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RESEARCH ARTICLE

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Understanding innovation diffusion and adoption strategies in megaproject networks through a fuzzy system dynamic model

Abstract Innovation and knowledge diffusion in megaprojects is one of the most complicated issues in project management. Compared with conventional projects, megaprojects typically entail large-scale investments, long construction periods, and conflicting stakeholder interests, which result in a distinctive pattern of innovation diffusion. However, traditional investigation of innovation diffusion relies on subjective feedback from experts and frequently neglects inter-organizational knowledge creation, which frequently emerges in megaprojects. Therefore, this study adopted project network theory and modeled innovation diffusion in megaprojects as intra- and inter-organizational learning processes. In addition, system dynamics and fuzzy systems were combined to interpret experts' subject options as quantitative coefficients of the project network model. This integrated model will assist in developing an insightful understanding of the mechanisms of innovation diffusion in megaprojects. Three typical network structures, namely, a traditional megaproject procurement organization (TMO), the environ megaproject organization (EMO), and an integrated megaproject organization (IMO), were examined under six management scenarios to verify the proposed analytic paradigm. Assessment of project network productivity suggested that the projectivity of the TMO was insensitive to technical and administrative innovations, the EMO could achieve substantial improvement from technical innovations, and the IMO trended incompatibly with administrative innovations. Thus, industry practitioners and project managers can design and reform agile project coordination by using the proposed quantitative model to encourage innovation adoption and reduce productivity loss at the start of newly established collaborations.

Keywords megaproject, innovation adoption, project network, system dynamic, fuzzy logic

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1 Introduction

Spurred by globalization and urbanization trends in previous decades, public infrastructure projects and international megaprojects have increased worldwide, especially in emerging markets. Most megaprojects are infrastructure projects (Mihm et al., 2003; Hu et al., 2015), such as railways (Davies et al., 2014), highways (Molenaar, 2005), airports (Davies et al., 2009), hydraulic plants (Pohlner, 2016), and tunnels (Chang, 2013). These projects are crucial for the modernization of a country, because they provide public goods and services to citizens and boost economic growth and social development (Guikema, 2009; Ansar et al., 2014). However, managing megaprojects is extremely challenging owing to large investments, long construction periods, and complex stakeholder interests (Frick, 2008; van Marrewijk et al., 2008; Hosseini et al., 2018). Innovation, as the core capability for enterprise competence and sustainability, is regarded as one of the most complicated issues in megaproject management (Zhang et al., 2016). Researchers frequently treat innovation as a unique learning process to simplify the strategic management of innovation. Existing research has successfully implemented quantitative analysis and questionnaires to understand the process of innovation diffusion in regular projects (Liu and Chan, 2017b), and numerous paradigms rely on subjective biases owing to constrained and specific samples (Chan et al., 2014). The present study proposes a novel fuzzy system and a dynamic-based project network model to address these issues. The proposed model extends the project network learning model (Unsal and Taylor, 2011) and quantitatively incorporates the complex innovation adoption process as multiple intra- and inter-organizational learning processes. In the model, the impact of innovations is represented as dynamic learning rates, and aggregated learning rates are interpreted by a fuzzy system and computed by a system dynamic (SD) mechanism. Thus, the complex megaproject innovation diffusion process can be effectively simplified as multiple learning processes influenced by various organizational management factors.

2 Background

2.1 Collaborations and innovations in megaprojects

The efficiency of cooperation for project teams determines the successful adoption of new technologies (Dietrich et al., 2010). A major challenge of adoption is raised by complicated interactions among parties (Mihm et al., 2003; Sommer and Loch, 2004; Ozorhon et al., 2016). Multiple learning processes in intra- and inter-organizational interactions have been proposed to examine and simplify such organizational interactions (Taylor et al., 2009; Sepasgozar et al., 2018). That is, when efficient collaborations exist among parties, the rate of inter-organizational learning increases to represent low transaction costs and high productivity. Given such simplification, the distribution and utility of new knowledge among project teams can also be modeled as a learning process and measured by the performance of an organization as a whole (Alegre and Chiva, 2008). Therefore, directly applying new knowledge across organizations is challenging, because new contexts for implemented innovation may arise during project collaboration (Ford et al., 2000; Carrillo et al., 2004). In addition, because a joint project company is a temporary endeavor and each party has its own agenda, a robust collaborative and harmonious relationship among parties ensures the success of innovative attempts. For example, in a study on the Swedish construction industry, Dubois and Gadde (2002) found that the decentralized and project-based nature of the construction business hinders innovation diffusion. Therefore, researchers have proposed understanding the dynamic process of innovation adoption as an iterative learning and evaluation experience in a multiparty cooperative environment (Davies et al., 2014).

2.2 Learning processes in project networks

Learning may occur at different levels, such as individual, group, and organizational levels, as well as in the entire industry (Hijazi et al., 1992; Lutz et al., 1994). Given that the adoption process of innovation is a typical learning process, Taylor et al. (2009) proposed to model these processes using a project network learning model. Various organizational structures complicate the process of innovation adoption and diffusion in project teams; thus, researchers have suggested studying such process using an interactive organizational model (Harty, 2008). In addition, innovation diffusion can be impeded by discontinuity in a project network caused by different project stages, areas of expertise, and participant discrepancy (Chen et al., 2018). Moreover, successful innovations are achieved not only by creating new knowledge in individual firms but also by associating with transfers and diffusion across firms (Smyth, 2010). In terms of interfirm cooperation, the learning process may also occur during collaboration among firms, which results in the sharing of experiences and the promotion of productivity (Alvanchi et al., 2012). Project network models utilize organizational learning to assess the impact of leadership, collaboration, and technologies within organizations (Powell, 2003). Thus, an effective inter-organizational relationship, such as innovation diffusion (Taylor and Levitt, 2007), can be regarded as a learning process (de Orue et al., 2009; Taylor et al., 2009; Alin et al., 2011; Liu and Chan, 2017a) that ensures the successful adoption of innovation and improvement in productivity during project execution (Wuyts and Geyskens, 2005).

Innovations in project networks can be viewed as perturbations to the learning process of organizational productivity when organized parties find new ways to solve problems and improve project performance (Van de Ven, 1986). Based on such assumptions, a project network interprets innovations within an organization as a combination of inter- and intra-organizational productivity changing and learning (Chen and Taylor, 2014). For example, Unsal and Taylor (2011) stipulated that inter-firm collaboration and hold-up problems are results driven by the reduction of transaction costs in a project network. McKee (1992) utilized a project network and explained how organizational learning processes may reinforce the cooperation of project collaboration efficiently. Chen and Taylor (2014) employed the inter-organizational learning processes of a project network to analyze skills decay and retention loss in project teams. Given that a project network model mimics complex inter-organizational interactions as multiple mutual learning processes, organizational learning rates should be properly determined to represent various organizational structures and contractual relationships. The aggregated learning rate is the major driver of learning dynamics in project network theory. Thus, this study implements a fuzzy SD model to determine varying learning rates at equilibrium. For example, radical innovations can be initially modeled as low organizational productivity but later as high productivity after long-term implementation. High learning rates indicate efficient knowledge adoption and less conflicts within an organization (Taylor et al., 2009). Similarly, the inter-organizational learning rate can be computed to quantify such inter-organizational working experience among parties. Therefore, rather than a conventional questionnaire measurement, this study adopts fuzzy logic theory and an SD model to translate empirical inputs into objective network coefficients.

