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Roozbeh Hesamamiri Mohammad Mahdavi Mazdeh Mostafa Jafari Kamran Shahanaghi

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Roozbeh Hesamamiri, Mohammad Mahdavi Mazdeh,
Mostafa Jafari and Kamran Shahanaghi
*Industrial Engineering Department, Iran University of Science & Technology,
Tehran, Iran*

Abstract

Purpose – A perfect knowledge management (KM) initiative is one that achieves its objectives without any failure during a pre-defined period. However, KM implementation is not perfect in every organization as it requires substantial changes in organizational infrastructures, including culture, structure, and technology. Therefore, the purpose of this paper is to propose a model for assessing the reliability of KM to help organizations evaluate their ability to implement KM successfully by identifying key reliability variables, modeling the complex interaction structure among variables, and determining the probability of failure for each KM capability.

Design/methodology/approach – In this study, relevant variables are identified by a thorough analysis of related references in literature. In order to determine the compound structure of complicated interactions among variables, a group-based approach is utilized. Based on the combined cognitive maps, a cognitive network is constructed as a framework for graphically representing the logical relationships between variables and capturing the uncertainty in the dependency among these variables using conditional probabilities. The applicability of the proposed approach and the efficacy of the model was verified and validated with data from a banking institution.

Findings – Results show that KM reliability can be defined by the degree to which required KM capabilities, including infrastructure and process capabilities, have the ability to perform as intended in a certain organizational environment. Furthermore, it is demonstrated that reliability assessment of KM through a hybrid approach of fuzzy cognitive map and Bayesian network is possible and useful.

Practical implications – The proposed reliability assessment model facilitates the process of understanding why and how failures occur in KM. Moreover, the proposed approach evaluates the probability of success for each variable as well as for the entire KM initiative. Therefore, it can provide insight for managers and executives into the degree of reliability for their existing KM and prevention of failures in vital factors through necessary actions.

Originality/value – The suggested approach to KM reliability assessment is a novel method that provides powerful arguments for a more holistic view of KM reliability factors, which is crucial for the successful implementation of KM.

Keywords Reliability analysis, Failure analysis, Knowledge management capabilities, Knowledge management processes, Organizational infrastructures

Paper type Research paper

1. Introduction

Over the past several years, the rapid proliferation of knowledge and its management has been a key factor in the evolution of business practice and one of the most important driving forces for business success and organizational performance (Holsapple and Wu, 2011; Junping and Hong, 2014). Based on Davenport and Prusak (1998), knowledge refers to a fluid mix of framed experience, values, contextual information, and expert insight that offers a framework for interpreting, assimilating, and integrating new experiences and information. In order to sustain a competitive advantage in today's knowledge-based

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economy, knowledge management (KM) initiatives, and systems have been utilized in organizations for integrating, growing, and reconciling the knowledge they possess (Nayir and Uzunçarsili, 2008; Lo and Chin, 2009; Squier and Snyman, 2004). Consequently, it is not surprising that spending on KM has increased significantly over the past years (Ajmal *et al.*, 2010). USA spending alone on KM initiatives grew by 16 percent, to account for $73 billion in 2007, according to a report by AMR research (McGreevy, 2007). In 2008, the US Federal Government spent approximately $1.3 billion on KM products and services, according to a report released by INPUT, an authority on government business. Moreover, the worldwide KM applications market was forecasted to reach $100 billion by 2008 (Taylor, 2006). The World Bank invests more than $600 million annually in knowledge services and its total spending on knowledge services through the loans, budget, and partnership activities is approximately $4 billion per year. Besides these huge amounts of investments in KM tools and systems, it has been stated that the amount of money that could be spend on knowledge is infinite because knowledge has no value *per se*, although it acquires value from appropriate use in organizations' deliverable products and services to customers (Denning, 2012).

Unfortunately, studies report that practitioners are facing failures and companies lose around $31.5 billion each year by failing to achieve their KM goals effectively (Babcock, 2004; Lam and Chua, 2005). Thus, analyses of KM success or failure became popular among researchers. Critical success factors (Wong, 2005), success and failure models (Kulkarni *et al.*, 2006), success roadmaps (Akhavan *et al.*, 2006), required organizational capabilities (Gold *et al.*, 2001), and analytical approaches (Chang and Wang, 2009) were developed with the purpose of preventing KM failures and achieving KM-related objectives. However, despite this trend in development of models, approaches, methods, and theories on KM failure, organizations still are not equally predisposed for successfully launching and maintaining KM systems, tools, or initiatives. A significant reason behind these failures is that organizations often do not have ideal organizational capabilities of KM (Gold *et al.*, 2001). This behavior is similar to engineering systems when based on practical and economical limitations; the use of imperfect components or systems is necessary. Thus, designers, manufacturers, and end users try to minimize the occurrence and reoccurrence of failures. This prevention of failures involves understanding the reason or cause of failures (the "why") and the manner in which failures occur (the "how") as well as appreciation of the related and underlying mechanisms. In systems engineering, this process is called "reliability analysis," which is a probabilistic process because all potential failures are not known or understood (Modarres *et al.*, 1999).

