FCM-ENABLED APPROACH FOR INVESTIGATING INTERDEPENDENCIES OF BIM PERFORMANCE FACTORS IN THE SUSTAINABLE BUILT ENVIRONMENT

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ABSTRACT: *In pursuit of a sustainable built environment, BIM plays a crucial role in the project's performance and has egressed as a powerful technology in the construction industry, impacting the outcome and the project delivery workflows. Numerous dynamic and interdependent factors influence BIM performance. However, Existing literature prominently focuses on exploring the influencing factors for BIM performance, ignoring the impact and strength of the interplay of these factors on one another, therefore offering an inadequate picture of optimizing BIM performance. The evolving nature and degree of complexity of construction projects necessitate the identification and comprehensive understanding of the interdependencies between factors contributing to BIM performance in the sustainable built environment. A Fuzzy Cognitive Map (FCM) is a modeling method that represents and analyses the interplay between the factors in a complex system. So, this study proposes an FCM-enabled approach to investigate the interdependencies of factors contributing to BIM performance and conduct what-if scenarios, including predictive analysis. The developed FCM model can help reveal the hidden cause-effect relationships among a complex system of BIM performance factors, enabling stakeholders to develop more informed strategies and proactively plan to optimize BIM Performance.*

KEYWORDS: *BIM performance, Fuzzy Cognitive Map (FCM), Built environment*

1. INTRODUCTION

Sustainable development has become the crucial state that all sectors aim to achieve, and the built environment is no exception. Sustainable development implies balancing human socioeconomic activities and the natural environment's capacity to provide resources and absorb waste on a global scale. In pursuing sustainable development, delivering construction projects with improved performance to achieve sustainable goals shall play a significant role. Studies in the literature have shown several factors influencing project performance. Chang et al. (2017) explored the factors that influence project performance and highlighted the technological aspects that significantly affect project performance, pushing stakeholders towards adopting the technology in the built environment. Building Information Modeling (BIM) has emerged as a promising digital technology in the AEC sector, enabling the ability to enhance performance in areas including design, procurement, prefabrication, construction, and post-construction(Wang et al., 2022). Although the BIM concept dates back to the 1970s, the adoption of the BIM was seen as significantly increasing since 2000 (Caglayan & Ozorhon, 2023). Effective adoption and continuous performance improvement of BIM requires maximizing the benefits and high exploitation of the capabilities of BIM, further pushing stakeholders to gain a holistic approach and a deep understanding of the dynamics of the influencing factors. Several studies have been conducted on BIM adoption and assessing its performance in various project phases, including design and construction. However, BIM performance is not an isolated aspect. Moreover, inefficiencies are caused by the influence exerted not by discrete factors but by the amalgamate impact of the combination of dynamically connected factors in construction projects. Therefore, identifying the causes of inefficiencies also becomes crucial (Zhang et al., 2021) to improve BIM performance. While existing studies have made momentous strides in identifying factors that influence BIM performance, there is a noticeable gap in understanding the dynamics between the factors whose influence propagates throughout the system of the construction project and eventually impacts the BIM performance. This study attempts to address this noticeable gap by proposing a Fuzzy Cognitive Map (FCM) model to explore the intricate mechanism of dynamic interconnections among the factors that influence BIM performance. The study aims to identify the factors (individually or in combination) causing inefficient BIM performance and provides a dynamic model that can be used to simulate the propagation of influence caused by policy modification through FCM theory.

2. LITERATURE REVIEW

2.1 BIM Influencing Factors

BIM has been extensively studied in the research community, attributed to its positive impact on project

Referee List (DOI: 10.36253/fup_referee_list)
FUP Best Practice in Scholarly Publishing (DOI 10.36253/fup_best_practice)
Pavan Kumar, Aritra Pal, Yun-Tsui Chang, Shang-Hsien Hsieh, *FCM-Enabled Approach for Investigating Interdependencies of BIM Performance Factors in the Sustainable Built Environment,* pp. 585-593, DOI 10.36253/979-12-215-0289-3.57