2.3 Fuzzy logic and SD models

A bottom-up method is impossible for complex megaproject network systems in terms of the incorporation of all factors and their interactions. Therefore, this study employs fuzzy logic theory to approximate a nonlinear system based on prior knowledge and expert experience. Zadeh (1965) introduced fuzzy logic theory, which has been widely applied to handle imprecise subjective inputs and uncertainties. Fuzzy logic models translate ambiguous linguistic information into standard and structured fuzzy sets with membership functions (Ross, 2016). Moreover, fuzzy sets and membership functions can be determined with a multiple-round Delphi survey to achieve consensus from professionals and experts (Hasson et al., 2000). Fuzzy logic theory has been implemented in project management and organizational studies from various perspectives. For example, Tah and Carr (2000) used fuzzy logic theory to break down the hierarchical structures of project risks for qualitative risk assessment. Zhang et al. (2017) highlighted a multi-attribute group decision-making model for the Pythagorean fuzzy information of organizations. Meanwhile, Qi et al. (2018) adopted fuzzy unbalanced linguistic sets to investigate the uncertainty nature and decision hesitancy of multi-attribute group decision making in large organizations. Xu et al. (2010) utilized fuzzy sets and fuzzified factors to improve risk allocation in public–private partnership (PPP) megaprojects. Lastly, Fayek et al. (2004) implemented a fuzzy system in construction management from a comprehensive perspective, such as cost overruns (Knight and Fayek, 2002; Shaheen et al., 2007), activities and schedules (Oliveros and Fayek, 2005), field rework (Fayek et al., 2004), and labor productivities (Fayek and Oduba, 2005).

The present study utilizes the SD model to simulate intricate interactions during project execution and computes the organizational learning rate as input for a project network model. SD theory is an effective tool for assessing SD with various interdependent decision variables. It involves multiple feedback processes, nonlinear relationships, and quantitative and qualitative data sets to present the complexity of a system (Sterman, 2000). As megaprojects require the collaboration of different teams to complete tasks, SD can represent a process involving experience transfer as faced by a large construction project that is fragmented and multifaceted such that the system may be decomposed into manageable pieces (Lê and Law, 2009).

3 Methodology

This research proposed to simulate innovations as perturbations during an organizational learning process in a project network model to investigate innovation diffusion in organizations involved in megaprojects. As perturbations result from changed learning rates, this research implemented the SD model to compute the dynamics of such rates. Moreover, this study employed fuzzy logic theory and a Delphi survey to acquire knowledge from experts and professionals to construct a proper quantitative SD model. Figure 1 shows the scheme of the proposed model.

3.1 Delphi survey and identified influencing factors

Identification of critical influencing indicators is the first and most important step in analyzing innovation adoption in megaprojects to recognize main factors efficiently. A Delphi survey was developed based on the study on organizational innovations by Subramanian and Nilakanta (1996) to acquire these factors. A survey with a five-point Likert scale (i.e., 1–very low, 2–low, 3–medium, 4–high, and 5–very high) was used to identify the most important influencing factors. A total of 33 experts in the construction industry with experience in megaprojects was invited to take the survey. Given that the number of experts with experience in megaprojects was relatively small compared with that in small-scale projects, a three-round survey was conducted for data determination. The Delphi survey involved the following steps.

Step 1: First-round Delphi survey

The first round of the survey required all the participants to score the impact of all the factors identified from the literature. Table 1 presents the basic information of the respondents, including years of employment work experience in generic and PPP projects, and relevant project categories. The results indicated that 31.25% of the respondents worked in the government, 50% worked in private companies, and 18.75% were in the academic field and thus may hold neutral opinions. The questionnaire was open ended to enable the participants to provide additional factors they deemed relevant.

Step 2: Second-round consistency survey

In the second round of the survey, a modified questionnaire with a summary of the results from the first-round questionnaire was distributed to the experts, who were then asked to score and prioritize the items. The participants were given a chance to revise their choices

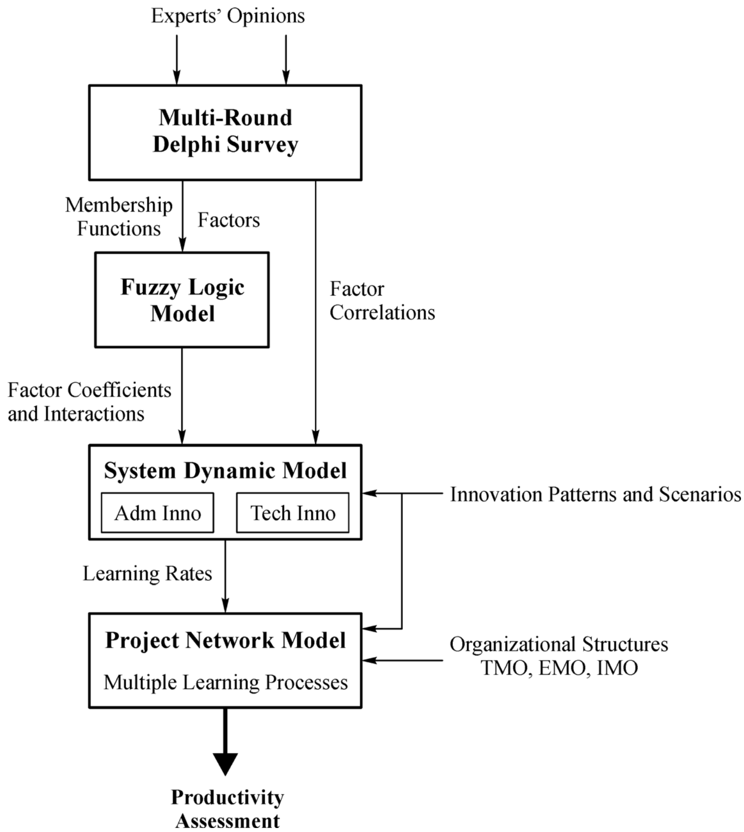

Fig. 1 Schematic plot of the proposed assessment model.

after they completed the updated survey. Finally, the results were aggregated and selected based on importance and relevance. The mean values and weights of the influence factor for membership function (IFMF) were calculated using the experts' scores, as shown in Table 2. A total of 13 key factors related to administrative and technical innovations was identified, where the first seven factors were common to both innovations. Apart from the common factors, IFMFs 8 to 10 represented features of administrative innovation, while IFMFs 11 to 13 denoted characteristics of technical innovation.

