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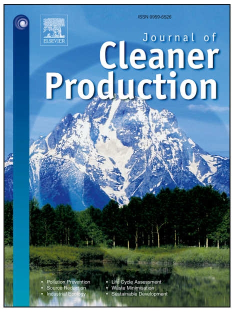

Optimizing the application of strategies promoting electronic procurement systems towards sustainable construction in the building lifecycle: A neurofuzzy model approach

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Abstract

Digital transformations in the built environment address inefficiencies and sustainability issues in the building lifecycle. Accordingly, electronic procurement systems (EPSs) have benefits that improve the economic, environmental and social initiatives for sustainable construction. However, the slow rate of EPSs uptake evinces the need for strategic approaches towards their widespread implementation. Scoping the previous studies on EPSs, there is a lack of research on the influence dynamics of these strategies for effective promotion of EPSs in the built environment. Therefore, this study investigates the dynamic influences of strategies by using the neurofuzzy model for the effective promotion of EPSs implementation. Through a comprehensive literature review, 14 strategies were employed in an expert survey. A total of 121 datasets were collected and analyzed in the study. From the analysis, five groups were derived: technology education, innovation culture management, technological stimulation environment, incentives and partnership mechanism and organizational integration support. Further, the neurofuzzy model and sensitivity analysis were used to predict and determine optimal strategies for promoting EPSs implementation. The findings showed dynamic ways of hybridizing the strategies for EPSs promotion. Two hybrid-approaches, in addition to other strategies, that actively enhance effective EPS implementation are 'innovation culture management – technology education' and 'innovation culture management – incentives and partnership mechanism'. Additionally, the combinations of strategies that result in low promotion of EPSs were also highlighted. This study provides a deepened understanding of the dynamic influences of strategies for researchers and practitioners to effectively promote the widespread implementation of EPSs in the built environment.

Keywords: Electronic procurement systems; Strategies; Sustainable construction; Neurofuzzy; Built environment; Construction industry.

1. Introduction

The success of digital applications in building projects heavily depend on decision-making in the built environment (Tan et al., 2021). Over the past decades, there have been increasing concerns about the impact of buildings and construction processes on the initiatives of sustainability (Dwaikat and Ali, 2018; Carvalho et al., 2019). Although the building sector has been frequently recognized for economic contributions to national growth (Piroozfar et al., 2019), it is also a main contributor to the consumption of raw materials, energy and natural resources (Goh et al., 2020). This shows that efforts to improve sustainability in the building sector contribute to sustainable development globally. In that regard, public agencies and organizations have shown particular interest in promoting more sustainable and efficient technologies in the building sector (Santos et al., 2019; Fatourehchi and Zarghami, 2020). Sustainable construction focuses on principles/practices and technologies that improve economic, social and environmental aspects of building projects, through efficient use of resources and creating a healthy environment (Kibert, 1994).

In recent years, the drive for digitalization paved the way for the introduction of electronic procurement systems (EPSs) to provide sustainable solutions and collaborative environments in the building lifecycle, via construction procurement (Yu et al., 2020). EPSs transform the conventional manual process of procurement into digital procurement systems, thereby, reducing the fragmentation and inefficiencies limiting the contribution of construction procurement to sustainable construction (Mehrbod and Grilo, 2018). The benefits of EPSs span vertically throughout the various stages of building projects and horizontally across the dimensions of sustainability. While EPSs reduce the time and cost of procurement processes for economic sustainability gains, they also ensure a paperless environment that conserve natural resources for the benefit of the environment (Eadie et al., 2011). Further, the benefits of EPSs provide transparency and collaboration opportunities to facilitate social sustainability initiatives in projects, e.g. local supplier inclusiveness (Yu et al., 2020). Despite these benefits, the rate of EPSs implementation on building projects has been slow over the years, especially in countries that are faced with reconciling the need for sustainability and rapid economic growth, e.g. developing countries (Wimalasena and Gunatilake, 2018; Bohari et al., 2017; Ibem and Laryea, 2015). Hence, the widespread uptake of EPSs required for them to significantly contribute to sustainable construction is affected (Yu et al., 2020).

In the process of finding strategies or measures that alleviate the slow rate of EPSs implementation and historical failures, several studies focused on identifying individual strategies for EPSs implementation (Wimalasena and Gunatilake, 2018; Aibinu and Al-Lawati, 2010). Although, the individual strategies are not implemented in isolation, the inherent clustering influences and interrelationships of these strategies have still not been explored in literature. Extant literature shows that individual strategies identified by many studies include change management, policies and management support (Wimalasena and Gunatilake, 2018; Kang et al., 2012; Aibinu and Al-Lawati, 2010). Strategies related to training, financial support and pilot projects have also been highlighted by other studies as substantial in promoting EPSs (Ozorhon et al., 2016; Kim et al., 2016). Additionally, evidence of EPSs benefits has been suggested as a strategy for the implementation of digital systems (Pala et al., 2016). Despite the significant efforts of previous studies in identifying these strategies, there is lack of knowledge and understanding on how these strategies interact to influence the effective promotion of EPSs implementation in the building sector. This limitation raises the question of how these strategies interact to ensure effective EPSs promotion. Thus, how the complex interrelationship patterns of strategies could be harnessed for synergistic impacts in the promotion of EPSs remain unknown in resource-constrained project environments.

The aim of this study is to investigate the influences of strategies for optimal approaches in the effective implementation of EPSs towards sustainable construction. To this end, the influences of strategies are examined in a survey, and the ensuing data is then modelled using the neurofuzzy technique. Based on the neurofuzzy model, sensitivity analysis was used to determine optimal approaches for hybridizing these strategies to attain an effective promotion of EPSs implementation in projects. The neurofuzzy technique and sensitivity analysis are robust in exploring complex nonlinear patterns of problems (Tiruneh et al., 2020). This study provides a guiding mechanism for the optimization of strategies in the promotion of EPSs implementation in project environments. The remainder of this paper consist of literature review, followed by research methodology and results. Subsequent sections include clustering analysis, neurofuzzy model development with sensitivity analysis, implications and conclusions.

2. Literature review

2.1.EPSs and building lifecycle

EPSs relate to the use of web-based systems to digitize and automate the conventional manual procurement process for building projects, which was paper-based (Mehrbod and Grilo, 2018). Procurement processes play a central role in the supply chain of building projects, from planning to resource selection and the execution of projects (Bohari et al., 2020). The future demands of the building sector require efficient delivery of building projects and the integration of technologies that enhance sustainable solutions and environmental responsiveness (Townsend and Gershon, 2020). Hence, EPSs comprise of several work-packages that conduct various functions of the procurement processes at any stage in the lifecycle of building projects (Ibem and Laryea, 2015). For example, the e-tendering/bidding work-package conducts tendering/bidding functions through online systems for projects at the planning stage of building projects. Also, the e-payment and progress monitoring work-package performs the functions of progress monitoring and payments at the building execution stage. Further, EPSs provide numerous work-packages that are utilized in the post-execution and maintenance stages of projects. These work-packages provide the functions of project auditing, resource allocation and maintenance supplier selection. EPSs work-packages can be fused into one tool based on the project need at every stage of the project (Grilo and Jardim-Goncalves, 2011). Moreover, several studies have explored the integration of EPSs with current digital applications such as building information modelling (BIM), cloud computing, construction digital market-places and social e-business in the building sector (Costa and Tavares, 2014; Mehrbod and Grilo, 2018; Grilo and Jardim-Goncalves, 2011). These research developments highlight the ameliorating opportunities of EPSs in providing sustainable solutions in the future for building projects.

2.2.Sustainable practices for sustainable construction

It has been noted in literature that the application of EPSs for building projects generates benefits that contribute to sustainable construction initiatives. Sustainable construction focuses on responsible creation and management of healthy building environments, considering efficient resource usage and environmental principles (Kibert, 1994). The initiatives of sustainable construction include minimizing resource consumption, maximizing resource reuse, environmental protection and pursuing quality in the built environment (Carvalho et al., 2019; Kibert, 1994). Previous studies acknowledged that EPSs significantly improves the efficiency and quality of construction procurement while advancing ecological principles (Walker and Brammer, 2012; Yu et al., 2020). Focusing the benefit of promoting paperless environment, EPSs reduce the generation of waste, and reduce energy and natural resources consumed in the procurement process, and this has benefits for environmental sustainability (Walker and Brammer, 2012). Moreover, EPSs help save cost, time and errors in the procurement process, thereby, conserving project resources and contributing to economic sustainability via optimized process performance (Ruparathna and Hewage, 2015; Yevu and Yu, 2020). By improving transparency and collaboration in construction procurement, EPSs facilitate social trust and local inclusiveness among various participants for the sustainable development of projects in localities (Ramkumar and Jenamani, 2014). The numerous benefits of EPSs enable construction procurement to contribute to sustainable construction initiatives, considering the future trajectory of digitalization in the built environment. To promote the widespread use of EPSs, there is a need for the development of suitable strategies that promote EPSs implementation effectively.

2.3. Strategies promoting EPSs in the lifecycle of projects

According to Mintzberg (1987), a strategy is a plan or some consciously intended course of action or guideline to deal with a situation. In this study, the term 'strategy' refers to an action, guide, scheme or plan that encourages successful implementation and continued use of EPSs. A strategy that promotes EPSs has attributes of mitigating the challenges to EPSs and facilitating EPSs implementation in building projects. As such, various strategies have been explored by previous studies. Strategies relating to change management, collaborative environments and management support have been widely identified in the literature from the perspectives of developed and developing countries (Kim et al., 2016; Wimalasena and Gunatilake, 2018; Lou and Alshawi, 2009). Kim et al. (2016) indicated that change management programs, open dialogues and change agents were significant to the success of implementing EPSs in the US. From the UK perspective, evidential proof of benefits and organizational alignment were identified as important strategies for the promotion of EPSs (Lou and Alshawi, 2009; Eadie et al., 2011). In addition, pilot projects and reward schemes were identified as critical strategies in the European and Australian contexts (Ozorhon et al., 2016; Aibinu and Al-Lawati, 2010). Wang et al. (2007) emphasized the importance of simplifying and standardizing processes to enhance EPSs implementation in China. In Sri Lanka and South Africa, institutional frameworks and financial supports were highlighted as important strategies for EPSs promotion in the construction industry (Wimalasena and Gunatilake, 2018; Ibem and Laryea, 2015).

