Applications of Bayesian approaches in construction management research: A systematic review

Abstract

Purpose - Bayesian approaches have been widely applied in construction management (CM) research due to their capacity to deal with uncertain and complicated problems. However, to date, there has been no systematic review of applications of Bayesian approaches in existing CM studies. This paper systematically reviews applications of Bayesian approaches in CM research and provides insights into potential benefits of this technique for driving innovation and productivity in the construction industry.

Design/methodology/approach - A total of 148 articles were retrieved for systematic review through two literature selection rounds.

Findings - The number of applications of Bayesian approaches in CM research has been increasing in past years. CM topics most frequently investigated using Bayesian approaches were safety management, risk management, contract management, and process control. The Bayesian Network (BN) was the most frequently employed Bayesian method. Elicitation from expert knowledge and case studies were the primary methods for BN development and validation, respectively. Prediction was the most popular type of reasoning with BNs, investigating outputs such as predicting the probability of cost overrun, time performance, and workplace accidents. Research limitations in existing studies mainly related to not fully realizing the potential of Bayesian approaches in CM functional areas, over-reliance on expert knowledge for BN model development, and lacking guides on BN model validation, together with pertinent recommendations for future research.

Originality/value - This systematic review contributes to providing a comprehensive understanding of the application of Bayesian approaches in CM research and highlights implications for future research and practice.

Keywords: Bayesian approaches, construction management, systematic review

Article type: Literature review

1. Introduction

Construction management (CM) is a process making use of construction resources to achieve the objectives of management, and plays an important role in the success of a construction project (Ko and Cheng, 2003). According to Kang *et al.* (2018), CM has 12 functional areas, namely project plan and scope management, project cost management, process control, project information management, risk management, contract management, quality management, safety management, environment management, design management, materials management, and stakeholder management. Hence, to deliver a project safely, on time, within budget and of specified quality standard, construction managers need to deal with various issues and challenges arising from the uncertain, complicated, and changeable nature of a construction project environment (Ko and Cheng, 2003; Vaux and Kirk, 2018; Keung and Shen, 2013).

Bayesian approaches have strengths in dealing with problems associated with high levels of uncertainty and complexity (Phan *et al.*, 2016), making them suitable for CM research and practice. Generally speaking, they have the capacity to incorporate subjective and objective data for quantitative relationship analysis, diagnosis, prediction, and monitoring (Chua and Goh, 2005; Chan *et al.*, 2018) and often act as the basis for machine learning applications in industry (Rongchen *et al.*, 2020). Their ability to combine different sources of information (e.g., expert knowledge, field data, modeling results, etc.) can provide a helpful and unique resource for construction managers to make better decisions (Qazi *et al.*, 2016). Bayesian approaches can handle incomplete data (Leu and Chang, 2015), which is of significant use for CM research because it is often difficult to obtain complete and perfect sets of data regarding construction projects (Zhang *et al.*, 2016). In particular, Bayesian Networks (BNs), the most commonly used Bayesian approach, can graphically represent the complexity of the CM environment through Directed Acyclic Graphs (DAGs) to show relationships among variables (Baudrit *et al.*, 2019), making it easier to understand. As a result, Bayesian approaches have been increasingly applied in various research areas of CM, such as schedule delay probability prediction (Luu *et al.*, 2009), cost overrun risks assessment (Islam *et al.*, 2019), and safe work behaviors (Jitwasinkul *et al.*, 2016).

Despite the potential benefits of Bayesian approaches in CM research, blind application of Bayesian approaches may lead to inappropriate influence of priors, wrong interpretation of results, and improper reporting of results. Most CM researchers are trained in frequentist statistics (i.e., p values and null hypothesis testing) instead of Bayesian statistics (van de Schoot

et al., 2017). The motivation for this systematic review is to increase CM researchers' awareness of the benefits of Bayesian approaches for certain functional areas of CM, and promote proper utilization of Bayesian approaches in CM research. Although some other research domains (e.g., psychology, medicine) have realized the need to review Bayesian articles published their respective domains in the past 25 years (van de Schoot *et al.*, 2017; Ashby, 2006), such a need has been overlooked in CM. It is thus time to conduct a systematic review of how Bayesian approaches have been utilized in CM research and generate best practice guidance for proper application of Bayesian approaches in CM research, such as data requirement, selection of algorithm, model development, and statistics reporting. A better understanding of these issues can improve the effectiveness of Bayesian-related applications in CM research and provide direction for future research.

The objectives of this systematic review are to reveal the trends of Bayesian applications in CM research; including which functional areas of CM have been the focus of Bayesian applications; evaluate existing practices in Bayesian applications in CM; and provide recommendations for improvement and future research. Findings will contribute to raising awareness of the benefits that Bayesian approaches can bring to CM practice, as well as raising CM researchers' awareness of Bayesian approaches and how to properly apply them. The significance of this paper lies in highlighting the potential for unique and specific learnings in CM practice via the application of Bayesian approaches, areas of improvement in applying Bayesian approaches in CM research and providing signposts for future research applications.

2. Bayesian approaches

Bayes' theorem is the basis of various Bayesian approaches. It was developed by the Rev. Thomas Bayes, an 18th century mathematician and theologian, and first published in 1763 (Bayes, 1991). However, it was Pierre-Simon Laplace who contributed to the promotion and application of Bayes' theorem in scientific research by introducing the general form of the theorem (Stigler, 1986; Hamelryck *et al.*, 2012). It can be mathematically expressed as the following formula:

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

where A and B are two random events; P(A) and P(B) are prior probabilities or marginal probabilities of A and B respectively, irrespective of the occurrence of each other; $P(A \mid B)$ is the conditional probability of A given B; $P(B \mid A)$ is the conditional probability of B given A.

Bayesian approaches in this systematic review refer to methods proposed based on Bayes' theorem. Bayesian inference and BNs are two popular Bayesian methods (Kelly, 2011; Weber, 2016). Bayesian inference is a method of statistical analysis based on Bayes' theorem to update the probability distribution according to the new observations (Gelman, 2013). It is flexible and practical because of the ability to incorporate multi-level randomness and integrate various sources of information (Wu *et al.*, 2020). The BN is motivated by Bayes' theorem to solve complex problems, which also is a common way to display Bayesian inference problems (Kelly, 2011).

A BN is a graphical representation of knowledge with intuitive structures and parameters, which was first introduced by Pearl (1986). BNs also are called Bayesian belief networks (BBNs), belief networks and influence networks (Mkrtchyan *et al.*, 2015). A BN model (**Fig. 1**) mainly consists of two parts: 1) a directed acyclic graph (DAG) qualitatively denoting the interdependency among variables and encoding conditional independence assumptions; and 2) conditional probability tables (CPTs) quantitatively representing the relationship between the node and its parent nodes (Wang and Chen, 2017). Developing these two parts requires structural learning and parameter learning, respectively. Generally, there are four basic steps to build a BN model: (1) identify variables which become the nodes of the graph; (2) determine relationships and the direction of their influence (directed edges of the graph); (3) quantify relationships (CPTs); and (4) validate the model (Nasir *et al.*, 2003). Three approaches can be used to build a BN model, including data learning, expert knowledge, and a combination of them (Leu and Chang, 2015). Various algorithms have been proposed to learn the structure and parameters of BNs. However, only a few common algorithms have been used in CM research, such as K2 algorithm for structure learning and Expectation-Maximization (EM) algorithm for parameter learning. The K2 algorithm learns from data a BN structure that maximizes the posterior probability of the resultant model. It uses prior specification of the order of input nodes to help address the exponential computational complexity of the learning problem (Chen *et al.*, 2008). In contrast, the EM algorithm is used purely for parameter estimation of conditional probabilities, assuming a set network structure. These are widely applied in part

due to their computational speed and their ability to impute missing data (Chen *et al.*, 2008; Ji *et al.*, 2015), which is common for complex problems encountered in the construction industry.

According to Korb and Nicholson (2011), there are four types of reasoning with BNs, namely predictive reasoning (i.e., the evidence flows from the cause to the effect), diagnostic reasoning (i.e., the evidence flows from the effect to the cause), intercausal reasoning (i.e., explore the mutual causes of a common effect), and combined the above types of reasoning. CM researchers could perform any type of reasoning with BNs depending on their research objectives, such as predicting safety performance (Xia *et al.*, 2018), diagnosing factors causing occupational accidents (*Abdat et al.*, 2014). The flexibility and practicability of BNs inspire researchers to extend the model to various forms such as dynamic BNs and fuzzy BNs (Chang *et al.*, 2019; Li *et al.*, 2012). The dynamic BN is a stochastic modelling method that extends static BN to the time domain by modelling temporal dependencies between nodes at different points or slices in time (Ma *et al.*, 2019). Typically, these dynamic BNs employ the Markovian assumption and time is represented as discrete points; for example, performance in year 3 is affected by factors in year 2 as well as factors in year 3. The fuzzy BN is the combination of fuzzy set theory and BNs, which has more strengths in dealing with uncertainties related to CM as compared to the traditional BN (Zhang *et al.*, 2016).

Variable A	T	F
Probability	0.3	0.7

Variable B	T	F
Probability	0.1	0.9

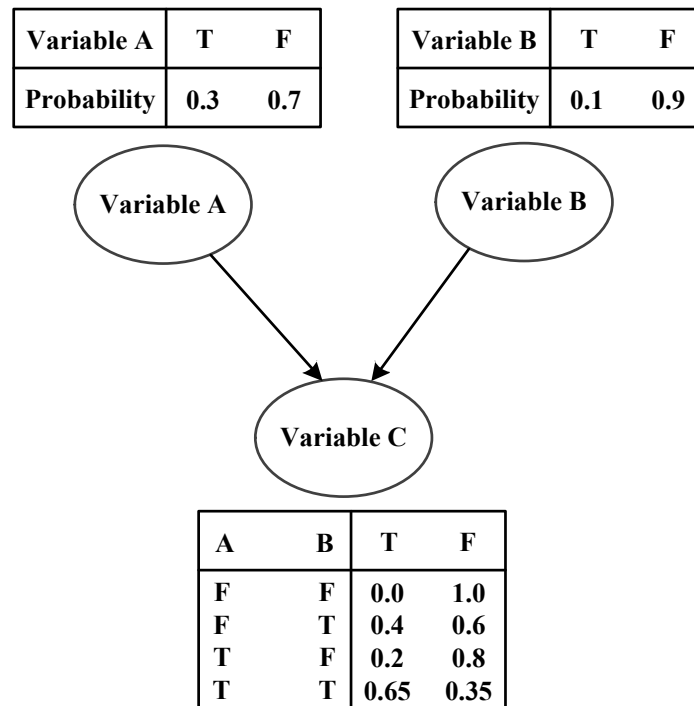| A	B	T	F
F	F	0.0	1.0
F	T	0.4	0.6
T	F	0.2	0.8
T	T	0.65	0.35

Fig. 1 An example of a BN structure and the conditional probability tables (CPT)

3. Research methodology

A systematic literature review mainly contains three stages including planning (e.g., formulating the review questions and the search strategy), conducting (e.g., literature searching, primary studies selection and data extraction), and reporting (e.g., synthesis and summary the results) (del Águila and del Sagrado, 2016). The research processes for conducting this systematic review are described as follows.

3.1 Databases and search terms

Google scholar was first used to have a general understanding of the application of Bayesian approaches in CM, thus helping us to select databases and search terms. Results showed that most journals that published the application of Bayesian approaches in CM are from Scopus and Web of Science (WoS). Therefore, the literature search commenced with these two databases, which also cover the mainstream CM journals (Hu *et al.*, 2016). Science-Direct and Emerald Insight also were checked to ensure the comprehensiveness of the literature search. All databases were searched from their start date until the end of June 2020. Relevant articles from these databases were searched by using a combination of ('Bayes*' OR 'belief network') and ('construction industry' OR 'construction project' OR 'construction management' OR 'engineering management' OR 'building management' OR 'building project' OR 'building industry' OR 'project management' OR 'infrastructure'). The search terms "project management" and "infrastructure" contain a large number of papers and most of them may not be associated with CM. As such, the search term "construction" also was required to limit the scope of searching articles. The asterisk "*" was used to include all the Bayesian approaches. The title, abstract and keywords of articles were scanned for the search terms.

3.2 Inclusion criteria

Two inclusion criteria were employed to select articles for further analysis. First, consistent with the systematic review conducted by Chan *et al.* (2020a), the publication should be written in English and appear in academic journals as an article (which excludes books, conference proceedings, reports, reviews). Second, the article needed to make use of Bayesian approaches in CM-related research. Therefore, articles focusing on topics such as structural or material performance analysis, real estate appraisal, and housing market research were excluded.

3.3 Selection process

A total of 563 articles were initially identified and imported into EndNote X9 to identity duplicated articles. In the first selection round, 303 articles were eliminated for duplication and 260 articles remained. After examining the titles and abstracts of the studies and applying the inclusion criteria in full text screening, 154 articles were deleted because they were irrelevant to CM. Thus, 106 articles published in 52 journals, most of which were construction and engineering journals, were retained for review. In the second selection round, the literature search was widened to the back catalogues of these 52 journals by using single term "Bayes*". This step uncovered another 42 articles that applied Bayesian approaches on CM areas but did not explicitly use keywords ('construction industry' OR 'construction project' OR 'construction management' OR 'engineering management' OR 'building management' OR 'building project' OR 'building industry' OR 'project management' OR 'infrastructure') in the title/ abstract/ keywords. Reference lists of the final 148 articles also were cross-checked, but no more relevant article was found. Thus, 148 articles were included for systematic review.