Step 3: Third-round factor correlation survey

In the third round of the survey, the experts were asked to identify the correlation between each pair of selected factors based on the factors related to administrative innovation. The correlation coefficient can be determined from the survey, which was used to formulate the equation in the SD model. Table 3 shows the result of the correlation of 10 indicators.

3.2 Fuzzy sets and membership functions

Given that the survey relied on the subjective and ambiguous judgment of experts to properly interpret and quantify outputs, this study implemented fuzzy logic modeling to quantify the input parameters of the SD model. Rather than using the mean scores of the survey results, the fuzzy logic model converted inputs into fuzzy sets through the fuzzification process. This step applied rules to compute fuzzified inputs and interpreted outputs through a defuzzification process. For each factor, a set of membership functions was defined as $f = \{f_1, f_2, ..., f_n\}$, where n is the number of scales. The weight of each factor was computed using the five-point Likert scale. As suggested by Chow (2005), weight $W = \{w_1, w_2, ..., w_n\}$ can be formulated as percentages as follows:

$$W_{\mathrm{IFMF}_a} = \frac{M_{\mathrm{IFMF}_a}}{\sum_k M_{\mathrm{IFMF}_a}}, \tag{1}$$

where W_{IFMF_a} is the weight of a selected IFMF_a, M_{IFMF_a} represents the value of a selected IFMF_a, and $\sum_k M_{\mathrm{IFMF}_a}$ denotes the sum mean rating of all selected IFMFs.

The membership function of innovation performance (*MFIP*), which consisted of administrative and technical innovations, can be calculated by the linear and additive model established by Yeung et al. (2007):

$$MFIP = \sum_{i=1}^{n} R \times L, \tag{2}$$

where R represents the degree of the *MFIP* in a megaproject, and L refers to the Likert scale score.

Table 1 Basic information of experts in the Delphi survey

Working experience	
⩽ 1 year	12.50%
1–2 years	37.50%
2–5 years	37.50%
5–10 years	6.25%
10–20 years	6.25%
Working experience on PPP projects	
1–2 years	42.86%
2–5 years	57.14%
Number of experts in PPP project categories	
Water supply, heating, sewerage	5
Refuse treatment	3
Utility tunnel	9
Road	15
Railway	6
Airport	10
Urban metro	7
Healthcare building	1
Tourism	1
Education	1
Elderly center	2
Heritage	2
Sports center	2
Government-subsidized housing	3
Water utilities	3
Agriculture	3
Forestry	1
Resources and environment protection	1
Urban redevelopment	3
New development of the area	3

The weighting process for innovation performance is similar to the weighting for innovation factors. The overall performance of innovation (*OPI*) was calculated as follows (Hu et al., 2016):

$$OPI = \sum_{i=1}^{n} MFIP_i \times W_i, \tag{3}$$

where $MFIP_i$ represents a selected *MFIP*, and W_i pertains to weight of a selected *MFIP*.

The factors were divided into two groups, that is, one related to management practices and the other related to technical issues (Subramanian and Nilakanta, 1996). As suggested by Xu et al. (2010), the present study selected the π function to represent membership functions. The following equation is the explicit expression of the π function:

$$\pi(x; a, b) = \begin{cases} S(x; b-a, b), & x \leqslant b \\ Z(x; b, b+a) = 1-S, & x > b \end{cases}. \tag{4}$$

Figure 2 illustrates the membership functions for the five Likert scales, and Table 4 summarizes the fuzzified inputs and weighting of all the factors.

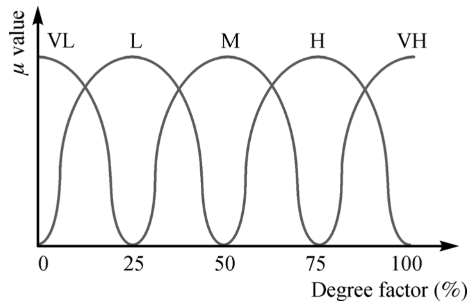

Fig. 2 π membership function (VL–very low, L–low, M–moderate, H–high, VH–very high).

Table 4 shows that the degree factors reflected how the survey results were weighted. We take "Centralization" as an example. If a fuzzy set is equal to 0.09, 0.18, 0.36, 0.27, and 0.09, then the percentage of the experts who acknowledged the influence of the factor on innovation, from very high to very low, is 9%, 18%, 36%, 27%, and 9%, respectively.

3.3 SD modeling

SD simulation combines qualitative and quantitative research methodologies, which enables complex dynamic and nonlinear problems to be solved through simulation models. Innovation was classified into two categories, namely, technological innovation and administrative innovation, to analyze the learning rate in a megaproject network (Subramanian and Nilakanta, 1996). The learning rate for technical innovation was used to represent technical difficulties and the absorption speed of innovations within a company, while that for administrative innovation was used to reflect mutual inter-organizational learning and innovation diffusion. Based on results of previous models, the SD modeling approach was adopted to compute the learning rates for technical and administrative innovations (Subramanian and Nilakanta, 1996). The determined learning rates were then coupled with the project network model and implement productivity as the measurement of innovation adoption. The model was an iterative simulation process; thus, an initial learning rate of 0.8 was selected, which is the industry average value of the learning rate (Chen and Taylor, 2014). Figure 3 depicts the SD model for the learning rate of technical innovation based on defuzzified scores and correlation coefficients.

Table 2 List of identified influencing factors

Code	Influencing Factors for Membership Functions (IFMF)	Description	Mean	Weighting	Reference
IFMF1	Consistency of innovation adoption	The innovativeness should consistent with the nature of innovations after adoption	3.73	0.090	Gambatese and Hallowell (2011)
IFMF2	Time of innovation adoption	The times of adoption practices have been taken for one innovation	2.36	0.057	Kramer et al. (2009)
IFMF3	Number of innovation adoption	The number of innovations that adopted after the consistency discussion	3.09	0.075	Gambatese and Hallowell (2011); Nikas et al. (2007)
IFMF4	Formalization	Existence of formal job descriptions, policies, and procedures for personnel	3.69	0.089	Damanpour and Schneider (2006)
IFMF5	Centralization*	Level of centralized authority for decision-making	4.09	0.099	Damanpour and Schneider (2006)
IFMF6	Specialization	Existence of personnel with specialized skills in various functional areas in an organization	2.36	0.057	Gambatese and Hallowell (2011)
IFMF7	Public policy	Potential government policies that may have effects on the megaproject execution	2.64	0.064	Pauget and Wald (2013)
IFMF8	Frequent supervision	Intensity and sequencing of the supervision in the innovation process	2.82	0.068	Koskela and Vrijhoef (2001)
IFMF9	Organization structure	A clear hierarchy of people, their function, the workflow, and the reporting system	3.18	0.077	Egbu (2004)
IFMF10	Organization size	The size of the organization during the adoption and implementation of innovations	2.55	0.062	Egbu (2004)
IFMF11	Firms funding	If the organizations provide sufficient funding to perform new innovations	3.88	0.094	Chan et al. (2014)
IFMF12	Knowledge limitation	The expertise in an organization who master and is familiar with the advanced technologies and innovations	3.23	0.078	Javernick-Will (2012); Ozorhon et al. (2016)
IFMF13	Slack resources	Existence of surplus resources that are available for experimenting with innovations	3.79	0.092	Dikmen et al. (2005)