From the perspective of other 'Sub-Saharan African countries', despite the limited literature on EPSs, few studies have made efforts in proposing strategies for EPSs implementation. In the Nigerian construction industry, Ibem et al. (2016) highlighted that organizations have to understand the benefits of EPSs, and that EPSs should be made available at affordable costs. Further, training workshops should be held for practitioners to promote a wider uptake of EPSs.

Similarly, Afolabi et al. (2019) emphasized that management support for EPSs infrastructure, proof of EPSs benefits, regulations and reliable internet infrastructure are critical in promoting EPSs in Nigeria. In addition, Oyediran and Akintola (2011) indicated that providing infrastructure such as power and communication facilities play a critical role in the promotion of EPSs in the African region. Based on these studies, strategies pertaining to management support, provision of infrastructure and training have been proffered to promote EPSs uptake in the African region. Though these studies propose various strategies within the Sub-Saharan African context, they did not consider how the strategies could be applied empirically in the promotion of EPSs implementation.

The literature documents various strategies for EPSs promotion from the perspectives of various countries. However, there is a notable lack of exploration into the relationships among the strategies. As EPSs promotion strategies are rarely implemented in isolation, it is important to understand the relationships among them. Such relationships are crucial because they offer insights into the optimal combinations of strategies that could widely promote EPSs implementation. Also, the review shows that there are limited studies that focus on developing countries. Thus, further research in developing countries such as Ghana is worthwhile due to socio-economic differences in comparison to the developed countries, for an effective promotion of EPSs implementation in the built environment.

2.4.Neurofuzzy model applications in construction research

Artificial intelligence (AI) has been increasingly employed to solve construction problems that are intrinsically complex, subjective and uncertain within the built environment (Tiruneh et al., 2020; Darko et al., 2020). AI techniques include but not limited to fuzzy systems, support vector machines, artificial neural network (ANN) and expert systems. More so, hybrid systems which combine two or more AI techniques, such as neurofuzzy models, have become dominant due to their ability to fuse the strengths and complement the weakness of stand-alone AI techniques (Akinade and Oyedele, 2019). Neurofuzzy models have the ability of attaining interoperability and accuracy (Lin, 1996), hence the adaptive neuro-fuzzy inference system (ANFIS) introduce by Jang (1993) was adopted in this study. The ANFIS combines fuzzy systems and ANNs for effective learning and reasoning capabilities (Jin, 2011). As a result of the integration, ANFIS provides robust, fast and more predictive capabilities in solving complex problems that are subjective, uncertain and nonlinear. ANFIS has been applied in solving several construction-related problems such as prediction, supplier evaluation and cost modelling in the built environment (Statkic et al., 2020; Tavana et al., 2016; Gerek, 2014).

3. Research methodology

This study adopted a multi-stage research approach to identify and analyze the strategies promoting EPSs in construction projects. This approach includes the identification of strategies from relevant literature, data collection and data analysis.

3.1.Identification of strategies for EPSs promotion

A systematic literature review was employed to identify the strategies that promote EPSs in the building sector, as adopted in previous construction engineering research to identify critical components related to decision-making (Nnaji and Karakhan, 2020). This systematic literature review involved three-steps. *Step-one,* journal search was conducted using the top journals in Wing's (1997) ranking of construction management journals and the Scopus search engine. Wing's (1997) ranking was selected because it is widely recognized in construction management research to provide a credible list of journals that focus on construction-related topics (Lu et al., 2015). More importantly, the top journals in Wing (1997) are reputable and still remain relevant in shaping the development of knowledge in construction management research and practice. To capture other journals that are recent and relevant to the research topic, Scopus was employed in this study (Yu et al., 2020). This is because Scopus has a wider journal coverage and an effective search engine for identifying current publications (Falagas et al., 2008). Therefore, recent journals that were excluded in the ranking by Wing (1997) would be included via Scopus search to enhance comprehensiveness in the study.

Based on the keywords – 'electronic procurement', 'e-procurement', 'strategies', 'promotion' and 'construction', 17 journals were identified to have relevant papers. These journals include, but not limited to, *Journal of Cleaner Production*, *Automation in Construction*, *Construction Management and Economics*, *Journal of Construction Engineering and Management*, *Engineering, Construction and Architectural and Management* and *Journal of Information Technology in Construction*. From the keywords search in these journals, 134 papers were initially identified. *Step-two*, the titles and contents of the initial papers identified were screened using the selection criteria; (i) papers that focused on strategies promoting EPSs, and/or (ii) papers that focus on overcoming EPSs challenges. In effect, 44 relevant papers were identified for full-text examination. During the full-text examination, numerous strategies that were proposed in these relevant papers were recorded. In *Step-three*, the numerous strategies in the recorded data were synthesized or integrated based on the commonalities existing between the strategies to reflect a core strategy that promotes EPSs implementation (Salim et al., 2019). Through the synthetization process, 14 potential strategies were identified in this study (Table 1). Since there exist similarities among the numerous strategies identified in literature, Cheng and Li (2002) emphasized the need to aggregate themes/factors having common lines of action in order to generate a comprehensive list of factors that is more usable, and clearer for respondents to apprehend. This is because having many factors in a list produces redundant and repetitive problems (Chan et al., 2018; Rowlinson, 1988). As such, strategies referring to subsidized cost of EPSs, lower implementation cost for EPSs and financial assistance for organizations, for example, were synthesized to reflect a core strategy termed as 'availability of financial support schemes for EPSs investment'. Therefore, this integrated method ensures that the 14 strategies resulting from the synthetization of factors, are extensive, measurable and relevant to industry practice and research (Pan et al., 2020).

Table 1. List of strategies promoting EPSs

Code	Strategies promoting EPSs	Reference
S01	Align EPSs to organisation's strategy and procurement procedures	[7]; [5]
S02	Reward schemes for EPSs adoption on projects	[2]; [4]; [7]
S03	Competent institutional framework and local promotion teams for effective EPSs implementation	[7]; [8];[17]
S04	Enable collaborative environment among organisations and partners	[1]; [2]; [3]; [4]; [6]; [9]; [18]
S05	EPSs related training programs for key stakeholders	[2]; [6]; [8]; [9]; [10];[17]
S06	Active and strengthened research and development for EPSs implementation	[8]; [12];[17]
S07	Pilot implementation projects for contextual learning and knowledge sharing	[2]; [12]; [13]
S08	Proactive change-management systems	[4]; [5]; [10]; [11]; [14];[17]
S09	Organisational leadership buy-in and commitment strategy for EPSs	[2]; [4]; [9]; [10]; [14];[17]
S10	Active publicity through media communications	[6]; [8]; [10]
S11	Availability of quantifiable evidence of EPSs benefits	[1]; [5]; [11]; [15]
S12	Ensure standardisation and simplification of process across systems	[16]
S13	Mandatory EPSs policies and regulations	[4]; [13]; [16]
S14	Availability of financial support schemes for EPSs investment	[2]; [4]; [7];

Note: [1]= Pala et al. (2016); [2]= Ozorhon et al. (2016); [3]= Costa and Tavares (2014); [4]= Wimalasena and Gunatilake (2018); [5]= Lou and Alshawi (2009); [6]= Dossick and Sakagami (2008); [7]= Adriaanse et al. (2010); [8]= Ibem and Laryea (2015); [9]= Altuwaijri and Khorsheed (2012); [10]= Kim et al. (2016); [11]= Lines et al. (2017); [12]= El-Diraby (2013); [13]= Aibinu and Al-Lawati (2010); [14]= Kang et al. (2012); [15]= Eadie et al. (2011) [16]= Wang et al. (2007); [17]= Yu et al., 2020; [18]= Jacobsson et al. (2017).

3.2.Data collection

In this study, the survey method, which systematically examines and gauges expert's views and experiences was adopted for data collection (Piroofar et al., 2019; Jin and Gambetese, 2020). The quantitative approach (i.e. questionnaire survey) was adopted in this study because it is an effective method in attaining objectiveness and quantifiability (Fellows and Liu, 2015; Saka and Chan, 2021). Unlike, the qualitative approach that employs interviews and has the limitation of a small number of participants (Pan and Pan, 2019; Fellows and Liu, 2015), the quantitative approach offers a wider coverage of participants to explore the magnitude of a phenomenon in a given industry (Jin and Gambetese, 2020). According to Wang et al. (2020), the quantitative approach helps to test the relationships and causes that influence outcomes for emerging issues on a broader scale. By adopting the questionnaire survey, this study explores the extent of influences these strategies have in promoting EPSs from a more broader industry perspective among many construction organizations.

