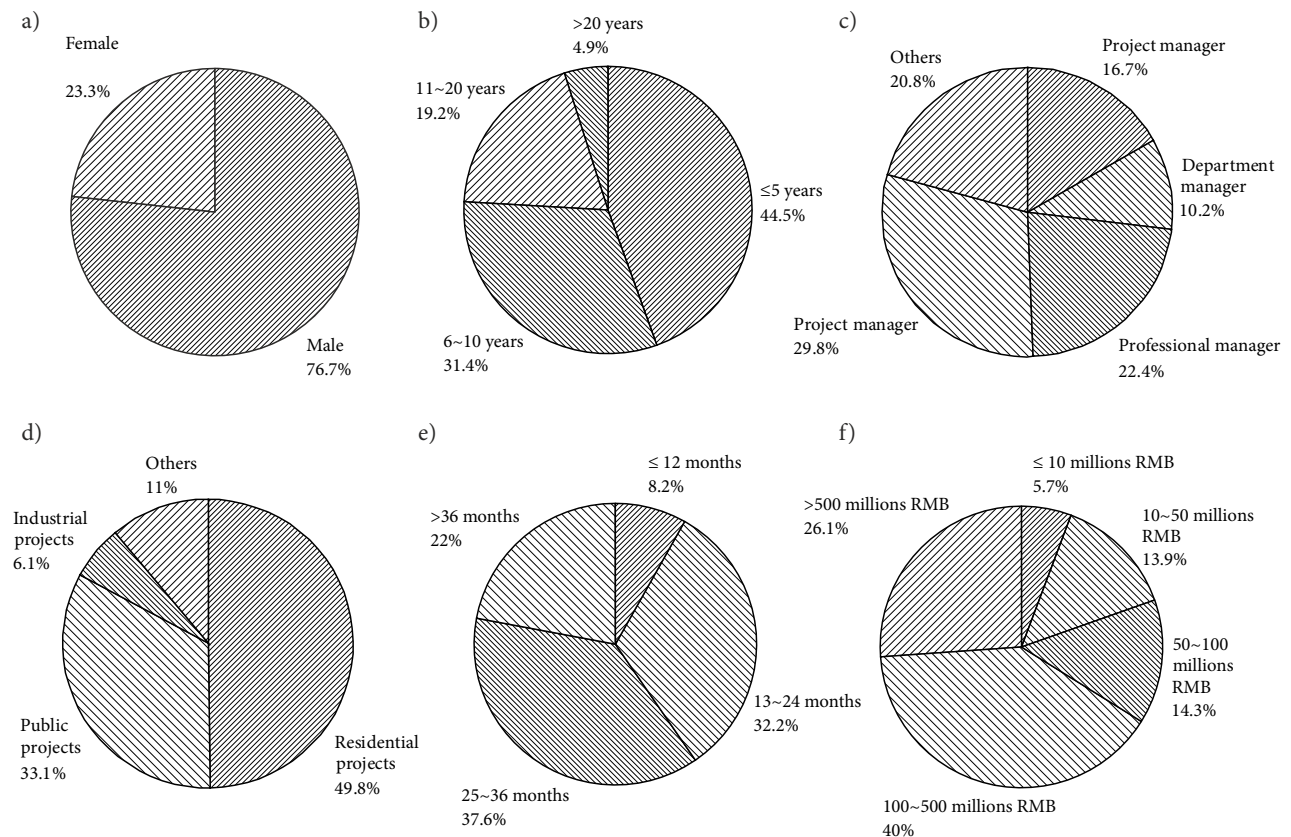


Figure 2. Demographic details of the returned 245 valid questionnaires by: (a) respondents' gender; (b) respondents' work experience; (c) respondents' designation; (d) project type; (e) project duration; (f) project size

2.2. Complexity model design

(1) Construct the network structure

A total of 225 training samples and expert knowledge are used to construct the network structure by structural learning. Structural learning is the process of constructing the BBN topology by analyzing the logical relationship between node variables from multiple angles. The K2 algorithm is chosen in this study to grading search. The calculation process consists of the definition of the scoring function and the setting of the search strategy (Cooper & Herskovits, 1992). The K2 algorithm proposed by Cooper and Herskovits (1992) uses posterior probability $P(G/D)$ as the scoring standard, also known as CH scoring function. The K2 algorithm uses a given order containing all node variables and a maximum number of parent nodes to limit the search space as the search constraint. Thus, the search space of the algorithm and computational workload can be reduced.

(2) Optimization of the structure

Machine learning is carried out according to the K2 algorithm, and the initial Bayesian network structure is obtained after completion. However, there will be unreasonable causality among the results of machine learning. Therefore, it is necessary to further optimize the network structure by judging the causal relationship between variables through expert knowledge on the basis of the initial structure. An expert group is used in this study to adjust the network structure. The expert group consists of three project managers, each with more 15 years of working experience in construction projects. Even if the judgments of experts are subjective, it is more reliable than individual statements, thus, more objective in its outcomes (Xia & Chan, 2012). After discussion and combining with experts' opinions, the logical relationship between complex factors is modified and improved to optimize the network structure.

(3) Determination of the conditional probability table

On the basis of establishing the optimal BBN structure, the parameter learning of BBN can be further carried out to calculate the CPT of each node variable. In general, there are two methods of parameter learning, including Bayesian Estimation (BE) and Maximum Likelihood Estimation (MLE). MLE has high computational efficiency and no prior probability needs to be defined artificially. The MLE is selected in this study for parameter learning to obtain the CPT of nodes. The principle of the MLE method is to determine the network parameters according to the maximum likelihood degree of sample data and network parameter.

2.3. Model validation

After the structure and the cause-effect relationships are developed, the cross-validation is used for model validation in this study (Vehtari et al., 2017). Two principles are

followed to divide the dataset into a training set and a test set. The first principle is to estimate the number of samples in the training set, generally at least 50% of the total number of samples. The second principle is that two sets must be sampled uniformly from the total samples. The dataset is randomly divided into a training set (225 data) and a test set (20 data), in which the 20 data is utilized for model validation. The processes are carried out as follows: i) input the evidence information into the developed PCMM of one sample record; ii) obtain the probability distribution of project complexity through model reasoning; iii) compare the simulation state and real level to get the validation results within allowance error range; iv) repeat these steps and verify the other 19 data respectively; v) finally get the validation results comprehensively. The model can be regarded as effective once the validity is above 80% (Cooper & Herskovits, 1992).

The accuracy of model measurement means that the result of the model measurement is consistent with the real level of project complexity under given variable conditions. The specific calculation principle of measurement accuracy is as follows: To the data i , the real level of complexity is represented as R_i . The probability distribution of project complexity can be obtained by PCMM, the state corresponding to the maximum value in the probability distribution is taken as S_{i1} , the state of second-largest probability is taken as S_{i2} . Following the optimal Bayesian decision theory, the state with the largest probability of probability distribution is regarded as the final decision (Berger, 2013; Yukalov & Sornette, 2015). Since the real level is gotten by individual grade from experts, this study has an allowable error range due to expert knowledge that the state of the second-largest probability is also taken into account. This study makes the following provisions: If $S_{i1} = R_i$, then the measurement result is completely accurate; If $S_{i1} \neq R_i$, and $S_{i2} = R_i$, then the measurement result is considered to be within the allowable error range; If $S_{i1} \neq R_i$ and $S_{i2} \neq R_i$, then the measurement result is considered to be inaccurate. When all the test data is fed into the model, respectively, the ratio of the accurate number of measurement results to the total number of test data is the accuracy rate of the measurement model. The accuracy rate of model measurement is then expressed in Eqn (1):

$$P = \frac{\sum_{i=1}^n X_i}{n}, \quad (1)$$

where X_i represents the measured result which is accurate or within the allowable error range, $i = 1, 2, \dots, n$ represents the number of test data.

