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Suitable organization forms for knowledge management to attain sustainable competitive advantage in the renewable energy industry

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ABSTRACT

The rapid growth of China's economy has accelerated its energy demand. The exploitation of renewable energy is essential because of limited conventional energy sources, high energy consumption, unstable and escalating oil prices, and detrimental environmental pollutions. Firms in the renewable energy industry are currently facing challenges to maintain competitiveness and productivity while minimizing environmental impacts. The ability to manage knowledge is a key feature in the process for firms to obtain competitive advantages. In addition, interactive learning framework provides a platform that can respond to the need for adjustment in time of great uncertainty. This paper adds evidence to the literature of interactive learning environment based on China context. It examines critical characteristics of interactive learning framework in the renewable energy industry, and then investigates suitable organization forms for knowledge management at different levels of a supply chain. On this basis, this paper proposes suitable organizational forms under different situations for sustainable competitive advantage.

1. Introduction

As one of the largest energy consumption countries in the world, China is facing the challenges of accommodating the ever-growing energy demands and confronting the increasing environment pollutions [1]. Renewable energy development has become a fundamental strategy for tackling the challenges. Due to industrial barriers (such as inadequate technical information, high capital cost, and rigid regulation), the development of renewable energy in China is still in its infancy period compared with developed countries [2]. Especially, the immature technology, management, and methodology in the renewable energy industry need to be improved to confront the aforementioned challenge.

Although some researchers have studied energy efficiency and energy policy in the Chinese renewable energy industry [3–5], relatively little attention has been paid to KM (knowledge management). In addition, among the works that have been done on the knowledge management, only few have examined learning effects through social learning network and intermediaries [6–8]. Actually, in a knowledge-intensive industry, knowledge is a critical factor for obtaining sustainable competitive advantage. Some gaps are still open for further examination, especially in the topic related to the selection of suitable organizational forms in an interactive learning framework. From the perspectives of three different stages of communities, including science and policy decision-making, renewable energy industry and local residents, a platform can promote participants to absorb, share and generate knowledge. Thus, this paper tries to investigate critical characteristics of interactive learning framework in the renewable energy industry and explore suitable organization forms for KM at different levels of a supply chain through empirical analysis.

The remainder of this paper is organized as follows. Section 2 provides a review of interactive learning framework and supply chain of the renewable energy industry. Section 3 establishes hypotheses and illustrates research methodology. Data collection and empirical research are conducted in Section 4. Conclusion is provided in the last section.

2. Literature review

Interactive learning and subsequent innovation have become the driving force to the economic growth in a rapid changing environment. As noted by Peng et al. [9], environment turbulence

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has a positive direct influence on interactive learning and interactive learning has a positive indirect influence on organization performance. Zhang and Zhang [10] developed a four-factor relation mode including firm knowledge, knowledge-source firm, knowledge-recipient firm, and learning environment. The authors detected that the four primary factors have a synthesized effect on the knowledge transfer process and consequently the learning process in firms' network. Thus, the network provides a platform for inter-organizational learning process. According to Yeunga et al. [11], knowledge-based manufacturers can acquire and exploit knowledge to achieve superior organization performance through creating an interactive learning framework. Recently, Chen and Wang [12] conducted a more sophisticated approach to the lag of interactive learning, finding that exploratory and exploitative learning are positively associated with organization performance while the environmental dynamism negatively moderates the relationship between exploratory/exploitative learning and organization performance.

The improved productivity in China is due to the increasing investment in the downstream supply chain of the renewable energy industry. Even so, knowledge-based manufacturers in China are still on the road to develop competitiveness in the global market by ensuring advanced technologies and resources supply, guaranteeing updated engineering equipment supply, and increasing production efficiency. In order to further study this issue, the supply chain of the renewable energy industry could be divided into downstream, midstream and upstream. Their gaps and possible solutions are described as follows.

2.1. Downstream: improving production efficiency

There is a huge demand in the renewable energy industry. To improve manufacturing cost, time and quality, more sophisticated methodologies with advanced automated technologies are necessary. This is the current weakness in the downstream supply chain of the renewable energy industry. Nevertheless, the gap between China and developed countries is becoming narrower through consecutive internal and mutual learnings. Internal and mutual experiences on advanced equipment, manufacturing technologies, and related knowledge flows, are guided by a mutually learning environment for specific engineering functions. The most suitable form for interactive learning framework shall be the one that has strong knowledge transfer for the specific expertise within the engineering functions.