A questionnaire survey was developed and conducted to assess the important strategies that promote EPSs. The development and design of the questionnaire was supported by the comprehensive literature review and the domain knowledge. In a two-step development process, a pilot study was carried out to evaluate the appropriateness and adequacy of the questionnaire. First, the clarity of expressions and structure of the survey questionnaire was evaluated by an academic (a professor with relevant experience in procurement). Second, interviews with three local industry experts were conducted to assess the comprehensiveness and relevance of the strategies in the questionnaire. Feedback from the pilot survey was used in an iterative process to revise and finalize the questionnaire. The final questionnaire firstly presented the research objective of the study and the connection between EPSs and sustainability initiatives in construction procurement. The second section elicited the background information of respondents, e.g. years of work experience and EPSs used at various projects stages. Further, the third section consisted of questions related to the 14 strategies identified from the literature review for respondents to assess their importance based on a five-point rating system (Delgado et al., 2019; Yas and Jaafer, 2020), where 1= not important, 2= less important, 3=neutral, 4= important and 5= very important. Additionally, in this section, the overall impact/influence of these strategies in promoting EPS in project environments were evaluated by respondents on a five-point rating scale with 1 being very low and 5 being very high. This study applied the five-point rating scale due to the 'seven plus or minus two' principle from Miller (1956) to ease participants' cognitive expression. Also, the five-point scale produces data that is easily readable for scalability (Dawes, 2008). Therefore, the five-point rating system adopted in this study aids respondents to easily express their experiences. Many studies in construction engineering and management research have used the five-point rating system in questionnaires to facilitate the quantification of experts' experiences in the development of theory and practice (Razkenari et al., 2020). This is because questionnaires adopting the five-point rating systems (as employed in the study), have advantages of yielding unambiguous results with easy expressions (Darko et al., 2018). More importantly, the study's questionnaire and the five-point technique ensure adequate quantification of respondents' experiences regarding the strategies of EPSs for further modelling analysis (see Jin, 2011). It is worth noting that this study forms part of a large-scale research project examining the benefits and promotion strategies of EPSs. While the benefits of EPSs show numerous sustainability gains in construction procurement and is reported in Yevu et al. (2021), the present study focuses on how EPSs implementation strategies would facilitate the widespread use of EPSs among organizations, in order to achieve these sustainability benefits of EPSs.

The non-probability sampling techniques were employed in this study to identify and select experts due to the unavailability of a sampling frame for all electronic procurement experts in the Ghanaian construction sector. These non-probability sampling techniques provide an effective means of attaining a representative sample when the sampling frame is unavailable (Pan et al., 2020; Zhao et al., 2015). Specifically, purposive and snowballing sampling techniques were simultaneously adopted in this study. The purposive sampling technique was used to target information-rich respondents (Piroozfar et al., 2019), using the selection criteria: (i) experts having extensive working experience in the construction industry, (ii) practitioners with expertise in at least one implementation of EPSs in building projects, and (iii) practitioners with knowledge and experience of applying the strategies to promote EPSs. Simultaneously, the snowballing sampling technique was used to request target respondents to recommend and invite other experts within their personal networks based on the selection criteria (Jin and Gambetese, 2020). Organizations involved in EPSs implementation for projects within the Ghanaian construction sector were initially approached to identify target respondents. The initial target respondents were subjected to the selection criteria for their inclusion in this study. Recommendation for the inclusion of other experts by the target respondents were examined based on the selection criteria. In using these two sampling techniques, the purposive sampling was used to directly distribute 208 questionnaires, while several target respondents confirmed inviting other experts through their personal networks. Hence, the total number of questionnaires distributed becomes difficult to estimate. A total number of 121 valid sets of responses were retrieved after filtering out incomplete and unanswered questionnaires. The sample was considered adequate for investigating the strategies promoting EPSs using the neurofuzzy model and compares favorably with many studies that used sample sizes less than 100 (Gerek, 2014; Jin, 2011).

The background information of the respondents is presented in Table 2. Most of the respondents (i.e. 95% and 90%) have more than five years of experience in the construction industry and have been involved in EPSs implementation for up of six years respectively. Regarding profession, most of the respondents' were project managers (24.8%), engineers (14.1%) and quantity surveyors (53.7%), with architects (4.1%) and procurement officers (3.3%) being in the minority from organizations involving consultants, contractors and regulatory agencies. This could be explained by the fact that, from the construction procurement perspective, professionals from quantity surveying, civil engineering and project management divisions are usually dominant in procurement positions in organizations, and this fact is evident in procurement-related studies (Aibinu and Al-Lawati, 2010; Eadie et al., 2010; Owusu et al., 2020), and from the African context (Ibem and Laryea, 2015). Because professionals from these three backgrounds have construction experiences and interact with procurement processes, organizations assign them with procurement functions at the senior or top management levels to make decisions. Therefore, engineers with construction procurement experience in such organizations make decisions on organizational efforts to implement EPSs for projects. For instance, a civil engineer leading the procurement and contracts section of a consultant organization would have the responsibility of supervising and implementing EPSs in projects.

According to Fig. 1, majority of the respondents have used EPSs tools – e-tendering and e-invoicing in more than three projects. This shows that the study's respondents, which includes engineers, have been reasonably involved in EPSs implementation on projects due to the procurement roles they play in their respective organizations. Fig. 2 shows that 71.1% of respondents have used EPSs at both the pre-contract and post-contract stages of projects. Therefore, the background information shows that the respondents in this study are experienced, diversified and knowledgeable to provide adequate and reliable information on the strategies promoting EPSs in building projects.

Table 2. Background information of respondents

Background Profile	Frequency	Percent	Years of experience							
			Construction sector					EPSs		
			1-5	6-10	11-15	16-20	>20	1-3	4-6	6-8
Organizations										
Consultant	67	55.4	1	14	27	17	8	28	38	1
Contractor	28	23.1	0	6	16	6	0	10	14	4
Regulatory Agency	26	21.5	5	9	4	6	2	11	8	7
Subtotal	121	100.0	6	29	47	29	10	49	60	12
% year subtotal			5.0	24.0	38.8	24.0	8.2	40.5	49.6	9.9
Professions										
Project Manager	30	24.8	1	5	6	15	3	4	22	4
Engineer	17	14.1	0	4	9	4	0	11	4	2
Quantity Surveyor	65	53.7	3	18	30	7	7	30	29	6
Architect	5	4.1	0	0	2	3	0	0	5	0
Procurement officer	4	3.3	2	2	0	0	0	4	0	0
Subtotal	121	100.0	6	29	47	29	10	49	60	12
% year subtotal			5.0	24.0	38.8	24.0	8.2	40.5	49.6	9.9

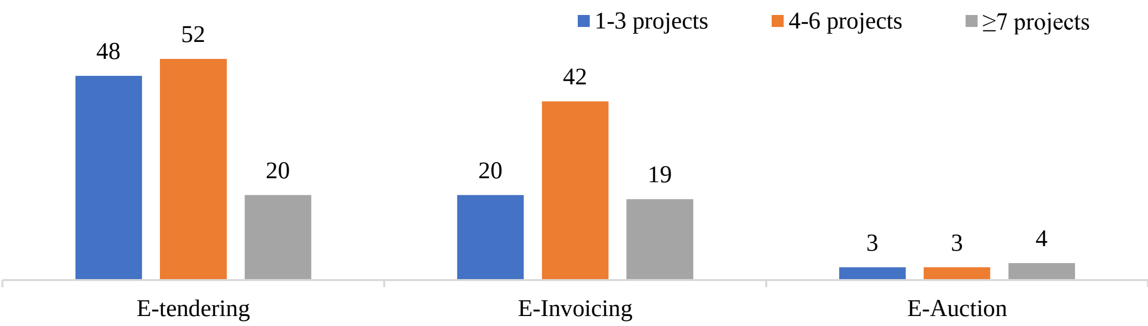

Fig. 1. Number of projects with EPSs tools implemented.

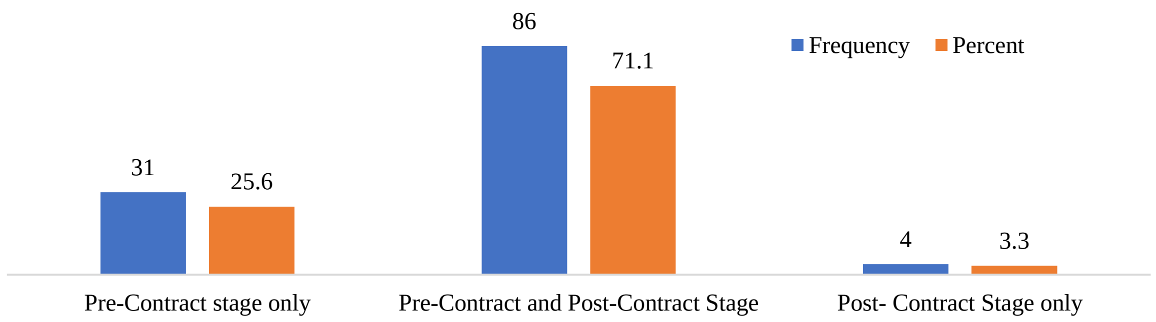

Fig. 2. EPSs implementation at project stages.

3.3.Data analysis

3.3.1. Reliability and normality analysis

The Cronbach's alpha method was adopted in this study to determine the reliability of the survey questionnaire. The Cronbach's alpha tests the internal consistency of a data instrument's items for reliability using a coefficient value (α), which ranges from 0 towards high reliability of 1 (Field, 2013). The overall α value of 0.705 for the 14 strategies in this study shows that the internal consistency and reliability of the data collected was high and acceptable (Field, 2013). Additionally, data normality check was carried out using the Shapiro-Wilk (SW) test. SW *p-values* ≤0.05 indicate that the data is not normally distributed (Royston, 1992). The *p-values* of the SW test for all 14 strategies in this study were less than 0.05, therefore the data collected is not normally distributed.

3.3.2. Mean, normalization and agreement analysis

The mean score technique has been widely employed in construction-related studies to rank the relative importance/criticality of factors (Razkenari et al., 2020; Olawumi et al., 2018). In this study, the mean score was used to evaluate the relative importance of EPSs promotion strategies. If two strategies have the same mean score, a higher rank is assigned to the strategy with lower standard deviation. Normalization analysis was conducted to determine strategies that are critical, i.e. strategies with normalized values ≥0.50 (Adabre et al., 2020). The Kendall's coefficient of concordance (Kendall's *W*) was used to measure agreement within the respondents' rankings (Field, 2013). Furthermore, the Kruskal-Wallis test was utilized to examine the difference in the ranking of the strategies from the three respondent groups in the survey (Chan et al., 2018).