Consequently, in order to prevent failures in KM, this study develops the application of "reliability theory" to KM, which describes the probability of the organization's KM completing its expected function during an interval of time by proposing a Bayesian assessment approach. In order to evaluate the desired reliability, the next section presents perspectives on KM failure studies, Bayesian reliability assessment, and fuzzy cognitive maps (FCM). The KM reliability assessment model is described in Section 3 and the results and discussions are presented in Section 4. Finally, research limitations and concluding remarks are addressed in Section 5.

2. Literature review

2.1 KM failure background

Given the current dynamic business environment, KM is suggested as the only way for firms to achieve competitive advantage. Accordingly, successful companies are those that continuously produce new knowledge, distribute it extensively throughout the organization, and rapidly embody it in their latest products (Metaxiotis *et al.*, 2005). Prusak (1999) estimated that about 80 percent of 1,000 global businesses are currently piloting KM action plans. Based on Mann (2007), many organizations have started at least one KM initiative with a considerably high investment, and they expect reported benefits through KM objectives. However, results reveal that the failure rate of these KM initiatives is more than 80 percent (Goodluck, 2011; Lucier and Torsiliera, 1997). The failure of KM not only destroys the allocated budget, but it also has a significant negative impact on organizational effectiveness (Yang and Wan, 2004). Empirically, KM has provided outstanding benefits to some firms, but at the same time, it has been a fiasco for others (Arora, 2002). In order to prevent these dramatic KM failures, the first and crucial step is to define KM failure and the second step is to investigate what critical factors turn a firm into a KM champion.

Jennex *et al.* (2009) defined KM success by the ability to capture the right knowledge, get the right knowledge to the right user, and use this knowledge to develop organizational and/or individual performance. Davenport *et al.* (1998) identified some indicators of KM project success, including development in the resources attached to the project, development in the volume of knowledge content and usage, the likelihood that the project will survive without dependency on a particular individual or manager, and financial returns. Besides in KM literature, critical success factors are defined as a limited number of areas in which satisfactory results ensure successful KM performance (Alazmi and Zairi, 2003).

In terms of critical success factors, Akhavan *et al.* (2006) introduced a road map for success of KM programs along with 16 KM critical success factors, such as knowledge strategy, training programs, top management support and commitment, business process reengineering, networks of experts, pilot projects, knowledge audit, knowledge architecture, etc. In small and medium enterprises, Wong (2005) addressed 11 success factors including management leadership and support, culture, information technology, strategy and purpose, measurement, organizational infrastructure, process and activities, etc. Picker *et al.* (2009) identified four elements of management promotion, infrastructure, strategy, and evaluation for KM implementation success. Moreover, many other studies suggest a variety of success or failure factors for KM, KM implementation, and KM systems (Lindner and Wald, 2011; Chang *et al.*, 2009, 2012; Handzic and Ozlen, 2013; Lehner *et al.*, 2008).

As a step forward in KM failure analysis, researchers introduced success models for KM implementation by recognizing critical success constructs and the interrelationships among these variables. Kulkarni *et al.* (2006) illustrated a KM success model that incorporates the quality of knowledge and KM systems as determinants of users' satisfaction with KM practices. On the other hand, the user satisfaction of KM initiatives affects knowledge use and better knowledge sharing and re-use. Similarly, Mas-Machuca and Martínez-Costa (2012) introduced strategic, cultural, and technological factors and a success model for better implementation of KM projects. Defining KM success constructs and their empirical validation is developed in a number of other studies (Halawi *et al.*, 2007; Alavi *et al.*, 2005; Muhammed *et al.*, 2009; Zhang, 2010).

Further investigations depict that some critical success factors are more fundamental than others. This category of factors is called KM enablers or organizational capabilities. Gold *et al.* (2001) identified knowledge infrastructure capabilities (including technology, structure, and culture), and process architecture capabilities (including acquisition, conversion, application, and protection) as major required organizational capabilities for effective KM. Likewise, O'Dell *et al.* (1998) present four critical enablers of infrastructure, technology, culture, and measure, while Cho *et al.* (2000) state KM is supported through people, process, and technology.

Furthermore, some researchers introduced KM adoption or readiness assessment models (Holt *et al.*, 2007; Nagarajan *et al.*, 2009). These readiness assessment models argue that although the success factors and capabilities are identified, organizations are faced with a significant change in their culture and structure. Before initiating KM, systematic planning is critical to ensure the implementation achieves the intended goals of KM. Therefore, Holt *et al.* (2007) propose an instrument to measure readiness for KM and prepare organizations and their employees before they start related KM initiatives. Nagarajan *et al.* (2009) highlight the importance of the readiness of organization toward the KM solution and develop a readiness assessment approach to access the readiness of people, process, and technology before the adoption of KM. Other studies introduced more analytical methods such as multi-criteria decision-making approaches (Wang and Chang, 2007; Chang and Wang, 2009) to assist organizations in predicting the chance of a successful KM initiative and identify the essential actions before KM implementation. This approach is designed to be used before KM implementation.

The next step is analyzing the behavior of the KM journey after its initiation. In this step, maturity models are developed and introduced to describe the development of KM overtime and to help understand systematically the current position of KM (Hsieh *et al.*, 2009; Kruger and Johnson, 2010). Hsieh *et al.* (2009) state that KM maturity levels are knowledge chaotic, knowledge conscientious, KM, KM advanced, and KM integration. The KM maturity model allows firms to make holistic evaluations of KM activities, thoroughly understand the current position of KM, overcome barriers, and make modifications to KM (Kruger and Johnson, 2010).