2.2. Midstream: ensuring local supply of engineering equipment

In the renewable energy industry, advanced equipment and facilities are foundations for mass production. If technologies for solar, wind, biomass, and wave energy are upgraded through a suitable interactive learning platform, mass production can be accomplished in the industry, and in turn, firms can also have extensive R&D infrastructures to improve advanced technology development. Although most firms have good experiences, their technologies are still far behind those in the developed countries. The cooperation with leaders in the renewable energy industry of the midstream supply chain can help ensure local supply of engineering equipment. Furthermore, internal knowledge flows, including human resources and core technologies, can be transferred into external teams, and at the same time, external knowledge can be transferred into the internal teams. Consequently, the most suitable form of interactive learning framework is the one that supports knowledge transfer within internal and external teams, as well as promotes specific knowledge transfer among teams.

2.3. Upstream: securing the supply of advanced technologies

One of the critical factors in maintaining high growth rate is the availability of feedstock [13]. Manufacturers in China are struggling to develop advanced and innovative technologies in the renewable energy industry because science and technology in this level of supply chain are not as sophisticated as those in the developed countries. The cooperation with leading partners in the renewable energy industry is the core principle for most manufacturers since advanced R&D procedures contain a lot of innovative elements which are hard to imitate. Thus, the information flow is small within the internal team, but it can be very high and relatively mutual within the external team. It is apparent that strengthening the interactive learning framework between the internal teams and the external teams becomes significant as knowledge flow from external teams should be learned by internal teams extensively. Finally, the most suitable form of interactive learning framework is the one that can accelerate both the strongest alignment with the strategies of development directions and the rapid spread of common knowledge among teams.

Overall, with the development of science and technology, firms should catch up with the pace of new developing knowledge in attempt to maintain competitive advantages in the markets [14,15]. In fact, knowledge search and knowledge distribution concentrate on the existing knowledge while knowledge creation is the key to technological innovation [16]. Ultimately, suitable organizational forms for KM need to be built to search and distribute existing knowledge, and thereby to stimulate knowledge creation for different processes in a supply chain.

3. Hypotheses and methodology

3.1. Proposed hypotheses

Based on prior research, five organization forms for KM are available, including: (1) sequential KM function: There are four sequential stages including acquiring, sharing, creating, and spreading knowledge stages. (2) central KM function: a CKO (chief knowledge officer) in a team of specialists leads all KM-related activities for projects; (3) project-decentralized KM task force: allocating KM-related activities to the project level and placing a project manager, called “project analyst,” in each task; (4) functionally located KM cells: there is no formal organizational unit for KM process, and functional heads of specialized departments take the responsibility of developing knowledge; (5) matrix KM function: automatically and simultaneously importing, absorbing, and exporting advanced knowledge in all procedures without specific KM task force [17–23]. In addition, research has demonstrated that information sources with relative credibility and legitimacy act as the most important roles in linking social network and information perception, risk perception and adaptation [24]. Moreover, salience, credibility, and legitimacy of available information are dominance factors when people make decisions [25]. Scientific community, decision-makers and local practitioners constitute an effective management level which promotes knowledge production and transformation into real practices. Therefore, information and knowledge flows include local information from personal contacts within local resident community, credible information from practical experiences within the renewable energy industry community, and legitimate information from scientific evidences within science and policy decision-making community. As a result, the spillover of knowledge, including absorption, distribution and creation, can be transferred from the policy decision-making community to the renewable energy industry community, and from the renewable energy industry community to the local resident community, and then the spillover can be recycled back to the policy decision-making community. In summary, there are three sequential and recycling stages: (1) in the stage of science and policy decision-making community: idea generation, policy research and development; (2) in the stage of the renewable energy industry community: manufacturing engineering and mass production; (3) in the stage of local resident community: personal experience and marketing demands [26]. Consequently, an interactive linkage among partners needs to be analyzed so as to exploit existing knowledge and distribute new knowledge in different stages effectively.

When developing knowledge flows in the stage of science and policy decision-making community, the most suitable form for interactive learning framework should be the one that strongly aligns with the strategic development in the renewable energy industry as well as provides a strong knowledge transfer among teams. Since knowledge is mostly learned from external teams and the execution procedures are not standardized, the central KM function could clarify responsibilities and guidelines for KM processes and actions.