3.3.3. Clustering, neurofuzzy systems and sensitivity analysis

In this study, factor analysis (FA) was employed to aggregate the underlying dimensions of strategies and identify the clustering set of principal strategies (Fernandes, 2006). FA examines high-dimensional data for interrelated variables to generate small groups of clusters that explain complex phenomena (Delgado et al., 2019). Prior to the FA, the appropriateness of the data was tested using the Kaiser-Meyer-Olkin (KMO) sampling adequacy measure and Bartlett's test of sphericity. The clustered strategies are used as input variables for the neurofuzzy model. Since experts' judgements and experiences of the critical strategies are linguistically expressed, uncertain and subjective, the neurofuzzy model was adopted. The neurofuzzy model combines the advantages of fuzzy systems and neural networks. This enables it to analyze complex, uncertain, subjective and nonlinear relationships that are intrinsic in the evaluation and prediction of effective strategies promoting EPSs in building projects (Statkic, 2020; Tiruneh, et al., 2020). The neurofuzzy model was designed and modeled in MATLAB programming environment. Details of the neurofuzzy model development process are presented in the subsequent sections.

4. Results

The results of the arithmetic mean analysis for strategies promoting EPSs are summarized in Table 3. From Table 3, the mean scores indicating the importance of strategies in the promotion of EPSs ranged from 3.12 to 4.52. Normalization computations were conducted and the strategies with normalized scores not less than 0.50 were identified as critical strategies in the promotion of EPSs implementation in projects.

Out of 14 strategies identified, 13 strategies had normalized values above 0.50 and were therefore deemed as critical strategies in the promotion of EPSs in building projects. The first ranked strategy with the highest mean value of 4.52 was "organizational leadership buy-in and commitment strategy for EPSs" (S09) (Table 3). This finding shows the prevalence of top management influences in EPSs adoption and further supports past studies indicating the significance of leadership buy-in in the promotion of EPSs in projects (Kang et al., 2012; Lines et al., 2017). The strategy "incentives and reward schemes for EPSs adoption on projects" (S02) was ranked second with mean value of 4.45, followed by "proactive change-management systems" (S08) with a mean value of 4.45. The fourth ranked strategy was "EPSs related training programs for key stakeholders" (S05) having a mean value of 4.29 and the fifth ranked strategy with a mean value of 4.28 was "availability of quantifiable evidence of EPSs benefits". This summary provides the top five critical strategies that are important in the promotion of EPSs from the perspectives of developing countries.

The Kendall's *W* value and significance level for the ranked 14 strategies were 0.188 and 0.000 respectively, indicating substantial level of agreement on the ranking of the strategies from the respondent groups. The Krushal-Wallis ANOVA test shows that all the strategies had no significant statistical difference (significance > 0.05), except two strategies (i.e. pilot implementation projects for contextual learning and knowledge sharing (S07) and mandatory e-procurement policies and regulations (S13)). The contractor group had relatively higher rankings for S07 and S13 while the consultant and regulatory agency group had lower rankings for these strategies. One possible explanation is that the contractor group relatively wants more evidence of EPSs benefits and regulations than the consultants and regulatory agency group in the promotion of EPSs in building projects. These EPSs benefits which have sustainability implications in the procurement process provide an avenue for quantitative benefit assessment to be conducted.

Table 3. Results of mean analysis for strategies promoting EPSs

Code	All respondents				Consultant			Contractor			Regulatory Agency			Kruskal-Wallis
	Mean	SDv.	Normalization[a]	Rank	Mean	SDv.	Rank	Mean	SDv.	Rank	Mean	SDv.	Rank	Test (ANOVA)
S09	4.52	0.684	1.00[b]	1	4.61	0.630	1	4.46	0.508	2[c]	4.37	0.926	3	0.242
S02	4.45	0.670	0.95[b]	2	4.42	0.609	3	4.43	0.573	4	4.52	0.893	1	0.288
S08	4.45	0.806	0.95[b]	3	4.50	0.639	2	4.64	0.621	1	4.11	1.188	7	0.242
S05	4.29	0.676	0.84[b]	4	4.24	0.725	7	4.46	0.508	2[c]	4.22	0.698	6	0.398
S11	4.28	0.635	0.83[b]	5	4.24	0.609	6	4.39	0.629	5[c]	4.26	0.712	5	0.539
S03	4.26	0.639	0.81[b]	6	4.27	0.596	4	4.39	0.629	5[c]	4.07	0.730	8	0.212
S04	4.24	0.671	0.80[b]	7	4.23	0.602	8	4.14	0.705	9	4.37	0.792	2	0.335
S06	4.22	0.652	0.79[b]	8	4.26	0.590	5	4.04	0.693	11	4.33	0.734	4	0.159
S14	4.03	0.774	0.65[b]	9	4.06	0.802	9	4.14	0.705	9	3.85	0.770	10	0.396
S07	3.98	0.841	0.61[b]	10	4.02	0.813	10	4.18	0.819	8	3.67	0.877	12	0.050[d]
S1	3.95	0.669	0.59[b]	11	3.88	0.691	11	4.00	0.385	12	4.07	0.829	9	0.438
S10	3.84	0.876	0.52[b]	12	3.86	0.857	13	3.79	0.876	13	3.85	0.949	11	0.936
S13	3.83	0.843	0.51[b]	13	3.86	0.699	12	4.21	0.833	7	3.33	0.961	13	0.002[d]
S12	3.12	0.808	0.00	14	3.14	0.839	14	2.89	0.737	14	3.30	0.775	14	0.183

Note: SDv. = Standard Deviation;
[a]Normalization = (Mean – Minimum Mean) / (Maximum Mean – Minimum Mean);
[b]The normalized value indicates that the barrier is critical (normalized value ≥ 0.50);
[c]Mean values with the same standard deviation;
[d]The Kruskall-Willis test value is significant at ≤ 0.05 significance level. The Shapiro-Wilk test value for all 14 strategies were ≤ 0.05 significant level. The Kendall's *W* for the 21 strategies was 0.188 with significance level of 0.000.

4.1. Clustering of critical strategies promoting EPSs

The underlying dimensions of the 13 critical strategies were grouped into clusters using the FA technique to better understand the complex phenomenon. For appropriateness of the data, the KMO value of 0.693 obtained in this study, is acceptable since it satisfies the minimum threshold of 0.50 (Hair et al., 2009). The Bartlett's test value was 300.378 with associated significance level of 0.000, indicates that the population correlation is not an identity matrix (Pallant, 2011). Both the KMO and Bartlett's tests demonstrated the suitability of the data for FA. Hence, the principal component analysis was used for factor extraction based on varimax rotation. Variables with factor loadings ≥0.50 and components with eigenvalues ≥1 were retained due to their significant contribution in the factor group and determining underlying clusters. Five components were extracted which accounted for 65.20% of variance, satisfying the > 50% acceptable threshold (Field, 2013) (Table 4). This implies that the five component clusters extracted can adequately represent the strategies promoting EPSs in construction projects. The clusters were subsequently labelled as: (1) technology education (TE), (2) innovation culture management (ICM), (3) technological stimulation environment (TSE), (4) incentives and partnership mechanism (IPM), and (5) organizational integration support (OIS). These five strategies clusters (SCs) serve as input parameters for the neurofuzzy model to evaluate the influence and complexity of the strategies promoting EPSs in building projects.

Table 4. Clustering of strategies promoting EPSs

Code Strategies promoting EPSs	Strategies clusters				
	1	2	3	4	5
SC1: Technology education (TE)					
S05 EPSs related training programs for key stakeholders	0.643	-	-	-	-
S06 Active and strengthened research and development for EPSs implementation	0.718	-	-	-	-
S07 Pilot implementation projects for contextual learning and knowledge sharing	0.592	-	-	-	-
S10 Active publicity through media communications	0.652	-	-	-	-
S11 Availability of quantifiable evidence of EPSs benefits	0.645	-	-	-	-
SC2: Innovation culture management (ICM)					
S08 Proactive change-management methods	-	0.733	-	-	-
S09 Organisational leadership buy-in and commitment strategy for EPSs	-	0.797	-	-	-
SC3: Technological stimulation environment (TSE)					
S13 Mandatory EPSs policies and regulations	-	-	0.863	-	-

S14 Availability of financial support schemes for EPSs investment	-	-	0.772	-	-
SC4: Incentives and partnership mechanism (IPM)	-	-	-	-	-
S02 Reward schemes for EPSs adoption on projects	-	-	-	0.695	-
S04 Enable collaborative environment among organisations and partners	-	-	-	0.818	-
SC5: Organizational integration support (OIS)					
S01 Align EPSs to organisation's strategy and procurement procedures.	-	-	-	-	0.747
S03 Competent institutional framework and local promotion teams for effective EPSs implementation	-	-	-	-	0.646
Eigenvalue	3.110	1.819	1.419	1.131	1.000
Variance (%)	23.923	13.993	10.916	8.703	7.666
Cumulative variance (%)	23.923	37.916	48.832	57.535	65.201

Note: Extraction method = principal component analysis; Rotation method = Varimax with Kaiser normalization

4.2. Neurofuzzy model development

The development of the neurofuzzy model involves the structure and parameter learning (Premkumar and Manikandan, 2015) as shown in Fig. 3. In the learning process, domain knowledge and experience are transformed into rules for fuzzy inference systems (Gerek, 2014). The fuzzy rules generated, together with its adjustments, enable the parameters of the neurofuzzy model to learn and integrate the fuzzy system and neural networks for solving complex problems (Jin, 2011).