performance. Several studies have been looking into the factors that impact BIM adoption and its performance. These factors are often called critical success factors, or risk factors, or key performance indicators (Caglayan & Ozorhon, 2023). Rogers et al. (2015) investigated the factors driving BIM adoption for engineering consulting services (ECS) in the Malaysian construction industry. Inadequacies of BIM experts, guidance, and government support were found to be hurdles for the ECS. Lee et al. (2018) Propose an innovative trust-centric contracting model to enhance BIM performance within Engineering, procurement, and construction (EPC) projects and explain trust's positive influence on BIM performance. Caglayan & Ozorhon (2023) propose a framework to determine BIM effectiveness and identify the project, industry, and company-based factors influencing BIM effectiveness. Project and company-based factors were identified to govern the BIM effectiveness. Badrinath et al. (2018) propose an empirical methodology to explore the factors for successful BIM projects and identifies highly governing factors groups such as the BIM technology, stakeholder skills, and competencies. Several studies have examined BIM performance and attempted to explore the influencing factors to exploit the full potential of BIM. However, the studies in the literature rarely considered the system complexity and dynamics of the interactions among the factors, ignoring the causal propagation of impacts of any discrepancies of influencing factors. Furthermore, inefficiencies are caused by various degrees of influence by factors. Hence, identifying and eradicating those causes are significant in preventing inefficiencies (Zhang et al., 2021). This necessitates analyzing the dynamic relationships among factors influencing BIM performance. Luo et al. (2022) highlighted several static methods available to study the influencing factors, such as the Fuzzy analytical hierarchy process (FAHP) and Fuzzy analytic network process(FANP), However, these methods pay little to no attention to the dynamic interaction and complexity of the system. Hence, this study employs the FCM method to investigate the dynamic interactions among BIM performance factors and aims to identify factors causing inefficiencies in BIM performance.

2.2 FCM Approach

FCM was introduced by Kosko (1986) to model and simulate dynamics systems. FCM helps mimic a complex system by considering the causal relationships between the concepts (Poczeta et al., 2020). It is a powerful method that can simulate the interaction of factors. FCM enables the systematic propagation of causal relationships between the factors, hence a suitable and systematic decision approach for analyzing and deriving insights into complex system performance (Zhang et al., 2021). Luo et al. (2022) used FCM to explore the dynamic relationship between influencing factors and prefabricated building cost, further, employed FCM to identify the root causes and sensitivity of factors to conclude that the scale effect has the greatest effect on the prefabricated cost. Zhang et al. (2021) employed the FCM method to measure the Tunnel Boring Machine (TBM) performance and conduct root-cause analysis and what-if scenario to explore the dynamic relationship between the factors that influence the TBM performance. Case et al. (2018) examine the application of FCM in modeling construction management problems and project complexities and details the construction of FCM models for construction management problems. Luo et al., (2020) propose a novel hybrid approach that combines the structural equations model (SEM) and FCM to examine the impacts of discrepancy in project complexity on the project's success. Luo et al. (2022) compared the four typical methods that are used for the simulation of the interaction between the factors.

3. METHODOLOGY

The methodology of this research involve FCM-enabled predictive analysis for BIM performance and consist of identifying concepts, determinination of relationships, and FCM computation and analyzing, as described in the following subsections.

3.1 FCM Development and Computation

3.1.1 Identification of Concepts

Identification of the concepts provides the basic structure for the FCM. FCM consists of several concepts, often called nodes or factors, referring to variables, elements, or attributes mimicking the various aspects of the system. Zhang et al. (2021) highlight the sources for identifying concepts such as accepted knowledge from the domain, empirical knowledge, and domain experts. Figure 1 illustrates a simple FCM model. These concepts (C_i) are connected by directed arcs, often called connections or edges, to represent the causal linkage between the concepts. Every concept in the FCM model bears a value ranging from 0 to 1 (Poczeta et al., 2020).