2.4. Model analytics

The model reasoning of a BBN is the process of calculating the probability. According to different reasoning directions, the reasoning modes widely used can be divided into the following three types: forward reasoning (predictive analysis), backward reasoning (diagnostic analysis), and explanation reasoning (sensitivity analysis and influ-

ence chain analysis). Predictive analysis is able to forecast future outcome when given evidence (Wee et al., 2015). Diagnostic analysis can diagnose the possible causes and influence by identifying the change of posterior probability of the target nodes (Wee et al., 2015). Sensitivity analysis attempts to calculate the occurrence of some causes resulting in a certain consequence and can be used to identify the suspected causes (Zhang et al., 2016). Influence chain analysis is used to study the degree of mutual influence between nodes to find the most possible way to cause the result to happen. Based on the developed PCMM, four types of what-if scenario analysis are performed to measure the magnitude of the project complexity. According to the results of model analytics, more suggestions can be proposed for pre-control of the project complexity.

3. Model development and validation

3.1. Factor identification

According to the literature review, 26 complexity factors are chosen as the project complexity nodes for PCMM. To simplify the calculation in this study, the 225 training samples collected from the questionnaire are processed into three states of complexity level. Low state stands for the levels of simple and mildly complex, Moderate state stands for the level of moderately complex, and High state stands for the levels of highly complex and extremely complex. The statistical distribution of states of complexity factors after transformed is shown in Table 3. Specifically, the Low state is defined as a state where the complexity level is in the negligible area. Thereby, measures to reduce the complexity level are not required. The complexity level in the Moderate state is acceptable even though some complexity factors in the project management process exist. Therefore, limited measures are required to reduce complexity. The High state is defined as a state that the system is very complex and immediate measures are needed to reduce the complexity level.

3.2. Network structure and CPT determination

Empirical research is undertaken to explore the current state of complexity management practices to identify the interdependencies between relevant project complexity factors within construction projects. The topology construction of a BBN is a complex process. It is difficult to depict the learning process through mathematical models purely by means of data promotion, which has certain limitations in reality. Therefore, in the process of structural learning, the software GeNIe 2.0 is used in this study to construct the BBN topology by integrating machine learning with expert knowledge.

During the modeling process, the aforementioned 26 complexity factors and the target variable project complexity are used as BBN nodes. Firstly, based on the expert background knowledge, the initial BBN structure is obtained by machine learning using the 225 training samples as the inputs. Secondly, the causal relationship analysis is

Table 3. Statistical distribution of complexity nodes under different states

| Complexity nodes | Low state | Moderate state | High state |
|------------------|-----------|----------------|------------|
| IC1 | 48.0% | 32.9% | 19.1% |
| IC2 | 44.9% | 35.1% | 20.0% |
| IC3 | 42.2% | 31.1% | 26.7% |
| IC4 | 37.3% | 38.2% | 24.4% |
| IC5 | 41.3% | 39.1% | 19.6% |
| IC6 | 44.4% | 31.1% | 24.4% |
| IC7 | 42.7% | 34.7% | 22.7% |
| IC8 | 44.4% | 33.3% | 22.2% |
| IC9 | 50.2% | 28.4% | 21.3% |
| TAC1 | 8.0% | 36.0% | 56.0% |
| TAC2 | 12.4% | 34.2% | 53.3% |
| TAC3 | 12.9% | 32.4% | 54.7% |
| TEC1 | 28.4% | 43.6% | 28.0% |
| TEC2 | 36.9% | 40.9% | 22.2% |
| TEC3 | 32.4% | 39.6% | 28.0% |
| TEC4 | 39.6% | 37.3% | 23.1% |
| OC1 | 23.6% | 35.6% | 40.9% |
| OC2 | 19.1% | 34.7% | 46.2% |
| EC1 | 42.7% | 35.1% | 22.2% |
| EC2 | 35.1% | 40.4% | 24.4% |
| EC3 | 26.7% | 40.9% | 32.4% |
| EC4 | 29.3% | 28.0% | 42.7% |
| GC1 | 16.9% | 39.1% | 44.0% |
| GC2 | 41.3% | 32.9% | 25.8% |
| GC3 | 59.6% | 22.7% | 17.8% |
| GC4 | 24.0% | 40.4% | 35.6% |

adjusted by the expert group on the basis of the initial network structure. For instance, the causal relationship is added from TAC1 to project complexity. Hence, the scientific and accuracy of the network structure is improved and the BBN-based project complexity measurement model that conforms to the objective reality is obtained. Finally, on the basis of the established Bayesian network structure, the parameter learning of Bayesian network is further done to obtain the CPT of each node variable in the network. Its function is to obtain the CPT of all the nodes, in order to provide the basis for the later model reasoning.

Following the above-mentioned procedures, the probability distributions of the complexity level and the specific complexity factors under three states are obtained, and the result is shown in Figure 3. It concludes from Figure 3 that the probability of the project complexity being the Low state is 27%, being the Moderate state is 49%, and being the High state is 25%. In recent years, the construction industry has seen rapid growth in projects of increasing size and complexity (Luo et al., 2017). This condition is proven by the results obtained through this research. It is noteworthy that the probability of the parameter learning

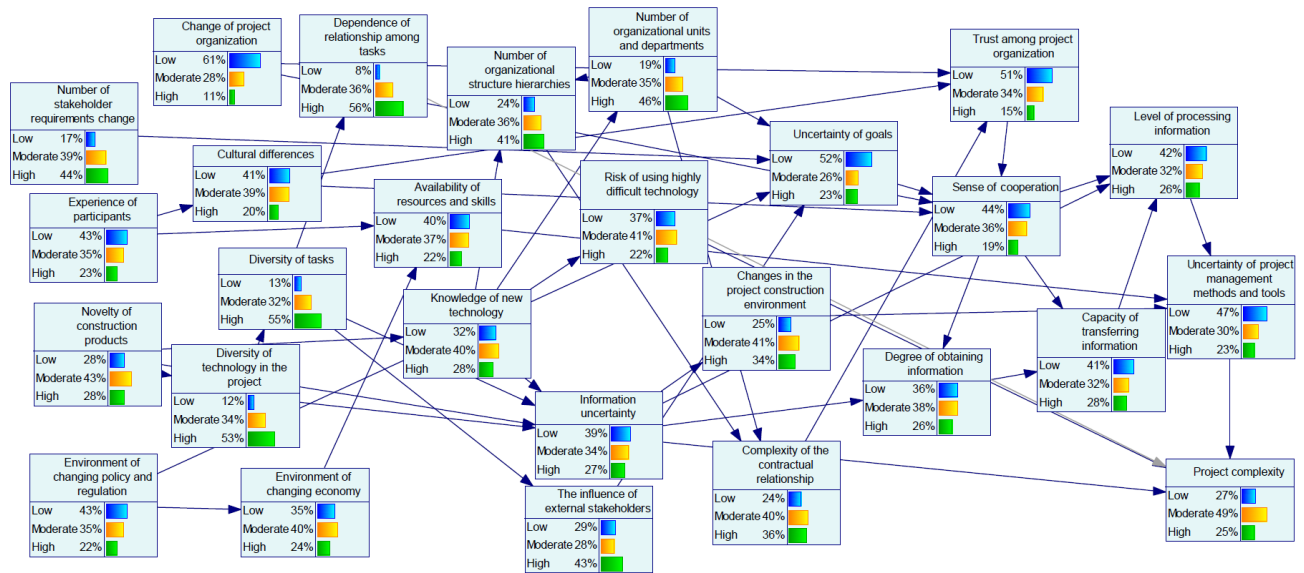


Figure 3. BBN-based PCMM in construction projects using machine learning and expert knowledge

is the conclusion under extensive investigation with a large number of data statistics, which reflects the overall situation of the complexity level of construction projects, not the complexity of one specific construction project.