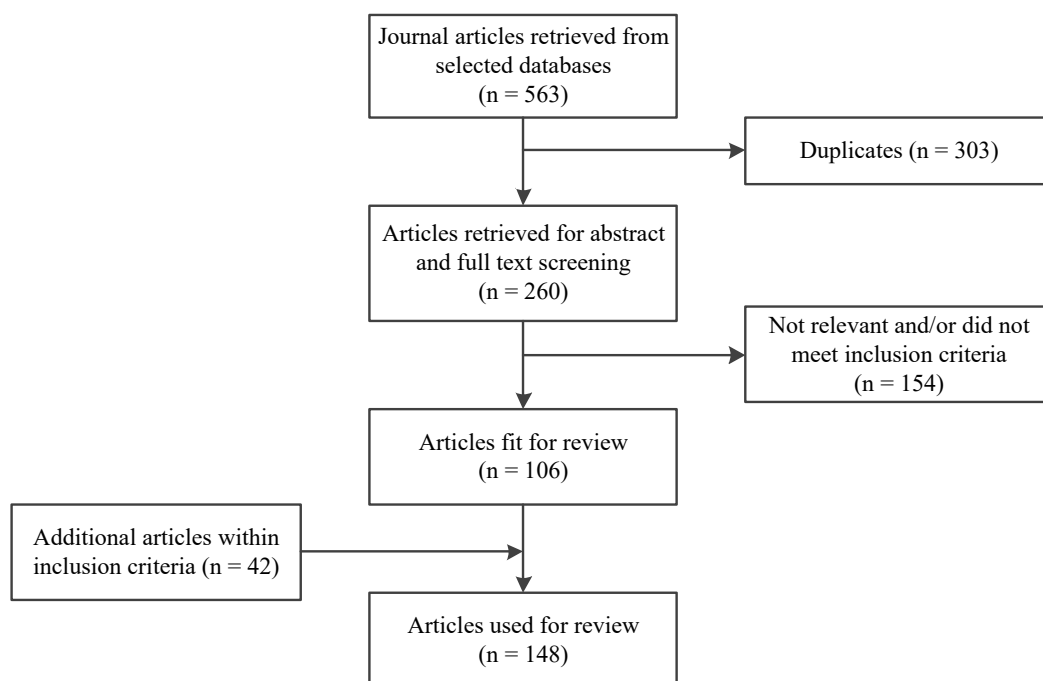**Fig. 2** shows the processes of eligible articles screening.

Fig.2 The flow chart of eligible articles screening

3.4 Synthesis methods

The data extraction of each article was recorded in an Excel file and thoroughly examined to ensure the consistency of information extraction criteria. Synthesis of the articles consisted of five parts. First, publication trends of articles were identified by extracting information such as journal sources and publication years. Second, the application fields of Bayesian approaches in CM research were categorized using Kang *et al.* (2018) 12 functional areas of CM. Then, the usage of Bayesian approaches was divided into BN modeling methods and other specific Bayesian methods. Last, BN model development activities and different types of BN reasoning were investigated. When the classification of an article was not clear, it was discussed among the research team until a consensus was reached.

4. Results

4.1 Research Trends

4.1.1　Journal distribution

The 148 articles were published in 52 different journals in multiple domains, reflecting the wide applicability of Bayesian approaches for a wide spectrum of CM functional areas and topics. **Table I** shows the journal distribution of the articles, with the majority of them from the construction engineering. Only journals with at least two articles were individually listed in **Table I**. For those with only one selected article, they were grouped into the category "Others" in **Table I** (the details of these journals are shown in **Appendix 1**). ASCE Journal of Construction Engineering and Management published the largest number of the articles (17 articles), followed by Journal of Computing in Civil Engineering (10 articles), Reliability Engineering and System Safety (8 articles), Journal of Civil Engineering and Management (7 articles), and Safety Science (7 articles).

Table I
Journal distribution of the articles.

Code	Journal title	Number of articles	SJR 2019*
1	Journal of Construction Engineering and Management	17	1.04 (Q1)
2	Journal of Computing in Civil Engineering	10	0.95 (Q1)
3	Reliability Engineering and System Safety	8	1.93 (Q1)
4	Journal of Civil Engineering and Management	7	0.54 (Q2)
5	Safety Science	7	1.24 (Q1)

6	Automation in Construction	6	1.69 (Q1)
7	Expert Systems with Applications	6	1.49 (Q1)
8	Risk Analysis	6	1.09 (Q1)
9	Computer-Aided Civil and Infrastructure Engineering	5	1.87 (Q1)
10	Tunnelling and Underground Space Technology	5	1.97 (Q1)
11	Structure and Infrastructure Engineering	4	1.06 (Q1)
12	Canadian Journal of Civil Engineering	4	0.35 (Q2)
13	International Journal of Project Management	4	2.66 (Q1)
14	Mathematical Problems in Engineering	4	0.28 (Q2)
15	Advanced Engineering Informatics	3	0.95 (Q1)
16	Construction Management and Economics	3	0.87 (Q1)
17	Engineering, Construction and Architectural Management	3	0.68 (Q1)
18	International Journal of Environmental Research and Public Health	3	0.74 (Q2)
19	KSCE Journal of Civil Engineering	3	0.47 (Q2)
20	Sustainability (Switzerland)	3	0.58 (Q2)
21	Accident Analysis and Prevention	2	1.69 (Q1)
22	International Journal of Construction Management	2	0.57 (Q2)
23	International Journal of Occupational Safety and Ergonomics	2	0.32 (Q2)
24	Journal of Engineering, Design and Technology	2	0.32 (Q2)
25	Revista de la Construccion	2	0.21 (Q3)
26	Others	27	
Total		148	

*SJR 2019 = Scimago Journal & Country Rank 2019

4.1.2 Years of publication

Fig. 3 shows the trend for years of publication. The year 2019 had the highest number of articles (20 articles). It should be noted that the 18 articles in 2020 were selected until the end of June. There was a sharp decrease in the number of publications in 2010. After that, although the number fluctuated slightly in 2015 and 2016, the overall trend was going upward. Moreover, Bayesian approaches have gained more attention in CM since 2014.

Fig. 3 Publication trend in years
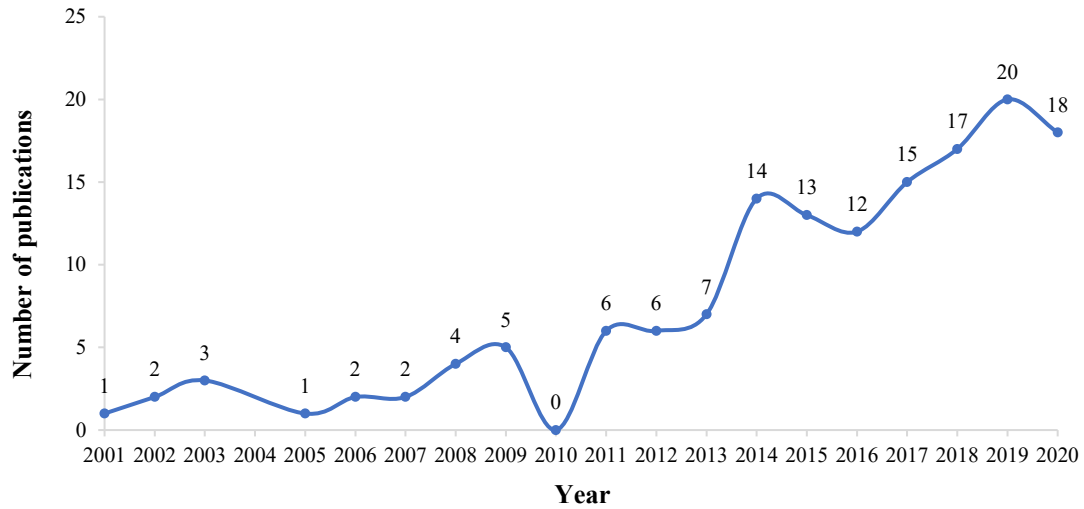
4.1.3 Locations where the research was conducted

Fig. 4 shows the location distributions where research of the selected publications was conducted in 33 different locations. Results indicated that CM research using Bayesian approaches were mostly conducted in the Mainland China (36 articles), followed by the USA (18 articles), Canada (14 articles), and Iran (13 articles).
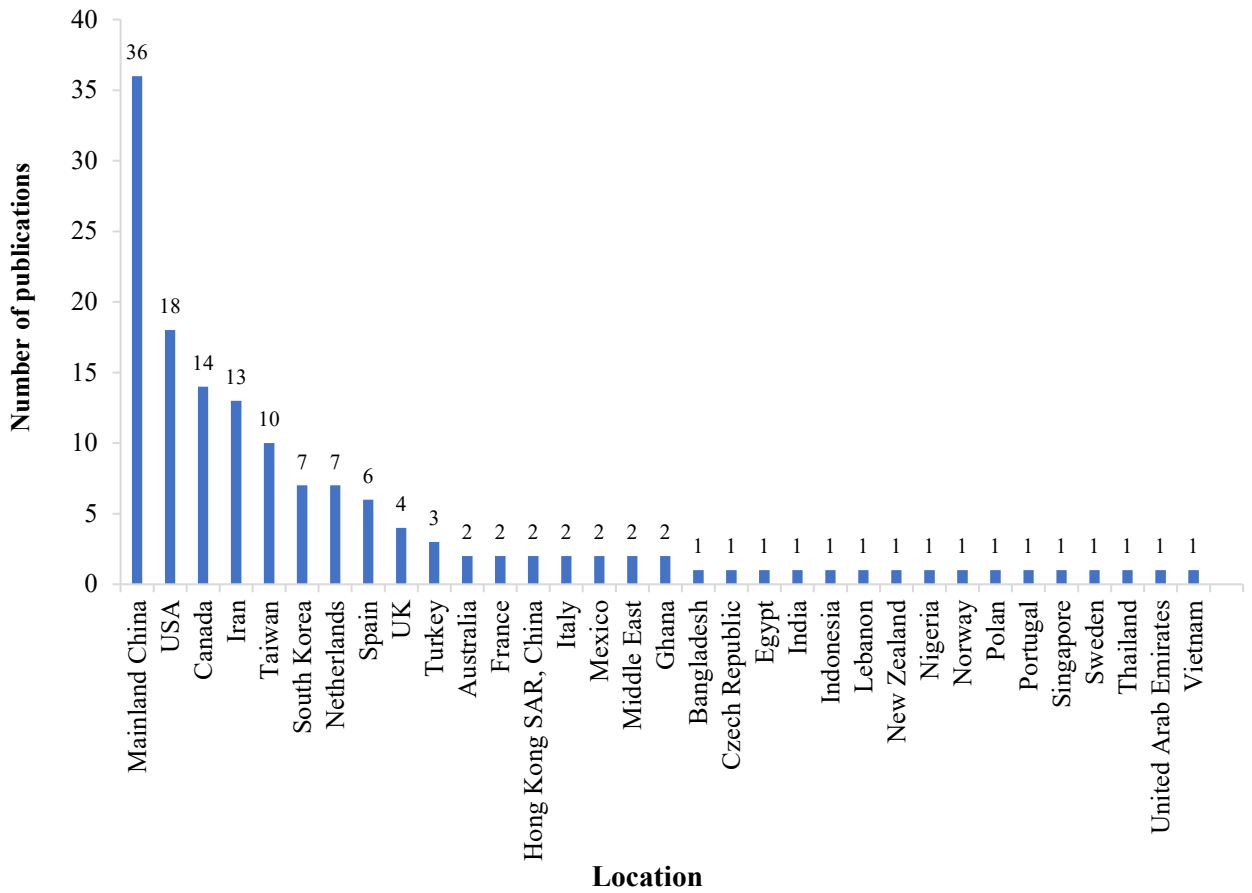
Fig. 4 Location distributions

4.2 Applications of Bayesian approaches in CM functional areas

We mapped the 148 articles against 12 CM functional areas as defined by Kang *et al.* (2018) to identify the major areas of Bayesian application in CM research. These articles spread across 11 out of 12 CM functional areas (**Appendix 2**). Bayesian approaches were most frequently applied in safety management (50 articles), followed by risk management (44 articles), contract management (18 articles), and process control (15 articles), demonstrating the merits of Bayesian approaches to deal with uncertainties and the interdependencies of multiple factors.

4.2.1   Safety management

The application of Bayesian approaches on safety management is mainly in four areas, namely factors affecting safety performance, selection of effective safety management strategies, safety supervision, and other safety-related topics.

Of the 50 articles using Bayesian approaches on safety management, 34 of them (i.e., 68%) analyzed   multiple   factors   influencing   safety   performance.   For   example,   BN   can

probabilistically represent the relationship between safety climate and safety performance even if the relationship is non-linear (Chan *et al.*, 2018; Zhou *et al.*, 2008), overcoming the drawback of structural equation modeling (SEM), which is suitable to predict linear relationships (Chan *et al.*, 2018). Xia *et al.* (2018) integrated BN and Human Factors Analysis and Classification System to proactively predict how organizational, environmental, and human factors affect safety performance. By considering the function of time, dynamic BN was adopted to analyze human errors over time, which has advantages of modeling the evolution of probabilistic relationships and fault tolerance for abnormal data compared to static BN (Ma *et al.*, 2019). Thus, Bayesian approaches (especially BNs) are useful for analyzing different levels of factors and transferring their complicated relationships into probabilistic networks.

Bayesian approaches also were utilized for selecting effective safety management strategies. Due to the ability to anticipate the influence of changes in some variables on other variables, BNs can be applied to choose effective intervention strategies through sensitivity analysis and Bayesian updating (Mofidi *et al.*, 2020; Ghasemi *et al.*, 2017; Mohammadfam *et al.*, 2017). Hierarchical Bayesian models have various levels and can be used to evaluate the efficacy of safety hazard control measures from more comprehensive perspectives (Luo *et al.*, 2017; Van Deurssen *et al.*, 2015).