Hypothesis (a). *When developing knowledge flows in the stage of science and policy decision-making community, the most suitable organization for knowledge management is the central KM function.*

When developing knowledge flows in the stage of the renewable energy industry community, the most suitable form for interactive learning framework should provide a platform for both sharing common knowledge and transferring specific knowledge among external and internal teams. Team members may change as projects advance through different stages of project development to guarantee that the most relevant expertise come into play at all instances.

Hypothesis (b). *When developing knowledge flows in the stage of the renewable energy industry community, the most suitable organization for knowledge management is the project-decentralized KM task force.*

When developing knowledge flows in the stage of local resident community, the most suitable form for interactive learning framework should enhance knowledge transfer related to specific engineering expertise within internal teams. Since the functionally located KM cells structure enhances the role of the specialized expertise, the KM mission is subordinated to their priorities or local politics. When functional managers realize the importance of widely shared project management role, their commitment to support the development of projects is promoted.

Hypothesis (c). *When developing knowledge flows in the stage of local resident community, the most suitable organization for knowledge management is the functionally located KM cells.*

3.2. Research methodology

This study applies a multivariate statistical analysis method. Factors were extracted first by factor analysis. Next, ANOVA and post-hoc test were employed to analyze the knowledge flows in three stages: science and policy decision-making, renewable energy industry and local resident community.

4. Data collection and analysis

This paper studies the renewable energy industry and makes the following assumptions. First, firms try to select suitable forms for interactive learning from five alternatives, including sequential KM function, central KM function, project-decentralized KM task force, functionally located KM cells, and matrix KM function. Second, three different stages of communities, including science and policy decision-making, renewable energy industry and local residents, are facilitators to search, distribute and create knowledge, aiming at enhancing competitive advantages.

4.1. Questionnaire and sampling data

4.1.1. Questionnaire

The critical factors of interactive learning environment in the renewable energy industry are evaluated through a questionnaire. The questionnaire contains questions like “to what extent do you think the importance of each factor is for the firm?” It is designed by a 5-point Likert scale, ranging from 1 (which means extremely unimportant) to 5 (which means extremely important). Besides, based on the critical characteristics of interactive learning environment, respondents will be asked “which suitable organization for KM should be implemented?” A 5-point Likert scale ranging from 1 (which means not highly recommended) to 5 (which means highly recommended) is also employed.

4.1.2. Sampling data

The initial draft of questionnaire was discussed by firms' executives, and tested in advance by 11 pilot interviews to make sure that each question was appropriate. Then, self-administered questionnaire was distributed to 257 renewable energy firms including upstream (32%), midstream (35%) and downstream (33%) and 50 different levels of communities. When collecting these data, a total of 68 face-to-face interviews were also randomly performed. Feedback from 2556 respondents were received in the end of 2013, composing of top (19%), middle (31%), and bottom (50%) management with a response rate of 16.4%. Statistical analysis of the returned questionnaire shows that both reliability coefficients (Cronbach α) and validity coefficients (average-variance extracted) in different stages were above 0.7. The data were analyzed using a t-test procedure, and there is no significant difference ($p < 0.05$) between the interview and mailed responses. Since some variables may have influence on results, variables such as age, gender, firm size, and level of education were examined. However, the results did not show any significant difference. Multivariate statistical analysis was conducted by SPSS 20 software package after data collection.

4.2. Data analysis

4.2.1. Factor analysis

This study first collected the factors regarding to interactive learning framework within a social network. Social network is related to determining factors of competitive advantage, such as organizational knowledge [27], intellectual capital [28], communities of practice [29], effective inter-organizational collaboration [30] and development of virtual communities [31]. From the perspective of firm members, a social network impels the possibilities of influencing and controlling other actors in the social structure [32]. In addition, a social network is driven by the shared activities and afflictions of their members, as well as the similarity of individuals' attributes [33]. From the perspective of firm strategy [34], claimed that the body of a social network in China included, but not limited to, individuals since companies gradually occupy the nodes in a network and treat the network as one of the strategic resources. From the perspective of knowledge management, a social network provides a platform for knowledge creation, extension and sharing among team members. Team discussion and decision making are influenced by social network, which motivates members to exchange knowledge, enhance knowledge and create knowledge [35,36]. From the perspective of social capital, Bian and Qiu [37] detected the ability of an economic enterprise to gain scarce resources through its hierarchical, horizontal, and social connections. They also find the positive relationship between social capital and technological innovation. Moreover, Landry et al. [38] tested how social capital is added to the other forms of capital as an explanatory variable of innovation by two-stage decision-making process. They provided the evidence that firms acquire innovation elements through social network in order to share knowledge and information.