3.3. Model validation

Through the above research, the BBN-based PCMM is constructed, and the CPT of all nodes is calculated in construction projects. On this basis, the 20 test samples are the inputs for model validation. The purpose of model validation is to prove the logical relationship and conditional probability of the nodes in the model are consistent with the complexity of the actual construction projects. The real level of 26 complexity factors of one data is fed into PCMM to calculate the probability distribution of project complexity. This iteration is repeated for the 20 test samples, and the result of the probability distribution of project complexity is illustrated in Figure 4. The



Figure 4. Results of BBN-based project complexity measurement model validation

largest possibility of project complexity is regarded as the predicted state. Figure 5 reveals a comparison of the predicted state and real value for the model validation.

It can be seen from Figure 5 that the simulation state of project complexity of ten data (No. 1, No. 3, No. 4, No. 7, No. 10, No. 12, No. 14, No. 15, No. 16, and No. 17) matches the real level. For example, the probability distribution of project complexity is 3% Low, 43% Moderate, and 54% High for No. 1 in Figure 4. It concludes that the largest possibility is a High state, which is consistent with the real level “4” (highly complex). Thus, it is regarded as matching totally in this study. Further, compared the second-largest probability of others data with the real level, it can be found that six data (No. 2, No. 5, No. 6, No. 9, No. 13, and No. 19) is within the allowable error range. Hence, the effective rate is $16 / 20 = 80\%$. This proves the validation of the model. Therefore, the network structure and CPT can be verified through the model validation, which can be used for model analytics. The complexity measurement model established in this study is feasible and can provide a reference for the complexity measurement of construction projects.

The reason for choosing the allowable error range of these six data is further explored. For example, the probability distribution of project complexity is 33% Low, 59% Moderate, and 8% High for No. 5 in Figure 4. It concludes that the largest possibility is a Moderate state, and the second-largest possibility is a Low state, which is consistent with the real level “2” (mildly complex). Therefore, it is regarded as matching in this study. This can also be proved by No. 2, No. 6, No. 9, No. 13, and No. 19. The reason is that the real level is obtained from the questionnaire, and one data is achieved only by one expert, thereby, there exists an error range due to expert knowledge about complexity estimation. Accordingly, choosing appropriate experts is very important to avoid bias, and the best way is to get the mean value through an expert group.

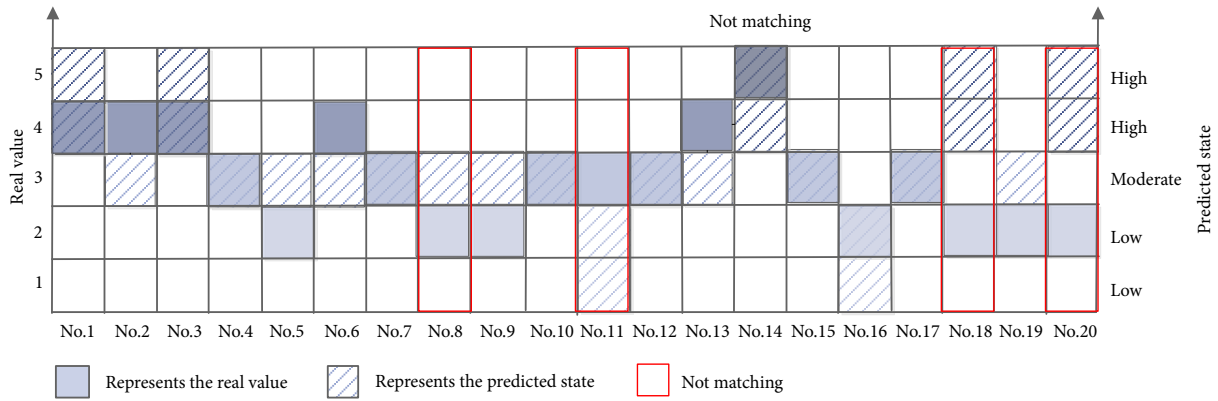


Figure 5. Comparison of the predicted state and real value for the 20 test samples

4. Model analytics

Adopting the inference function in BBN, PCMM is used to measure the magnitude of the project complexity with given evidence under different scenarios. Four types of what-if scenario analysis, predictive, diagnostic, sensitivity, and influence chain analysis are performed to measure the magnitude of the project complexity. Accordingly, the optimization strategies can be made for managing complexity in construction projects.

4.1. Predictive analysis

Predictive analysis is also known as the forward reasoning, which can reason the result according to the direction of the directed arc of the connecting nodes based on updating the reason information. Predictive analysis aims to forecast future outcome under different scenarios given evidence (Wee et al., 2015). In PCMM, the propagation of evidence of complexity factors allows an update of the

probability distribution of project complexity in the network in the light of the newly found evidence. Six dimensions of project complexity are set as different scenarios to forecast the project complexity, and the result is shown in Table 4 and Figure 6.

From the scenarios of a single dimension, when all the factors of technological complexity (TEC) are set to evidence, the project complexity has the largest probability with 38% High state. The second-ranking is information complexity (IC), which leads to the probability distribution of project complexity as 17% Low, 50% Moderate and 33% High. Other four dimensions have a similar predictive result of project complexity. It concludes that technological complexity has the largest influence on project complexity, and information complexity is the second-largest dimension. Thus, six dimensions of project complexity are classified into three groups as TEC, IC, and TAC/OC/GC/EC to further explore the predictive analysis of combinational dimensions under ten scenarios.

Table 4. Results of the predictive analysis under different scenarios

| Scenarios | High state | Evidence | Results (Low, Moderate, High) |
|--------------------------|------------|--|-------------------------------|
| Single dimension | 1 | IC = High | 17%, 50%, 33% |
| | 2 | TAC = High | 25%, 49%, 26% |
| | 3 | TEC = High | 15%, 47%, 38% |
| | 4 | OC = High | 26%, 49%, 25% |
| | 5 | EC = High | 25%, 49%, 26% |
| | 6 | GC = High | 27%, 49%, 25% |
| Combinational dimensions | 7 | TEC = High, IC = High | 4%, 67%, 29% |
| | 8 | IC = High, TAC = High | 17%, 50%, 33% |
| | 9 | TEC = High, TAC = High | 14%, 48%, 39% |
| | 10 | TAC = High, OC = High | 25%, 48%, 27% |
| | 11 | TEC = High, IC = High, TAC = High | 4%, 67%, 29% |
| | 12 | TAC = High, OC = High, GC = High | 25%, 48%, 27% |
| | 13 | TEC = High, IC = High, TAC = High, OC = High | 4%, 67%, 29% |
| | 14 | TAC = High, OC = High, GC = High, EC = High | 23%, 48%, 29% |
| | 15 | TEC = High, IC = High, TAC = High, OC = High, GC = High | 4%, 67%, 29% |
| | 16 | TEC = High, IC = High, TAC = High, OC = High, GC = High, GC = High | 4%, 67%, 29% |

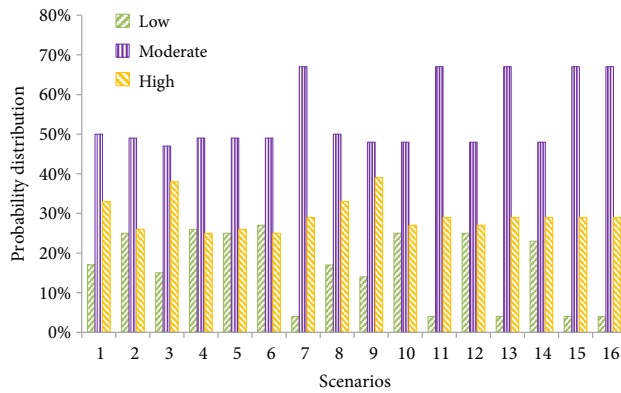


Figure 6. Probability distribution of project complexity of the predictive analysis under different scenarios

From the result of combinational dimensions, comparing scenarios 10, 12, and 14, the probability distribution of project complexity is similar to the single dimension when any combinational dimensions of TAC/OC/GC/EC are set to High state. Thus, it can be verified that TAC/OC/GC/EC does not have much influence on project complexity. Comparing scenarios 7, 11, 13, 15, and 16, all the probability distribution of project complexity is 4% Low, 67% Moderate, and 29% High, which means that the predictive result of project complexity depends on the technological complexity and information complexity and no matter the states of the other four dimensions. Comparing scenarios 8 and 9 with a single dimension of scenario 1 and 3, respectively, it could be found that the probability

distribution of project complexity is similar to the single dimension. Thus, it can prove that task complexity does not impact project complexity. Comparing scenario 7 with scenarios 1 and 3, respectively, it can be found that the probability distribution of project complexity of combinational dimensions is lower than the single dimension of information complexity and technological complexity. This represents that information complexity and technological complexity have a negative impact on each other. Accordingly, the major focus of concern for complexity management is technological complexity and information complexity in construction projects.