For safety supervision, assembling Convolutional Neural Network classifiers in a Bayesian framework has a great potential for monitoring construction workers' safety compliance (e.g., using personal protective equipment) (Nath *et al.*, 2020). Due to the ability to deal with few data, and continuously update the probability, Bayesian approaches can be used to monitor the hazard state of workers (Luo *et al.*, 2014). Other safety-related topics include life-cycle safety control (Zhang *et al.*, 2013), safety design (Borg *et al.*, 2014), and extracting recurrent scenarios from narrative texts for accident diagnosis (Abdat *et al.*, 2014), all proved the utility of Bayesian approaches.

Existing Bayesian applications in safety management research relate mainly to a few physical hazards. The full potential of Bayesian approaches to analyze the interdependencies of a wide range of physical and psychosocial hazards is yet to be exploited. Existing Bayesian research on safety performance has mainly adopted a static approach, whereas the potential to use dynamic BNs to capture the changes of safety performance overtime (e.g., before and after implementation of safety interventions or in different project phases) has been under-utilized.

4.2.2   Risk management

Risk assessment is the most popular application field of Bayesian approaches in risk management. BN has advantages of showing the propagation influence of risks in a network and updating the interdependency among risks when new information is available, overcoming the limitation of SEM, artificial neural networks and other simulation techniques in analyzing risks (Qazi *et al.*, 2020). Therefore, it has been widely applied to risk assessment in construction-related research (Liu *et al.*, 2019; Sun *et al.*, 2018; Eshtehardian and Khodaverdi, 2016; Wu *et al.*, 2015a). The integration of a normal Cloud model and BN for risk assessment allows to discover structure automatically from data and develop network dynamically, which predicts risks better than conventional BNs (Chen *et al.*, 2020). Beyond the assessment of single project risks, BN also can be used to model and analyze portfolio risks (Ghasemi *et al.*, 2018).

Risk assessment includes two main processes: estimating the occurrence probability and impacts of certain events in order to calculate risk (Tah and Carr, 2000). Some studies adopted Bayesian approaches to calculate risk occurrence probabilities based on their interactions (Wang and Zhang, 2018; Castaldo *et al.*, 2018; Novi, 2018; Špačková and Straub, 2013), but their impacts/severity were overlooked. Therefore, in order to overcome this drawback, Namazian and Haji Yakhchali (2018) presented an equation to evaluate the aggregated impact of project portfolio risk on time and cost. Qazi and Dikmen (2019) introduced new risk metrics to capture the holistic impact of each risk. Wang *et al.* (2014) proposed a hybrid approach based on BN and a Relevance Vector Machine (RVM), which can identify risk scenarios and quantify the probability and severity of possible risks.

Although Bayesian approaches have been widely applied to manage risks in construction-related research, the interaction and propagation of risks throughout the whole lifecycle of construction projects is relatively understudied (Xia *et al.*, 2017). To solve this, Xia *et al.* (2017) proposed a modified BN to consider risk propagation in different stages. The ranked nodes/paths and Bayesian truth serum also were adopted to facilitate model quantification and reduce the bias of subjective data. In addition, most studies focus on the specific risk management process (e.g., risk identification, risk assessment), but neglect the integration of all risk management processes (Qazi *et al.*, 2016). Thus, Qazi *et al.* (2016) introduced a comprehensive risk management process namely 'Project Complexity and Risk Management (ProCRiM)' based on the theoretical framework of Expected Utility Theory and BNs,

establishing causal paths across project complexity attributes, risks and their consequences affecting the project objectives. This process also can be used throughout the lifecycle of construction projects.

Bayesian approaches for risk management have been applied to various types of projects, such as excavation projects (Wang *et al.*, 2014; Cárdenas *et al.*, 2014b; Cárdenas *et al.*, 2014a; Castaldo *et al.*, 2018), deep foundation pit construction (Zhou and Zhang, 2011), buried infrastructure (Kabir *et al.*, 2018), and high-speed rail projects (Xue and Xiang, 2020). For these projects, the historical data are limited and difficult to obtain. Bayesian approaches are able to combine both objective data from field observation and subjective data from expert knowledge, which can improve the quality of input data and achieve a relatively high assessment precision even with a small number of samples (Wang and Zhang, 2018; Zhou and Zhang, 2011).

Generally, applying Bayesian approaches to risk management still has room for improvement in dynamic risk management (i.e., covering all stages of the project), whole process risk management (i.e., covering all steps of risk management), and comprehensive consideration of the risk occurrence probability and impact degree.

4.2.3   Contract management

Bayesian approaches were used in contract management field to analyze construction contractual risks, deal with disputes, improve the effectiveness of bidding decisions and the efficiency of required contractual text extraction. A total of 18 articles applied Bayesian approaches in contract management.

For construction contractual risks, Adams (2006) analyzed them by combining Bayesian analysis and an expert elicitation model. This method was then applied to a case study, which assessed the probability of payment delays and the impact of the payment delay risk on projects (Adams, 2008).

In terms of dispute resolution, Karakas *et al.* (2013), Ren *et al.* (2003), and Ren and Anumba (2002) adopted Bayesian learning method to develop a multi-agent system for construction claims negotiation, which allows agents to estimate their opponents' key negotiation data and update the estimation with incomplete information. Bayesian approaches also were used to forecast PPP projects dispute resolutions during different project phases (Chou, 2012). Lu *et*

al. (2016) applied Bayesian learning to simulate the dynamic bargaining process for construction claim negotiations. Bayesian fuzzy-game model was applied to improve the effectiveness of negotiation in construction procurement (Leu *et al.*, 2015c; Leu *et al.*, 2015b; Leu *et al.*, 2015a).

A competitive tender bid increases the probability of winning a construction project. However, the accuracy of bidding models can be influenced by incomplete competitors' historic bid data and the dynamic behavior of competitors. To overcome these problems, Abotaleb and El-Adaway (2017) presented an advanced bidding model based on a Bayesian framework to estimate the optimum markup in future bids. The Bayesian statistical method can be used for the correlated competitive bidding model to quantity uncertainties and their effects on markup decisions (Yuan, 2012). The Naïve Bayes and the Bayesian Markov Chain Monte Carlo model were applied to screen a good project and determine the optimum tender price, respectively (Jang *et al.*, 2015; Kim *et al.*, 2014).

In order to improve the efficiency of identifying contractual requirements from construction contract documents, Hassan and Le (2020) adopted machine learning algorithms (including Naïve Bayes) to develop models to automatically extract the required contractual text.

Further studies are needed to explore the application of Bayesian approaches in contract management, such as expanding the influence of single contractual risk to a set of contractual risks in a construction project, and applying the established model to more scenarios (e.g., different types of construction projects and market conditions).

4.2.4   Process control

Process control includes various activities, such as management of project schedule, productivity, and resource allocation for achieving project success. 15 articles were identified as the application of Bayesian approaches in process control.

Managing a project schedule is an important activity in process control. Bayesian approaches have been mainly used for predicting the schedule performance of construction projects (Sabillon *et al.*, 2020; Špačková *et al.*, 2013). Conducting schedule prediction in the early stage of a construction project is likely to be more useful than that in the later stage (Pareek *et al.*, 2016). However, objective and reliable performance data are limited early in the project (Kim and Reinschmidt, 2009). Bayesian approaches are suitable for solving such problems due to

the ability to incorporate different sources of information (Luu *et al.*, 2009; Kim and Reinschmidt, 2009). Bayesian updating technique was proposed to constantly update the change in data during the construction process for a relatively precise schedule estimation (Pareek *et al.*, 2016; Zhang *et al.*, 2014b; Gardoni *et al.*, 2007).

As to productivity management during process control, Bayesian approaches can be used to predict the overall productivity (Ko and Han, 2015), and quantify the influencing factors of the false erection productivity (Tischer and Kuprenas, 2003). Other applications of Bayesian approaches in process control, such as predicting the success of the construction project implementation process (Cheng *et al.*, 2013), improving the quality of construction process simulation (Chung *et al.*, 2006), progress monitoring (Golparvar-Fard *et al.*, 2015), and performance measurement (McCabe and AbouRizk, 2001), also were identified.

Although Bayesian approaches have been adopted in the above areas of process control, the application in each area still needs to be further investigated in different contexts. There also is limited application of Bayesian approaches for efficient allocation of resources and the workforce in specific construction projects, which might be a new research direction in process control.

4.2.5 Project cost management

Eight articles applied Bayesian approaches in the cost management domain. In specific, Bayesian regression (Nasrazadani *et al.*, 2017), BBN (Attoh-Okine, 2002), the combination of Bayesian inference and Bayesian model averaging (Kim and Reinschmidt, 2011) have been used for cost prediction. Bayesian approaches can be adopted to forecast the probability of errors associated with cost estimation (Hwang, 2016) and establish the collaborative decision-making model to improve cost estimation (Xue and Jin, 2016). Two articles applied Bayesian regularization to develop neural networks for construction cost estimation (Arabzadeh *et al.*, 2018; Sonmez, 2011). Dynamic BNs were proposed to predict the probability of future damage and maintenance budget for bridge components, taking into account the correlation among failure events (Cho *et al.*, 2014).

There is a lack of research applying Bayesian approaches for dynamic monitoring and prediction of construction costs across the whole project cycle. Dynamic Bayesian approaches have great potential to predict variations in project costs and develop a cost management plan.

It also is feasible to integrate Bayesian approaches with other construction technology and tools (e.g., BIM, i.e., building information modeling) to improve the efficiency of cost management.

4.2.6 Quality management

Five selected articles utilized Bayesian approaches in quality management. Specifically, Yu *et al.* (2019) evaluated the impacts of stakeholders on the occurrence of quality defects in offsite construction projects by using BN. Movaghar and Mohammadzadeh (2019) presented the intelligent index for railway track quality evaluation based on Bayesian approaches. Bayesian inference was used in pipe frication or welding for evaluating operator welding-quality performance (Ji *et al.*, 2019), and improving quality management practices (Ji and Abourizk, 2018; Ji and AbouRizk, 2017).

Current research on Bayesian approaches to quality management is mainly limited to very narrow types of projects or construction work, such as offsite construction projects, railway, and welding. Thus, the Bayesian application on quality management has potential to be expanded to other areas. For example, there have been many studies on building materials after the Grenfell Tower Fire. Bayesian approaches could be applied to examine building materials compliance for fire safety. Furthermore, while there has been research using Bayesian approaches to develop quality indices, originating factors causing quality problems in construction projects awaits further investigation (Movaghar and Mohammadzadeh, 2019).

4.2.7 Others

Bayesian approaches have great application potentials for other CM research and practice. Along with the applications mentioned above, Bayesian approaches have been used in design management (improving the accuracy of clash detection; selecting the best design solution and optimize design parameters for the design; predicting the benefits of virtual design and construction) (Hu and Castro-Lacouture, 2019; Rischmoller *et al.*, 2012; Naticchia *et al.*, 2007), project information management (recognizing workers' activities in far-field surveillance videos, learning and classifying actions of construction workers and equipment) (Luo *et al.*, 2019; Gong *et al.*, 2011), environment management (analyzing behavioral determinants towards construction waste management) (Bakshan *et al.*, 2017), materials management (acquisition and disposal of construction equipment) (Liu *et al.*, 2020), and stakeholder management (analyzing the relationship between political skill and emotional intelligence for managing stakeholder relationships) (Sunindijo and Maghrebi, 2020).

4.3 The usage of Bayesian approaches

As shown in **Fig. 5**, 91 out of 148 (61%) articles applied BN modeling methods, including various forms of models based on BN, namely fuzzy Bayesian network, dynamic BN, non-parametric BN, hierarchical probabilistic relational models (a relational extension of BNs), fuzzy canonical model (a combination of fuzzy logic and a modified BN), fuzzy comprehensive BN (a combination of fuzzy comprehensive evaluation method and BN), multiply connected belief network, and Bayesian fuzzy-game model. As BN modeling methods are the most commonly employed in CM research, the next section will focus on these in detail to identify trends and opportunities for future research.
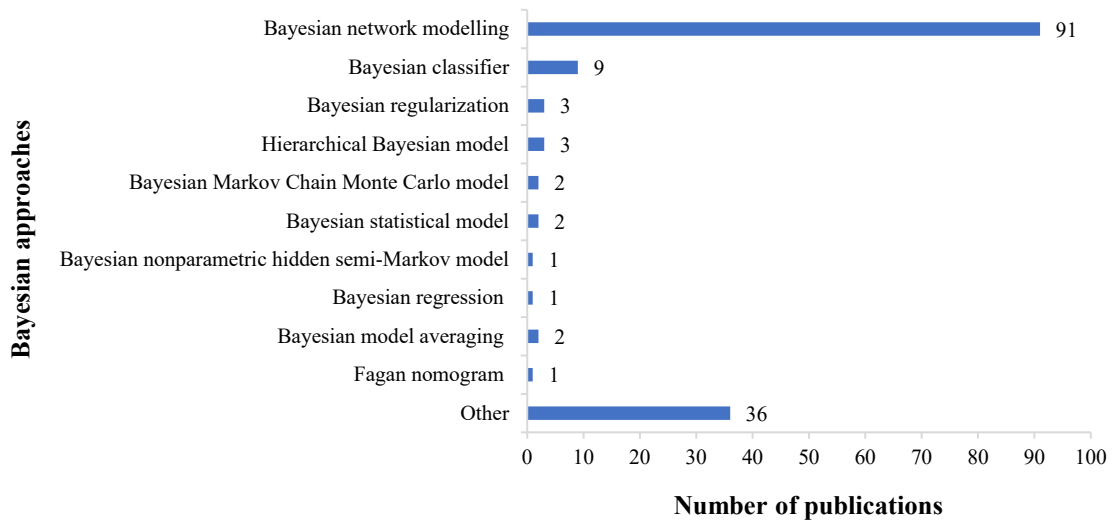
Fig. 5 Bayesian approaches classification

Another nine articles applied the Bayesian classifier, in which eight used the Naïve Bayes classifier and one adopted Tree-augmented Naïve Bayesian classifier. Although these classifiers are regarded as simple forms of BN (Gong *et al.*, 2011), they were not classified as BN modeling methods in our systematic review, because they were mainly used as machine learning algorithms for probability computation based on objective data in reviewed articles.