Consequently, 38 characteristics were collected, and factor analysis was performed. The results are shown in Table 1. Eigenvalues, variance and cumulative variance of the nine selected factors explain 75.76% of the variance in the original data sets. Varimax rotation with Kaiser Normalization was adopted for the extracted factors. The factors with a loading value of greater than 0.40 were selected, and the evaluation factors belonging to the same group of factors were brought together. Ultimately, the most important extracted factors of interactive learning within a social network were selected: customer relationships, propensity to change, interdependence, existing technology skills, need for innovation, regulation, minimizing uncertainty and risk, improving business performance, and dispersion.

4.2.2. Cluster analysis

Different stages of knowledge distribution and transferring were compared regarding different forms of organization learning for KM by ANOVA test with Benforroni post-hoc pairwise comparison test.

4.2.2.1. Cluster analysis of the most important extracted factors. Questions about different sequential and recycling stages were asked using a 5-point Likert scale inquiring how important each characteristic is (described in 4.2.1). Table 2 displays that respondents within three different sequential and recycling stages have different relationships with the most important characteristics of a social network. The solutions for different stages, science and policy decision-making community, renewable energy industry community and local resident community, are significantly different at 5% level, except for two characteristics “customer relationship” and “dispersion”. The most important characteristics are “need for innovation” and “propensity to change” for the stage of science and policy decision-making community. The results make sense since this stage concentrates on exploratory and product innovation with vague environment. For the stage of the renewable energy industry community, the most important characteristics are “existing technology skills” and “improving performance”. The results are meaningful as this stage concentrates on the spirit of exploitation and process innovation. Oppositely, for the stage of local resident community, the most important characteristics are “interdependence”, “minimizing uncertainty” and “regulation.” This is mainly because the stage focuses on the effectiveness and efficiency of commercialization. Finally, the categorized questionnaires were employed in the subsequent investigation.

4.2.2.2. Cluster analysis of upstream supply chain (511 usable questionnaires). Whether different stages adopt different organization forms for KM in the upstream supply chain of the renewable energy industry is examined, and the null hypothesis is that the mean scores for different organizational forms are equal. Table 3 shows the results of the suitable organizational forms for different stages. In fact, Chinese manufacturers are exposed to a rather high degree of risk when developing new products. The basic infrastructures and technologies are not as mature as those in the western countries, especially in the stage of science and policy decision-making community in the upstream supply chain. Therefore, the central KM function is suggested for the stage of science and policy decision-making community, which contributes to clarify the mission and the actions required. The project-decentralized KM task force is advised for the stage of renewable energy industry community as KM tasks and responsibilities are much less formalized and are more directly driven by the projects' operational needs. The functionally located KM cells are recommended for the stage of local resident community because of the strong need for knowledge creation and dissemination of professional knowledge. Then Hypotheses (a), (b), and (c) are supported.

4.2.2.3. Cluster analysis of midstream supply chain (1008 usable questionnaires). Table 4 shows the results of the suitable organization forms for different stages in the midstream supply chain of the renewable energy industry. At this stage, Chinese manufacturers have basic infrastructure and knowledge of technologies,

Table 1
Factors, eigenvalues, variance, and cumulative variance in each dimension.

	Dimension name Critical factors of social network	Eigenvalue	Variance (%)	Cumulative variance (%)
1.	Customer relationships Buying and selling, supplier relationship, partner, strategic alliance, internet marketing, mutual trust.	6.53	15.38	15.38
2.	Propensity to change Organizational change, growing demand, business environment change, technical condition change, staff turnover.	5.14	13.47	28.85
3.	Interdependence Synergistic benefits, same production line, social cohesion, localization, mutual utilization.	3.89	11.91	40.76
4.	Existing technology skills Mass media, technology support, increased productivity, technology diffusion and transfer.	3.58	9.87	50.63
5.	Need for innovation Technology absorption, innovation consciousness, system reform, long-term orientation, risk taking.	3.04	7.59	58.22
6.	Regulation Uniformity, consistency, business rules, shared vision.	2.53	5.44	63.66
7.	Minimizing uncertainty and risk Belonging to a group, market uncertainty, obeying rules, conservatism.	2.20	5.12	68.78
8.	Improving business performance Market opportunity, lower costs, profit maximization, economic value, financial target.	1.31	3.85	72.63
9.	Dispersion Flexibility, volatility, network density, reliability.	1.16	3.13	75.76

Table 2
Respondents with three different sequential and recycling stages.