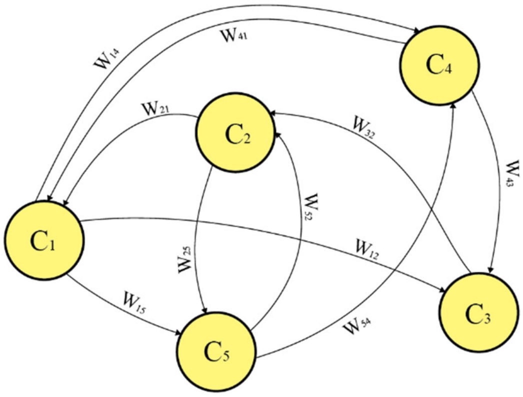

Fig.1. Illustration of simple FCM

In this study, BIM performance influencing concepts are derived through a literature review and further reduced and added after a brainstorming session with experts. Finally, 18 BIM performance controlling concepts are finalized. Concepts include BIM knowledge of the project participants (C_1), BIM training (C_2), BIM motivation (C_3), Consistent views on BIM between stakeholders (C_4), Top management support/BIM leadership (C_5), Project delivery methods encouraging collaboration (C_6), Collaboration and communication (C_7), Change management (C_8), Project complexity (C_9), Availability of BIM guidelines/protocol (C_{10}), Provisions in contracts on data security (C_{11}), Provisions in contracts on liability & risk (C_{12}), Provisions of agreed standard of rules to protect the BIM employees (C_{13}), BIM execution plan (C_{14}), Hardware and software infrastructure (C_{15}), The capability of hardware and software infrastructure (C_{16}), Information Quality (C_{17}), BIM experience of the stakeholder's company (C_{18}) and BIM Performance (C_T). The descriptions of concepts are described in Table 1.

Table 1. Concept identification for BIM Performance.

ID	Concept	Description	Reference
C_1	BIM knowledge of the project participants	Competence of project participants in using BIM tools and methodologies.	(Caglayan & Ozorhon, 2023)
C_2	BIM training	Training programs to develop BIM-related skills and knowledge among project participants.	(Einur Azrin Baharuddin et al., 2019)
C_3	BIM motivation	Incentives and drivers for project participants to adopt and implement BIM.	Suggested by expert
C_4	Consistent views on BIM between stakeholders	Alignment and agreement among stakeholders on the goals and benefits of implementing BIM.	(Al-Mohammad et al., 2023)
C_5	Top management support/BIM leadership	Endorsement and active support from top-level management for successful BIM implementation.	(Caglayan & Ozorhon, 2023)
C_6	Project delivery methods encouraging collaboration	Project delivery method facilitating better collaboration among stakeholders (for example, integrated project delivery).	(Salim & Mahjoob, 2020)
C_7	Collaboration and communication	Effective collaboration and communication processes among project participants using BIM.	(Oraee et al., 2019)
C_8	Change management	A systematic approach to managing and implementing changes associated with BIM adoption.	Suggested by expert
C_9	Project complexity	Level of complexity and size of the construction project.	(Jiang et al., 2021a)

C_{10}	Availability of BIM guidelines/protocol	Internal guidelines/protocols for consistent BIM implementation in the project.	(Al-Mohammad et al., 2023)
C_{11}	Provisions in contracts on data security	Provisions in contracts addressing data security, privacy, and confidentiality in BIM projects.	(Al-Mohammad et al., 2023)
C_{12}	Provisions in contracts on liability & risk	Provisions in contracts addressing liability and risk allocation for stakeholders in relation to BIM implementation.	(Al-Mohammad et al., 2023)
C_{13}	Provisions of agreed standard of rules to protect the BIM employees	Agreed standards of rules protecting the rights and liabilities of individuals involved in BIM projects.	(Al-Mohammad et al., 2023)
C_{14}	BIM execution plan	A comprehensive plan outlining BIM implementation strategy, processes, and deliverables.	(Franz & Messner, 2019a)
C_{15}	Hardware and software infrastructure	Adequate hardware and software resources for BIM implementation.	(Al-Mohammad et al., 2023)
C_{16}	The capability of hardware and software infrastructure	BIM software capability to meet project requirements, handle complex geometries, and more. (interoperability)	(Al-Mohammad et al., 2023)
C_{17}	Information quality	Accuracy, completeness, and reliability of information within BIM models and datasets.	(Song et al., 2017)
C_{18}	BIM experience of the stakeholder's company	Level of experience and familiarity with BIM technologies and processes within the company.	(Caglayan & Ozorhon, 2023)
C_T	BIM Performance	Effectiveness of BIM adoption and utilization in a project, aiming to maximize efficiency, return on investment, and harness the full potential of BIM across all project phases.	(Caglayan & Ozorhon, 2023)