Note: *Centralization in this paper refers to the "centralization as a management factor".

Table 3 Correlation of the influencing factors

	CI	TI	NI	Fo	Ce	Sp	PP	FS	OS1	OS2
CI	1.00	0.35	0.36	0.63	0.45	0.23	0.27	0.35	−0.22	−0.26
TI	0.35	1.00	0.40	0.52	0.33	0.26	0.30	0.27	−0.39	−0.20
NI	0.36	0.40	1.00	0.64	0.48	0.23	0.41	0.40	−0.36	−0.22
Fo	0.63	0.52	0.64	1.00	0.63	0.46	0.54	0.58	−0.44	−0.41
Ce	0.45	0.33	0.48	0.63	1.00	0.51	0.62	0.59	−0.31	−0.43
Sp	0.23	0.26	0.23	0.46	0.51	1.00	0.63	0.44	−0.28	−0.40
PP	0.27	0.30	0.41	0.54	0.62	0.63	1.00	0.53	−0.27	−0.37
FS	0.35	0.27	0.40	0.58	0.59	0.44	0.53	1.00	−0.21	−0.37
OS1	−0.22	−0.39	−0.36	−0.44	−0.31	−0.28	−0.27	−0.21	1.00	0.32
OS2	−0.26	−0.20	−0.22	−0.41	−0.43	−0.40	−0.37	−0.37	0.32	1.00

Note: Consistency of innovation adoption (CI); Time of innovation adoption (TI); Number of innovation adoption (NI); Formalization (Fo); Centralization (Ce); Specialization (Sp); Public policy (PP); Frequent supervision (FS); Organization structure (OS1); Organization size (OS2).

The highly correlated variables were connected with the casual feedback loop diagram. In the model, the arrow between two factors indicated a positive relationship. Similarly, Fig. 4 depicts the SD model for the learning rate of administrative innovation. The learning rate was embedded in the SD model, where productivity was used to measure innovation adoption. Figures 3 and 4 represent the two types of innovations, respectively. Linear and nonlinear relationships were formulated with the calculated defuzzified parameters and correlation coefficient.

Table 4 Membership functions for influencing factors

Innovation factors	Weighting	Membership function (degree factors)				
		VL	L	M	H	VH
Management Factors[1]						
Time of innovation adoption	0.077	0.45	0.00	0.36	0.09	0.09
Number of innovation adoption	0.101	0.09	0.36	0.09	0.27	0.18
Formalization	0.121	0.09	0.27	0.18	0.36	0.09
Centralization	0.134	0.09	0.18	0.36	0.27	0.09
Specialization	0.077	0.18	0.36	0.36	0.09	0.00
Public policy	0.087	0.09	0.36	0.36	0.18	0.00
Frequent supervision	0.092	0.09	0.27	0.36	0.27	0.00
Organization structure	0.104	0.09	0.18	0.27	0.36	0.09
Organization size	0.084	0.09	0.27	0.64	0.00	0.00
Technical Factors[2]						
Consistency of innovation adoption	0.114	0.27	0.09	0.45	0.18	0.00
Time of innovation adoption	0.072	0.09	0.09	0.45	0.36	0.00
Number of innovation adoption	0.094	0.09	0.18	0.27	0.36	0.09
Formalization	0.113	0.09	0.27	0.27	0.27	0.09
Centralization	0.125	0.09	0.18	0.55	0.09	0.09
Specialization	0.072	0.09	0.27	0.27	0.18	0.18
Organization size	0.078	0.09	0.18	0.25	0.29	0.19
Firms funding	0.118	0.09	0.18	0.34	0.36	0.03
Knowledge limitation	0.099	0.09	0.18	0.47	0.22	0.04
Slack resources	0.116	0.09	0.18	0.36	0.23	0.14

Note: 1. Overall membership function for management factors (0.125, 0.218, 0.336, 0.199, 0.112); 2. Overall membership function for technical factors (0.111, 0.180, 0.376, 0.249, 0.081).

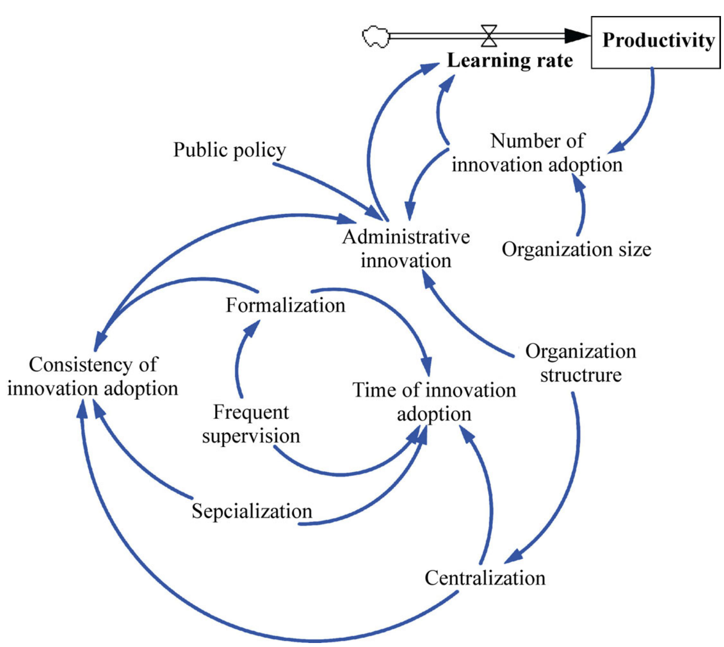

Fig. 3 System dynamic models for technical innovation learning rate.