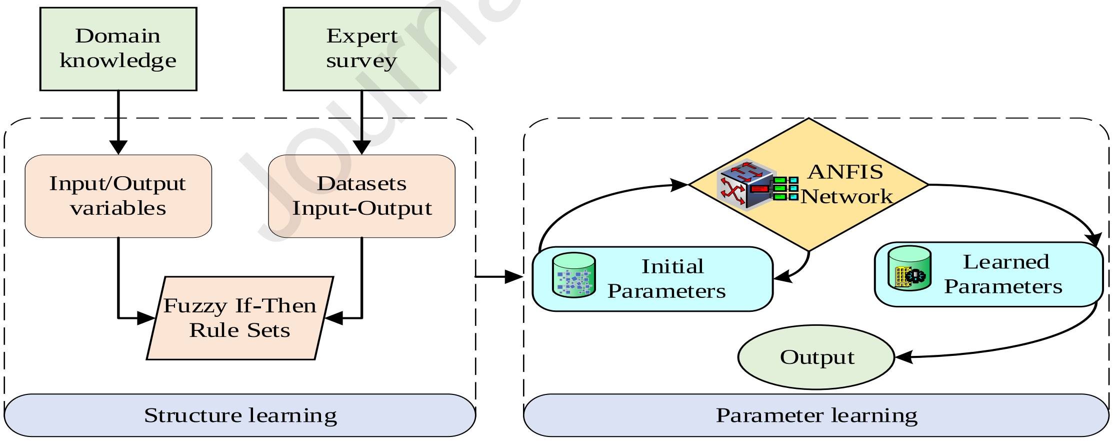

Fig. 3. Neurofuzzy model structure

4.2.1. Structure learning

The structure learning determines and generates fuzzy rules of the input and output variables from the data set. The structure resolves fuzzy if-then rules and membership function approximations for inputs and outputs (Rashidi et al., 2011). Generally, the fuzzy if-then rules are expressed as follows:

Rule 1: If x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + z_1$,
Rule 2: If x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + z_2$.
where $f(x, y)$ is the Sugeno fuzzy first-order polynomial, x and y are numerical inputs, and f is the output, and A and B are numerical variables, and p, q and z are parameters determining relationships of inputs-outputs.

The variable inputs as derived from Table 4 for the neurofuzzy model are; VI_1 (Technology education), VI_2 (Innovation culture management), VI_3 (Technological stimulation environment), VI_4 (Incentives and partnership mechanism) and VI_5 (Organizational integration support). The prioritized mean weight (PMW) was employed in this study to compute the input values of the neurofuzzy model. The PMW computes the corresponding weight of a factor within a group based on factor loadings and expert ratings for summation. This enables corresponding weights of factors to be shown in the group. The PMW expresses the importance of VI using Eq. (1):

$$PMW_k = \frac{1}{h}\sum_{i=1}^{h} v_{ki} \quad , v_{ki} = w_c d \qquad (1)$$

where PMW_k is score of kth group of VI_k (k = 1, 2, …, 5), and v_{ki} is the ith strategy score of the kth VI group, w_c is the coefficient weight of a factor's loading divided by the sum of factor loadings in that group, d is the expert's strategy rating, and h is the number of strategies within the VI.

The VIs were assessed based on three fuzzy rules (low (L), medium (M) and high (H)). The values of VIs were determined from the variables observed and the *PMW* developed. The membership function (MF) determines the fuzzy set which in turn defines each fuzzy value (Rashidi, 2011). The gaussian functions were adopted in this study from the commonly used MFs such as triangular and trapezoidal functions, because it has good capabilities in avoiding zero as denominator in MFs and achieves smoothness (Jin, 2011). Hence, its wide application in construction-related research. The Gaussian function is defined as follows:

$$\mu(x;\ \sigma, c) = e^{\frac{[-(x-c)^2]}{(2\sigma^2)}} \quad (2)$$

where *c* is the curve mean and σ is the variance. These are the premise parameters.

Table 5 shows the initial MFs and value parameters. The output variable indicates the impact level of strategies in promoting EPSs. The OV possible values ($f \in \{1, 2, 3, 4, 5\}$), where $\{1, 2, 3, 4, 5\}$ indicates the rating scale for the level of impact in a continuous range from 1 representing low level, through 3 representing medium level to 5 representing high level. The overall number of MFs for the OV is the same number of fuzzy if-then rules created with the fuzzy sets since the first-order Sugeno-type was initially used in the neurofuzzy model. The MFs of the OVs are expressed as $f_i = p_i x_1 + q_i x_2 + r_i x_3 + s_i x_4 + t_i x_5 + z_i$, where $(p_i, q_i, r_i, s_i, t_i, z_i)$ denotes the *i*th fuzzy if-then rule of the consequent parameter set and *i* represents fuzzy if-then rules. Consequent parameters are initialized based on the output target and the corresponding data pair. Considering the initial values, parameter (z_i) is designated with the output target value and the zero is designated to the remaining parameters. For instance, a data pair with output target of 4 has initial parameters as {0, 0, 0, 0, 0, 4}.

Concise rules enable the learning process of the networks structure to be reliable, fast and more intuitive (Jin, 2011). Hence, the fuzzy rules created from the numerical input-output dataset were a straightforward approach that reduce the training time in neural networks. Using a three-step procedure, the approach by Wang and Mendel (1992) was employed in this study. The MFs are firstly determined for all fuzzy values relating to each input value of a given data pair. Using example case 1 = (4.45, 4.14, 3.88, 3.57, 4.02 and 4.00), the first five and last values represent input and output values, respectively. The first step calculations are shown in Table 5. Secondly, fuzzy values are assigned to each input value corresponding to the maximum membership value of that input. Lastly, one rule is created for each given input-output data pair. For example case 1, the rule is created as:

IF VI_1 = high, and IV_2 = high, and VI_3 = medium, and VI_4 = medium, and VI_5 = high, THEN OV is $f_1 = p_1 \text{x } 4.45 + q_1 \text{ x } 4.14 + r_1 \text{ x } 3.88 + s_1 \text{ x } 3.57 + t_1 \text{ x } 4.02 + z_1 = 4$. From this approach, a total of 243 rules were created for the neuro-fuzzy model.

Table 5. Fuzzy if-then rule development using example case 1.

Variable	Code (Linguistic Value)	Numerical value	Initial MF $\mu(x;\ \sigma, c)$	Membership value (fuzzy value)	Assigned fuzzy value
VI_1	H (High) M (Medium) L (Low)	4.45	$e^{[-(x-5.0)^2]/[2(0.37)^2]}$ $e^{[-(x-4.14)^2]/[2(0.37)^2]}$ $e^{[-(x-3.14)^2]/[2(0.37)^2]}$	0.591(H) 0.355(M) 0.055(L)	High
VI_2	H (High) M (Medium) L (Low)	4.14	$e^{[-(x-5)^2]/[2(0.72)^2]}$ $e^{[-(x-3.23)^2]/[2(0.72)^2]}$ $e^{[-(x-1.47)^2]/[2(0.72)^2]}$	0.936(H) 0.055(M) 0.009(L)	High
VI_3	H (High) M (Medium) L (Low)	3.88	$e^{[-(x-5)^2]/[2(0.53)^2]}$ $e^{[-(x-3.96)^2]/[2(0.53)^2]}$ $e^{[-(x-2.59)^2]/[2(0.53)^2]}$	0.527(H) 0.455(M) 0.018(L)	Medium
VI_4	H (High) M (Medium) L (Low)	3.57	$e^{[-(x-5)^2]/[2(0.42)^2]}$ $e^{[-(x-4.24)^2]/[2(0.42)^2]}$ $e^{[-(x-3.13)^2]/[2(0.42)^2]}$	0.545(H) 0.409(M) 0.045(L)	Medium
VI_5	H (High) M (Medium) L (Low)	4.02	$e^{[-(x-5)^2]/[2(0.39)^2]}$ $e^{[-(x-3.86)^2]/[2(0.39)^2]}$ $e^{[-(x-3.02)^2]/[2(0.39)^2]}$	0.745(H) 0.191(M) 0.064(L)	High

4.2.2. Parameter learning

Determining input and output variables enables the fuzzy rules created to be used in the parameter learning. The parameter learning tunes the MFs to maximize performance or reduce output error through modifying the parameters (Rashidi, 2011; Gerek, 2014). The ANFIS was used for the parameter learning. Jang (1993) introduced the ANFIS architecture to integrate fuzzy reasoning and adaptive networks for learning from input-output dataset. The fuzzy reasoning uses the sugeno FIS to create two rules (if-then). The algorithm for ANFIS learning combines the gradient-descent optimization methods and least squares estimate. The detailed architecture of ANFIS and the learning algorithm are explained in the subsequent sections.

4.2.2.1. The ANFIS network architecture

The ANFIS network architecture has several connected nodes and each node is defined by a function as shown in Fig. 4. The proposed ANFIS architecture is the multilayer neural network based on first-order Sugeno-type system due to its compactness and effectiveness to linear techniques adaptation and optimization (Takagi and Sugeno, 1985; Gerek, 2014). The ANFIS architecture has five hidden layers, excluding the input and output layers. The functions of the hidden layer nodes are based on fuzzy rules and MFs, which makes them have an advantage over conventional neural networks that are difficult to interpret (Tavana et al., 2016).