4.2. Diagnostic analysis

Diagnostic analysis is also known as backward reasoning. Setting evidence on a domain variable may affect the probability distribution of domain factors by propagating backward against the direction of the link. Hence, BBN is able to diagnose the possible causes and influence by identifying the change of posterior probability of the target nodes (Wee et al., 2015). It is assumed that the target node “project complexity” at the High state is set to 100%. Therefore, when the project complexity is at the level of highly complex and extremely complex, the factors with the most significant influence on the project complexity in the Bayesian network can be identified. These factors are then set to the High state gradually to perform diagnostic analysis under different scenarios, and the result is demonstrated in Figure 7.

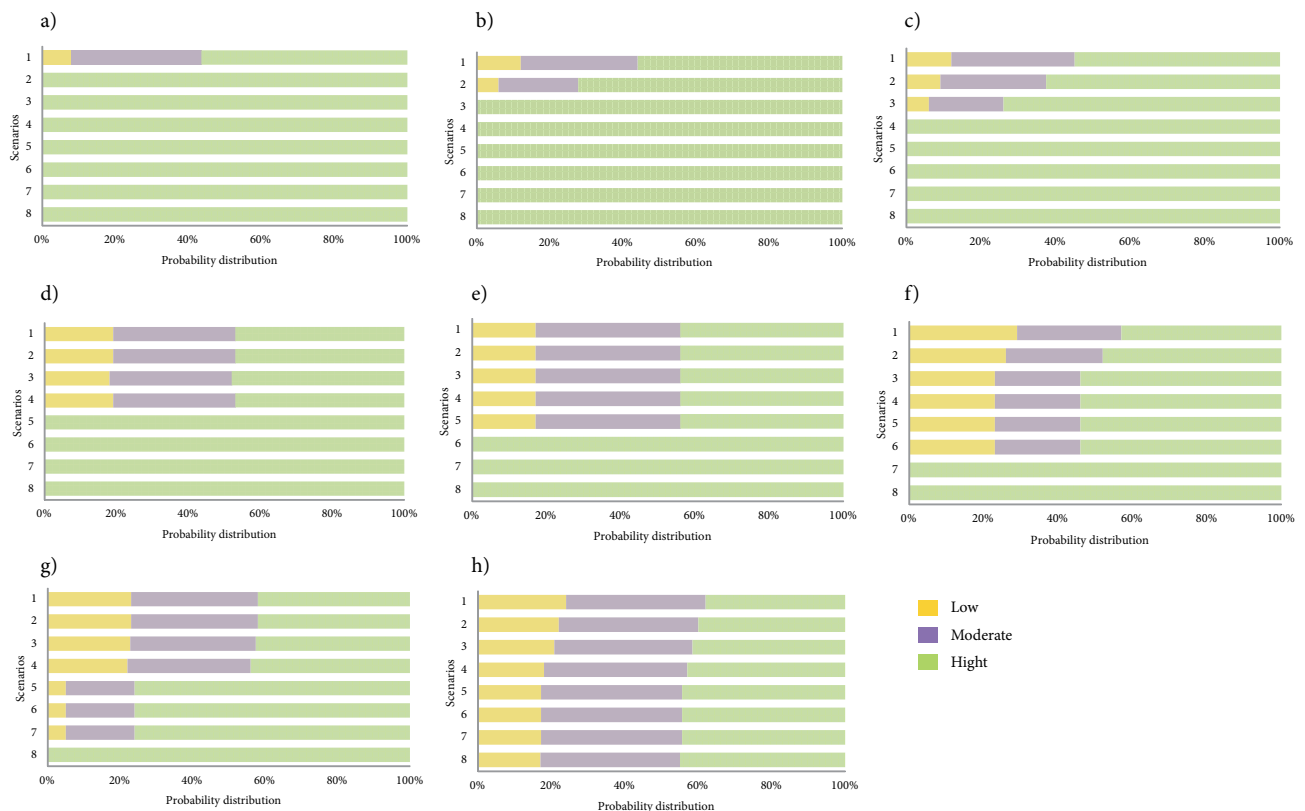


Figure 7. Probability distribution of the eight factors in diagnostic analysis under different scenarios: (a) TAC1; (b) TAC3; (c) TAC2; (d) OC2; (e) GC1; (f) EC4; (g) OC1; and (h) IC8

It can be indicated that the increase in project complexity is likely caused by eight factors. When the probability of “project complexity” being High state is 100%, eight factors are diagnosed as the key factors influencing project complexity: Dependence of relationship among tasks (TAC1), Diversity of tasks (TAC3), Diversity of technology in the project (TAC2), Number of organizational units and departments (OC2), Number of stakeholder requirements change (GC1), The influence of external stakeholders (EC4), Number of organizational structure hierarchies (OC1), and Information uncertainty (IC8). These eight factors are ranked by the probability of being High state and are set to a High state to simulate the different scenarios, respectively.

From the Figure 7, comparing the scenarios 2~5, the probability of the High state of every cause factor increases when the TAC1, TAC3, TAC2, and OC2 are set to a High state, step by step. It concludes that TAC1, TAC3, TAC2, and OC2 are the main causes to project complexity. Accordingly, more attention is required to the causing factors TAC1, TAC3, TAC2, and OC2 during complexity management. After that, comparing scenarios 6, 7 and 8, the probability distribution of other causing factors maintains the same ones, which indicates that these factors GC1, EC4, OC1, and IC8 are not the main causes under these scenarios. In addition, factors TEC1 and TEC3 have a high probability of High state and become likely causing factors. Accordingly, the major focus of concern for complexity management can be shifted among different scenarios during the process of project management.

4.3. Sensitivity analysis

Sensitivity analysis attempts to calculate the occurrence of some causes resulting in a certain consequence and can be used to identify the suspected causes once an accident occurs (Zhang et al., 2016). The purpose of sensitivity

analysis in this study is to identify which complexity factors have the greatest influence on the project complexity when subjected to change. It can help managers to focus on tracking the complexity factors that can cause a significant change in the probability of project complexity with a slight change. The probability of each node is set to change to the same degree, and then the influence on the posterior probability of the target node can be calculated. The network nodes are colored to indicate sensitive parameters, and the result is shown in Figure 8.

It could be found from Figure 8 that the sensitive factors influencing the project complexity which are colored in red. These sensitive factors include Novelty of construction products (TEC1), Risk of using highly difficult technology (TEC2), Information uncertainty (IC8), Level of processing information (IC6), Diversity of tasks (TAC3), Diversity of technology in the project (TAC2), Knowledge of new technology (TEC3), Changes in the project construction environment (EC3), Uncertainty of project management methods and tools (IC9), Degree of obtaining information (IC4), Capacity of transferring information (IC3). Small changes in the above factors may have a large impact on the project complexity. Hence, special attention should be paid to these sensitive factors and corresponding measures should be taken to improve the capacity of complexity management.