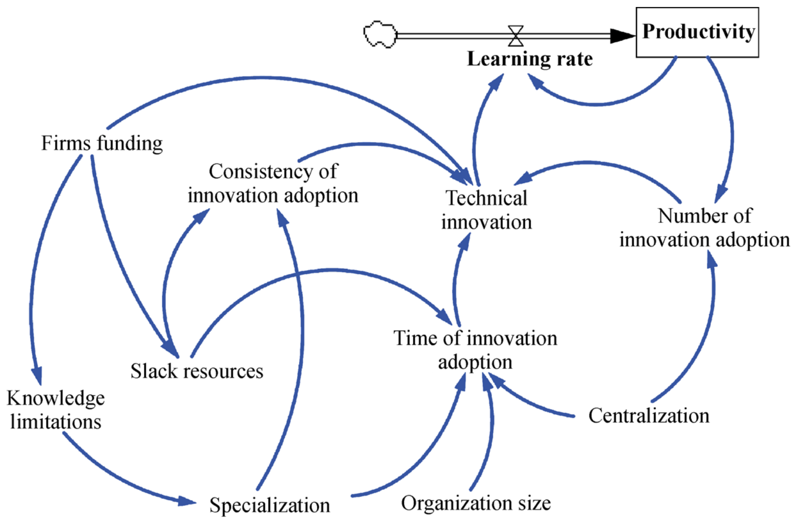

Fig. 4 System dynamic models for administrative innovation learning rate.

However, in real systems, a combination of reinforcing and balancing feedback structures can form complex dynamic behaviors that can be characterized using sophisticated system archetypes (Mirchi et al., 2012). Thus, this study hypothesized that all indicators comprised positive feedback loops, in which the equations mapped in the model can perform the final output by evaluating productivity. Arrows in the causal feedback loop connected the variables with high correlations.

3.4 Modeling the project network

Parties in a megaproject team complicate contractual relationships and interactions; therefore, the project network model was suited to mimic the innovation diffusion process with multiple learning processes. Moreover, the process can quantitatively reflect the performance of the overall project network with aggregated productivity improvement. According to Subramanian and Nilakanta (1996), an improvement in productivity is a result of organizational evolvement and technical innovation. In the present study, productivity was a reference factor that was originally assigned as 1 to illustrate the improvements of project network production over time. In the simulation model of the following sector, it was represented as the normalized completion time.

Therefore, as the most critical factor of a project network, learning rate was determined by the management policy and maturity level of organizational collaboration. In contrast to the conventional industry average, this study utilized dynamic learning rates as computed by the SD model with adaptive inputs for the project network system. Based on the project network model of Taylor et al. (2009), the productivity of firm i (Π_i) can be presented as follows:

$$\Pi_i = \Pi_0 (n_i)^{L_i}, \tag{5}$$

where Π_0 denotes the initial length of time to complete a project task, n_i pertains to the number of separated tasks implemented by company i, and $L_i = \log\lambda_i$ is the characteristic learning index for company i, in which λ_i is the learning rate.

T_{R_i} is assumed as the productivity for completing the first task by company i in role R_i. The total time for completing one task can be recorded as follows:

$$T_i = \Pi_i T_{R_i}. \tag{6}$$

Given that a megaproject team involves numerous companies, inter-organizational learning was defined as cross-party productivity. For collaborating companies i and j, the productivity of their cooperation is derived as follows (Subramanian and Nilakanta, 1996):

$$\Pi_{ij} = \Pi_{00} (n_{ij})^{L_{ij}}, \tag{7}$$

where Π_{ij} stands for the productivity of the collaboration, Π_{00} represents the initial length of time to complete an interdependent project task with collaboration, n_{ij} pertains to the number of interdependent tasks implemented by the collaboration, and $L_{ij} = \log\lambda_{ij}$ is the characteristic learning index for the collaboration, in which λ_{ij} is the learning rate of companies i and j.

The amount of time that firm i spends on executing T_{R_i} is record as X_{ij}. This part of the work is finished within a given time of:

$$T_{ij} = \Pi_{ij} X_{ij} T_{R_i}, \tag{8}$$

where X_{ij} is the level of interdependence of the tasks among firms.

The total time spent finishing a project (T_{p}) can be computed by summing up the individual time for each firm as follows:

$$T_{\rm p}=\sum_{i}^{M}T_i+\sum_{i}^{M}\sum_{j\neq i}^{M}T_{ij},\quad \forall i,j\in P, \tag{9}$$

where M is the set of firms with the same role and P is the set of all firms.

As different organizational structures can have various scales, time can be normalized as a factor as follows:

$$T_{\rm N}=\sum_{i}^{M}T_{R_i}+\sum_{i}^{M}\sum_{j\neq i}^{M}X_{ij}T_{R_i}, \tag{10}$$

$$\overline{T_{\rm p}}=\frac{T_{\rm p}}{T_{\rm N}}. \tag{11}$$

The final normalized time and productivity can serve as updated inputs. The final outcome can be assessed or optimized by adjusting the organizational structure and management policies of the SD model.

4 Dynamics of innovation diffusion and adoption in megaproject organizations

Three features determine the complexity of an organization in project networks, namely, the number of firms per role, the number of tasks, and the percentage of interdependent overlap. As specialization and experience can affect the proficiency of an individual company, the model in this study assumes that all roles have equal experiences at the start of project execution. This study selects three typical contractual relationships of a megaproject team to assess the impact of innovation diffusion. Figure 5 shows a traditional megaproject procurement organization (TMO), where developers are responsible for financing and managing as well as hiring a construction firm to handle construction procurement and execution. Figure 6 shows a vague project arrangement of the environ megaproject organization (EMO), as identified by Evans et al. (2005), while Fig. 7 is an integrated megaproject organization (IMO) introduced by Chung et al. (2009). In addition, Newcombe (2003) introduced and discussed the IMO in the Swindon redevelopment project.

This study examines six typical scenarios to understand the dynamics of innovation adoption and diffusion. These scenarios vary in terms of organizational settings and contractual relationships based on the results of the Delphi survey and can be used to develop effective organizational structures and strategies for megaproject innovation absorption. The scenarios can be categorized as administrative and technical variations corresponding to the variation in the dynamic model of the learning rates of administrative and technical innovations. Table 5 summarizes all scenarios, namely, a simplified organization (S1), a financially sufficient organization (S2), a centralized organization (S3), technology with supervision inference (S4), technology with specialization (S5), and technology with government incentives (S6).

This study utilizes normalized productivities in equilibrium with the entire project network to compare the performance of organization coordination. As the learning process is dynamic over multiple rounds of collaborations,

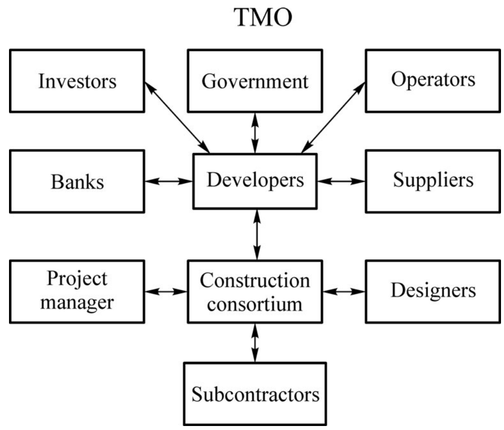

Fig. 5 Contractual scheme of the traditional megaproject procurement organization (TMO).