Three articles applied Bayesian regularization to the neural network for reducing the over fitting of model. Some other Bayesian models also were identified, including hierarchical Bayesian model, Bayesian Markov chain Monte Carlo model, Bayesian statistical model, Bayesian nonparametric hidden semi-Markov model, and Bayesian regression model. For the

purposes of this systematic review, the difference between BN modeling methods and these Bayesian models is that the latter are dedicated to parameter estimation while the former focuses on both structural and parameter learning. Bayesian model averaging is for model selection based on Bayesian inference (Kim and Reinschmidt, 2011). Fagan nomogram incorporates Bayes theorem and presents it in the form of nomogram (Ma *et al.*, 2020). It should be noted that, although some articles used different terms (e.g., Bayesian updating, Bayesian probability method, Bayesian statistics), they were all based on the Bayesian inference. As such, these methods were grouped as "other".

In addition, Bayesian approaches were incorporated into other techniques or applied separately for different objectives, such as BIM (Hu and Castro-Lacouture, 2019), multi-agent systems (Karakas *et al.*, 2013), and SEM (Zhao *et al.*, 2020), which shows the great flexibility and application potential of Bayesian approaches.

4.4 Model development activities and reasoning with BN modeling methods

This part focuses on analyzing those 91 articles that applied BN modeling methods. The main steps to build a BN model have been presented in section 2. This section discusses how the model construction and validation issues have been addressed and the reasoning with BNs in CM-related research.

4.4.1   BN model construction methods

The majority of the articles identified variables of the model through literature reviews and interviews with experts. These two methods can provide historical data and field data, respectively. Based on Phan *et al.* (2016), six sources were identified to construct DAG and calculate the CPTs (as shown in **Table II**). Expert knowledge includes the judgment of academics and industry professionals. Objective data refers to field or observational data collected by authors directly or derived from databases, records, and the scientific literature. Model simulation represents outputs of other established models or frameworks, such as Fault Trees Analysis and influence diagrams.

Table II

Data sources of model development.

Data sources	Number of publications			
	DAG	%	CPT	%

Expert knowledge	44	48.35	51	56.04
Objective data	6	6.59	21	23.08
Model simulations	4	4.407	1	1.10
Expert knowledge + objective data	24	26.37	18	19.78
Expert knowledge + model simulations	10	10.99	0	0
Expert knowledge + objective data + model simulations	3	3.30	0	0
Total	91	100	91	100

Expert knowledge was used frequently for both the development of DAG and CPT in CM research, accounting for 48% and 56% of the articles, respectively. Expert knowledge is valuable because it can be treated as a preliminary model to help observers to develop their knowledge and collect data more efficiently (Low-Choy *et al.*, 2014). It is necessary to conduct expert knowledge elicitation in a systematic and well-structured way (Low-Choy *et al.*, 2014). This phenomenon could be explained by difficulties in accessing abundant data for the uncertain and changeable characteristics of construction environment (Luo *et al.*, 2017; Chua and Goh, 2005; Zhang *et al.*, 2016). Expert knowledge can be used when a large number of data were inaccessible. However, there is criticism about the subjectivity of the obtained data (Kabir and Papadopoulos, 2019; Wang and Zhang, 2018). In addition, the elicitation of data from expert knowledge may be inconsistent when the model is complex because some experts may not have profound knowledge of the research area and BN (Leu and Chang, 2013).

Contrary to elicitation from expert knowledge, data learning can be utilized when the objective data are extensive (Leu and Chang, 2013; Abdat *et al.*, 2014). Objective data were used in six articles for DAG construction and 21 articles for CPT computation. Among these, four algorithms for structural learning were identified, including PC algorithm, K2 algorithm, Naïve Bayes algorithm, and Tree Augmented Naïve Bayes algorithm. For parameter learning, Expectation-Maximization (EM) algorithm is the most popularly used, followed by Maximum Likelihood Estimation (MLE). EM algorithm is suitable for incomplete data while MLE is a

common strategy for parameter learning of complete data (Ji *et al.*, 2015). Some other articles may conduct algorithm learning, but these articles did not mention the specific algorithm employed. In practice, there may still be issues regarding the representativeness of data, which can be challenging in a complex CM system. These challenges might explain the trend to combine expert knowledge with objective data from other sources.

For model simulations, 12 articles converted Fault Tree Analysis to build BN structure, which also was frequently applied with expert knowledge across the articles. Output from interpretive structural modeling, Event Tree Analysis, and influence diagram also can provide references to determine the relationships among variables.

Some of the articles combined the data sources from expert knowledge, objective data, and model simulations. For DAG construction, 37 articles applied combined approaches, including 24 for "expert knowledge + objective data", ten for "expert knowledge + model simulations", and three of them combined all these data sources. As for CPT calculation, 18 articles applied "expert knowledge + objective data".

4.4.2 BN model validation methods

It is important to validate the reliability and effectiveness of the BN model to evaluate whether it is applicable to the specific research. Several model validation methods were identified (**Fig. 6**).
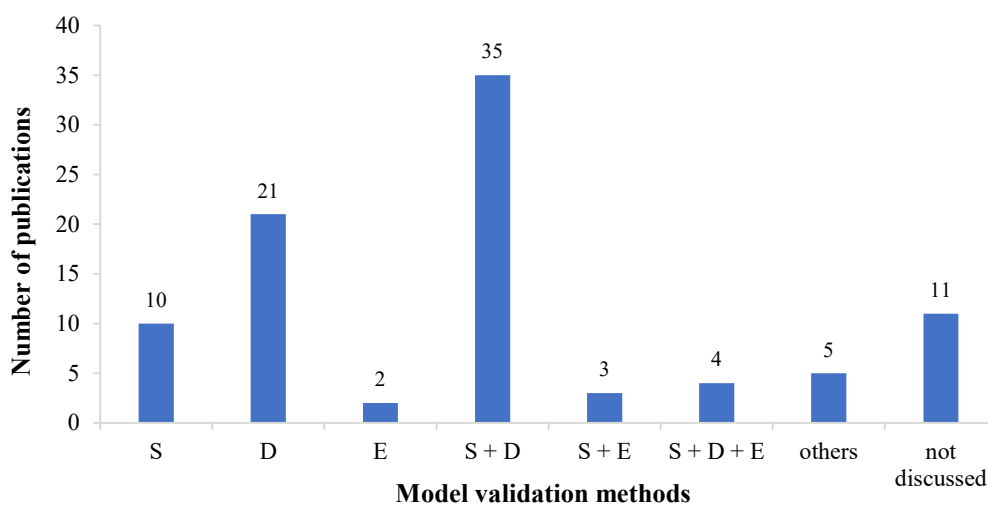
(Note: S = sensitivity analysis, D = data driven evaluation, E = expert evaluation)

Fig. 6 Model validation methods

Sensitivity analysis is one such validation method which can be used for various purposes (Phan *et al.*, 2016). For example, it can identify the influence of changing the parameter of one variable on the target variable in the system. Furthermore, it can ascertain the predictive validity of the model (Qazi *et al.*, 2020). Almost every BN can conduct sensitivity analysis. However, it may not comprehensively verify the reliability of the model (Liao *et al.*, 2018a). In practice, most researchers combine sensitivity analysis with other methods to validate the model. The combination of sensitivity analysis and data driven evaluation was the most frequently employed method to validate BN models in reviewed CM research. The results of sensitivity analysis also can be evaluated by experts based on their experience for model validation.

Data driven evaluation includes case studies, outcome comparisons with other models, cross validation, and other independent data testing. Among them, case studies (43 articles) were most commonly applied to verify the reliability of the proposed model, followed by cross validation (9 articles), and comparing with other results (7 articles). In addition to combining with other methods (39 articles), 21 articles validated the model only based on data driven evaluation. Around 66% of the articles applied data driven evaluation for model validation. Therefore, as long as there is sufficient data, this model validation method appears to be favoured by researchers.

47 articles (around 52%) used more than one method to validate the model. However, 11 articles did not discuss this step at all. This may be because there were insufficient data for evaluation. Another reason may be some of them were illustrative rather than applied research.

In addition, various other combinations of other methods were utilized to validate the model, including "partial validation + scenario analysis + sensitivity analysis" (Islam *et al.*, 2019), "extreme-condition test + scenario analysis + sensitivity analysis + partial validation + expert evaluation" (Kabir *et al.*, 2018), "Monte Carlo simulation + sensitivity analysis" (Eshtehardian and Khodaverdi, 2016), "discrepancy analysis + experts review + compute entropy and mutual information measures + sensitivity analysis" (Cárdenas *et al.*, 2014b), and "discrepancy analysis + experts evaluation + sensitivity analysis" (Cárdenas *et al.*, 2013). However, their usage has not been widely promoted in CM-related research.

4.4.3 Reasoning with BNs

As shown in **Fig. 7**, most of the 91 BN studies applied predictive reasoning (59 articles), with the output such as predicting the probability of cost overrun, time performance, and workplace accidents. The diagnostic function (3 studies) of BNs is relatively underutilized compared to prediction, with diagnosing the risk or accident scenarios and causes of poor performance as the output. 29 studies performed more than one reasoning to get different output from BNs.
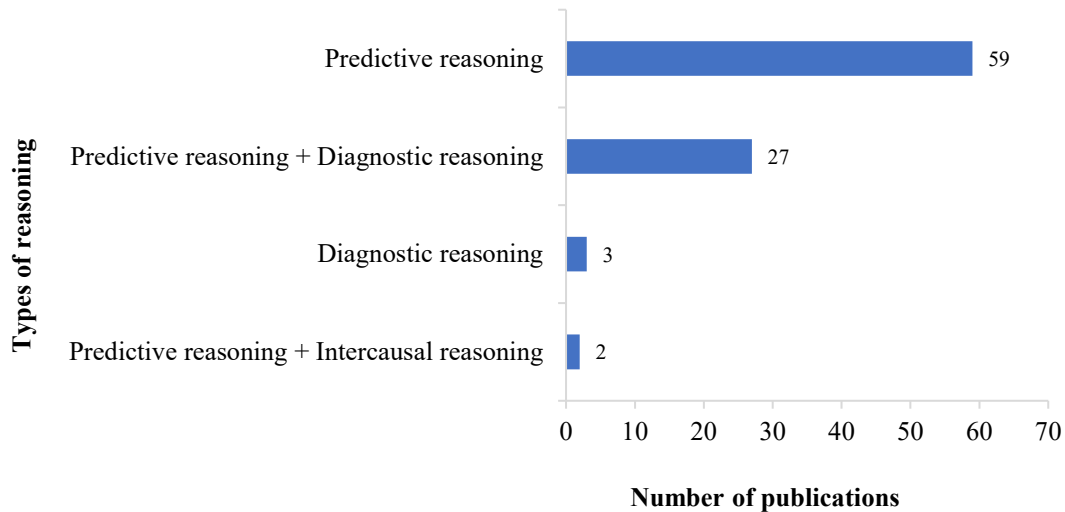

Fig. 7 Reasoning with BNs

5. Discussion

5.1 Applications of Bayesian approaches to CM research

5.1.1 Merits

Ability to deal with complex problems in CM with small and incomplete information. Research using Bayesian approaches was found in 11 CM functional areas, indicating that Bayesian approaches can be applied to solve various CM-related problems with real world implications for safety, productivity, project performance, and project costs. Because many CM research problems need to be tackled by complex modeling of multiple inter-dependent factors and uncertainties, Bayesian approaches can facilitate such modeling. Compared to the frequentist statistical approach, Bayesian approaches have the advantage of integrating data from various sources (e.g., expert knowledge, data learning, or their combination) for prior distributions (SAS, 2019), DAGs and CPTs construction (e.g., BNs), and ultimately achieve relatively accurate results even with scarce data (Zhou and Zhang, 2011), so they are useful in a complex CM system.

Well-suited to investigate risk in CM. The majority of Bayesian studies investigated safety management and risk management. In both fields, Bayesian approaches were mainly used to analyze influencing factors. These types of research are particularly suitable to use Bayesian approaches. Factors affecting safety and other business risks are likely to be complex and have uncertainties. Safety and risk experts have implicit knowledge that can be used as priors. Bayesian approaches allow convergence of these complex models which cannot be done in other ways (van de Schoot *et al.*, 2017). In addition, Bayesian approaches have the ability to quantitatively represent the relationships among variables in the form of probabilities, which can be updated when new information is obtained (Xia *et al.*, 2017). This aspect of Bayesian approaches is very useful to predict and control influencing factors in construction sites and support for more accurate and scientific decision-making.