3.1.2 Identification of causal relationship and computation

The concepts are linked by causal relationships. The direction of the causal relationship is represented by the connections or arcs describing the degree of influence between the concept C_i and C_j, often referred to as weights (W_{ij}) (S. Lee et al., 2004) that can be positive or negative, with values ranging from -1 and +1. In the complex system, in the case of any variation in the state of C_i results in a variation in the state of C_j, the arc is used to represent the causal relationship between C_i and C_j. $W_{ij} > 0$ represents the increase or decrease in the C_i leads to an increase or decrease in C_j, respectively, while $W_{ij} < 0$ represents an increase or decrease in C_i leads to a decrease or increase in C_j, respectively. Furthermore, if the W_{ij} equals zero, it indicates the absence of a causal relationship(Maitra & Banerjee, 2014). Identification of the causal relationship is the key component of building a FCM. Luo et al. (2022) highlight the two approaches to determine the degree of causal influence between the concepts, such as the learning method, which demands a large number of historical data, and the expert method. This study employs expert methods and uses fuzzy semantics to describe the degree of causality among concepts using nine levels of fuzzy semantics such as negatively very strong, negatively strong, negatively moderate, negatively weak, neutral, positively weak, positively moderate, positively strong, positively very strong with membership vales as -1, -0.75, -0.50, -0.25, 0, 0.25, 0.50, 0.75 and 1 respectively.

Causal interconnections of the FCM are mathematically presented by the n x n matrix(Zhang et al., 2021), and the state value of concept C_i at the time t+1 can be obtained through the following equation (Stylios & Groumpos, 2004)

$$A(t+1) = f\left(A_i(t) + \sum_{j=1, j\neq i}^{n}\left(W_{ji} \times A_j(t)\right)\right) \tag{1}$$

where $A_i(t+1)$ represents the state value of the concept of C_i at time t +1 as $A_i(t)$ and $A_j(t)$ represents the state value of concept C_i and C_j at time t, respectively.

Two types of threshold functions are employed in the FCM framework, i.e., sigmoid and hyperbolic tangent functions.

$$f(x)=(1/(1+e^{-cx})) \tag{2}$$

$$f(x)=\tanh(x)=((e^{x}-e^{-x})/(e^{x}+e^{-x})) \tag{3}$$

Eq. (2) is employed to map values between 0 and 1, whereas Eq. (3) is employed to map the values between -1 and +1 (Zhang et al., 2021). In dynamic FCM models, usually, the connection values range from -1 and 1(Barbrook-Johnson & Penn, 2022). In this study, experts' responses on causal relationships are taken in the range of -1 and 1 to understand the dynamic interaction between the influencing BIM factors. Hence we choose the hyperbolic tangent function [Eq. (3)]

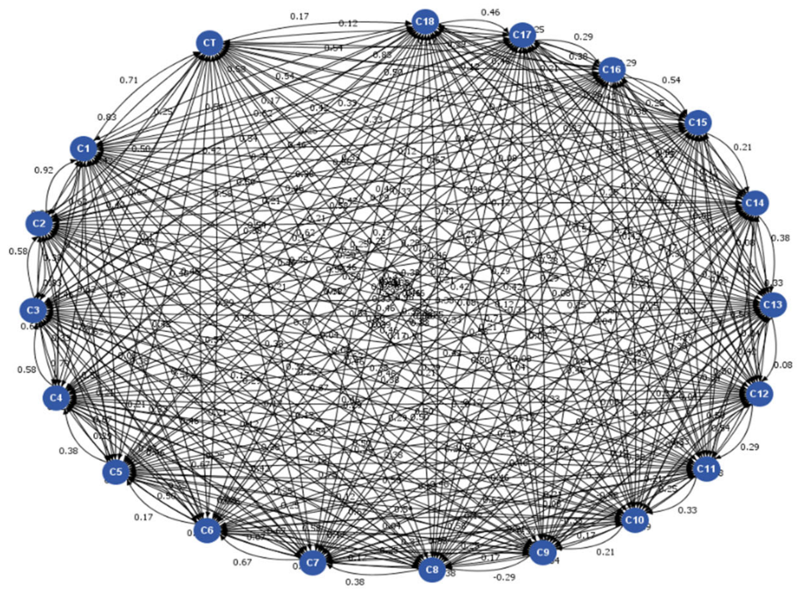

Fig. 2. Fuzzy Cognitive Map of BIM Performance

The responses of a totally 6 experts from India and Taiwan were received for the questionnaire and respondent background is shown in Table 2. The answers from the experts are further complied to calculate the weight for each concept by the center of gravity (COG) method. For example, W_{1T} is aggregated to be 0.71 as three experts rated positively strong, two experts rated positively moderate, and another rated positively very strong.