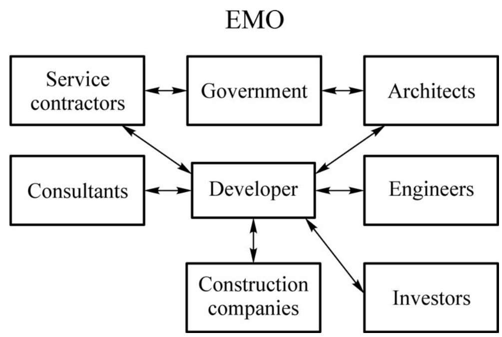

Fig. 6 Contractual scheme of the environ megaproject organization (EMO).

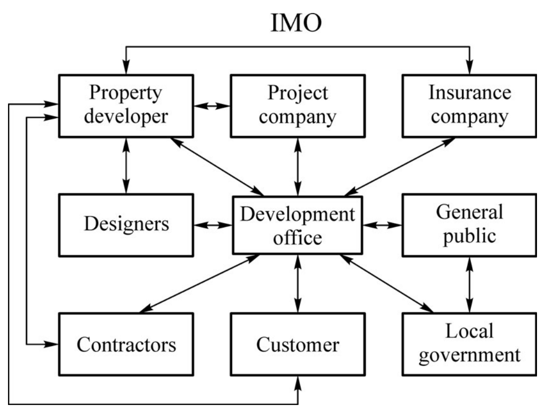

Fig. 7 Contractual scheme of the integrated megaproject organization (IMO).

Table 5 Summary of the potential scenarios to promote the innovation diffusion in megaproject organizations

Code	Scenarios	Coefficients setting
–	Baseline	All coefficients of the system dynamic models were set based on the Delphi survey results
Administrative variations		
S1	Simplified organization	Lower organization size coefficient
S2	Financially sufficient organization	Higher firm funding coefficient
S3	Centralized organization	Higher centralization coefficient
Technical variations		
S4	Technology with supervision interference	Higher supervision frequency coefficient
S5	Technology with specialization	Higher specialization coefficient
S6	Technology with government incentives	Higher public policy coefficient

the performance of single project is subject to randomness. In addition, learning rates vary over the years and decrease in the long run. Moreover, individual organizations are subject to changing learning rates after switching partners in a project network. Therefore, converged performance in equilibrium is adopted for easy comparison across project networks. Figure 8 shows the normalized productivity of different project networks with organizational variations of over 40 simulation iterations with 10000 simulation runs. As project network productivity converges in equilibrium, only the first 40 iterations are included. The simulation model is examined across the six scenarios (Table 5) to conduct sensitivity analysis. The coefficient setting of each strategy will create a different scenario with an updated coefficient. For example, "S1–simplified organization–lower organization size coefficient" has an organization size coefficient that is 10% lower than the baseline model. Notably, productivity in the results is measured by the normalized completion time for a project (initial value is 0.5). In other words, the lower the normalized project completion time, the higher the project efficiency. Given that the simulation mimics the development of productivities of an entire project network after learning over time, each iteration represents a successful project collaboration among the network collaborations. For most of the scenarios, the normalized completion time will converge in equilibrium after 12 iterations. In the first three scenarios, the performances of the TMO and EMO are similar, which suggests a similarity in the innovation diffusion dynamic pattern of both networks under administrative variations. For S1, S2, and S3, the TMO and EMO restore the original productivity level; however, only the IMO benefits from administrative variation and receives high productivity. For all technical variations, the TMO and IMO display a slight improvement in productivity; however, the EMO receives a substantial penalty. These results suggest that the EMO can initially adapt to innovation quickly but will suffer from long-term instability, which is caused by evolving technical changes.

Figure 8 shows that the six scenarios have the same trends after 12 iterations, which indicate that the performances of the different assumptions will converge to a local equilibrium within a certain time. The first three scenarios, namely, S1, S2, and S3, belong to administrative innovation. The performances of the TMO and EMO are similar, which indicate that productivity increases to approximately 30% to 40% along with a 10% increase in factors S1 to S3. By contrast, the IMO has a completely reversed trend. That is, a change in management strategies has a negative effect on IMO productivity. For all technical variations, the TMO and IMO have a slight improvement in productivity, whereas the opposite is true for the EMO. Although the TMO and IMO are nearly restored to their original levels of productivity, the EMO benefits from technical variation, thereby showing a high level of productivity. This situation indicates that the EMO mode may take time to adapt to new technical changes but demonstrates an optimistic long-term trend.

Figures 9, 10, and 11 show the normalized productivity of the TMO, EMO, and IMO, respectively, under all scenarios. The figures indicate that the performance of S1, S2, and S3 (the administrative group) are similar with that of S4, S5, and S6 (the technical group). For the TMO, the administrative group shows a typical learning curve and obvious improvement, whereas the completion time for the technical group is slightly higher than its original level. For the EMO, the administrative group remains on the same productivity level after innovation adoption but that of the technical group has deteriorated. For the IMO, the efficiency of the technical group is slightly improved, whereas the administrative group's performance is worse.

To identify effective strategies across innovations, Figs. 9, 10, and 11 show the normalized productivities of the TMO, EMO, and IMO under the six scenarios. The results show that the performances of different types in the same innovation group are similar. We take the TMO type as an example (Fig. 9). The technical group shows a rising learning curve and a slight improvement, whereas the administrative group's completion time is lower than its original level. The strategies of technical innovation (S4 to S6) perform better than those of the administrative group (S1 to S2). The result reflects that improving technology in