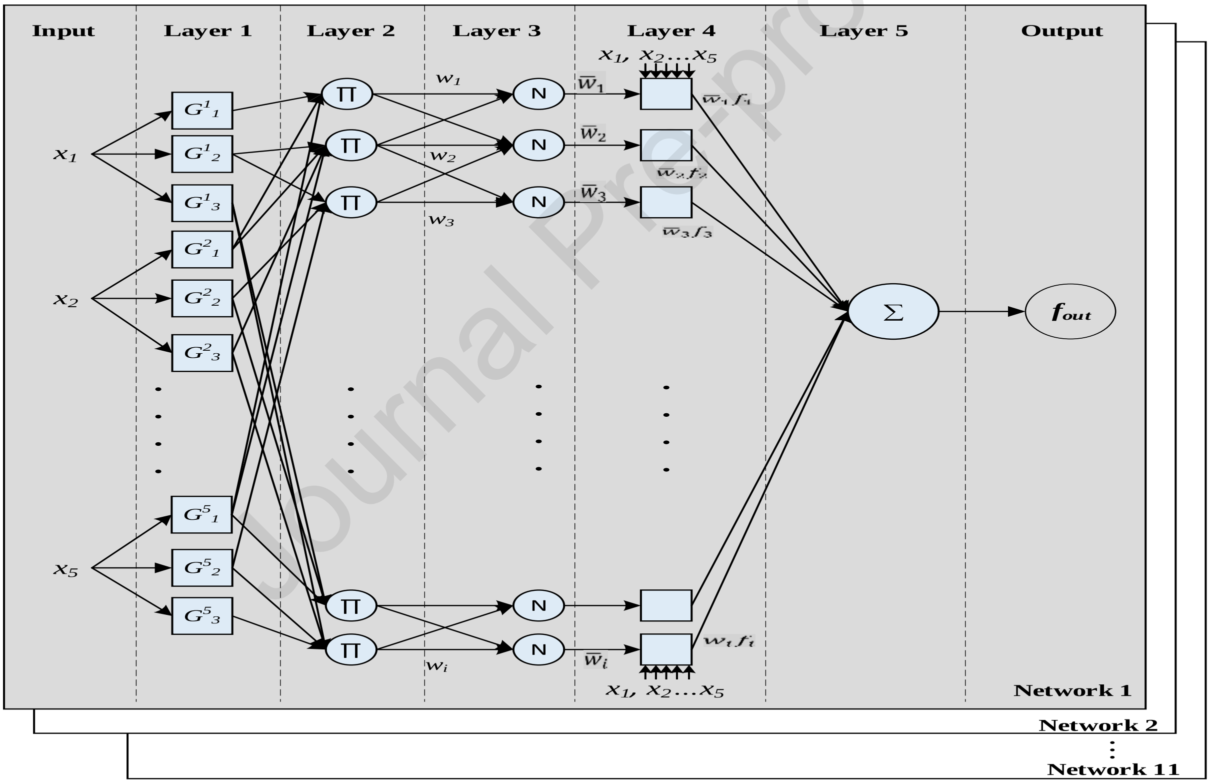

Fig. 4. ANFIS network architecture

Input layer: The input layer defines the crisp values of inputs connected to nodes in layer 1. The vth VI value is represented by x_v, where $v \in \{1, 2, \ldots, 5\}$.

Layer 1: Nodes in layer one (G_n^v) have MFs representing fuzzy values of VI. Outputs of this layer are membership values of crisps input values x_v. The Gaussian function for determining MFs are defined in Eq. (3):

$$O_j^{(1)} = \mu_{G_j}(x) = e^{[-(x_v - c_j^v)^2]/2\sigma_j^{v2}} \quad (3)$$

where O_j^1 is the MF of $\mu_{G_j}(x)$; c_j^v and σ_j^v are premise parameters of the MF representing *m*th fuzzy value of the *v*th VI; (1) represents layer 1; *v* ∈ {1, 2, …, 5}; and *j* ∈ {1, 2, 3}(i.e. three fuzzy values).

Layer 2: This layer consists of nodes (π) denoting the if-part of fuzzy rules. Each node multiplies the incoming signals and the product is the output representing the firing strength (w_i).

$$O_i^{(2)} = w_i = \prod_{v=1}^{5} O_j^{(1)} \quad (4)$$

where (2) represents layer 2; *i* denotes the index of fuzzy rules; and *i* ∈ {1, 2, …, *n*}, in which *n* is the number of fuzzy rules generated in the structure learning.

Layer 3: In this layer, every node is adaptive and computes the ratio of *i*th rule's firing strength to the sum of all rules firing strength.

$$O_i^{(3)} = \overline{w}_i = \frac{w_i}{w_1 + w_2 + \cdots + w_n} \quad (5)$$

where w_n represents the last firing strength. A node's output represents the normalized firing strength.

Layer 4: In this layer, each node *i* is adaptive and endowed with a node function f_i. The node output is given by:

$$O_i^{(4)} = \overline{w}_i f_i = \overline{w}_i(p_i x_1 + q_i x_2 + r_i x_3 + s_i x_4 + t_i x_5 + z_i) \quad (6)$$

where $\overline{w}_i$ is the output of layer 3 and p_i, q_i, r_i, s_i, t_i *and* z_i are adjusted consequent parameters.

Layer 5: This layer computes the overall output of ANFIS from layer 4.

$$O_i^{(5)} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (7)$$

where $\bar{w}_i$ is normalized firing strength.

Output layer: This layer receives the final node from layer 5 to present the final output of the ANFIS system.

4.2.2.2. Learning parameter algorithms

As indicated by Jang (1993), the learning process of ANFIS consists of adaptations of learning weights and nonlinear MFs through the tuning of premise and consequent parameters using suitable algorithms. ANFIS applies a hybrid learning algorithm which integrates the gradient descent-based back propagation algorithms with least squares estimator for premise and consequent parameter optimization (Jang, 1993). The transmission of forward pass and backward pass enables the hybrid algorithms to learn from the dataset. The ANFIS algorithms have been adopted to solve problems in construction engineering research, such as selection of important performance factors (Statkic et al., 2020), prediction and optimization (Akinade and Oyedele, 2019) and supplier modelling in supply chains (Tavana et al., 2016).

4.3. Neurofuzzy model training

The training and evaluation of the neurofuzzy model was conducted using the dataset gathered in this study. To train the model, the dataset was divided into two: the training dataset and the evaluation dataset. For training purposes, the training dataset was subsequently divided into estimation subset for model selection, and the testing subset for validating the model. Dividing the dataset facilitates the examination of models to guard against overfitting when checked with the evaluation dataset for generalization (Haykin, 2007). To ensure that while learning new things the learning model preserves knowledge and remains adaptive, the early-stopping method was adopted to tackle overfitting (Amari, 1996).

The multi-fold cross-validation technique was employed to partition the training dataset. This technique uses separate data from the total dataset to estimate a model's prediction of outputs from an untrained dataset (Wong, 2015). From the total of 121 datasets, 110 were used for training the model based on 85:15 percent ratio – i.e. 85% as estimating subset and 15% as testing subset. For every round of training, a different set of data (15%) was left out for model testing purposes. The model training system of the ANFIS models is shown in Fig. 4.

Table 6 provides a summary of the 11 models trained in the ANFIS network architecture. The root-mean square error (RMSE) as used in previous studies (Statkic et al., 2020; Akinade and Oyedele, 2019), was used to estimate and validate the models for the selection of best performing model. As shown in Table 6, model 4 had the minimum values of mean square error and RMSE, indicating that it is the best performing model. Hence, model 4 is selected for model evaluation.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{t_i - y_i}{n}} \quad (8)$$

where n = number of datasets; t_i = impact level observed in the ith case; and y_i = predicted impact level in the ith case by the model.

Table 6. Training results of neurofuzzy models

Neurofuzzy model	$MSE_{est.}$	$MSE_{val.}$	$RMSE_{est.}$	$RMSE_{val.}$
Model 1	0.000000020	4.179251287	0.000140659	2.044321718
Model 2	0.000000023	2.617873441	0.000152047	1.617984376
Model 3	0.000000080	1.187227328	0.000282462	1.089599618
Model 4	0.000000019	0.353560378	0.000138735	0.594609433
Model 5	0.007168469	2.081999698	0.084666814	1.442913614
Model 6	0.978492486	2.544078967	0.989187791	1.595016917
Model 7	0.000000072	1.919390059	0.000268809	1.385420535
Model 8	0.000000013	1.697372746	0.000114065	1.302832586
Model 9	0.000000015	0.383727118	0.000120928	0.619457115
Model 10	0.000001086	1.285167876	0.001042278	1.13365245
Model 11	0.000001518	1.233871298	0.001232054	1.110797596

4.4. Neurofuzzy model evaluation and sensitivity analysis

The performance of the neurofuzzy model was evaluated using data from the evaluation dataset. The evaluation dataset, which is different from the testing dataset, contains 11 sets of data cases obtained from the total sample collected in this study. In addition to RMSE, performance indexes including mean percentage error (MPE) and mean absolute percentage error (MAPE) were used to evaluate the developed model. The MPE indicates the model's tendencies to over-or-under forecast while MAPE estimates the magnitude of errors that may be contained in the forecast (Jin, 2011). These performance indexes have been widely used to evaluate model performance (Statkic et al., 2020; Akinade and Oyedele, 2019; Gerek, 2014).

$$MPE = \sum_{i=1}^{n} \frac{y_{t_i} - y_{o_i}}{y_{t_i}} \text{ x } 100\%/n \quad (9)$$

$$MAPE = \left| \sum_{i=1}^{n} \frac{y_{t_i} - y_{o_i}}{y_{t_i}} \text{ x } 100\% \right| /n \quad (10)$$

where n = 11; y_{t_i} *and* y_{o_i} represent the observed and model output of the *i*th data case.

The values of VIs for each evaluation data pair were entered into the trained neurofuzzy model, respectively. The model's predicted impact levels of the strategies were evaluated against the observed impact levels of strategies. The results of the evaluation are shown in Table 7 and Fig. 5.

Table 7. Evaluation results of predicted values and observed values

Data case	Observed impact level	Predicted impact level	$E_{eval.}$
1	5	5.4425	-0.4425
2	4	2.9575	1.0425
3	5	4.9999	0.0001
4	5	5.0000	0.0000
5	5	5.0000	0.0000
6	5	3.9998	1.0002
7	5	5.0000	0.0000
8	5	4.8386	0.1614
9	5	4.8933	0.1067
10	5	4.9994	0.0006
11	5	3.8595	1.1405
Model RMSE = 0.573758582			
Model MPE = 5.945681818			
Model MAPE = 7.554772727			

Note: $E_{eval.}$ = Error margin in neuro-fuzzy model evaluation.

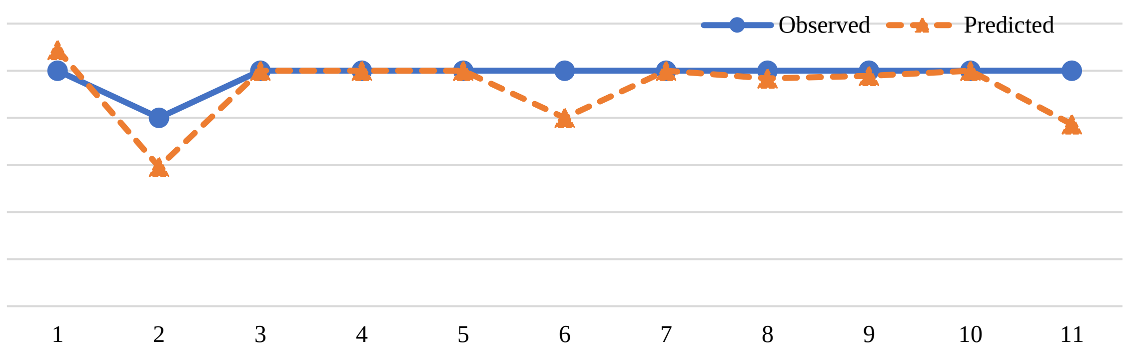

Fig. 5. Evaluation of model performance.