Flexibility to be used along with other methods. Bayesian approaches could be combined with other methods to solve CM issues efficiently. This is mainly manifested in two aspects. One is flexible to import mathematical methods to improve the ability to organize and process data. For example, Markov chain Monte Carlo (MCMC) is commonly used with Bayesian approaches to determine the posterior distribution and draw random samples, which strengthens the predictive ability and statistical quality of Bayesian approaches (Ji and AbouRizk, 2017). The other aspect is flexible to combine with techniques such as BIM, the Geographic Information System (GIS), multi-agent systems, neural networks. This combination could expand the artificial intelligence and machine learning to the CM field. It also improves the applicability of Bayesian approaches in CM as combined application could take advantage of each method, thereby providing powerful tools to tackle complex CM issues.

5.1.2 Drawbacks and gaps to be addressed

The use of Bayesian approaches in CM domain is not free of drawbacks. It is worth exploring research gaps and providing insights and recommendations for future applications.

The potential of Bayesian approaches is not fully realized in many CM studies. While most studies examined multiple safety or risk factors, these factors may be from one particular facet instead of being multi-faceted. Although Bayesian approaches can still be applicable for single facet research with multiple factors, the power of Bayesian approaches can be better realized in more complex multi-faceted and multi-factorial research problems. In addition, some CM research problems are dynamic and would involve factors that change along the project

lifecycle, most of the existing Bayesian research in CM has ignored such project dynamics. It also is noticeable that Bayesian approaches when applied in safety management tend to be on organizational factors (e.g., safety climate). With the increasing interesting in psychological safety and health in CM research, there is potential to employ Bayesian approaches in this emerging research area. Moreover, there are potentials to employ Bayesian approaches to conduct finer modeling of potential hazards (forwards inference) and most likely causes of an adverse outcome (backwards inference) according to different roles/trades in the construction industry. As for risk management, most of the articles focused on risk assessment, whereas few of them considered all stages of the standard risk management processes. Bayesian approaches were frequently applied to calculate the probability of risk occurrences; however, the severity of risks was typically overlooked. And on a final note, the diagnostic reasoning of BNs has more space to be explored in CM, such as construction fault diagnosis and energy/materials consumption diagnosis.

Potential issues from relying on expert knowledge. In this systematic review, expert knowledge was the dominant source of information for DAG construction and population of CPTs across articles applied BN modeling methods. The high percentage indicates that, due to the incompleteness and limited availability of data for modeling in CM research, expert-based methods are usually employed to construct BN models. Although experts can have significant knowledge and experience in CM, they may still find it difficult to turn their tacit knowledge into quantitative data for determining the interdependencies of factors and their causal relationships in complex construction systems (Leu and Chang, 2015). In addition, the results may be biased and unreliable because of the subjective nature of the data. This problem may be particularly prominent if their inputs are not verified independently (Phan *et al.*, 2016). Researchers should be aware of this issue and determine strategies to overcome such weakness. Selection criteria should be carefully defined to minimize any potential bias from experts. Using a combination of data sources should be considered. For example, expert knowledge and model simulations can applied when data are scarce and unreliable for developing models (Phan *et al.*, 2016; Low-Choy *et al.*, 2014). Algorithms are then used to obtain the optimum model structure and calculate CPTs by collecting empirical data (Phan *et al.*, 2016). The combinations of these methods may be a mainstream trend in the future CM research to achieve more precise and flexible models.

Lack of established practice for Bayesian network model validation in CM research. Validation is an important process to check the reliability of models. However, 11 articles did not include this step. This may be due to the lack of data and some of them were illustrative rather than applied research. Indeed, it is an inherent problem for insufficient data applications (Mkrtchyan *et al.*, 2015), which may always be a challenge for a complex CM system. Most of the articles used case studies in model validation. It should be noted that, although case studies can play an important role in model validation when the field data are insufficient, every project is unique and its characteristics may not be able to be reflected in the validation process. Only a few articles used sensitivity analysis or expert evaluation alone to validate the model. The combination of various model validation methods is the main trend to improve the comprehensiveness and reliability of this step (Liao *et al.*, 2018a). There also has been work looking at different types of validation, in addition to conventional data-intensive validation, which may provide insights for enhancing the BN validation in CM research. For example, a novel and practical validation framework was proposed to robust the validation of expert knowledge-based BN by combining existing BN validation methods with validation tests from psychometrics (e.g., face validity, content validity, concurrent validity) (Pitchforth and Mengersen, 2013).

5.2 Future outlook

According to the findings and gaps discussed above, future research directions are suggested as follows.

5.2.1   Future potential CM topics for BN applications

For better applications in safety management, more indicators of safety performance can be considered in BN analysis, such as psychological factors of construction workers. Dynamic Bayesian methods can be applied to different stages of construction projects for safety risk analysis and explore the dynamic interaction between incidents and their causes by considering the time sequence (Murphy, 2002). Dynamic BN can more accurately represent safety accident scenarios under dynamic environment of construction projects. By introducing temporal nodes, changes to safety performance as a result of relevant factors influencing safety performance at the current time or in the past can be examined. Typically, the value of some factors influencing safety performance at time T will affect those at time T+1. The value of safety performance also will change over time because of the dynamic interactions with factors influencing safety performance (Ghahramani, 1997; Nwadigo et al., 2020). With recent technology advancement,

such as digital engineering, internet of things, sensors and wearable devices, Bayesian approaches also have potential to be applied to real-time safety monitoring and design for safety.

As for risk management, risks throughout the project life cycle need to be considered. In addition to risk assessment, the applications of Bayesian approaches in other risk management processes should be explored. Severity of risk factors is another topic that can be analyzed using Bayesian approaches. Bayesian optimization can be applied to minimize risks by optimizing risk occurrence probabilities and severity.

Future Bayesian applications can be extended to those under explored CM functional areas. For example, environment management, materials management, and stakeholder management. Bayesian approaches can model uncertain and complex ecosystem and environment management problem (Uusitalo, 2007) to help decision making and strategy formulation. Topics, such as building energy consumption, carbon emission of manufactured materials, lifecycle costing of sustainable construction, involve multi-facet factors are likely to be benefited from the advantages of using Bayesian approaches.

5.2.2   Future improvements of Bayesian approaches

Adopt more advanced Bayesian modeling techniques. Future research can consider more advanced Bayesian applications by combining Bayesian approaches with other statistical, mathematical, or simulation methods, such as BIM and multi-agent systems, to explore innovative application potentials. For example, Wu *et al.* (2014) integrated stochastic queuing theory with BN to model airport passenger facilitation. The same technique can be applicable to simulate the complex process of construction, investigating the causal relationships between different factors in a dynamic environment.

Validate Bayesian models. Future studies should explore more systematic and effective model validation methods, even with insufficient data. Incomplete data poses both an opportunity and an inherent challenge for the construction industry. It motivates the need for more sophisticated statistical methods to a large extent, such as Bayesian approaches. However, sometimes it is inevitable that subjective data are collected. Suitable methods would be needed to mitigate any bias for model development, such as evaluating the reliability of data elicited from expert knowledge before modeling and developing methods to automatically acquire data regarding different knowledge sources (Zhang *et al.*, 2016).

Follow good practice of Bayesian applications. CM researchers need to follow good Bayesian research practices to ensure research rigour, transparency, and replication. For example, Depaoli and van de Schoot (2017) developed the WAMBS-checklist to provide guidance for novice researchers on how to avoid misusing Bayesian statistics. Good reporting of Bayesian statistics needs to be encouraged. Bayesian approaches are still relatively new and unfamiliar to many CM researchers with frequentist statistics background. As Bayesian approaches are becoming more and more popular in CM research, it is important for CM researchers to be familiar with or at least be aware of good Bayesian research practices. This can be started during doctoral research education. Similar to frequentist statistics, Bayesian statistics can be considered to be included in the quantitative research training of higher degree research students.

6. Conclusions

Bayesian approaches are suitable to explore CM problems due to their capacities to solve uncertain and complex problems. This systematic review revealed that Bayesian approaches have been increasingly employed in CM research. They were applied in research across 11 CM functional areas, with safety management and risk management being the two most prevalent. BNs were the most commonly used Bayesian methods. In addition, due to the lack of field data, most BN models were built based on expert knowledge and validated by case studies. Prediction was the most popular types of reasoning with BNs, investigating outcomes such as cost overrun, performance, and workplace accidents. Moreover, research gaps of existing articles also were identified, including some application issues in CM functional areas, over-reliance on expert knowledge for BN model development, and lacking guides on BN model validation. To fill these gaps, future research directions and recommendations were proposed, including exploring the potential of Bayesian approaches in CM and how they combine with other methods to solve CM issues, evaluating subjective data, developing automatic data extraction method and systematic model validation method.

Overall, this systematic review provides a better understanding of the applications of Bayesian approaches in CM research and presents signposts for future research. Specifically, through the analysis of application trends and usage of Bayesian approaches, we have provided a general knowledge framework of Bayesian approaches for CM researchers. The description of model development activities not only provides the methods to build and validate a model, but also reflects the drawbacks of current applications of the BN model that need to be further enhanced

and improved. The classification of application fields shows where Bayesian approaches can be used and how they can be used in the CM domain. In conclusion, the findings and gaps identified in this systematic review will provide reference for future practice of Bayesian approaches.

Appendices

Appendix 1

Journals with one selected article

Code	Journal title	Number of articles	SJR 2018
1	Annals of Occupational Hygiene	1	/
2	Applied Ergonomics	1	1.24 (Q1)
3	Applied Soft Computing Journal	1	1.41 (Q1)
4	ARPN Journal of Engineering and Applied Sciences	1	0.24 (Q2)
5	Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM	1	0.41 (Q2)
6	ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering	1	0.64 (Q2)
7	BMC Public Health	1	1.20 (Q1)
8	Civil Engineering and Environmental Systems	1	0.52 (Q2)
9	Construction Innovation	1	0.60 (Q1)
10	Energy and Buildings	1	2.06 (Q1)
11	IEEE Transactions on Engineering Management	1	1.07 (Q1)
12	International Journal of Industrial Ergonomics	1	0.60 (Q2)
13	International Journal of Managing Projects in Business	1	0.84 (Q1)
14	International Journal of Simulation: Systems, Science and Technology	1	0.11 (Q4)
15	International Journal of Systems Assurance Engineering and Management	1	0.35 (Q3)
16	Journal of Asian Architecture and Building Engineering	1	0.24 (Q1)
17	Journal of Architectural Engineering	1	0.45 (Q1)
18	Journal of Cleaner Production	1	1.89 (Q1)
19	Journal of Industrial Engineering International	1	0.57 (Q2)
20	Journal of Legal Affairs and Dispute Resolution in Engineering and Construction	1	0.23 (Q2)
21	Journal of Management in Engineering	1	1.26 (Q1)
22	Journal of Research in Health Sciences	1	0.4 (Q3)
23	Nonlinear Dynamics	1	1.39 (Q1)
24	Quality and Reliability Engineering International	1	1.03 (Q1)

25	Resources, Conservation and Recycling	1	2.22 (Q1)
26	TECHNE	1	0.17 (Q2)
27	WSEAS Transactions on Business and Economics	1	0.13 (Q4)
Total		27	

Appendix 2

Bayesian approaches application fields in CM

Code	Application fields	No. of articles	References
1	Safety management	50	(Zhang *et al.*, 2020), (Nath *et al.*, 2020), (Mofidi *et al.*, 2020), (Ma *et al.*, 2020), (Guo *et al.*, 2020), (Chan *et al.*, 2020b), (Zhang *et al.*, 2019), (Wang *et al.*, 2019), (Pan *et al.*, 2019), (Mariscal *et al.*, 2019), (Ma *et al.*, 2019), (Zhou *et al.*, 2018), (Xia *et al.*, 2018), (Wang *et al.*, 2018), (Liao *et al.*, 2018b), (Liao *et al.*, 2018a), (Efe *et al.*, 2018), (Chan *et al.*, 2018), (Wang and Chen, 2017), (Mohammadfam *et al.*, 2017), (Martín *et al.*, 2017), (Luo *et al.*, 2017), (Ghasemi *et al.*, 2017), (Gerassis *et al.*, 2017b), (Gerassis *et al.*, 2017a), (Chen and Wang, 2017), (Zhang *et al.*, 2016), (Wang *et al.*, 2016), (Nguyen *et al.*, 2016), (Kabir *et al.*, 2016), (Jitwasinkul *et al.*, 2016), (Wu *et al.*, 2015b), (Van Deurssen *et al.*, 2015), (Papazoglou *et al.*, 2015), (Leu and Chang, 2015), (Alizadeh *et al.*, 2015), (Zhang *et al.*, 2014a), (Luo *et al.*, 2014), (Chen and Leu, 2014), (Borg *et al.*, 2014), (Abdat *et al.*, 2014), (Zhang *et al.*, 2013), (Leu and Chang, 2013), (Rivas *et al.*, 2011), (Suddle, 2009), (Martín *et al.*, 2009), (Zhou *et al.*, 2008), (Visscher *et al.*, 2008), (McCabe *et al.*, 2008), (Chua and Goh, 2005)
2	Risk management	44	(Zhao *et al.*, 2020), (Xue and Xiang, 2020), (Qazi *et al.*, 2020), (Luo *et al.*, 2020), (Gondia *et al.*, 2020), (Enshassi *et al.*, 2020), (Chen *et al.*, 2020), (Wen *et al.*, 2019), (Sharma *et al.*, 2019), (Qazi and Dikmen, 2019), (Namazian *et al.*, 2019), (Liu *et al.*, 2019), (Leśniak and Janowiec, 2019), (Islam *et al.*, 2019), (Chung *et al.*, 2019), (Baudrit *et al.*, 2019), (Wang and Zhang, 2018), (Sun *et al.*, 2018), (Novi, 2018), (Namazian and Haji Yakhchali, 2018), (Kabir *et al.*, 2018), (Ghasemi *et al.*, 2018), (Castaldo *et al.*, 2018), (Yu *et al.*, 2017), (Xia *et al.*, 2017), (Khanzadi *et al.*, 2017), (Qazi *et al.*, 2016), (Joko Wahyu Adi *et al.*, 2016), (Eshtehardian and Khodaverdi, 2016), (Wu *et al.*, 2015a), (Wang *et al.*, 2014), (Morales-Nápoles *et al.*, 2014), (Khodakarami and Abdi, 2014), (Delgado-Hernández *et al.*, 2014), (Cárdenas *et al.*, 2014b), (Cárdenas *et al.*, 2014a), (Špačková and Straub, 2013), (Cárdenas *et al.*, 2013), (Sousa and Einstein, 2012), (Matthews and Philip, 2012), (Zhou and Zhang, 2011), (Luu *et al.*, 2009), (Lee *et al.*, 2009), (Nasir *et al.*, 2003)
3	Contract management	18	(Hassan and Le, 2020), (Mahfouz *et al.*, 2018), (Abotaleb and El-Adaway, 2017), (Lu *et al.*, 2016), (Leu *et al.*, 2015c), (Leu *et al.*, 2015b), (Leu *et al.*, 2015a), (Jang *et al.*, 2015), (Kim *et al.*, 2014), (Karakas *et al.*, 2013), (Yuan, 2012), (Mahfouz and Kandil, 2012), (Chou, 2012), (Yuan, 2011), (Adams, 2008), (Adams, 2006), (Ren *et al.*, 2003), (Ren and Anumba, 2002)