Despite the extensive research on critical success factors, enablers, required organizational capabilities, and maturity models, practitioners indicate that failures still occur in KM initiatives (Ajmal *et al.*, 2010). The latest literature claims that the key to successful KM is to create a cognitive infrastructure that enables simultaneous adaptive learning and provides an organizational reliability infrastructure through the identification and management of unwanted, unanticipated, and unexplained failures in KM's required capabilities (Mahdavi Mazdeh and Hesamamiri, 2014). In order to assess the ability of an organization to keep KM-required capabilities from unexpected, unwanted, or unmanaged failures, Hesamamiri *et al.* (2013) developed a KM reliability theory and a measurement instrument that involves the dimensions of KM reliability, including preoccupation with failure in KM, sensitivity to KM operations, commitment to KM resilience, and deference to expertise. Based on the KM reliability theory, a perfect KM initiative is one that achieves KM objectives without any failure during a pre-defined duration. However, KM prerequisites, design, and implementation is not perfect in every organization because it requires substantial changes in organizational infrastructures, including culture, structure, technology, and processes.

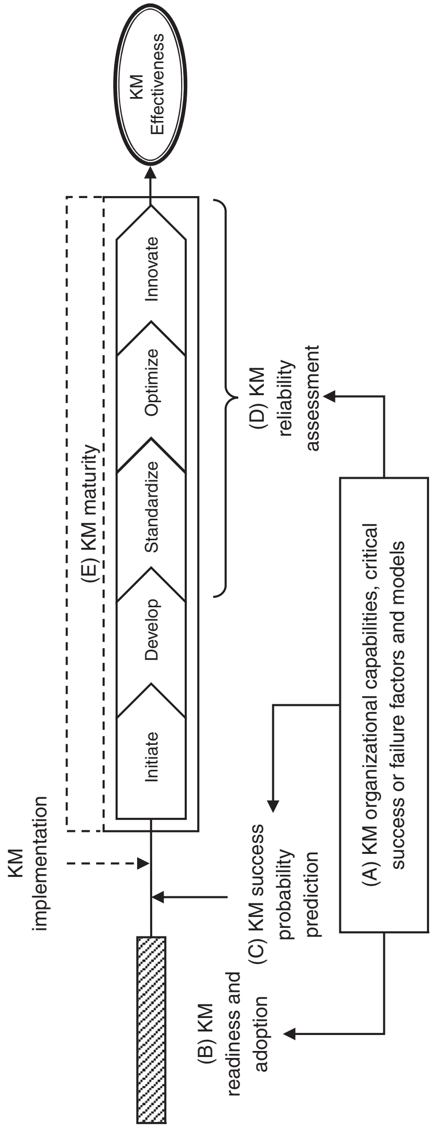
Preoccupation with failure in KM focusses on predicting and eliminating shortcomings or failures in KM infrastructure and process capabilities rather than just reacting to them. Sensitivity to KM operations maintains strong communications between employees to make sure KM problems are quickly identified and dealt with. Commitment to KM resilience engages employees and resources to eliminate errors or difficulties that may be seen as potential failures in KM infrastructure and process capabilities. Deference to expertise in KM is about influencing employees to work as a team and defer to experts when it is necessary.

Based on the above-mentioned discussion, the dimensions of KM success or failure studies are identified through KM success or failure factors, KM success models and frameworks, KM-required capabilities, enablers, and drivers, KM success probability assessment, KM maturity or growth models, KM readiness and adoption models, KM reliability theory, and KM effectiveness studies. These dimensions are briefly described in Table I. In order to achieve an acceptable level of KM effectiveness, KM organizational capabilities, critical success or failure factors, and models are used to assess KM readiness or adoption degree. This readiness assessment is based on the extent to which organizations can provide KM preconditions, including infrastructural and process capabilities. Furthermore, this assessment is enhanced by KM success probability prediction, which is an analytical approach that illustrates the capabilities of KM. With an acceptable level of readiness or success probability, organizations initiate their KM implementation and start their KM journey or maturity. At this level, KM reliability is the key that guarantees a successful KM in terms of reaching KM objectives. The conceptual relationship among these dimensions is illustrated in Figure 1.

KM reliability theory is a new concept which suffers from an analytical approach that helps organizations evaluate their level of reliability in order to assess the

	Purpose	Researchers
KM success or failure factors	Identify and examine various factors that influence the success or failure of KM initiatives (KM critical success/failure factors)	Akhavan *et al.* (2006), Bishop *et al.* (2008), Ajmal *et al.* (2010) and Huang and Lai (2012)
KM success models and frameworks	Recognize KM success constructs and the relationship between them	Massey *et al.* (2002), Kulkarni *et al.* (2006) and Mas-Machuca and Martínez-Costa (2012)
KM maturity or growth models	Describe the development of KM overtime and help systematically understand the current position of KM throughout an implementation journey	Hsieh *et al.* (2009) and Kruger and Johnson (2010)
KM success probability assessment	Helps organizations predict the chance of successful KM initiative, and identify the actions necessary before implementing KM	Wang and Chang (2007 and 2009)
KM readiness and adoption models	Concerns assessing the degree of KM preconditions and preparing organizations and their employees as they begin KM initiatives	Holt *et al.* (2007) and Nagarajan *et al.* (2009)
KM effectiveness studies	Refers to the measurement of extent to which an organization reaches its KM objectives	Wen (2009) and Oltra (2005)
KM required capabilities, enablers, and drivers	Examine the issue of effective KM from the perspective of organizational capabilities or preconditions	Gold *et al.* (2001) and Kamhawi (2012)
KM reliability	Evaluates the ability of an organization to keep KM-required capabilities from unexpected, unwanted, or unmanaged failures	Hesamamiri *et al.* (2013) and Mahdavi Mazdeh and Hesamamiri (2014)