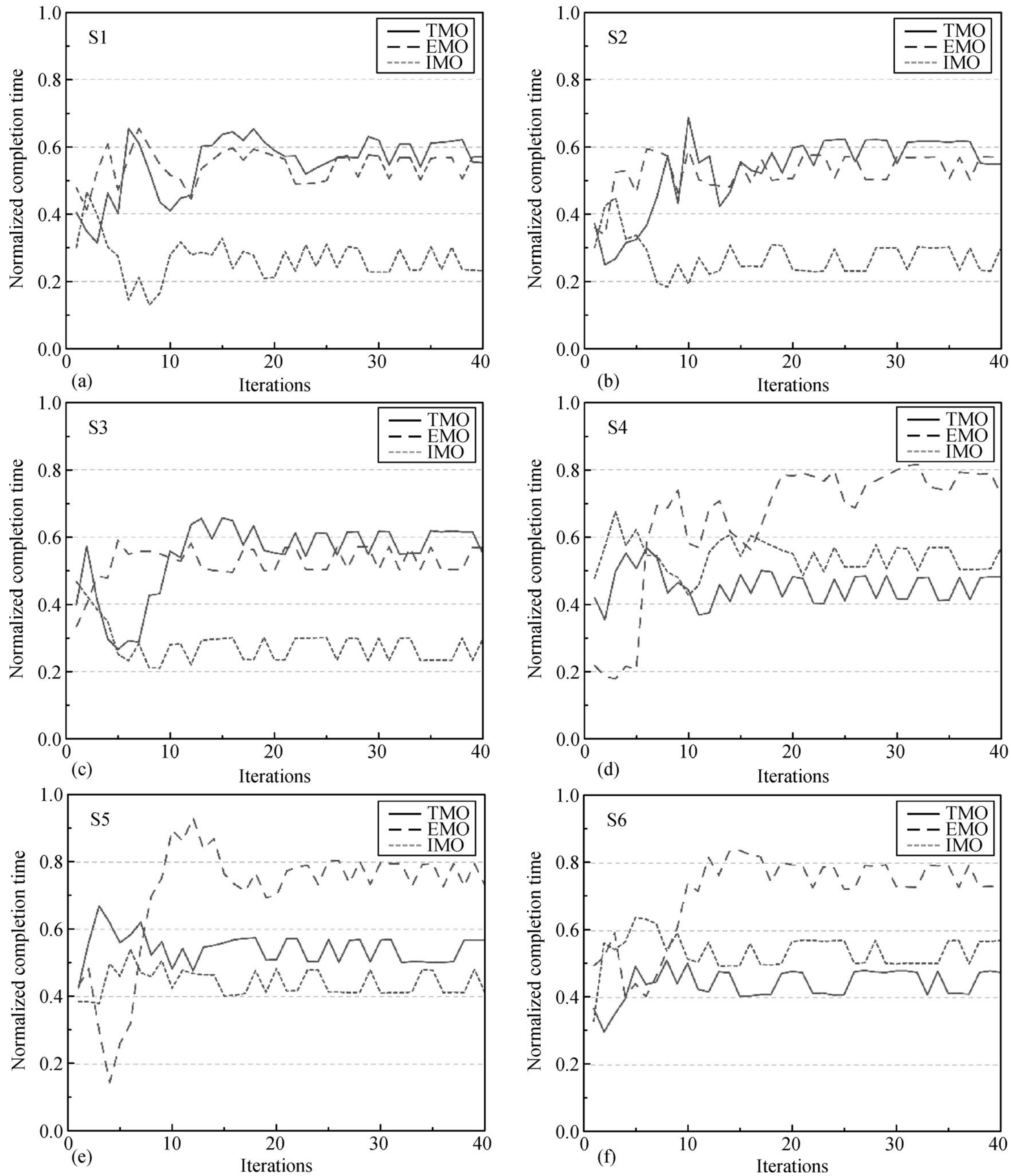

Fig. 8 Normalized project network productivity under different scenarios.

the TMO mode can lead to a growth in productivity. However, implementing administrative innovation in the TMO structure is not suggested. Any change in strategy for the EMO network (Fig. 10) will enhance productivity. Specifically, technical innovation has a better performance compared with administrative innovation. Productivities with the improvement of technology remain steady at approximately 0.75, whereas a slight growth in productivity can be observed in administrative evolution, which fluctuates by approximately 0.5.

Figure 11 shows an opposite trend, in which implementing administrative innovation is encouraged under the IMO type, because strategies belonging to an administrative revolution will result in high productivity. Although a decreasing trend is observed in the initial execution of S1 and S2, productivity continues to increase post collaboration. Nevertheless, change in technical innovation has little effect on productivity.

To assess overall performance, Table 6 summarizes the aggregated learning rates of all organizations under different scenarios to represent the impact of innovation on organizational productivity. Negative learning rates suggest an improvement in organizational productivity for all simulation iterations. The results show that the TMO

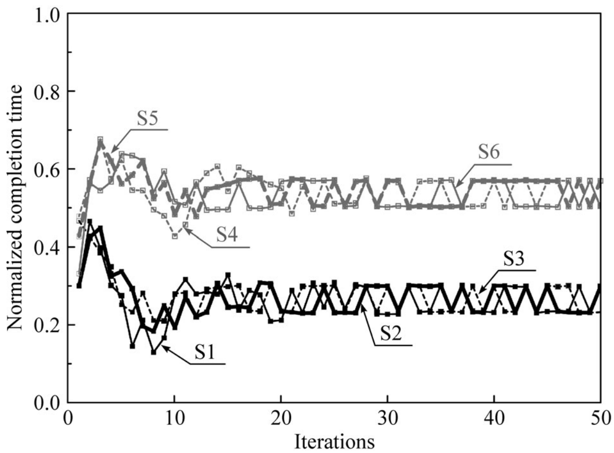

Fig. 9 The normalized project network productivity of TMO for all scenarios.

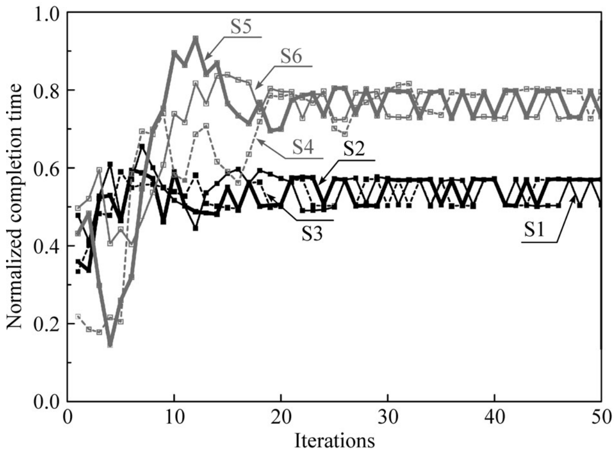

Fig. 10 The normalized project network productivity of EMO for all scenarios.

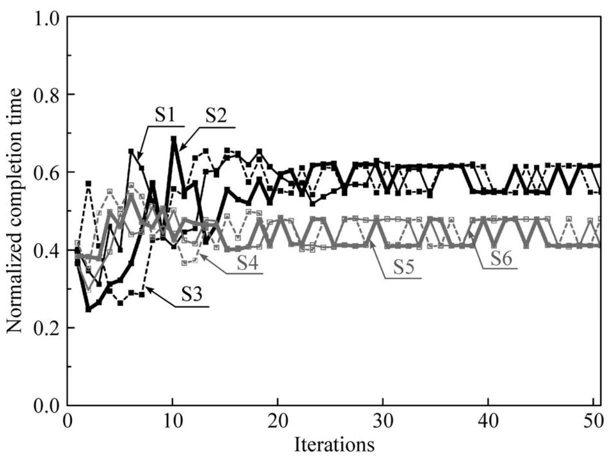

Fig. 11 The normalized project network productivity of IMO for all scenarios.

can benefit from administrative and technical innovations, and the EMO is vulnerable to changes within organizations, which will result in decreased productivity.