4	Process control	15	(Sabillon *et al.*, 2020), (Ahmadu *et al.*, 2020), (Asiedu and Gyadu-Asiedu, 2019), (Pareek *et al.*, 2016), (Ko and Han, 2015), (Heravi and Eslamdoost, 2015), (Golparvar-Fard *et al.*, 2015), (Zhang *et al.*, 2014b), (Špačková *et al.*, 2013), (Cheng *et al.*, 2013), (Kim and Reinschmidt, 2009), (Gardoni *et al.*, 2007), (Chung *et al.*, 2006), (Tischer and Kuprenas, 2003), (McCabe and AbouRizk, 2001)
5	Project cost management	8	(Arabzadeh *et al.*, 2018), (Nasrazadani *et al.*, 2017), (Xue and Jin, 2016), (Hwang, 2016), (Cho *et al.*, 2014), (Sonmez, 2011), (Kim and Reinschmidt, 2011), (Attoh-Okine, 2002)
6	Quality management	5	(Yu *et al.*, 2019), (Movaghar and Mohammadzadeh, 2019), (Ji *et al.*, 2019), (Ji and Abourizk, 2018), (Ji and AbouRizk, 2017)
7	Design management	3	(Hu and Castro-Lacouture, 2019), (Rischmoller *et al.*, 2012), (Naticchia *et al.*, 2007)
8	Project information management	2	(Luo *et al.*, 2019), (Gong *et al.*, 2011)
9	Environment management	1	(Bakshan *et al.*, 2017)
10	Materials management	1	(Liu *et al.*, 2020)
11	Stakeholder management	1	(Sunindijo and Maghrebi, 2020)
Total		148	

References

Abdat, F., Leclercq, S., Cuny, X. & Tissot, C. 2014. Extracting recurrent scenarios from narrative texts using a Bayesian network: Application to serious occupational accidents with movement disturbance. *Accident Analysis and Prevention,* 70**,** 155-166.

Abotaleb, I. S. & El-Adaway, I. H. 2017. Construction bidding markup estimation using a multistage decision theory approach. *Journal of Construction Engineering and Management,* 143.

Adams, F. K. 2006. Expert elicitation and Bayesian analysis of construction contract risks: An investigation. *Construction Management and Economics,* 24**,** 81-96.

Adams, F. K. 2008. Risk perception and Bayesian analysis of international construction contract risks: The case of payment delays in a developing economy. *International Journal of Project Management,* 26**,** 138-148.

Ahmadu, H. A., Ibrahim, A. D., Ibrahim, Y. M. & Adogbo, K. J. 2020. Incorporating aleatory and epistemic uncertainties in the modelling of construction duration. *Engineering, Construction and Architectural Management.*

Alizadeh, S. S., Mortazavi, S. B. & Sepehri, M. M. 2015. Assessment of accident severity in the construction industry using the Bayesian theorem. *International Journal of Occupational Safety and Ergonomics,* 21**,** 551-557.

Arabzadeh, V., Niaki, S. T. A. & Arabzadeh, V. 2018. Construction cost estimation of spherical storage tanks: artificial neural networks and hybrid regression—GA algorithms. *Journal of Industrial Engineering International,* 14**,** 747-756.

Ashby, D. 2006. Bayesian statistics in medicine: A 25 year review. *Statistics in Medicine,* 25**,** 3589-3631.

Asiedu, R. O. & Gyadu-Asiedu, W. 2019. Assessing the predictability of construction time overruns using multiple linear regression and Markov chain Monte Carlo. *Journal of Engineering, Design and Technology,* 18**,** 583-600.

Attoh-Okine, N. O. 2002. Probabilistic analysis of factors affecting highway construction costs: A belief network approach. *Canadian Journal of Civil Engineering,* 29**,** 369-374.

Bakshan, A., Srour, I., Chehab, G., El-Fadel, M. & Karaziwan, J. 2017. Behavioral determinants towards enhancing construction waste management: A Bayesian Network analysis. *Resources, Conservation and Recycling,* 117**,** 274-284.

Baudrit, C., Taillandier, F., Tran, T. T. P. & Breysse, D. 2019. Uncertainty processing and risk monitoring in construction projects using hierarchical probabilistic relational models. *Computer-Aided Civil and Infrastructure Engineering,* 34**,** 97-115.

Bayes, T. 1991. An essay towards solving a problem in the doctrine of chances. 1763. *M.D. computing : computers in medical practice,* 8**,** 157-171.

Borg, A., Bjelland, H. & Njå, O. 2014. Reflections on Bayesian Network models for road tunnel safety design: A case study from Norway. *Tunnelling and Underground Space Technology,* 43**,** 300-314.

Cárdenas, I. C., Al-Jibouri, S. S., Halman, J. I. & Van Tol, F. A. 2013. Capturing and integrating knowledge for managing risks in tunnel works. *Risk Analysis,* 33**,** 92-108.

Cárdenas, I. C., Al-Jibouri, S. S. H., Halman, J. I. M., Van De Linde, W. & Kaalberg, F. 2014a. Using prior risk-related knowledge to support risk management decisions: Lessons learnt from a tunneling project. *Risk Analysis,* 34**,** 1923-1943.

Cárdenas, I. C., Al-Jibouri, S. S. H., Halman, J. I. M. & Van Tol, F. A. 2014b. Modeling risk-related knowledge in tunneling projects. *Risk Analysis,* 34**,** 323-339.

Castaldo, P., Jalayer, F. & Palazzo, B. 2018. Probabilistic assessment of groundwater leakage in diaphragm wall joints for deep excavations. *Tunnelling and Underground Space Technology,* 71**,** 531-543.

Chan, A. P. C., Nwaogu, J. M. & Naslund, J. A. 2020a. Mental ill-health risk factors in the construction industry: Systematic review. *Journal of Construction Engineering and Management,* 146.

Chan, A. P. C., Wong, F. K. W., Hon, C. K. H. & Choi, T. N. Y. 2020b. Construction of a Bayesian network model for improving the safety performance of electrical and mechanical (E&M) works in repair, maintenance, alteration and addition (RMAA) projects. *Safety Science,* 131**,** 104893.

Chan, A. P. C., Wong, F. K. W., Hon, C. K. H. & Choi, T. N. Y. 2018. A Bayesian network model for reducing accident rates of electrical and mechanical (E&M) work. *International Journal of Environmental Research and Public Health,* 15.

Chang, Y., Wu, X., Zhang, C., Chen, G., Liu, X., Li, J., Cai, B. & Xu, L. 2019. Dynamic Bayesian networks based approach for risk analysis of subsea wellhead fatigue failure during service life. *Reliability Engineering and System Safety,* 188**,** 454-462.

Chen, C., Zhang, L. & Tiong, R. L. K. 2020. A novel learning cloud Bayesian network for risk measurement. *Applied Soft Computing Journal,* 87.

Chen, T. T. & Leu, S. S. 2014. Fall risk assessment of cantilever bridge projects using Bayesian network. *Safety Science,* 70**,** 161-171.

Chen, T. T. & Wang, C. H. 2017. Fall risk assessment of bridge construction using Bayesian network transferring from fault tree analysis. *Journal of Civil Engineering and Management,* 23**,** 273-282.

Chen, X. W., Anantha, G. & Lin, X. 2008. Improving bayesian network structure learning with mutual information-based node ordering in the K2 algorithm. *IEEE Transactions on Knowledge and Data Engineering,* 20**,** 628-640.

Cheng, M. Y., Huang, C. C. & Roy, A. F. V. 2013. Predicting project success in construction using an evolutionary gaussian process inference model. *Journal of Civil Engineering and Management,* 19**,** S202-S211.

Cho, T., Kim, S. S. & Kim, T. S. 2014. A quadratic hierarchical Bayesian dynamic prediction model for infrastructure maintenance. *Nonlinear Dynamics,* 76**,** 609-626.

Chou, J. S. 2012. Comparison of multilabel classification models to forecast project dispute resolutions. *Expert Systems with Applications,* 39**,** 10202-10211.

Chua, D. K. H. & Goh, Y. M. 2005. Poisson model of construction incident occurrence. *Journal of Construction Engineering and Management,* 131**,** 715-722.

Chung, H., Lee, I. M., Jung, J. H. & Park, J. 2019. Bayesian networks-based shield TBM risk management system: Methodology development and application. *KSCE Journal of Civil Engineering,* 23**,** 452-465.

Chung, T. H., Mohamed, Y. & Abourizk, S. 2006. Bayesian updating application into simulation in the North Edmonton Sanitary Trunk tunnel project. *Journal of Construction Engineering and Management,* 132**,** 882-894.

Del Águila, I. M. & Del Sagrado, J. 2016. Bayesian networks for enhancement of requirements engineering: a literature review. *Requirements Engineering,* 21**,** 461-480.

Delgado-Hernández, D. J., Morales-Nápoles, O., De-León-Escobedo, D. & Arteaga-Arcos, J. C. 2014. A continuous Bayesian network for earth dams' risk assessment: an application. *Structure and Infrastructure Engineering,* 10**,** 225-238.

Depaoli, S. & Van De Schoot, R. 2017. Improving transparency and replication in Bayesian statistics: The WAMBS-checklist. *Psychological Methods,* 22**,** 240-261.

Efe, B., Kurt, M. & Efe, Ö. F. 2018. Hazard analysis using a Bayesian network and linear programming. *International Journal of Occupational Safety and Ergonomics*.

Enshassi, M. S. A., Walbridge, S., West, J. S. & Haas, C. T. 2020. Dynamic and proactive risk-based methodology for managing excessive geometric variability issues in modular construction projects using Bayesian theory. *Journal of Construction Engineering and Management,* 146.

Eshtehardian, E. & Khodaverdi, S. 2016. A Multiply Connected Belief Network approach for schedule risk analysis of metropolitan construction projects. *Civil Engineering and Environmental Systems,* 33**,** 227-246.

Gardoni, P., Reinschmidt, K. F. & Kumar, R. 2007. A probabilistic framework for Bayesian adaptive forecasting of project progress. *Computer-Aided Civil and Infrastructure Engineering,* 22**,** 182-196.

Gelman, A. 2013. *Bayesian data analysis,* Boca Raton, Florida, CRC Press.

Gerassis, S., Martín, J. E., García, J. T., Saavedra, A. & Taboada, J. 2017a. Bayesian decision tool for the analysis of occupational accidents in the construction of embankments. *Journal of Construction Engineering and Management,* 143.

Gerassis, S., Saavedra, Á., García, J. F., Martín, J. E. & Taboada, J. 2017b. Risk analysis in tunnel construction with Bayesian networks using mutual information for safety policy decisions. *WSEAS Transactions on Business and Economics,* 14**,** 215-224.

Ghahramani, Z. Learning dynamic Bayesian networks. International School on Neural Networks, Initiated by IIASS and EMFCSC, 1997. Springer, 168-197.

Ghasemi, F., Kalatpour, O., Moghimbeigi, A. & Mohammadfam, I. 2017. Selecting strategies to reduce high-risk unsafe work behaviors using the safety behavior sampling technique and bayesian network analysis. *Journal of Research in Health Sciences,* 17.

Ghasemi, F., Sari, M. H. M., Yousefi, V., Falsafi, R. & Tamošaitiene, J. 2018. Project portfolio risk identification and analysis, considering project risk interactions and using Bayesian Networks. *Sustainability (Switzerland),* 10.

Golparvar-Fard, M., Peña-Mora, F. & Savarese, S. 2015. Automated progress monitoring using unordered daily construction photographs and IFC-based building information models. *Journal of Computing in Civil Engineering,* 29.

Gondia, A., Siam, A., El-Dakhakhni, W. & Nassar, A. H. 2020. Machine learning algorithms for construction projects delay risk prediction. *Journal of Construction Engineering and Management,* 146.

Gong, J., Caldas, C. H. & Gordon, C. 2011. Learning and classifying actions of construction workers and equipment using Bag-of-Video-Feature-Words and Bayesian network models. *Advanced Engineering Informatics,* 25**,** 771-782.