Table I.
The classification of KM success or failure studies



Note: KM maturity evaluation steps are adapted from "Road Map to Knowledge Management Results: Stages of Implementation" O'Dell (2000)

Figure 1.
The conceptual model of KM success or failure studies

cognitive infrastructure that enables simultaneous adaptive learning and provides organizational reliability infrastructure through the management of unwanted, unanticipated, and unexplainable failures in KM-required capabilities.

2.2 The FCM

Cognitive maps (CMs) were first introduced by psychologists. Tolman (1948) announced the key concept of CMs in order to analyze complex topological memorizing behavior. Axelrod (1976) defined CMs as interconnected signed diagraphs, and utilized them in decision theory applied to political economics. Correspondingly, CMs were designed to illustrate the causal relationships and belief structure in accordance with a specific domain and use that structure to investigate the effects of a certain choice on specific objectives. FCM, introduced by Kosko (1986), extend the idea of CMs by allowing the concepts to be represented linguistically with an associated fuzzy set rather than requiring that they be precise. Kosko suggests using numbers or linguistic terms in order to describe the degree of relationship between concepts.

2.3 Bayesian approach to reliability assessment

Bayesian networks (BNs), also known as a Bayesian belief networks (BBNs), are directed acyclic graphs that provide a strong framework for reasoning with uncertainty. A BBN provides a framework for explicitly illustrating the logical relationships between variables and capturing the uncertainty in the dependency between these variables using conditional probabilities (Jensen, 1996). As a network diagram, variables are represented by nodes and the dependencies are represented by arcs. Additionally, a set of conditional probabilities is defined for each node (except root nodes) to depict the influence of the values of the node's parents on its value. Practically, the BBN captures the perceived causal relationships between variables and uses conditional probabilities to show the degree of belief in these interactions (Mahadevan *et al.*, 2001).

In order to study the reliability of humans in complex and interconnected systems, several techniques have been developed over the last three decades. These traditional perspectives aim to provide accurate predictions about system reliability using historical or test data; however, this approach is only valid whenever the system success or failure behavior is well understood. These traditional reliability frameworks and techniques are not able to model individuals, interrelationships, and the dynamics of a human-related system that usually require intervention of a domain expert (Ramos-Martins and Coelho-Maturana, 2013). Hence, reliability assessment models are limited by the availability of empirical data. To address these challenges, one of the most important advantages of a BBN is that it is able to incorporate experts' judgments and aggregate probability estimates (Podofillini and Dang, 2013). Furthermore, Bayesian approaches to reliability assessment have received a considerable attention due to current improvements in computational and modelling techniques in human reliability analysis (HRA) (Cai *et al.*, 2012).

Nowadays, BBNs have become common in reliability analysis of human dynamic systems as an effective HRA methodology (Zhong *et al.*, 2010; Ramos-Martins and Coelho-Maturana, 2013). Recently, BBNs are a common HRA method in a variety of sectors such as offshore emergency (Musharraf *et al.*, 2013), maritime (Norrington *et al.*, 2008), mature oil wells (López-Droguett *et al.*, 2008), subsea blowout preventer (Cai *et al.*, 2012), maritime transportation (Trucco *et al.*, 2008), and general reliability modelling (Doguc and Ramirez-Marquez, 2009).

3. KM reliability assessment

In this study, a FCMs-aided systematic BBN generation method is used because the elicitation of conditional probability tables (CPTs) from domain experts is often a significant challenge with BBN. Moreover, the number of probabilistic values required to specify a CPT grows exponentially with the number of causal effects, and BBN is less user-friendly than FCM for domain experts. Thus, systematic causal knowledge acquisition methodology of this paper is adapted from Cheah *et al.* (2011). In this approach, a number of FCMs are constructed by domain experts and aggregated systematically into a final FCM. Then the FCM is converted into the BBN in order to assess the reliability of KM. This conversion is based on Cheah *et al.* (2011) and results in construction of BBN structure and calculation of CPTs.

This paper aims to use BBN to represent relationships among KM reliability and the organizational capabilities of KM. The main steps of the proposed approach are shown in a flowchart (Figure 2). The approach starts with capability identification. In this step, required capabilities of KM are determined and their related aspects are considered. Then for each expert, an FCM is constructed which demonstrates the causal relationships between variables and their corresponding weights. Following that, these FCM matrixes are augmented into a single, final FCM. In the next step, the FCM is converted into a BBN systematically based on the approach proposed by Cheah *et al.* (2011). According to this approach, the network structure and CPTs are derived from FCM and the likelihood of variable states is defined by experts. Once the KM reliability BBN is constructed, it is possible to calculate KM reliability and related target capabilities. BBNs are updated each time there is new knowledge, evidence, or expertise available.