Table 2. Expert's background

Respondent	Professional background	Educational background
Expert 1	BIM Manager	Master
Expert 2	Researcher	Doctor
Expert 3	BIM Manager	Master
Expert 4	BIM Engineer	Bachelor
Expert 5	BIM Manager	Master
Expert 6	BIM Strategist	Doctor

There are several tools to facilitate the development of the FCM model. Nápoles et al. (2018) identified and compared several FCM tools and proposed a tool called FCM Expert, which facilitates adequate graphical support and higher experimental options. In this study, FCM Expert tool is employed, considering its advantages of FCM Expert over other tools. Creating the concepts and assigning aggregated weights to the concepts, results in the FCM model of BIM performance that is graphically presented in Fig. 2. FCM facilitates to simulate the behavior of systems and enables the what-if experiments (Papageorgiou & Salmeron, 2013). In order to identify the concepts influencing BIM performance, considering the dynamic interplay among the concepts, FCM, once modeled, allows the predictive analysis.

3.2 Predictive Analysis and Discussion

FCM-enabled predictive analysis facilitates the forecast of the outcome or impact of a cause when information or evidence of the cause is available (Zhang et al., 2021). It allows to curate the experiments involving simulation of impacts of the target variable (C_T) when evidence of change is available in the influencing variables (Luo et al., 2022). To address the uncertain nature of the concepts, a five-point linguistic scale: very favorable, favorable, neutral, unfavorable, and very unfavorable, with numerical values as 1, 0.5, 0, -0.5, and -1, respectively. The dynamic propagation of the effect of change in nature (very favorable, favorable, neutral, unfavorable, and very unfavorable) of influencing concepts (C_1 to C_{18}) on CT in a system of network simulated and the effect of the target variable (C_T), i.e., BIM Performance is observed. For example, the initial nature of all the concepts is set to neutral except C_9, whose nature is assumed to be very favorable, favorable, unfavorable, or very unfavorable, to observe the effect on BIM Performance (C_T) until it stabilizes. Table 3. Presents the stable values of CT after a set of iterations in different values (1,0.5, -0.5,1) of C_1 to C_{18}. For example, the stable value of C_T when C_1 is very favorable (=1) is 0.948, implying a positive correlation between C_T and C_1. All the concepts except C_9 tend to have a positive correlation with the target variable, i.e., BIM Performance. The stable value of C_T when C_9 is very unfavorable (=-1) is 0.951, implying the negative correlation between them. Fig.3 illustrates the impact of the concepts C_1 and C_9 on C_T. Predictive analysis results showed that concepts C_1 (BIM knowledge of the project participants), C_2 (BIM training), C_9 (Project complexity), and C_{14} (BIM execution plan) have a high influence on BIM performance. Similar results are demonstrated by other studies, such as Caglayan & Ozorhon, (2023) demonstrate that project-based factors such as BIM training and BIM knowledge of the individuals on the BIM project have a direct impact and great influence on the effectiveness of the BIM. Project complexity (C_9) has a significant impact on BIM performance. The negative correlation here implies poor BIM performance resulting from the combination of the influence of BIM knowledge and training. Jiang et al. (2021b) study BIM performance, project complexity, and user satisfaction and highlight project complexity as the key factor for BIM performance and user satisfaction. Furthermore, Franz & Messner, (2019b) shows the positive impact of the BIM execution plan, not only on participating members but also the performance. Similarly, the results of predictive analysis tend to show the positive influence of the BIM execution plan (C_{14}) on BIM performance. The predictive analysis aids the deeper understanding in enhancing the effectiveness of BIM adoption and aiming to use the full potential of BIM.