Guo, S., He, J., Li, J. & Tang, B. 2020. Exploring the impact of unsafe behaviors on building construction accidents using a Bayesian network. *International Journal of Environmental Research and Public Health,* 17.

Hamelryck, T., Mardia, K. & Ferkinghoff-Borg, J. 2012. *Bayesian methods in structural bioinformatics*, Springer.

Hassan, F. U. & Le, T. 2020. Automated requirements identification from construction contract documents using natural language processing. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction,* 12.

Heravi, G. & Eslamdoost, E. 2015. Applying artificial neural networks for measuring and predicting construction-labor productivity. *Journal of Construction Engineering and Management,* 141.

Hu, X., Xia, B., Skitmore, M. & Chen, Q. 2016. The application of case-based reasoning in construction management research: An overview. *Automation in Construction,* 72**,** 65-74.

Hu, Y. & Castro-Lacouture, D. 2019. Clash relevance prediction based on machine learning. *Journal of Computing in Civil Engineering,* 33.

Hwang, S. 2016. A Bayesian approach for forecasting errors of budget cost estimates. *Journal of Civil Engineering and Management,* 22**,** 178-186.

Islam, M. S., Nepal, M. P., Skitmore, M. & Kabir, G. 2019. A knowledge-based expert system to assess power plant project cost overrun risks. *Expert Systems with Applications,* 136**,** 12-32.

Jang, W., Lee, J. K., Lee, J. & Han, S. H. 2015. Naive Bayesian classifier for selecting good/bad projects during the early stage of international construction bidding decisions. *Mathematical Problems in Engineering,* 2015.

Ji, W. & Abourizk, S. M. 2017. Credible interval estimation for fraction nonconforming: Analytical and numerical solutions. *Automation in Construction,* 83**,** 56-67.

Ji, W. & Abourizk, S. M. 2018. Simulation-based analytics for quality control decision support: Pipe welding case study. *Journal of Computing in Civil Engineering,* 32.

Ji, W., Li, Y. & Abourizk, S. M. 2019. Integrated data-driven approach for analyzing pipe welding operator-quality performance. *Automation in Construction,* 106.

Ji, Z., Xia, Q. & Meng, G. A review of parameter learning methods in Bayesian network. International Conference on Intelligent Computing, 2015. Springer, 3-12.

Jitwasinkul, B., Hadikusumo, B. H. W. & Memon, A. Q. 2016. A Bayesian Belief Network model of organizational factors for improving safe work behaviors in Thai construction industry. *Safety Science,* 82**,** 264-273.

Joko Wahyu Adi, T., Anwar, N. & Fahirah, F. 2016. Probabilistic prediction of time performance in building construction project using Bayesian Belief Networks-Markov Chain. *ARPN Journal of Engineering and Applied Sciences,* 11**,** 9454-9460.

Kabir, G., Balek, N. B. C. & Tesfamariam, S. 2018. Consequence-based framework for buried infrastructure systems: A Bayesian belief network model. *Reliability Engineering and System Safety,* 180**,** 290-301.

Kabir, G., Sadiq, R. & Tesfamariam, S. 2016. A fuzzy Bayesian belief network for safety assessment of oil and gas pipelines. *Structure and Infrastructure Engineering,* 12**,** 874-889.

Kabir, S. & Papadopoulos, Y. 2019. Applications of Bayesian networks and Petri nets in safety, reliability, and risk assessments: A review. *Safety Science,* 115**,** 154-175.

Kang, Y., Jin, Z., Hyun, C. & Park, H. 2018. Construction Management Functions for Developing Countries: Case of Cambodia. *Journal of Management in Engineering,* 34.

Karakas, K., Dikmen, I. & Birgonul, M. T. 2013. Multiagent system to simulate risk-allocation and cost-sharing processes in construction projects. *Journal of Computing in Civil Engineering,* 27**,** 307-319.

Kelly, D. 2011. *Bayesian Inference for Probabilistic Risk Assessment A Practitioner's Guidebook,* London, Springer London.

Keung, C. C. W. & Shen, L. Y. 2013. Measuring the networking performance for contractors in practicing construction management. *Journal of Management in Engineering,* 29**,** 400-406.

Khanzadi, M., Eshtehardian, E. & Mokhlespour Esfahani, M. 2017. Cash flow forecasting with risk consideration using Bayesian Belief Networks (BBNS). *Journal of Civil Engineering and Management,* 23**,** 1045-1059.

Khodakarami, V. & Abdi, A. 2014. Project cost risk analysis: A Bayesian networks approach for modeling dependencies between cost items. *International Journal of Project Management,* 32**,** 1233-1245.

Kim, B. C. & Reinschmidt, K. F. 2009. Probabilistic forecasting of project duration using bayesian inference and the beta distribution. *Journal of Construction Engineering and Management,* 135**,** 178-186.

Kim, B. C. & Reinschmidt, K. F. 2011. Combination of project cost forecasts in earned value management. *Journal of Construction Engineering and Management,* 137**,** 958-966.

Kim, S., Kim, G. H. & Lee, D. 2014. Bayesian Markov chain Monte Carlo model for determining optimum tender price in multifamily housing projects. *Journal of Computing in Civil Engineering,* 28.

Ko, C. H. & Cheng, M. Y. 2003. Hybrid use of AI techniques in developing construction management tools. *Automation in Construction,* 12**,** 271-281.

Ko, Y. & Han, S. 2015. Development of construction performance monitoring methodology using the bayesian probabilistic approach. *Journal of Asian Architecture and Building Engineering,* 14**,** 73-80.

Korb, K. B. & Nicholson, A. E. 2011. *Bayesian artificial intelligence,* Boca Raton, FL, CRC Press.

Lee, E., Park, Y. & Shin, J. G. 2009. Large engineering project risk management using a Bayesian belief network. *Expert Systems with Applications,* 36**,** 5880-5887.

Leśniak, A. & Janowiec, F. 2019. Risk assessment of additional works in railway construction investments using the Bayes network. *Sustainability (Switzerland),* 11.

Leu, S. S. & Chang, C. M. 2013. Bayesian-network-based safety risk assessment for steel construction projects. *Accident Analysis and Prevention,* 54**,** 122-133.

Leu, S. S. & Chang, C. M. 2015. Bayesian-network-based fall risk evaluation of steel construction projects by fault tree transformation. *Journal of Civil Engineering and Management,* 21**,** 334-342.

Leu, S. S., Hong Son, P. V. & Hong Nhung, P. T. 2015a. Optimize negotiation price in construction procurement using Bayesian Fuzzy Game Model. *KSCE Journal of Civil Engineering,* 19**,** 1566-1572.

Leu, S. S., Pham, V. H. S. & Pham, T. H. N. 2015b. Development of recursive decision making model in bilateral construction procurement negotiation. *Automation in Construction,* 53**,** 131-140.

Leu, S. S., Son, P. V. H. & Nhung, P. T. H. 2015c. Hybrid Bayesian Fuzzy-Game Model for improving the negotiation effectiveness of construction material procurement. *Journal of Computing in Civil Engineering,* 29.

Li, P. C., Chen, G. H., Dai, L. C. & Zhang, L. 2012. A fuzzy Bayesian network approach to improve the quantification of organizational influences in HRA frameworks. *Safety Science,* 50**,** 1569-1583.

Liao, P. C., Ma, Z. & Chong, H. Y. 2018a. Identifying effective management factors across human errors – A case in elevator installation. *KSCE Journal of Civil Engineering,* 22**,** 3204-3214.

Liao, P. C., Shi, H., Su, Y. & Luo, X. 2018b. Development of data-driven influence model to relate the workplace environment to human error. *Journal of Construction Engineering and Management,* 144.

Liu, C., Lei, Z., Morley, D. & Abourizk, S. M. 2020. Dynamic, data-driven decision-support approach for construction equipment acquisition and disposal. *Journal of Computing in Civil Engineering,* 34.

Liu, Y., Xia, Y., Lu, H. & Xiong, Z. 2019. Risk control technology for water inrush during the construction of deep, long tunnels. *Mathematical Problems in Engineering,* 2019.

Low-Choy, S., James, A., Murray, J. & Mengersen, K. 2014. *Elicitator: A user-friendly, interactive tool to support scenario-based elicitation of expert knowledge*, Springer New York.

Lu, W., Zhang, L. & Bai, F. 2016. Bilateral learning model in construction claim negotiations. *Engineering, Construction and Architectural Management,* 23**,** 448-463.

Luo, X., Li, H., Dai, F., Cao, D., Yang, X. & Guo, H. 2017. Hierarchical Bayesian model of worker response to proximity warnings of construction safety hazards: Toward constant review of safety risk control measures. *Journal of Construction Engineering and Management,* 143.

Luo, L., Zhang, L. & Wu, G. 2020. Bayesian belief network-based project complexity measurement considering causal relationships. *Journal of Civil Engineering and Management,* 26**,** 200-215.

Luo, X., Li, H., Yang, X., Yu, Y. & Cao, D. 2019. Capturing and understanding workers' activities in far-field surveillance videos with deep action recognition and Bayesian nonparametric learning. *Computer-Aided Civil and Infrastructure Engineering,* 34**,** 333-351.

Luo, X., O'brien, W. J., Leite, F. & Goulet, J. A. 2014. Exploring approaches to improve the performance of autonomous monitoring with imperfect data in location-aware wireless sensor networks. *Advanced Engineering Informatics,* 28**,** 287-296.

Luu, V. T., Kim, S. Y., Tuan, N. V. & Ogunlana, S. O. 2009. Quantifying schedule risk in construction projects using Bayesian belief networks. *International Journal of Project Management,* 27**,** 39-50.

Ma, Z., Chong, H. Y. & Liao, P. C. 2019. Development of a time-variant causal model of human error in construction with dynamic Bayesian network. *Engineering, Construction and Architectural Management*.

Ma, Z., Chong, H. Y. & Liao, P. C. 2020. Real-time safety inspection and planning: A first application of the fagan nomogram. *Canadian Journal of Civil Engineering,* 47**,** 438-449.

Mahfouz, T. & Kandil, A. 2012. Litigation outcome prediction of differing site condition disputes through machine learning models. *Journal of Computing in Civil Engineering,* 26**,** 298-308.

Mahfouz, T., Kandil, A. & Davlyatov, S. 2018. Identification of latent legal knowledge in differing site condition (DSC) litigations. *Automation in Construction,* 94**,** 104-111.

Mariscal, M. A., López-Perea, E. M., López-García, J. R., Herrera, S. & García-Herrero, S. 2019. The influence of employee training and information on the probability of accident rates. *International Journal of Industrial Ergonomics,* 72**,** 311-319.

Martín, J. E., Rivas, T., Matías, J. M., Taboada, J. & Argüelles, A. 2009. A Bayesian network analysis of workplace accidents caused by falls from a height. *Safety Science,* 47**,** 206-214.

Martín, J. E., Taboada-García, J., Gerassis, S., Saavedra, Á. & Martínez-Alegría, R. 2017. Bayesian network analysis of accident risk in information-deficient scenarios. *Revista de la Construccion,* 16**,** 439-446.

Matthews, P. C. & Philip, A. D. M. 2012. Bayesian project diagnosis for the construction design process. *Artificial Intelligence for Engineering Design Analysis and Manufacturing,* 26**,** 375-391.

Mccabe, B. & Abourizk, S. M. 2001. Performance measurement indices for simulated construction operations. *Canadian Journal of Civil Engineering,* 28**,** 383-393.

Mccabe, B., Loughlin, C., Munteanu, R., Tucker, S. & Lam, A. 2008. Individual safety and health outcomes in the construction industry. *Canadian Journal of Civil Engineering,* 35**,** 1455-1467.

Mkrtchyan, L., Podofillini, L. & Dang, V. N. 2015. Bayesian belief networks for human reliability analysis: A review of applications and gaps. *Reliability Engineering and System Safety,* 139**,** 1-16.

Mofidi, A., Tompa, E., Mortazavi, S. B., Esfahanipour, A. & Demers, P. A. 2020. A probabilistic approach for economic evaluation of occupational health and safety interventions: A case study of silica exposure reduction interventions in the construction sector. *BMC Public Health,* 20.

Mohammadfam, I., Ghasemi, F., Kalatpour, O. & Moghimbeigi, A. 2017. Constructing a Bayesian network model for improving safety behavior of employees at workplaces. *Applied Ergonomics,* 58**,** 35-47.

Morales-Nápoles, O., Delgado-Hernández, D. J., De-León-Escobedo, D. & Arteaga-Arcos, J. C. 2014. A continuous Bayesian network for earth dams' risk assessment: Methodology and quantification. *Structure and Infrastructure Engineering,* 10**,** 589-603.

Movaghar, M. & Mohammadzadeh, S. 2019. Intelligent index for railway track quality evaluation based on Bayesian approaches. *Structure and Infrastructure Engineering.*

Murphy, K. 2002. *Dynamic Bayesian networks: Representation, inference and learning.* ProQuest Dissertations Publishing.

Namazian, A., Yakhchali, S. H., Yousefi, V. & Tamošaitienė, J. 2019. Combining Monte Carlo simulation and bayesian networks methods for assessing completion time of projects under risk. *International Journal of Environmental Research and Public Health,* 16.

Namazian, A. & Haji Yakhchali, S. 2018. Modified Bayesian network–based risk analysis of construction projects: Case study of south Pars gas field development projects. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering,* 4.

Nasir, D., Mccabe, B. & Hartono, L. 2003. Evaluating risk in construction-schedule model (ERIC-S): Construction schedule risk model. *Journal of Construction Engineering and Management,* 129**,** 518-527.