In order to illustrate the applicability and usefulness of the proposed approach, the developed model was verified and validated using data from a banking institution. The incentive behind selecting a banking organization as the case study is that these organizations are among the most knowledge intensive ones while they increasingly

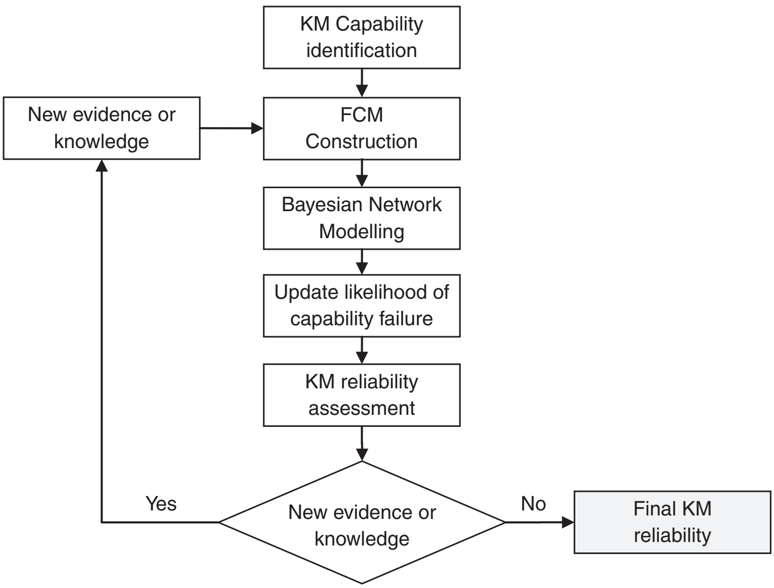


Figure 2. The proposed Bayesian belief network approach flowchart

use KM tools and systems for improving performance as well as moving along their strategies (Cebi *et al.*, 2010). Besides, "knowledge" plays a key role in competitive differentiation, and it is identified to be more relevant than money in service industries such as banks (Curado, 2008).

The banking institution used as the case is among the six largest private banks in country, and it has been planning to investigate its KM reliability in recent years. This (anonymized) bank agreed to use the proposed hybrid approach to measure its KM ability to perform the required functions one year after its implementation in 2012. Thus, a group of three experts, including a chief knowledge officer and two KM project representatives who were highly educated and experienced in the bank, was formed to determine the reliability of the bank's KM. In the first introductory meeting, all members of the group confirmed that there were unwanted, unforeseen, and unanticipated failures in the organizational capabilities of KM in the bank including failures in process and infrastructure capabilities based on explanations provided by the research team. The group aimed to calculate the probability of achieving KM goals and objectives in the second year of KM implementation. It was determined that all members would have complete information about the details of KM implementation project of the bank. For example, different aspects of the project such as KM strategy, the bank's cultural environment, related organizational policies, initiated KM tools and systems, and management support were discussed thoroughly with no conflicts. It was also clarified that all knowledge processes including acquisition, conversion, application, and protection were designed and had been active in the bank for around a year. Following the preliminary meetings, the group agreed to utilize the proposed BBN-based model of KM reliability assessment.

3.1 Capability identification

Based on Gold *et al.* (2001), knowledge infrastructure capabilities (technology, structure, and culture) and process architecture capabilities (acquisition, conversion, application, and protection) are required to have an effective or successful KM. Table II shows different aspects of these capabilities and their related dimensions in organization. Each of these social and technological dimensions of knowledge infrastructure contributes to the overall capability of an organization to effectively manage its knowledge. The knowledge processes enable organizations to capture, reconcile, and transfer knowledge in an efficient manner.

As the first step, the group started to identify required capabilities of KM in the bank. Discussions depicted that both infrastructure and process capabilities are highly required in the organization. However, some capabilities, such as culture and KM processes, seem to be more important than others. Besides, it was determined that there were minor failures in these capabilities over the past year of KM experience. Once all capabilities are identified, the team started to build their CMs.

3.2 The FCM construction

After eliciting the KM capabilities, the next step was to ask the experts to determine their mutual causal relationships based on the FCM approach. It was explained that the causal effect is either positive or negative. The weight determines the relative strength of the causal effect. It is easier for a human expert to specify discrete linguistic weights rather than continuous numerical weights between [−1,+1]. In this study, discrete linguistic weights and corresponding bipolar causal values were agreed to be: very weak (0.1), weak (0.3), medium (0.5), strong (0.7), and very strong (0.9). The next step is to incorporate the opinions of the three group members and combine FCMs into a final augmented FCM.