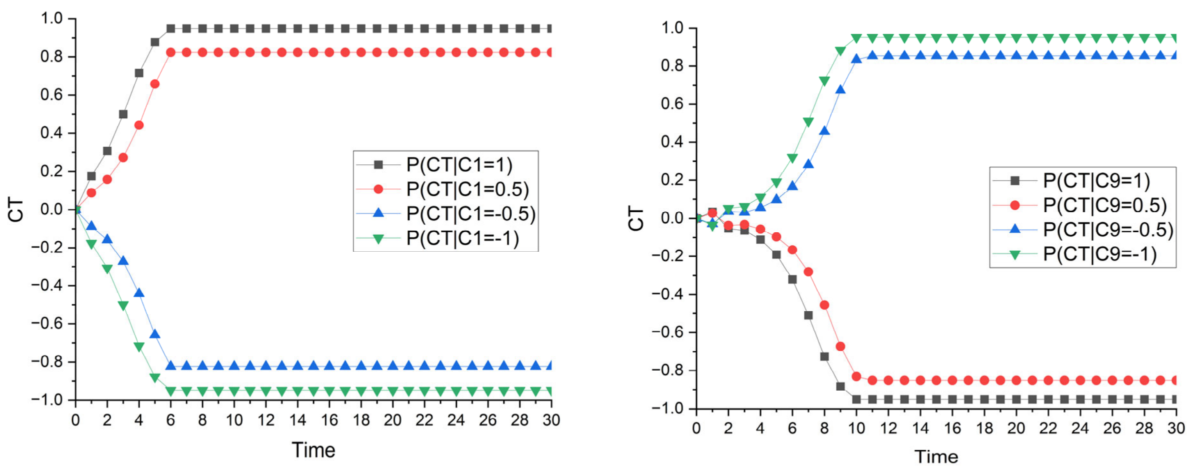

Fig.3. Impact of concepts C_1 (BIM knowledge of the project participants), C_9 (Project complexity) on C_T (BIM Performance)

Table 3. Stable values of C_T under different scenarios

Concept ID	$Ci = 1$	$Ci = 0.5$	$Ci = -0.5$	$Ci = -1$
C_1	0.948	0.823	-0.823	-0.948
C_2	0.942	0.839	-0.839	-0.942
C_3	0.811	0.621	-0.621	-0.811
C_4	0.830	0.682	-0.682	-0.830
C_5	0.835	0.689	-0.689	-0.835
C_6	0.890	0.747	-0.747	-0.890
C_7	0.911	0.793	-0.793	-0.911
C_8	0.942	0.808	-0.808	-0.942
C_9	-0.951	-0.832	0.832	0.951
C_{10}	0.892	0.763	-0.763	-0.892
C_{11}	0.780	0.611	-0.611	-0.780
C_{12}	0.690	0.609	-0.609	-0.690
C_{13}	0.780	0.619	-0.619	-0.780
C_{14}	0.979	0.900	-0.900	-0.979
C_{15}	0.849	0.721	-0.721	-0.849
C_{16}	0.908	0.790	-0.790	-0.908
C_{17}	0.940	0.807	-0.807	-0.940
C_{18}	0.903	0.788	-0.788	-0.903

4. CONCLUSION

BIM adoption and enhancing its performance in construction projects is a complex system where several factors influence its effectiveness in exploiting the high potential of BIM. It is crucial to pinpoint the factors causing the strong influence on BIM performance, considering the dynamic relationship among them. FCM models are better suited to explore and reflect the cause-effect relationship among the concepts (Luo et al., 2022). FCM's approach to understanding the dynamic relationship between factors that influence BIM performance is suitable due to its dynamic complexity. Furthermore, it allows predictive analysis to forecast the behavior of the network of the system. The concepts for the BIM performance were identified from the literature and further filtered through brainstorming sessions with experts to finalize 18 concepts. Relationships between the concepts were captured through a survey, and FCM was developed to enable predictive analysis. The results showed a high positive influence from the concepts: BIM knowledge of the project participants (C_1), BIM training (C_2), and BIM execution plan (C_{14}) have a big influence on BIM performance, whereas Project complexity (C_9) tend to show the negative correlation implying the special precautions to be taken by stakeholders to enhance the effectiveness of the BIM adoption to leverage the full potential of BIM in high complexity in the construction project.

In the course of this study, highlighting encountered limitations shall aid the improvement in future studies. The factors identified for the study are pivotal for exploring the dynamic interaction among the BIM performance influencing factors and are not extensive. Additionally, the reliability of the FCM employed could be strengthened with high responses and the widespread input of experts.

The exploration of the relationships among the factors is enabled through several methods, as mentioned before. However, understanding the dynamic relationship among them and the propagation of ripple effects among the network system is better understood through adopting less static models like FAEM and FMEA. In order to capture the dynamic complexity, the systems thinking approach can be used to understand the behavior of the system of BIM and assess BIM's performance with higher experts' involvement. To date, several construction activities are highly dependent on the experience of the experts; the FCM can be used to capture crucial human knowledge in the context of effective BIM adoption to aid better decision-making for the stakeholders involved.

ACKNOWLEDGMENT

This research has been supported by the Ministry of Science and Technology, Taiwan, with grant MOST 111-2923-E-002-010-MY3.

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