Nasrazadani, H., Mahsuli, M., Talebiyan, H. & Kashani, H. 2017. Probabilistic modeling framework for prediction of seismic retrofit cost of buildings. *Journal of Construction Engineering and Management,* 143.

Nath, N. D., Behzadan, A. H. & Paal, S. G. 2020. Deep learning for site safety: Real-time detection of personal protective equipment. *Automation in Construction,* 112.

Naticchia, B., Fernandez-Gonzalez, A. & Carbonari, A. 2007. Bayesian Network model for the design of roofpond equipped buildings. *Energy and Buildings,* 39**,** 258-272.

Nguyen, L. D., Tran, D. Q. & Chandrawinata, M. P. 2016. Predicting safety risk of working at heights using Bayesian networks. *Journal of Construction Engineering and Management,* 142.

Novi, F. 2018. Bayesian networks as a resilience tool for decision-making processes in uncertainty conditions. *Techne-Journal of Technology for Architecture and Environment,* 15**,** 341-347.

Nwadigo, O., Naismith, N. N., Ghaffarianhoseini, A., Ghaffarian Hoseini, A. & Tookey, J. 2020. Dynamic Bayesian network modelling for predicting adaptability of time performance during time influencing factors disruptions in construction enterprise. *Engineering, Construction and Architectural Management.*

Pan, Y., Ou, S., Zhang, L., Zhang, W., Wu, X. & Li, H. 2019. Modeling risks in dependent systems: A Copula-Bayesian approach. *Reliability Engineering and System Safety,* 188**,** 416-431.

Papazoglou, I. A., Aneziris, O., Bellamy, L., Ale, B. J. M. & Oh, J. I. H. 2015. Uncertainty assessment in the quantification of risk rates of occupational accidents. *Risk Analysis,* 35**,** 1536-1561.

Pareek, P., Han, S. & Misra, S. 2016. Application of Bayesian updating for real-time schedule estimation in a concreting operation. *International Journal of Construction Management,* 16**,** 54-66.

Pearl, J. 1986. Fusion, propagation, and structuring in belief networks. *Artificial Intelligence,* 29**,** 241-288.

Phan, T. D., Smart, J. C. R., Capon, S. J., Hadwen, W. L. & Sahin, O. 2016. Applications of Bayesian belief networks in water resource management: A systematic review. *Environmental Modeling and Software,* 85**,** 98-111.

Pitchforth, J. & Mengersen, K. 2013. A proposed validation framework for expert elicited Bayesian Networks. *Expert Systems with Applications,* 40**,** 162-167.

Qazi, A. & Dikmen, I. 2019. From risk matrices to risk networks in construction projects. *IEEE Transactions on Engineering Management.*

Qazi, A., Dikmen, I. & Birgonul, M. T. 2020. Prioritization of interdependent uncertainties in projects. *International Journal of Managing Projects in Business.*

Qazi, A., Quigley, J., Dickson, A. & Kirytopoulos, K. 2016. Project Complexity and Risk Management (ProCRiM): Towards modeling project complexity driven risk paths in construction projects. *International Journal of Project Management,* 34**,** 1183-1198.

Ren, Z. & Anumba, C. J. 2002. Learning in multi-agent systems: A case study of construction claims negotiation. *Advanced Engineering Informatics,* 16**,** 265-275.

Ren, Z., Anumba, C. J. & Ugwu, O. O. 2003. Multiagent system for construction claims negotiation. *Journal of Computing in Civil Engineering,* 17**,** 180-188.

Rischmoller, L., Fischer, M. & Kunz, J. 2012. A study of virtual design and construction implementation and benefits using a bayesian approach. *Revista de la Construcción,* 11**,** 74-87.

Rivas, T., Paz, M., Martín, J. E., Matías, J. M., García, J. F. & Taboada, J. 2011. Explaining and predicting workplace accidents using data-mining techniques. *Reliability Engineering and System Safety,* 96**,** 739-747.

Rongchen, Z., Xiaofeng, H., Jiaqi, H. & Xin, L. 2020. Application of machine learning techniques for predicting the consequences of construction accidents in China. *Process Safety and Environmental Protection.*

Sabillon, C., Rashidi, A., Samanta, B., Davenport, M. A. & Anderson, D. V. 2020. Audio-based Bayesian model for productivity estimation of cyclic construction activities. *Journal of Computing in Civil Engineering,* 34.

SAS. 2019. *Introduction to Bayesian Analysis Procedures* [Online]. Available: https://documentation.sas.com/doc/en/pgmsascdc/9.4_3.4/statug/statug_introbayes_se ct004.htm [Accessed].

Sharma, V. K., Sharma, S. K. & Singh, A. P. 2019. Risk enablers modelling for infrastructure projects using Bayesian belief network. *International Journal of Construction Management*.

Sonmez, R. 2011. Range estimation of construction costs using neural networks with bootstrap prediction intervals. *Expert Systems with Applications,* 38**,** 9913-9917.

Sousa, R. L. & Einstein, H. H. 2012. Risk analysis during tunnel construction using Bayesian Networks: Porto Metro case study. *Tunnelling and Underground Space Technology,* 27**,** 86-100.

Špačková, O., Šejnoha, J. & Straub, D. 2013. Probabilistic assessment of tunnel construction performance based on data. *Tunnelling and Underground Space Technology,* 37**,** 62-78.

Špačková, O. & Straub, D. 2013. Dynamic Bayesian network for probabilistic modeling of tunnel excavation processes. *Computer-Aided Civil and Infrastructure Engineering,* 28**,** 1-21.

Stigler, S. M. 1986. *The history of statistics: The measurement of uncertainty before 1900,* Harvard University Press.

Suddle, S. 2009. The risk management of third parties during construction in multifunctional urban locations. *Risk Analysis,* 29**,** 1024-1040.

Sun, J., Liu, B., Chu, Z., Chen, L. & Li, X. 2018. Tunnel collapse risk assessment based on multistate fuzzy Bayesian networks. *Quality and Reliability Engineering International,* 34**,** 1646-1662.

Sunindijo, R. Y. & Maghrebi, M. 2020. Political skill improves the effectiveness of emotional intelligence: Bayesian network analysis in the construction industry. *Journal of Architectural Engineering,* 26.

Tah, J. H. M. & Carr, V. 2000. A proposal for construction project risk assessment using fuzzy logic. *Construction Management and Economics,* 18**,** 491-500.

Tischer, T. E. & Kuprenas, J. A. 2003. Bridge falsework productivity - Measurement and influences. *Journal of Construction Engineering and Management,* 129**,** 243-250.

Uusitalo, L. 2007. Advantages and challenges of Bayesian networks in environmental modeling. *Ecological Modeling,* 203, 312-318.

Van De Schoot, R., Winter, S. D., Ryan, O., Zondervan-Zwijnenburg, M. & Depaoli, S. 2017. A systematic review of Bayesian articles in psychology: The last 25 years. *Psychological Methods,* 22**,** 217-239.

Van Deurssen, E., Meijster, T., Oude Hengel, K. M., Boessen, R., Spaan, S., Tielemans, E., Heederik, D. & Pronk, A. 2015. Effectiveness of a multidimensional randomized control intervention to reduce quartz exposure among construction workers. *Annals of Occupational Hygiene,* 59**,** 959-971.

Vaux, J. S. & Kirk, W. M. 2018. Relationship conflict in construction management: Performance and productivity problem. *Journal of Construction Engineering and Management,* 144.

Visscher, H., Suddle, S. & Meijer, F. 2008. Quantitative risk analysis as a supporting tool for safety protocols at multi-functional urban locations. *Construction Innovation,* 8**,** 269-279.

Wang, F., Ding, L., Love, P. E. D. & Edwards, D. J. 2016. Modeling tunnel construction risk dynamics: Addressing the production versus protection problem. *Safety Science,* 87**,** 101-115.

Wang, F., Ding, L. Y., Luo, H. B. & Love, P. E. D. 2014. Probabilistic risk assessment of tunneling-induced damage to existing properties. *Expert Systems with Applications,* 41**,** 951-961.

Wang, F., Li, H., Dong, C. & Ding, L. 2019. Knowledge representation using non-parametric Bayesian networks for tunneling risk analysis. *Reliability Engineering and System Safety,* 191.

Wang, L. G. & Zhang, X. Q. 2018. Bayesian analytics for estimating risk probability in PPP waste-to-energy projects. *Journal of Management in Engineering,* 34.

Wang, N., Xu, C. S., Du, X. L. & Zhang, M. J. 2018. A risk assessment method of deep excavation based on Bayesian analysis and expert elicitation. *International Journal of Systems Assurance Engineering and Management,* 9**,** 452-466.

Wang, Z. Z. & Chen, C. 2017. Fuzzy comprehensive Bayesian network-based safety risk assessment for metro construction projects. *Tunnelling and Underground Space Technology,* 70**,** 330-342.

Weber, P. 2016. *Benefits of Bayesian network models,* Hoboken, NJ, Wiley-ISTE.

Wen, Z., Xia, Y., Ji, Y., Liu, Y., Xiong, Z. & Lu, H. 2019. Study on risk control of water inrush in tunnel construction period considering uncertainty. *Journal of Civil Engineering and Management,* 25**,** 757-772.

Wu, L., Ji, W. & Abourizk, S. M. 2020. Bayesian inference with Markov Chain Monte Carlo-based numerical approach for input model updating. *Journal of Computing in Civil Engineering,* 34.

Wu, P. P. Y., Pitchforth, J. & Mengersen, K. 2014. A Hybrid Queue-based Bayesian Network framework for passenger facilitation modeling. *Transportation Research Part C: Emerging Technologies,* 46**,** 247-260.

Wu, W. S., Yang, C. F., Chang, J. C., Château, P. A. & Chang, Y. C. 2015a. Risk assessment by integrating interpretive structural modeling and Bayesian network, case of offshore pipeline project. *Reliability Engineering and System Safety,* 142**,** 515-524.

Wu, X., Liu, H., Zhang, L., Skibniewski, M. J., Deng, Q. & Teng, J. 2015b. A dynamic Bayesian network based approach to safety decision support in tunnel construction. *Reliability Engineering and System Safety,* 134**,** 157-168.

Xia, N., Wang, X., Wang, Y., Yang, Q. & Liu, X. 2017. Lifecycle cost risk analysis for infrastructure projects with modified Bayesian networks. *Journal of Engineering, Design and Technology,* 15**,** 79-103.

Xia, N., Zou, P. X. W., Liu, X., Wang, X. & Zhu, R. 2018. A hybrid BN-HFACS model for predicting safety performance in construction projects. *Safety Science,* 101**,** 332-343.

Xue, L. & Jin, Y. 2016. Economic incentive policy making plan of green buildings based on BIM. *International Journal of Simulation: Systems, Science and Technology,* 17**,** 12.1-12.5.

Xue, Y. & Xiang, P. 2020. The social risk of high-speed rail projects in China: A Bayesian network analysis. *Sustainability (Switzerland),* 12.

Yu, J., Zhong, D., Ren, B., Tong, D. & Hong, K. 2017. Probabilistic risk analysis of diversion tunnel construction simulation. *Computer-Aided Civil and Infrastructure Engineering,* 32**,** 748-771.

Yu, T., Man, Q., Wang, Y., Shen, G. Q., Hong, J., Zhang, J. & Zhong, J. 2019. Evaluating different stakeholder impacts on the occurrence of quality defects in offsite construction projects: A Bayesian-network-based model. *Journal of Cleaner Production,* 241.

Yuan, X. X. 2012. Bayesian method for the correlated competitive bidding model. *Construction Management and Economics,* 30**,** 477-491.

Yuan, X. X. 2011. A correlated bidding model for markup size decisions. *Construction Management and Economics,* 29**,** 1101-1119.

Zhang, F., Fleyeh, H., Wang, X. & Lu, M. 2019. Construction site accident analysis using text mining and natural language processing techniques. *Automation in Construction,* 99**,** 238-248.

Zhang, G., Wang, C., Jiao, Y., Wang, H., Qin, W., Chen, W. & Zhong, G. 2020. Collapse risk analysis of deep foundation pits in metro stations using a fuzzy Bayesian network and a fuzzy AHP. *Mathematical Problems in Engineering,* 2020.

Zhang, L., Wu, X., Ding, L., Skibniewski, M. J. & Yan, Y. 2013. Decision support analysis for safety control in complex project environments based on Bayesian Networks. *Expert Systems with Applications,* 40**,** 4273-4282.

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**,** 278-301.

Zhang, L., Wu, X., Skibniewski, M. J., Zhong, J. & Lu, Y. 2014a. Bayesian-network-based safety risk analysis in construction projects. *Reliability Engineering and System Safety,* 131**,** 29-39.

Zhang, S., Du, C., Sa, W., Wang, C. & Wang, G. 2014b. Bayesian-based hybrid simulation approach to project completion forecasting for underground construction. *Journal of Construction Engineering and Management,* 140.

Zhao, L., Mbachu, J. & Liu, Z. 2020. Identifying significant cost-influencing factors for sustainable development in construction industry using structural equation modeling. *Mathematical Problems in Engineering,* 2020.

Zhou, H. B. & Zhang, H. 2011. Risk assessment methodology for a deep foundation pit construction project in Shanghai, China. *Journal of Construction Engineering and Management,* 137**,** 1185-1194.

Zhou, Q., Fang, D. & Wang, X. 2008. A method to identify strategies for the improvement of human safety behavior by considering safety climate and personal experience. *Safety Science,* 46**,** 1406-1419.

Zhou, Y., Li, C., Zhou, C. & Luo, H. 2018. Using Bayesian network for safety risk analysis of diaphragm wall deflection based on field data. *Reliability Engineering and System Safety,* 180**,** 152-167.