Category/process	Proposed dimensions
Infrastructure capabilities	
Technology	Standard and flexible knowledge structure, business intelligence, collaboration, distributed learning, knowledge discovery, knowledge ontologies and repositories, KM system and tools, measurement, knowledge mapping, opportunity generation, knowledge security, project management, intranet-based systems, content-based systems, work flow, artificial intelligence systems, innovation support tools, knowledge portals
Culture	Management style, organizational objectives and strategies, problem-solving behavior, attitudes, and values, principles, norms, top management support, trust, communication, sharing, innovation culture, shared vision, leadership, change management strategies
Structure	Organizational structure, policies, business processes, system of rewards and incentives, hypertext structure, roles and responsibilities
Process capabilities	
Acquisition	Search, sourcing, and grafting
Creation	Socialization, externalization, internalization, and combination
Refinement and storage	Explication, drawing inferences, encoding, evaluation, selection for inclusion in memory
Utilization	Elaboration, infusion Thoroughness to facilitate innovation, individual learning, collective learning, collaborative problem-solving, embedding knowledge, creating dynamic capabilities, knowledge re-use

Source: Category and proposed dimensions of process capabilities are adapted from King *et al.* (2008). Adapted from Hesamamiri *et al.* (2013)

Table II. Organizational capabilities of KM

In this step, Kosko's model is adopted, in which consensus is modeled as the average of the experts' beliefs (Kosko, 1997). All members drew their CMs with the help of research team. Based on the three maps, the augmented FCM model of KM reliability in the case under investigation is depicted in Figure 3. The FCM denotes that both infrastructure (0.833) and process capabilities (0.767) have a causal relationship to the reliability of KM. Infrastructure capability also has a causal relationship to process capability with the weight of 0.267. Furthermore, the FCM shows the following major causal links and their respective weights: (technological capability +0.833→infrastructure capability), (technological capability +0.767→structural capability), (cultural capability +0.833→infrastructure capability), (knowledge acquisition +0.767→process capability), (knowledge creation + 0.833→process capability), (knowledge refine and storage +0.767→process capability), and (knowledge utilization +0.9→process capability).

3.3 The BBN construction

After an FCM has been constructed, it is systematically converted into a corresponding BBN by the research team. Based on Cheah *et al.* (2011), the conversion of FCM to BBN is specifically defined as the generation of a complete set of CPTs from combination effect tables (CETs). This process consists of the following three stages: first, combine multiple causal effects; second, normalize probability conditions; and third, rescale for maintaining the initial intention about combination causal effect via a probability rescaling function. Table III shows a CET for the combination of multiple causal effects on infrastructure capability from three causes including technological, structural, and cultural