The sensitive factors can be ranked according to the exact sensitive value of the variable. The rank is following: Risk of using highly difficult technology (TEC2) > Novelty of construction products (TEC1) > Information uncertainty (IC8) > Knowledge of new technology (TEC3) > Diversity of tasks (TAC3) > Level of processing information (IC6) > Diversity of technology in the project (TAC2) > Changes in the project construction environment (EC3) > Uncertainty of project management methods and tools (IC9) > Degree of obtaining information (IC4) > Capacity of transferring information (IC3). It concludes that

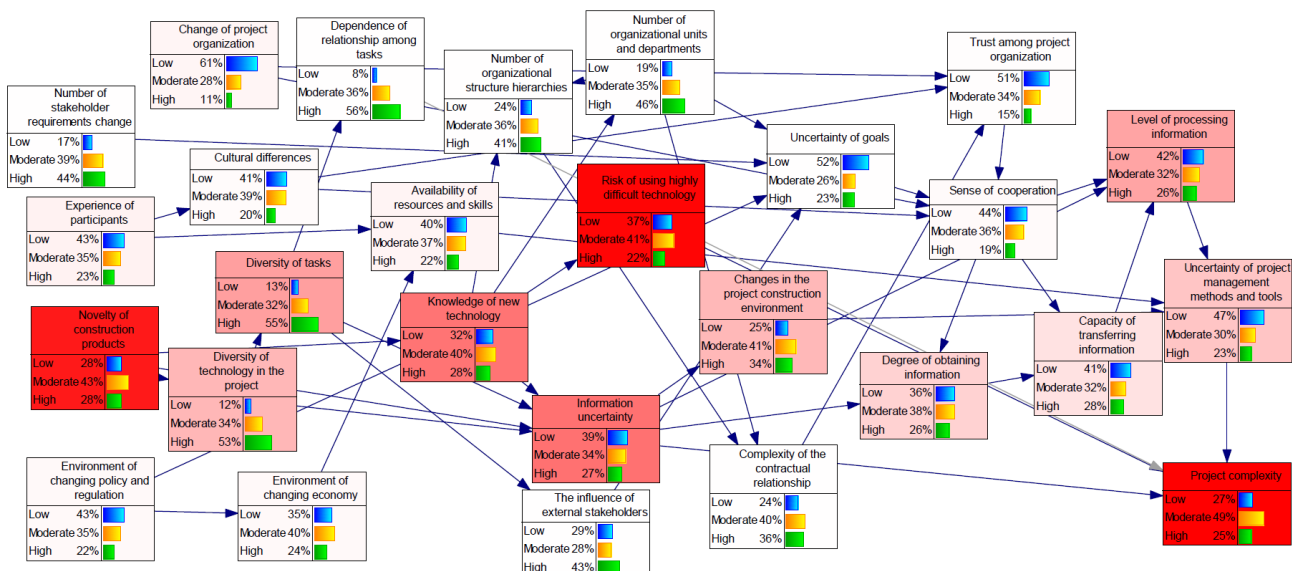


Figure 8. Result of the sensitivity analysis of BBN-based project complexity measurement model

these sensitive factors can be classified into dimensions of technological complexity, information complexity, and task complexity, which is consistent with the above result.

4.4. Influence chain analysis

The strength of influence chain analysis is used to depict the degree of mutual influence between nodes. Influence chain analysis describes the dependence degree between conditional probabilities, with the aim of exploring the most possible way which leads to the result. The width of the directional arcs describes the influence intensity between the node variables it connects, which is the influence of the parent on the child node. If several nodes with strong influence relations form a link, and the target node exists in the link, then the link is the maximum influence causal chain. In this study, the state of project complexity is set to “High = 100%”, and then the strength of influence analysis is carried out, and the result is shown in Figure 9.

From Figure 9, it can be seen that two influencing causative chains appear as shown as the thickened link. The first one is “Novelty of construction products (TEC1)→Diversity of technology in the project (TAC2)→Information uncertainty (IC8)→Project complexity”. According to the results, the novelty of construction products will influence the diversity of technology in the project, which will influence project complexity through information complexity. It concludes that technological complexity and task complexity play an important role in project complexity, which proves the consistency with the above conclusion.

The second one is “Experience of participants (IC7)→Cultural differences (IC5)→Trust among project organization (IC1)→Sense of cooperation (IC2)→Degree of obtaining information (IC4)→Capacity of transferring information (IC3)→Level of processing information (IC6)→Uncertainty of project management methods and

tools (IC9)→Project complexity”. The result means that the experience of participants will influence cultural differences and trust and sense of cooperation, which leads to the difficulty of information management. All these factors belong to the dimension of information complexity, which is consistent with the result that information complexity has an impact on project complexity. Thereby, the strategy of complexity management is offering training courses for the project team to enhance their knowledge and skills, and choosing the professional participants and encouraging close collaborations between project stakeholders during the early phase of the project (Hwang et al., 2018).

5. Discussions

5.1. Theoretical implications

Project complexity has been regarded as vital to the achievements of project success (Luo et al., 2016). Although researchers have realized the importance of measuring the project complexity in construction projects, effect methods for addressing the challenges are limited. The existing research forms an endeavor to narrow the gap, in which the magnitude of complexity and its causal relationships are investigated with the BBN-based PCMM approach.

Initially, the contribution of the study lies in the advancement of the body of knowledge of complexity management in construction projects. The study has resulted in the development of a simulation model that can clearly depict the interrelationships among factors of project complexity as shown in Figure 3. Such descriptions could largely extend the understanding of complexity factors and how the factors influence project complexity. As stated by He et al. (2015), project complexity is a result of composing many interconnected parts within a project.

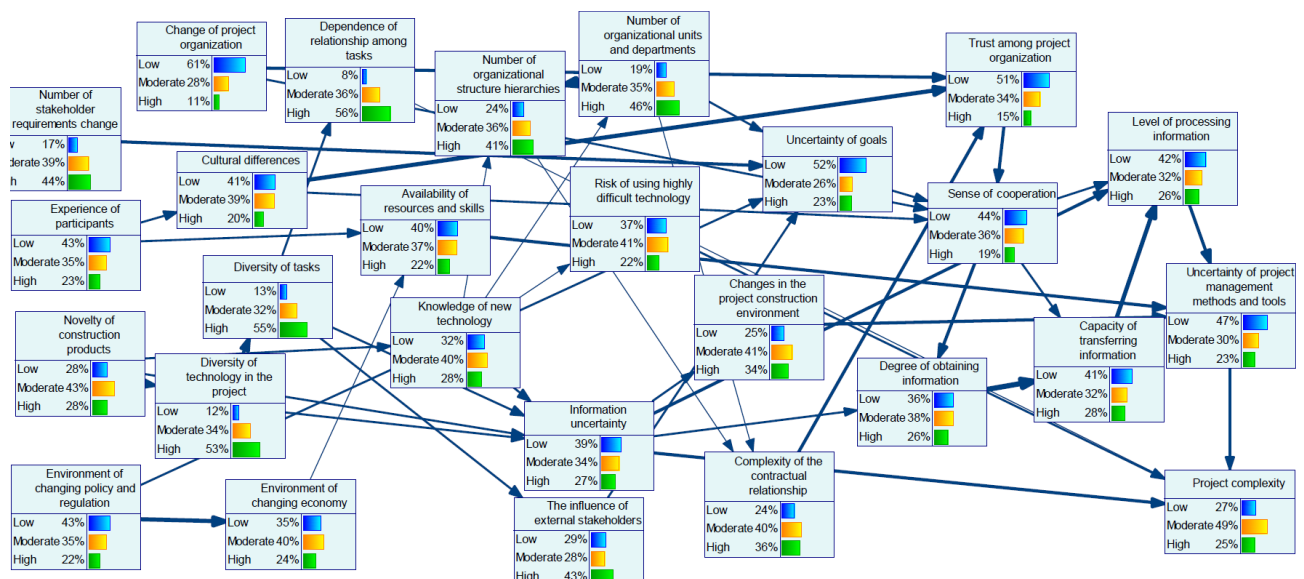


Figure 9. Results of influence chain analysis of BBN-based project complexity measurement model

Comparing with existing research, this study improves the complexity theory considering the cause-effect relationships of complexity factors in construction projects.