The low performance indexes obtained from the evaluation result indicate that the neurofuzzy model developed has high capabilities of estimating the impact level of strategies in the promotion of EPSs. To this end, Table 7 shows that 9 out of 11 (82%) of data cases were accurately predicted by the trained neurofuzzy model. The performance indexes suggest that the model may generate an error of 0.574 averagely and may have little over forecasting (+5.95%) which may contain an average error of 7.55% in the forecast. Due to the uncertain and subjective nature of experts' judgements, the model developed with approximately 82% prediction accuracy, was deemed adequate to better reveal and predict the complex and nonlinear relationships of strategies impacting the promotion of EPSs implementation in building projects.

Sensitivity analysis was conducted in this study to assess the impact levels from various SCs influences (Ikram et al., 2020), considering resource-constraints present within project environments. By varying the influence values of specific inputs while the remaining inputs are kept at preferred values (El-Gohary et al., 2017), sensitivity analysis provides an approach for identifying ways that optimize the strategies for promoting EPSs. In determining the influence values of strategies, due to the subjective nature of experts' judgments, the assigned values and MFs ranges in Table 5 were employed. This enables subjective and imprecise experiences to be adequately represented using the linguistic expressions that are characteristic of project environments. The sensitivity analysis was conducted based on project cases (PC) representing typical project environments with limitations in resources for EPSs promotion. A PC depicts a project situation with selected inputs of strategies varied to medium level while the remaining strategies are high. Table 8 shows the results of the sensitivity analysis, starting from one input variation to three inputs variations successively. Fig. 6 shows the scatter plot of PC results from the sensitivity analysis.

Table 8. Sensitivity analysis using neurofuzzy model

Project Case	Strategies clusters						Project Case	Strategies clusters					
	TE	ICM	TSE	IPM	OIS	Output		TE	ICM	TSE	IPM	OIS	Output
PC1	M	H	H	H	H	4.7191 (H)	PC12	H	M	H	H	M	3.6171(M)
PC2	H	M	H	H	H	4.1035 (H)	PC13	H	H	M	M	H	4.1101(H)
PC3	H	H	M	H	H	4.5427 (H)	PC14	H	H	M	H	M	4.5388(H)
PC4	H	H	H	M	H	4.4022 (H)	PC15	H	H	H	M	M	4.0656(H)
PC5	H	H	H	H	M	4.7413 (H)	PC16	M	M	M	H	H	1.7881(L)
PC6	M	M	H	H	H	3.5572 (M)	PC17	M	H	M	M	H	2.2998(L)
PC7	M	H	M	H	H	4.8694 (H)	PC18	M	H	H	M	M	2.1215(L)
PC8	M	H	H	M	H	3.2813 (M)	PC19	H	M	M	M	H	1.7419(L)
PC9	M	H	H	H	M	4.4816 (H)	PC20	H	M	H	M	M	2.1018(L)
PC10	H	M	M	H	H	2.0620 (L)	PC21	H	H	M	M	M	1.9645(L)
PC11	H	M	H	M	H	3.2342 (M)							

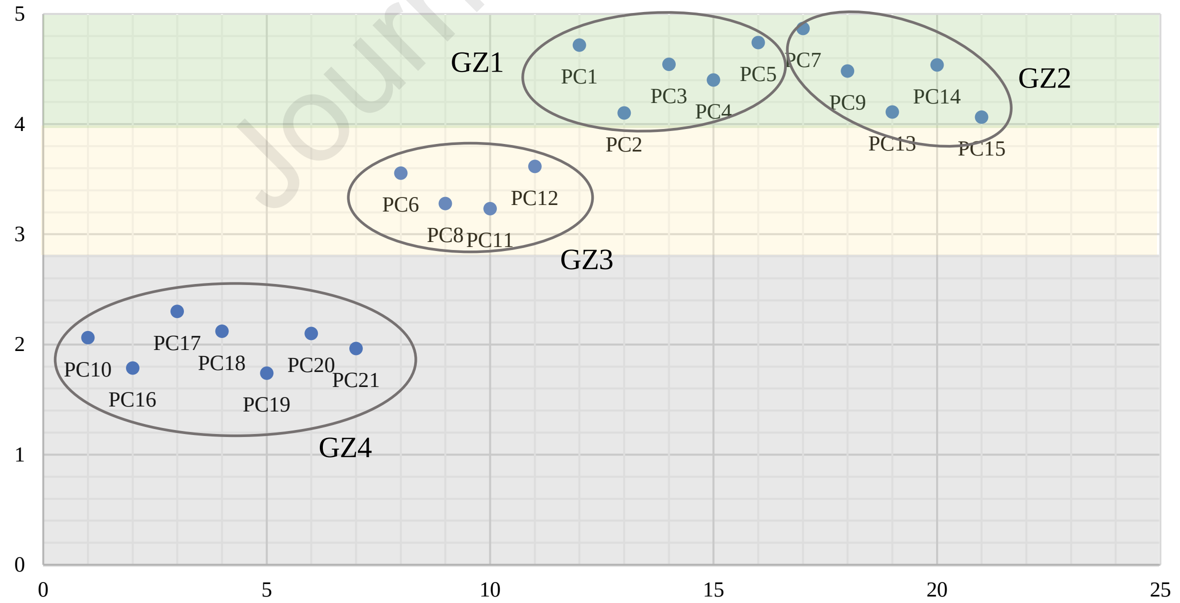

Fig. 6. Scatter plot of PC results from sensitivity analysis.

5. Discussion

As shown in Table 8, high impact levels of strategy measures were reported although specific individual influences of strategies clusters (PC1-PC5) were varied to medium influence levels. This finding suggests that within the ecosystem of SCs, SCs actively promote EPSs implementation in project environments even though one SC may not have a high influence. This shows that while high levels for innovation culture management have been emphasized in previous studies, other SCs can be collectively employed to promote EPSs use. For instance, Ozorhon et al. (2016) indicated that having an adaptive project culture encourages team members to be receptive to change and innovation, and Pan and Pan (2019) indicated leadership commitment as a main enabler in shaping the project environments for innovation adoption. Meanwhile, Kim et al. (2016) suggests that to develop a proactive change culture in organizations, top management should focus on people-centric approaches. Evidently, the significant role innovation culture plays in technology adoption has been documented in extant literature (Zhang et al., 2020), but having high innovation culture alone may not promote EPSs sufficiently. The existence of complementary relationships in the SCs ecosystem, as shown in this study, underscores the need to engage other SCs in addition to innovation culture for effective EPSs implementation. To depict these complementary relationships, Fig. 6 shows the impact of these combined SCs with one SC varied (see PC1-PC5), and this resulted in the high-level zone, labelled as GZ1. Nevertheless, Table 8 further shows different impact levels for situations in which two SCs (see PC6-PC15) were varied. These PCs were subsequently grouped based on their impact levels (GZ2 – high impact and GZ3 – medium impact).

The PCs in GZ2 (i.e. PC7, PC9, PC13, PC14 and PC15) provide a hybrid-approach to achieve high promotion of EPSs in typical resource constrained construction project environments. For PC7 and PC9, high influences of ICM and IPM combined with OIS or TSE have great capabilities of promoting EPSs in building projects. This shows that innovation culture can be associated with rewards, collaboration and technological support as a key promotion strategy in the implementation of EPSs. Although, this finding partly supports studies that assert the importance of providing technology adoption incentives and support (Wimalasena and Gunatilake, 2018; Costa and Tavares, 2014), it further establishes their association with innovation culture as an effective path to promote EPSs in project organizations. Additionally, attaching a stimulating environment for technology via mandatory policies and financial support to innovation culture and incentive schemes enable EPSs implementation. With Jacobsson et al. (2017) and Xu et al. (2020) emphasizing the need for policies in technology adoption, it is evident that a more suitable approach is to align such technology adoption policies with proactive innovation culture and incentives for a desirable outcome.

Alternatively, the hybrid-approach of – TE and ICM can be combined with TSE/IPM/OIS as depicted in PC13, PC14 and PC15 (Table 8), to facilitate the high impact of strategies for the promotion of EPSs implementation (Fig. 6). Several studies (Matthews et al., 2018; Yu et al., 2020) have examined the positive impact of technological training on construction stakeholders in adopting a technology. This training could be a continuous learning approach or integrated into organizational competency programs. In turn, the technological skills of practitioners are boosted, and this would enable them to be more receptive to changes in their technological culture (Yu et al., 2020). This highlights the synergistic influence of technological education and culture (TE-ICM) in the SCs ecosystem, although these two strategies alone may not have a high impact (see PC21). Previous studies have independently advocated for increased technological education (Ibem and Laryea, 2015; Kim et al., 2016) and innovation culture via proactive change management and leadership support (Ozorhon et al., 2016; Pan and Pan, 2019; Altuwaijri and Khorsheed, 2012). However, this study identified that more will be needed to ensure this approach is effective by enhancing organizational support, incentives and partnerships and a technological environment. Possible explanation for the finding is that organizations with a high innovation culture tend to encourage technological learning, which creates a suitable climate that propels other SCs for optimized results. Also, as indicated earlier, the ICM-IPM approach provides alternative hybrid-approaches for attaining optimized strategies for effective promotion of EPSs implementation.