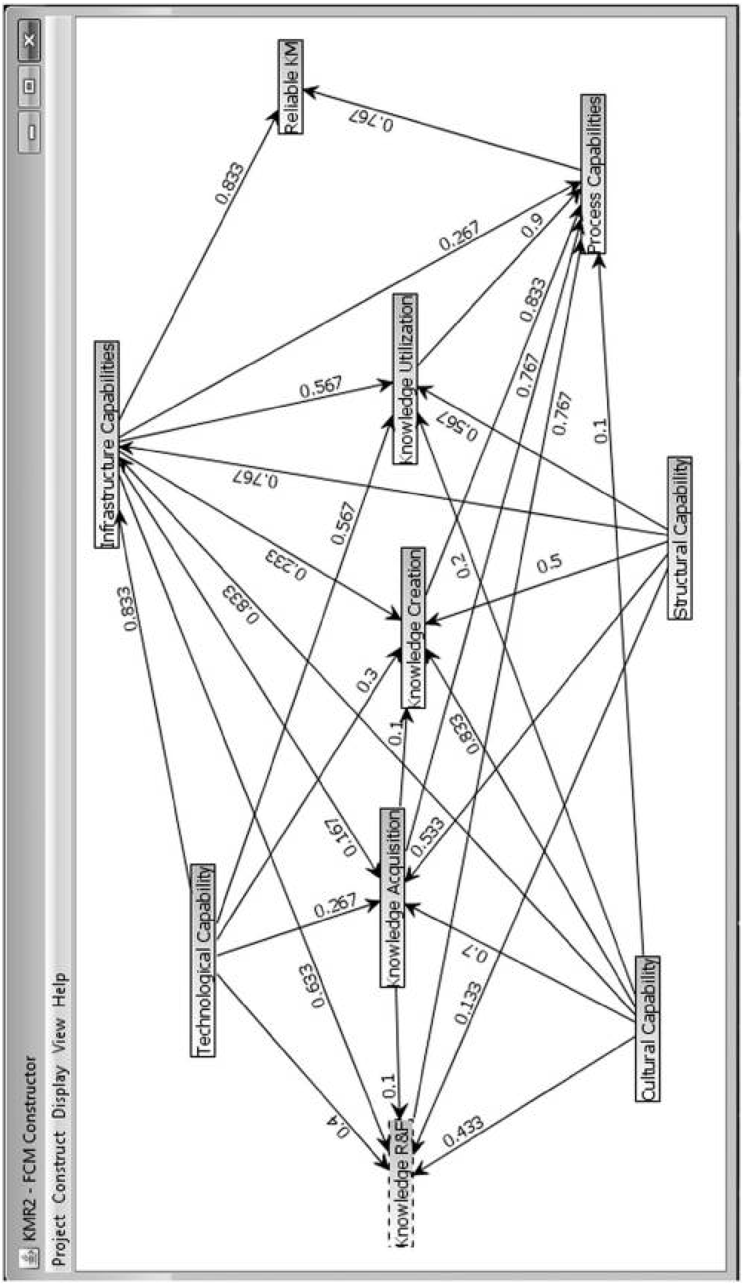


Figure 3.
The FCM model
of KM reliability
assessment

capabilities. For example, combination effect of cause variables (technological capability – success, cultural capability – success, and structural capability – success) to effect variable is the sum of weights of state variables which is 2.433. On the other hand, combination effect of cause variables (technological capability – success, cultural capability – success, and structural capability – failure) to effect variable is 0.899. In the next step, the CPT is normalized as depicted in Table IV. These values demonstrate, for example, that when both technological and cultural capabilities are increased, and the structural capability factor is decreased, all three factors have a total causal effect of 0.37 on the (+) state of infrastructural capability, which is the state of interest. However, there is no knowledge about the causal effect on the counterpart state (i.e. −state). If it is assumed that the effect on (−) state is 0.63 (1−0.37), there would be a semantic problem because it implies that the collective effect of the three factors is more likely to decrease infrastructural capability (0.63) rather than to increase it (0.37). In order to deal with this bias due to presumptive probabilities, Cheah *et al.* (2011) suggest using a simple rescaling method. The method involves scaling down the probability range for the state of interest, from 1 to 0.5, and uplifting the minimum probability from 0 to 0.5. Using this simple method, the final rescaled CPT values are depicted in Table IV. Building CPTs are the same for all other factors such as process capability, knowledge utilization, and knowledge creation. The BBN is then constructed using CPTs for all variables of the KM reliability model (Figure 4). The BBN is then described to the group members comprehensively and their opinions were captured.

Combination of state changes			
Technological capability (0.833)	Cultural capability (0.833)	Structural capability (0.767)	Combination effect to infrastructural capabilities
+	+	+	2.433
+	+	−	0.899
+	−	+	0.767
−	+	+	0.767
+	−	−	−0.767
−	+	−	−0.767
−	−	+	−0.899
−	−	−	−2.433

Table III. CET for the combination of multiple causal effects on infrastructural capabilities

Combination of state changes for cause variables			Probability of states for infrastructural capabilities	
Technological capability (0.833)	Cultural capability (0.833)	Structural capability (0.767)	+	−
+	+	+	1.000 (1.00)[a]	
+	+	−	0.370 (0.685)	
+	−	+	0.315 (0.658)	
−	+	+	0.315 (0.658)	
+	−	−		0.315 (0.658)
−	+	−		0.315 (0.658)
−	−	+		0.370 (0.685)
−	−	−		1.000 (1.000)

Note: [a]Values defined in parentheses are rescaled and final probability values

Table IV. Normalized CPT of infrastructural capabilities given the cause variables