Furthermore, this study proposes a novel simulation approach for measuring project complexity under different scenarios based on BBN. According to the literature review, most of the current research cannot measure project complexity under what-if scenarios such as FAHP (Nguyen et al., 2015), AHP (Vidal et al., 2011b), FANP (He et al., 2015), and SEM (Qureshi & Kang, 2015). In this study, BBN-based PCMM approach is capable of measuring the magnitude of project complexity under different scenarios. In addition, on the basis of the machine learning of collected data, the BBN simulation approach in this study can reduce the errors and biases of expert judgments in the PCMM development compared with existing BBN method.

5.2. Practical implications

Complexity management is the ultimate goal of complexity research. The BBN-based PCMM developed in this study is useful for measuring the project complexity and managerial effort can be adjusted accordingly for better management of construction projects. There are some practical implications for this developed approach.

First of all, PCMM has flexible simulation capacities to explore the interrelationships among factors of project complexity, which is clearly demonstrated by the model validation and analytics. The comparison between the different analysis helps deepen project practitioners' understanding of interactions among complexity factors, as well as how such factor interrelations would affect the project complexity. This can help raise their awareness about the importance of interactions. Hence, the project complexity can be managed with the help of the PCMM as it allows project managers to measure the project complexity under different scenarios. By doing so, practitioners can use the findings of this study to improve project management practices.

In accordance with the results of model analytics, additional attention is required on technological complexity, information complexity, and task complexity in the process of complexity management. The results are approved by other researches and practices. For instance, Puddicombe (2011) demonstrated that technological complexity is a key characteristic of projects that have distinct effects on project performance. Luo et al. (2016) concluded that information complexity has significant negative effects on project success. To address technological complexity and task complexity, it is recommended to execute standard procedures that provide consistency to the team in terms of members' interaction with one another and the accomplishment of tasks (An et al., 2018). To address information complexity, it is recommended to utilize the central program control information system to realize timely collection and analysis of progress information and meet the information needs of decision-makers (He et al., 2015; Ma et al., 2018).

Besides, the PCMM can be applied easily and conveniently into practical cases. The network and CPT in BBN-

based PCMM are determined based on a general survey of project practitioners in construction projects. Thus, the model has a wide range that can be applied to measure complexity. In this study, the construction project of World EXPO 2010 Shanghai China (EXPO 2010) is chosen as a case study for model application. The reason for choosing EXPO 2010 is that it involves various participants with cultural differences and coordinating difficulty due to complex relationships (He et al., 2015). The mean score of 26 complexity factors in He et al. (2015) is used for the application of PCMM, in which 20 managers participated in the EXPO 2010 are invited to rate the complexity level from 1 to 5. The complexity level is transformed into three states (tabulated in Table 5), and the reasoning result is demonstrated in Figure 10. It can be found from Figure 10 that the probability distribution of project complexity is 3% Low, 48% Moderate, and 48% High. The finding is consistent with He et al. (2015) that the overall complexity level of the EXPO 2010 is highly complex, and the complexity could also be controlled at a moderately complex level if proper strategies are developed and carried out. Thus, PCMM can be applied to measure the complexity level of a particular construction project.

Table 5. Complexity variables information of the EXPO 2010 Shanghai China project

| No. | Factors | Mean value | Complexity level | States | | |
|-----|---------|------------|------------------|--------|----------|------|
| | | | | Low | Moderate | High |
| 1 | IC1 | 3.7 | 4 | | | √ |
| 2 | IC2 | 3.7 | 4 | | | √ |
| 3 | IC3 | 3.1 | 3 | | √ | |
| 4 | IC4 | 3.4 | 3 | | √ | |
| 5 | IC5 | 3.4 | 3 | | √ | |
| 6 | IC6 | 3.1 | 3 | | √ | |
| 7 | IC7 | 3.3 | 3 | | √ | |
| 8 | IC8 | 3.2 | 3 | | √ | |
| 9 | IC9 | 3.1 | 3 | | √ | |
| 10 | TAC1 | 3.3 | 3 | | √ | |
| 11 | TAC2 | 3.1 | 3 | | √ | |
| 12 | TAC3 | 3.1 | 3 | | √ | |
| 13 | TEC1 | 3.0 | 3 | | √ | |
| 14 | TEC2 | 3.5 | 4 | | | √ |
| 15 | TEC3 | 3.0 | 3 | | √ | |
| 16 | TEC4 | 3.1 | 3 | | √ | |
| 17 | OC1 | 3.0 | 3 | | √ | |
| 18 | OC2 | 3.9 | 4 | | | √ |
| 19 | EC1 | 3.3 | 3 | | √ | |
| 20 | EC2 | 3.1 | 3 | | √ | |
| 21 | EC3 | 3.0 | 3 | | √ | |
| 22 | EC4 | 3.2 | 3 | | √ | |
| 23 | GC1 | 3.2 | 3 | | √ | |
| 24 | GC2 | 3.8 | 4 | | | √ |
| 25 | GC3 | 3.1 | 3 | | √ | |
| 26 | GC4 | 3.9 | 4 | | | √ |

Note: If the mean value has a decimal, then the value is rounded to the nearest whole number as the complexity states.

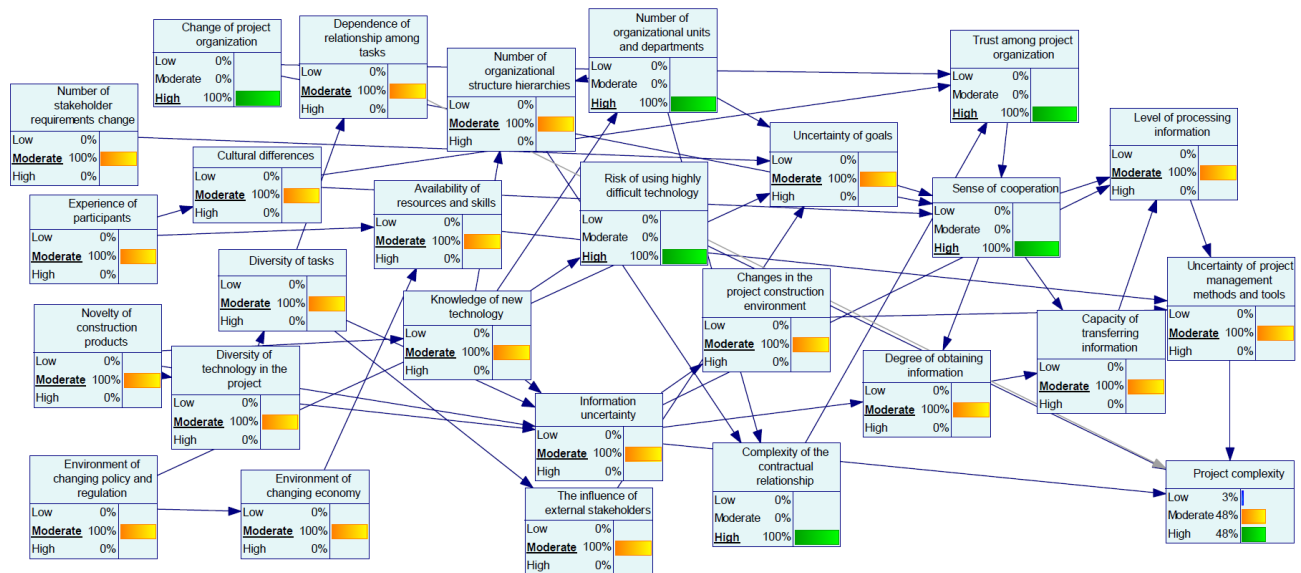


Figure 10. Project complexity measurement result of the EXPO 2010 Shanghai China project

Conclusions and future works

A BBN-based PCMM is proposed to measure the project complexity with the causal relationships among complexity factors taken into account. In this study, 26 project complexity nodes are identified for model development based on the literature review. The PCMM is then constructed with 225 training samples and is validated with 20 test samples. On the basis of developed PCMM, predictive, diagnostic, sensitivity, and influence chain analysis are carried out for decision making. This contribution of this research lies in proposing a method that is capable of measuring the complexity level in construction projects considering cause-effect relationships. It can help predict the level of project complexity and facilitate stakeholders to take appropriate management actions to reduce the potential risks that might be induced to different levels of project complexity.