On the contrary, Table 8 also shows that approaches in GZ3 (i.e. PC6, PC8, PC11and PC12) result in only medium impact levels, and hence needs to be critically examined and improved for optimum results. This finding is reflective of the assertion by Sepasgozar et al. (2018) that an understanding of the pathways for successful technology adoption is needed, since not all the combination of strategies may be effective in promoting EPSs implementation. For instance, high TSE and OIS combined with ICM or TE or IPM produced medium impact levels, suggesting that the technological environment and organizational support (TSE-OIS) with another SC approach requires improvement for the strategies to be effective. Furthermore, combining high TE, TSE and IPM would generate medium impact levels, hence such combinations may not be adequate in actively promoting EPSs. This shows that there are dynamic relationships between the SCs. For example, although high ICM and TE were respectively combined with other SCs in PC8 and PC11, the resulting impact was medium. This finding is different from that of previous studies, that suggest focusing solely on individual strategies that are deemed important (Wimalasena and Gunatilake (2018). Instead, it should be based on careful selection of SCs (Fig. 6). To significantly improve the GZ3 approaches, a fourth SC should be increased to high levels, which would transform GZ3 to GZ1. A similar approach could be used to improve PC10 that has high TE, IPM and OIS, yet low impact.

The approaches in GZ4, which had three SCs varied, are considered not suitable for the optimization of strategies promoting EPSs implementation in construction projects. This is because all the PCs (i.e. PC16-PC21) resulted in low impact levels (Fig. 6). This finding could explain the reluctance for EPSs implementation in project environments experiencing passive or average influences of any three SCs concurrently.

The findings in this study show the complex interactions of SCs in determining the impact of strategic measures on promoting EPSs implementation. Therefore, the extent of implementation and continued use of EPSs are based on, or affected by, the optimal selection of SCs for effective promotion of EPSs implementation in building projects.

6. Optimizing the application of SCs and implications

The findings of this study have significant implications for practice and theory regarding EPSs developments in the building sector. This research provides practitioners and decision-makers with various hybrid-approaches to ensure optimized application of strategies for effective EPSs implementation. Considering the need for efficient resource allocation due to constraints and limitations in projects, this study provides practitioners with essential knowledge for effective application of the strategies. Moreover, the findings suggest that combining technological education and innovation culture management with other SCs is a key hybrid-approach with high potential of ensuring effective implementation of EPSs. Practitioners and decision-makers would have to refine their efforts through this approach in project situations that three of the SCs have to be improved for EPSs use. Alternatively, practitioners can adopt the incentives and partnership mechanism and innovation culture management together with other SCs approach to facilitate EPSs implementation. The presence of innovation culture management in the two main hybrid-approaches indicate the critical influence of factors related to culture in the adoption of EPSs. Specifically, technological culture at both the individual and organizational levels, form the foundation for synergistic compatibilities with other significant SCs. Since EPSs usage involve people (users) in organizations, having people-centric solutions to a proactive culture of innovation in organizations changes the organizations' outlook for technological advancements. For instance, leadership commitment and support in a technologically changing environment can have a huge impact on the sustained use of EPSs.

Nonetheless, as noted earlier, improving organizational innovation culture alone, via leadership commitment and change management, would not be sufficient to ensure EPSs implementation. As innovation culture requires strategic combinations with other strategies to make the promotion of EPSs implementation successful.

The findings show that the relationships between the SCs are highly complementary. Hence, for practitioners, this means that SCs have adaptable capabilities that can be suitably applied in various project situations for optimal promotion of EPSs use. Fig. 7. shows the hybrid-approaches of integrating and optimizing the SCs applications for effective EPSs implementation. The bold lines represent hybrid-approaches with high potentials to effectively promote EPSs while the dashed lines represent hybrid-approaches that require improvements in order to be more effective at promoting EPSs implementation.

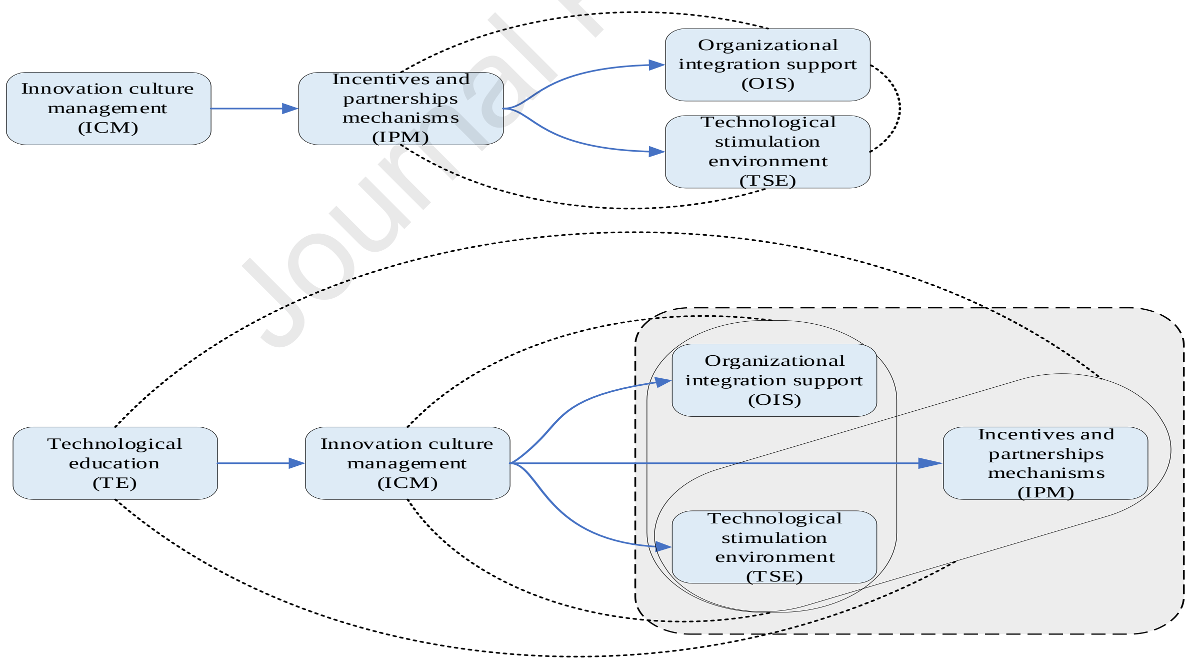

Fig. 7. Hybrid-approaches for optimizing EPSs promotion strategies

In the context of developing counties, specifically Ghana, the findings of this study enable the development of integrated strategies that are flexible and adaptive in various project environments. This helps industry practitioners and decision-makers to deepen their understanding when devising targeted strategies for effective promotion of EPSs in building projects. Consequently, the widespread use of EPSs by applying these hybrid-approaches of strategies, enhance construction procurement to reduce waste in the process, conserve resources, facilitate local inclusiveness and improve process efficiency. In effect, construction procurement is aligned to contribute to the initiatives of sustainability in the Ghanaian project environment. Government agencies and technology advocates can use the study's findings as a guide in decision making to evaluate project environments for the identification of potential strategies that need to be optimally applied in the effective implementation of EPSs.

Further, this study has significant theorical contributions and implications for EPSs research in the building sector. This study highlights that there are complex nonlinear interrelationships between the SCs and the co-existence of complementary relationships manifesting in the collective combination of SCs. This provides researchers with deep insights into the dynamic patterns and influences of SCs for further investigation and helps address the issue of limited studies on SCs influences. This study also reveals the diversity in applying the SCs approaches to provide new dimensions on cultural and educational influences in the promotion of EPSs in the construction industry.

7. Conclusions and future work

Although EPSs provide benefits that offer sustainable solutions in a building project's lifecycle, their implementation and continue use have been slow. This study investigated the impact of various strategies for effective promotion of EPSs in building projects, to facilitate digital transformations for sustainable construction. Fourteen strategies were identified through a comprehensive literature review. The findings from the survey in Ghana first indicated that 13 out of the 14 strategies were critical strategies in the promotion of EPSs. The critical strategies were clustered through factor analysis as technology education (TE), innovation culture management (ICM), technological stimulation environment (TSE), incentives and partnership mechanism (IPM) and organizational integration support (OIS). The neurofuzzy model was applied to the SCs to determine the complex and nonlinear relationships influencing their impact on EPSs promotion. In addition, sensitivity analysis was conducted to examine effective hybrid-approaches that optimize EPSs promotion strategies in typical resource constrained project environments. The findings show that at least three SCs have to be carefully selected in two approaches (i.e. ICM-IPM and TE-ICM) (Fig. 6) to enable the optimization of SCs for effective EPSs promotion. The findings further demonstrate that the SCs are highly interrelated, and their complementary relationships may provide explanations on why focusing on innovation culture and/or technological education alone has not been sufficient in actively promoting the wider use of EPSs in projects.

The findings of this study make significant contribution to the body of knowledge and practice on EPSs in the building sector. Theoretically, the model and the optimized approaches developed enable holistic evaluation and selection of SCs in various project environments for effective promotion of EPSs, as illustrated in the case of Ghana and may be extended as a guide to other countries. The nonlinear pattern of relationships identified in the study would help to deepen understanding on the SCs dynamic ecosystem, which was lacking in literature. Practically, this study provides knowledge on suitable approaches for optimized application of SCs to ensure effective implementation and continued use of EPSs in building projects for future technological developments.

Building upon this study's findings and contributions to knowledge, future research is recommended for some limitations in this study for knowledge advancement. Due to the relatively small sample size from the study's region, future research should focus on expanding this research to other regions with different social-economic conditions, to enhance more collection of data to further substantiate and improve the model's performance. Since this study revealed the patterns of SCs relationships, more studies are needed on the quantification of interrelationships between the SCs influences to improve the development of models for effective decision-making on technology implementation. Further studies could investigate the role of incentives and partnership mechanism in facilitating EPSs use as this study identifies its relationship with innovation culture as essential in promoting EPSs implementation.

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Highlights

- Electronic procurement systems facilitate sustainable practices.
- Lack of research on synergistic influences of promotion strategies for electronic procurement systems
- Neurofuzzy modelling of the clustering influences of strategies.
- Hybrid-approaches for optimizing the application of strategies promoting electronic procurement systems.

Declaration of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.