5 Results and discussion

This study develops a quantitative assessment of productivity improvement for several complex organizational structures during innovation adoption. Strategic cooperation relationships have substantial effects on innovation adoption from various perspectives, such as professionalism and credibility. Thus, establishing an innovative and pro-organizational environment is key to successful innovation adoption (Liu et al., 2014). This simulation study investigates three typical strategic cooperation relationships to quantitatively extend the understanding of the innovation adoption process. The simulation shows that productivity of the TMO and EMO converge at the same level under administrative innovation. The EMO distinctively outperforms the two other organizational types under technical innovation. The proposed fuzzy SD-enhanced project network model can not only help a project team select appropriate contractual relationships but also formulate a process to systematically analyze the performance of various organizational structures. Furthermore, such a model can help understand the efficiency of innovation adoption for an entire megaproject network and can also be used to assess the team performance of each party. For megaprojects with established collaboration relationships, the team-level adoption rate can be improved by adopting different strategy variations. We take TMO as an example, which is appropriate for administrative innovation but not for technical innovation. When S1 is adopted, network productivity reaches its peak faster than S2 and S3. For technical innovations in the TMO, S6 has a high productivity rate, which indicates that government subsidies or enforcement can effectively promote a project's technological development. For the IMO, administrative innovation causes inefficiency, whereas technical innovation offers a controlled improvement. In addition, administrative innovation leads to low-efficiency productivity, whereas technical innovation complements this deficiency in the IMO. The structure of the EMO is resistant to changes occurring among organizations, thereby resulting in poor productivity. The best strategic operation can be identified by comparing various options that can substantially facilitate innovation creation and diffusion in megaprojects.

Assessing the performance of megaproject teams is difficult owing to the complicated organizational structure. This study extends the understanding of diffusion dynamics with a project network model and implements the model as a platform for assessing the influence of different organizational factors and strategies. However, determining proper learning rates to reflect different

Table 6 The equivalent project network learning rates over iterations

R-square	S1	S2	S3	S4	S5	S6
TMO	–0.069 (0.4666)	–0.104 (0.6739)	–0.082 (0.4265)	0.004 (0.0061)	–0.001 (0.0001)	–0.024 (0.2111)
EMO	0.013 (0.0559)	0.037 (0.3178)	0.029 (0.2538)	0.193 (0.7705)	0.146 (0.4911)	0.109 (0.5580)
IMO	0.021 (0.0893)	0.025 (0.1543)	0.038 (0.3575)	–0.008 (0.0220)	–0.008 (0.0251)	–0.005 (0.0080)

strategies is challenging in a conventional project network learning model (Unsal and Taylor, 2011). This study introduces an objective fuzzy SD model to deepen the current understanding and resolution of such a challenge. The model has several advantages. First, it enables a dynamic aggregated learning rate to represent the efficiency and frequency of innovation adoption (Shenhar, 2001). Second, it allows integrated interactions among numerous participants, such as governments, contractors, subcontractors, suppliers, investors, and third parties, through a dynamic system (Sterman, 2001). This notion emulates complicated interactions and constraints in actual projects, such as legislation, regulations, industry standards, and funding agencies (Kardes et al., 2013). Third, project network theory treats interactions between and within project teams as a black box. That is, all organizational interactions are determined by subjective coefficients. Therefore, to obtain objective inputs for the project network, the Delphi survey and fuzzy logic systems are combined to acquire organizational coefficients. Both tools have been proven valid for studying megaprojects from different perspectives, such as delay (Lyneis and Ford, 2007), quality control (Park and Peña-Mora, 2003), bidding strategies (Chang, 2013), and risk assessment (Ackermann et al., 2007). Thus, this study proposes a comprehensive model that can characterize intertwined project team interactions as a logically linked dynamic system. Moreover, it has broad impacts on practical implementation for the industry. Megaprojects involve a large variety of entities and resources; thus, failure in coordination may result in substantial economic losses. The proposed model can assist project coordinators design effective and absorptive organizations that promote recent technologies applied across an entire supply chain and working process. Furthermore, it can be used as a risk assessment tool to evaluate the potential benefits and hazards of pushing certain new technologies (after their effect on learning rates is assessed). Industry practitioners can use the model to assess an organization’s responses to various events and market conditions, predict the outcomes of corresponding solutions, and assist and optimize the decision-making process. In addition, given that the proposed model assumes the development of productivity over continuous cooperation as a learning process, it can also serve as a reference for developing policies and strategies for removing learning barriers and reducing productivity losses when a new collaboration is established.

As a synthetic and simplified assessment tool for innovation adoption and corresponding strategies, the proposed method yields several limitations. First, the SD model is dependent on reliable and accurate interactions among decision variables. Although the multiple-round Delphi survey is designed to maximize consistency among the experts and minimize subjectivity, the results can inevitably lack objectivity and comprehensiveness owing to the small sample size. Therefore, future studies are encouraged to employ additional objective indicators and a large pool of experts. Second, the organizational strategies are simplified as the variables of the SD model. However, in reality, management strategies exert profound and comprehensive impacts on all aspects of a project. Thus, developing additional insightful models is suggested in future studies to reflect these far-reaching impacts. Third, the inputs of the SD model are oversimplified. For example, the inputs of the SD model are discrete and could not fully represent performance at dynamic equilibrium, and all parties in the simulation are assigned the same level of experience for ease of simulation. In the future, realistic inputs should be derived from the performance of actual project networks.

6 Conclusions

Innovation diffusion and knowledge management in megaprojects are complex owing to the large number of participants. Experienced experts were invited to assess the significance of various organizational factors to assess project performance under the comprehensive factors of megaproject management. However, the experts’ opinions were frequently vague and unusable for quantitative analysis owing to the complexity of the megaproject execution. Three organizational structures (i.e., the TMO, EMO, and IMO) suggested by the literature were combined with six scenarios and examined with the proposed model to understand the dynamics of innovation. According to the results of the systemic dynamics simulation, the TMO and EMO had similar productivity under administrative innovation strategies over a few network collaborations. The IMO over-performed the other two organizations, thereby suggesting its advantages in adopting administrative innovation. By contrast, the TMO benefitted from technological innovations, whereas the EMO performed poorly under a similar condition. The results suggested that the proposed model can be a valid tool for understanding the innovation process in megaprojects and designing effective organization coordination.

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