In terms of the empirical studies, the obtained research findings are presented as follows. (1) Based on the questionnaire survey and expert knowledge, the BBN based PCMM is established, and the model is further validated with 20 test samples, which proves that the PCMM model established in this study is effective. (2) PCMM that reflects the causal relationship between complexity factors and project complexity, can forecast the complexity level through predictive analysis, and identify the most likely possible causes through diagnostic analysis. In addition, it can discern the sensitive factors and the most general chain of causes affecting the project complexity. The research results indicate that more attention should be paid on technological complexity, information complexity, and task complexity in the process of complexity management. (3) The EXPO 2010 is chosen as a typical case for PCMM application. It proves that the model proposed in this study is feasible and applicable, and provides an effective and convenient predicting tool for the complexity level of

construction projects. According to the PCMM, the level of project complexity can be measured for better resource utilization in the process of project management.

However, the developed PCMM method has some limitations. The PCMM in this study is constructed based on the survey data from all the construction projects. It never differentiates the types of construction projects like public projects, private projects, and hybrid projects. Considering that the construction projects can be classified into various categories of projects (Xia & Chan, 2012), the complexity of different types of projects varies in the key influencing factors, sensitive factors, and influence chain. Therefore, the characteristics of different project types should be considered in the future to measure the complexity of the specific type of projects.

Acknowledgements

This study is supported by the National Natural Science Foundation of China (71640012, 71901113, 71972018), and China Scholarship Council Project (201806825066).

Funding

This work was supported by the <National Natural Science Foundation of China> under Grant [number 71640012, 71901113, 71972018]; and < China Scholarship Council Project > under Grant [number 201806825066].

Author contributions

Lan Luo and Limao Zhang conceived the study and were responsible for the design and structure of the paper. Lan Luo was responsible for data collection and analysis. Limao Zhang was responsible for data interpretation. Lan Luo wrote drafts of the article. Limao Zhang and Guang-dong Wu are supervisors.

Disclosure statement

Nothing to declare.

References

- An, Y., Rogers, J., Kingsley, G., Matisoff, D. C., Mistur, E., & Ashuri, B. (2018). Influence of task complexity in shaping environmental review and engineering design durations. *Journal of Management in Engineering*, 34(6), 04018043. [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000649](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000649)
- Applegate, C. J., & Tien, I. (2018). Framework for probabilistic vulnerability analysis of interdependent infrastructure systems. *Journal of Computing in Civil Engineering*, 33(1), 04018058. [https://doi.org/10.1061/\(ASCE\)CP.1943-5487.0000801](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000801)
- Baccarini, D. (1996). The concept of project complexity – a review. *International Journal of Project Management*, 14(4), 201–204. [https://doi.org/10.1016/0263-7863\(95\)00093-3](https://doi.org/10.1016/0263-7863(95)00093-3)
- Bakhshi, J., Ireland, V., & Gorod, A. (2016). Clarifying the project complexity construct: Past, present and future. *International Journal of Project Management*, 34(7), 1199–1213. <https://doi.org/10.1016/j.ijproman.2016.06.002>
- Berger, J. O. (2013). *Statistical decision theory and Bayesian analysis*. Springer Science & Business Media.
- Bosch-Rekvelde, M. G. C. (2011). *Managing project complexity: A study into adapting early project phases to improve project performance in large engineering projects*. Delft University of Technology, Delft, Netherlands.
- Bosch-Rekvelde, M., Jongkind, Y., Mooi, H., Bakker, H., & Verbraeck, A. (2011). Grasping project complexity in large engineering projects: The TOE (Technical, Organizational and Environmental) framework. *International Journal of Project Management*, 29(6), 728–739. <https://doi.org/10.1016/j.ijproman.2010.07.008>
- Coenen, J., Van der Heijden, R. E., & van Riel, A. C. (2018). Understanding approaches to complexity and uncertainty in closed-loop supply chain management: Past findings and future directions. *Journal of Cleaner Production*, 201, 1–13. <https://doi.org/10.1016/j.jclepro.2018.07.216>
- Cooper, G. F., & Herskovits, E. (1992). A Bayesian method for the induction of probabilistic networks from data. *Machine Learning*, 9(4), 309–347. <https://doi.org/10.1007/BF00994110>
- Diallo, T. M., Henry, S., Ouzrout, Y., & Bouras, A. (2018). Data-based fault diagnosis model using a Bayesian causal analysis framework. *International Journal of Information Technology & Decision Making*, 17(2), 583–620. <https://doi.org/10.1142/S0219622018500025>
- Dikmen, I., Budayan, C., Talat Birgonul, M., & Hayat, E. (2018). Effects of risk attitude and controllability assumption on risk ratings: Observational study on international construction project risk assessment. *Journal of Management in Engineering*, 34(6), 04018037. [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000643](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000643)
- Ellinas, C., Allan, N., & Johansson, A. (2018). Toward project complexity evaluation: A structural perspective. *IEEE Systems Journal*, 12(1), 228–239. <https://doi.org/10.1109/JSYST.2016.2562358>
- Gao, N., Chen, Y., Wang, W., & Wang, Y. (2018). Addressing project complexity: The role of contractual functions. *Journal of Management in Engineering*, 34(3), 04018011. [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000613](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000613)
- Girmscheid, G., & Brockmann, C. (2008). The inherent complexity of large scale engineering projects. *Project Perspectives*, 29, 22–26.
- Gransberg, D. D., Shane, J. S., Strong, K., & del Puerto, C. L. (2012). Project complexity mapping in five dimensions for complex transportation projects. *Journal of Management in Engineering*, 29(4), 316–326. [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000163](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000163)
- He, Q., Luo, L., Hu, Y., & Chan, A. P. (2015). Measuring the complexity of mega construction projects in China – A fuzzy analytic network process analysis. *International Journal of Project Management*, 33(3), 549–563. <https://doi.org/10.1016/j.ijproman.2014.07.009>
- Hwang, B.-G., Shan, M., & Looi, K.-Y. (2018). Key constraints and mitigation strategies for prefabricated prefinished volumetric construction. *Journal of Cleaner Production*, 183, 183–193. <https://doi.org/10.1016/j.jclepro.2018.02.136>
- Jarkas, A. M. (2017). Contractors' perspective of construction project complexity: Definitions, principles, and relevant contributors. *Journal of Professional Issues in Engineering Education and Practice*, 143(4), 04017007. [https://doi.org/10.1061/\(ASCE\)EI.1943-5541.0000337](https://doi.org/10.1061/(ASCE)EI.1943-5541.0000337)
- Lebcir, R. M., & Choudrie, J. (2011). A dynamic model of the effects of project complexity on time to complete construction projects. *International Journal of Innovation, Management and Technology*, 2(6), 477–483.
- Lessard, D., Sakhrani, V., & Miller, R. (2014). House of project complexity – understanding complexity in large infrastructure projects. *Engineering Project Organization Journal*, 4(4), 170–192. <https://doi.org/10.1080/21573727.2014.907151>
- Lu, Y., Luo, L., Wang, H., Le, Y., & Shi, Q. (2015). Measurement model of project complexity for large-scale projects from task and organization perspective. *International Journal of Project Management*, 33(3), 610–622. <https://doi.org/10.1016/j.ijproman.2014.12.005>
- Luo, L., He, Q., Xie, J., Yang, D., & Wu, G. (2016). Investigating the relationship between project complexity and success in complex construction projects. *Journal of Management in Engineering*, 33(2), 04016036. [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000471](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000471)
- Luo, L., He, Q., Jaselskis, E. J., & Xie, J. (2017). Construction project complexity: research trends and implications. *Journal of Construction Engineering and Management*, 143(7), 04017019. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001306](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001306)
- Ma, X., Xiong, F., Olawumi, T. O., Dong, N., & Chan, A. P. (2018). Conceptual framework and roadmap approach for integrating BIM into lifecycle project management. *Journal of Management in Engineering*, 34(6), 05018011. [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000647](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000647)
- Maylor, H., Vidgen, R., & Carver, S. (2008). Managerial complexity in project-based operations: A grounded model and its implications for practice. *Project Management Journal*, 39(S1), S15–S26. <https://doi.org/10.1002/pmj.20057>
- Mihm, J., Loch, C., & Huchzermeier, A. (2003). Problem-solving oscillations in complex engineering projects. *Management Science*, 49(6), 733–750. <https://doi.org/10.1287/mnsc.49.6.733.16021>
- Nguyen, A. T., Nguyen, L. D., Le-Hoai, L., & Dang, C. N. (2015). Quantifying the complexity of transportation projects using the fuzzy analytic hierarchy process. *International Journal of Project Management*, 33(6), 1364–1376. <https://doi.org/10.1016/j.ijproman.2015.02.007>
- Owens, J., Ahn, J., Shane, J. S., Strong, K. C., & Gransberg, D. D. (2012). Defining complex project management of large US transportation projects: A comparative case study analysis. *Public Works Management & Policy*, 17(2), 170–188. <https://doi.org/10.1177/1087724X11419306>