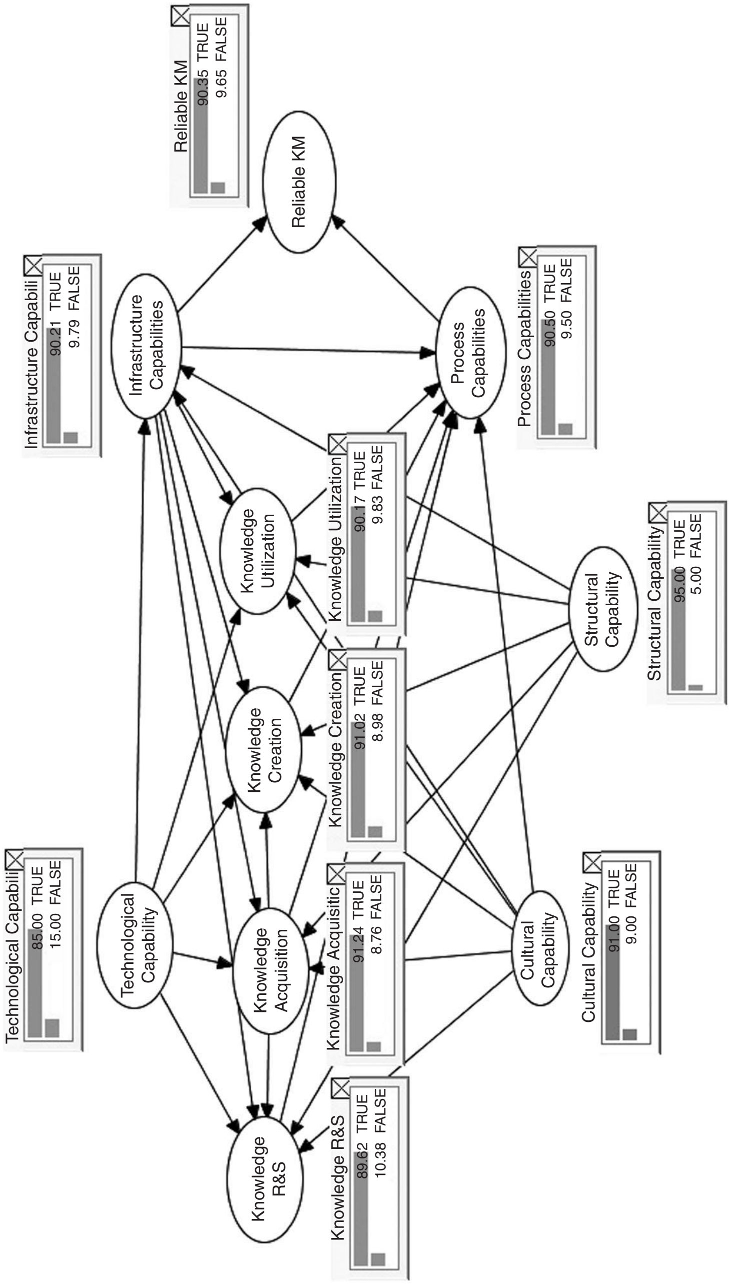


Figure 4.
The corresponding Bayesian belief network for KM reliability

4. Results and discussions

Using the proposed Bayesian approach, the likelihood of KM reliability aspects are calculated, as depicted in Table V using a professional software package that supports decision making in complex domains on the basis of partial, uncertain, or unknown information (HUGIN Lite v7.8). In this study, the failure likelihood of technological, cultural, and structural capabilities are parameters that are estimated by the group members. In this study, the failure likelihood of technological, cultural, and structural capabilities are defined as 15, 9, and 5 percent, respectively. These likelihoods were extracted from focussed sessions about different aspects of current failures or situations in the bank's KM systems and tools. However, information provided from systems or databases might be applied using different methods, such as data-mining. The specified capabilities are considered as the infrastructure for KM processes and systems. Therefore, the failure likelihoods of process capabilities were not defined by experts but they were calculated using the complex interactions captured in the corresponding FCM and constructed BBN.

Based on these parameter values depicted in Table V and the CPTs computed from the final FCM, the KM initiative (system) failure likelihood is calculated as 9.65 percent. Consequently, the reliability of the bank's KM is estimated as 90.35 percent (100−9.65 percent) by considering both infrastructural ($R = 90.21$ percent) and process capabilities ($R = 90.5$ percent). Following that process and infrastructure capabilities have 9.50 and 9.79 percent likelihood of failure in the organization under investigation. Furthermore, knowledge refinement and storage process turned out to be the least reliable and the most critical KM processes with the failure likelihood of 10.38 percent. Following that is knowledge utilization process with the reliability of 90.17 percent. The final reliability of KM (90.35 percent) is discussed with the group members. On the other hand, sensitivity analysis on parameter values reveals that KM reliability is more sensitive to cultural capability (0.37) rather than technological capability (0.32), and structural capability (0.31). This finding of the current study is consistent with those of Donate and Guadamillas (2010); however, further research should be done to investigate the detailed relationships in banking sector.

Based on the opinions regarding the value of reliability determined to be satisfactory at this stage, there were concerns about this value in the future. In this regard, the group decided to assess the KM reliability periodically every six months and study the trends. Meanwhile, the group would arrange preventive and

Reliability aspect	Failure likelihood (%)	Reliability (%)	Sensitivity value
Knowledge management initiative	9.65	90.35	–
Process capability	9.50	90.50	–
Infrastructure capability	9.79	90.21	–
Technological capability[a]	15.0	85.00	0.32
Cultural capability[a]	9.00	91.00	0.37
Structural capability[a]	5.00	95.00	0.31
Knowledge acquisition	8.76	91.24	–
Knowledge creation	8.98	91.02	–
Knowledge utilization	9.83	90.17	–
Knowledge refine and storage	10.38	89.62	–

Note: [a]Technological, cultural, and structural capabilities are fixed parameters

Table V. The likelihood of failure and sensitivity values for KM reliability aspects using Bayesian approach correcting actions plans based on their evaluation of KM reliability. In this case study, the following implications were confirmed for the proposed BBN-based KM reliability assessment approach:

(1) The whole process of KM reliability assessment takes only two weeks, while the collected opinions of group members that constitute the input to our BBN-based approach and the recommendations are known immediately. Thus, the proposed approach does not require much time and this facilitates periodic reliability assessments.

(2) Using FCM instead of asking experts directly to determine the conditional probabilities of the BBN model is more efficient, user-friendly, accurate, straightforward, flexible, and less time consuming. On the other hand, it is possible to learn FCM from data if applicable and compare with experts' opinions.

(3) The whole KM reliability assessment process is group based and capable of determining and incorporating all group opinions and judgments in both BN construction and probabilities. Thus, this approach promotes teamwork and knowledge sharing among group members and KM leaders of the organization.

(4) Understanding, calculating, and discussing KM reliability facilitates KM failure prevention, lower cost and time of KM development and maintenance, improved employee trust and motivation, better KM process stability, higher levels of KM effectiveness and efficiency, etc.

(5) Reliability analysis of KM assists and accelerates its continuous improvement.

5. Conclusion

A reliable KM initiative is one that reaches its goals without any failure during a pre-defined period. However, KM implementation is not perfect in every organization, as it requires significant modifications in infrastructures including culture, structure, and technology. This paper develops the KM reliability concept and an analytical BBN-based approach to calculate this concept in organizations based on the reliability of required organizational capabilities. In order to facilitate the process of incorporating a group of experts and conditional probability elicitation, the FCM approach is used. Based on the fact that the concept of KM reliability is novel, no other approaches existed to compare results. However, this study considered a thorough and real-world case study for demonstrating the applicability and implications of the proposed approach. On the other hand, the flowchart of the method is depicted and explained to clarify the process of KM reliability assessment. There is a need for further research on some areas including extending the concept of KM reliability theoretically, developing further analytical approaches to assess KM reliability, and applying the proposed model in other types of organizations rather than banking and financial sector and comparing the results.

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Corresponding author
Roozbeh Hesamamiri can be contacted at: amiri@iust.ac.ir

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