- Pan, Y., Zhang, L., Li, Z., & Ding, L. (2019). Improved fuzzy Bayesian network-based risk analysis with interval-valued fuzzy sets and DS evidence theory. *IEEE Transactions on Fuzzy Systems*. <https://doi.org/10.1109/TFUZZ.2019.2929024>
- Puddicombe, M. S. (2011). Novelty and technical complexity: Critical constructs in capital projects. *Journal of Construction Engineering and Management*, 138(5), 613–620. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0000459](https://doi.org/10.1061/(ASCE)CO.1943-7862.0000459)
- Qazi, A., Quigley, J., Dickson, A., & Kirytopoulos, K. (2016). Project complexity and risk management (ProCRiM): Towards modelling project complexity driven risk paths in construction projects. *International Journal of Project Management*, 34(7), 1183–1198. <https://doi.org/10.1016/j.ijproman.2016.05.008>
- Qureshi, S. M., & Kang, C. (2015). Analysing the organizational factors of project complexity using structural equation modelling. *International Journal of Project Management*, 33(1), 165–176. <https://doi.org/10.1016/j.ijproman.2014.04.006>
- Remington, K., & Pollack, J. (2016). *Tools for complex projects*. Routledge. <https://doi.org/10.4324/9781315591810>
- Remington, K., Zolin, R., & Turner, R. (2009). A model of project complexity: distinguishing dimensions of complexity from severity. In *Proceedings of the 9th International Research Network of Project Management Conference*, Berlin, Germany.
- Santana, G. (1990). Classification of construction projects by scales of complexity. *International Journal of Project Management*, 8(2), 102–104. [https://doi.org/10.1016/0263-7863\(90\)90044-C](https://doi.org/10.1016/0263-7863(90)90044-C)
- Shafiei-Monfared, S., & Jenab, K. (2012). A novel approach for complexity measure analysis in design projects. *Journal of Engineering Design*, 23(3), 185–194. <https://doi.org/10.1080/09544828.2011.554389>
- Sinha, S., Kumar, B., & Thomson, A. (2006). Measuring project complexity: a project manager's tool. *Architectural Engineering and Design Management*, 2(3), 187–202. <https://doi.org/10.1080/17452007.2006.9684615>
- Tatikonda, M. V., & Rosenthal, S. R. (2000). Technology novelty, project complexity, and product development project execution success: a deeper look at task uncertainty in product innovation. *IEEE Transactions on Engineering Management*, 47(1), 74–87. <https://doi.org/10.1109/17.820727>
- Thomas, J., & Mengel, T. (2008). Preparing project managers to deal with complexity – Advanced project management education. *International Journal of Project Management*, 26(3), 304–315. <https://doi.org/10.1016/j.ijproman.2008.01.001>
- Vehtari, A., Gelman, A., & Gabry, J. (2017). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*, 27(5), 1413–1432. <https://doi.org/10.1007/s11222-016-9696-4>
- Vidal, L.-A., & Marle, F. (2008). Understanding project complexity: implications on project management. *Kybernetes*, 37(8), 1094–1110. <https://doi.org/10.1108/03684920810884928>
- Vidal, L.-A., Marle, F., & Bocquet, J.-C. (2011a). Measuring project complexity using the Analytic Hierarchy Process. *International Journal of Project Management*, 29(6), 718–727. <https://doi.org/10.1016/j.ijproman.2010.07.005>
- Vidal, L., Marle, F., & Bocquet, J. (2011b). Using a Delphi process and the Analytic Hierarchy Process (AHP) to evaluate the complexity of projects. *Expert Systems with Applications*, 38(5), 5388–5405. <https://doi.org/10.1016/j.eswa.2010.10.016>
- Wallner, H. P. (1999). Towards sustainable development of industry: networking, complexity and eco-clusters. *Journal of Cleaner Production*, 7(1), 49–58. [https://doi.org/10.1016/S0959-6526\(98\)00036-5](https://doi.org/10.1016/S0959-6526(98)00036-5)
- Wang, L., & Zhang, X. (2018). Bayesian analytics for estimating risk probability in PPP waste-to-energy projects. *Journal of Management in Engineering*, 34(6), 04018047. [https://doi.org/10.1061/\(ASCE\)ME.1943-5479.0000658](https://doi.org/10.1061/(ASCE)ME.1943-5479.0000658)
- Wang, Y., Zhang, X., & Wang, Z. (2018). A proactive decision support system for online event streams. *International Journal of Information Technology & Decision Making*, 17(6), 1891–1913. <https://doi.org/10.1142/S0219622018500463>
- Wee, Y. Y., Cheah, W. P., Tan, S. C., & Wee, K. (2015). A method for root cause analysis with a Bayesian belief network and fuzzy cognitive map. *Expert Systems with Applications*, 42(1), 468–487. <https://doi.org/10.1016/j.eswa.2014.06.037>
- Williams, T. M. (1999). The need for new paradigms for complex projects. *International Journal of Project Management*, 17(5), 269–273. [https://doi.org/10.1016/S0263-7863\(98\)00047-7](https://doi.org/10.1016/S0263-7863(98)00047-7)
- Wu, X., Liu, H., Zhang, L., Skibniewski, M. J., Deng, Q., & Teng, J. (2015). A dynamic Bayesian network based approach to safety decision support in tunnel construction. *Reliability Engineering & System Safety*, 134, 157–168. <https://doi.org/10.1016/j.res.2014.10.021>
- Xia, B., & Chan, A. P. (2012). Measuring complexity for building projects: a Delphi study. *Engineering, Construction and Architectural Management*, 19(1), 7–24. <https://doi.org/10.1108/09699981211192544>
- Yukalov, V. I., & Sornette, D. (2015). Role of information in decision making of social agents. *International Journal of Information Technology & Decision Making*, 14(5), 1129–1166. <https://doi.org/10.1142/S0219622014500564>
- Zhang, L., Wu, X., Skibniewski, M. J., Zhong, J., & Lu, Y. (2014). Bayesian-network-based safety risk analysis in construction projects. *Reliability Engineering & System Safety*, 131, 29–39. <https://doi.org/10.1016/j.res.2014.06.006>
- Zhang, L., Wu, X., Qin, Y., Skibniewski, M. J., & Liu, W. (2016). Towards a fuzzy Bayesian network based approach for safety risk analysis of tunnel – Induced pipeline damage. *Risk Analysis*, 36(2), 278–301. <https://doi.org/10.1111/risa.12448>
- Zhu, J., & Mostafavi, A. (2017). Discovering complexity and emergent properties in project systems: A new approach to understanding project performance. *International Journal of Project Management*, 35(1), 1–12. <https://doi.org/10.1016/j.ijproman.2016.10.004>