Most important dimensions	Sequential and cycling stages			
	Science & policy decision-making community	Renewable energy industry	Local resident community	F (or K)
Customer Relationships				
Cluster mean	3.32	2.95	3.42	2.13[c] $p < 0.113$
Propensity to Change				
Cluster mean	3.86[a] (2,3)[b]	2.73 (1,3)	1.83 (1,2)	13.52 $p < 0.036$
Interdependence				
Cluster mean	1.39 (2,3)	2.52 (1,3)	4.03 (1,2)	15.29 $p < 0.033$
Existing Technology Skills				
Cluster mean	2.46 (2,3)	4.09 (1,3)	1.76 (1,2)	11.57 $p < 0.045$
Need to Innovation				
Cluster mean	4.23 (2,3)	2.93 (1,3)	1.63 (1,2)	17.38 $p < 0.024$
Regulation				
Cluster mean	2.56 (3)	2.75 (3)	3.59 (1,2)	19.08 $p < 0.019$
Minimizing Uncertainty				
Cluster mean	1.73 (2,3)	2.53 (1,3)	3.86 (1,2)	16.52 $p < 0.031$
Improving Performance				
Cluster mean	2.43 (2)	4.05 (1,3)	2.66 (2)	11.35 $p < 0.048$
Dispersion				
Cluster mean	2.89	2.53	2.63	7.52 $p < 0.097$

[a] *Note*: Mean based on 5-point Likert scale comparing the data collected in the end of 2013.
[b] *Note*: Numbers in parentheses indicate the cluster groups from which this cluster is significantly different at $\alpha = 0.05$ according to the Bonferroni, post-hoc pairwise comparison procedures.
[c] *Note*: F and corresponding p-values based on ANOVA test.

and they are exposed to limited risk in developing new products. The project-decentralized KM task force is suggested for the stage of science and policy decision-making community, as well as the stage of renewable energy industry community. The renewable energy industry community boosts the understanding about KM practices, tools and methods in the area. The functionally located KM cells are proposed for the stage of local resident community because participants take their tasks seriously and develop advantageous knowledge in their specialized field. Therefore, Hypotheses (b) and (c) are proved.

4.2.2.4. Cluster analysis of downstream supply chain (1037 usable questionnaires). Table 5 shows the results of the suitable organization forms for different stages in the downstream supply chain of the renewable energy industry. As Chinese manufacturers have sufficient experiences in engineering technologies, the project-decentralized KM task force is advised for the stage of science and policy decision-making community as people are driven by the needs of each project and participate in operational work from a pragmatic perspective. Functionally located KM cells are proposed for both stages of renewable energy industry and local resident communities. It is inferred that the strong transfer within the product supply chain function requires participants to focus on state-of-the-art knowledge and expertise. Therefore, only Hypothesis (c) is supported.

5. Discussion and conclusion

With the above discussion, a hierarchical structure of suitable organization forms for KM is constructed, as shown in Fig. 1. In the

Table 3
Suitable organization forms for upstream supply chain.

Suitable forms of organization	Sequential and cycling stages			
	Science & policy decision-making community	Renewable energy Industry	Local resident community	F (or K)
Sequential KM function				
Cluster mean	2.35[a] (2,3)[b]	1.97 (1,3)	2.72 (2)	4.13[c] $p < 0.094$
Central KM function				
Cluster mean	3.89 (2,3)	2.53 (1,3)	1.91 (1,2)	15.52 $p < 0.031$
Project-decentralized KM task force				
Cluster mean	2.47 (2)	4.04 (1)	3.23 (2)	11.34 $p < 0.048$
Functionally located KM cells				
Cluster mean	2.36 (3)	2.32 (3)	3.96 (1,2)	8.39 $p < 0.061$
Matrix KM function				
Cluster mean	1.26 (3)	1.82 (3)	2.23 (1,2)	3.29 $p < 0.103$

[a] *Note*: Mean based on 5-point Likert scale comparing the data collected in the end of 2013.
[b] *Note*: Numbers in parentheses indicate the cluster groups from which this cluster is significantly different at $\alpha = 0.05$ according to the Bonferroni, post-hoc pairwise comparison procedures.
[c] *Note*: F and corresponding p-values based on ANOVA test.

Table 4
Suitable organization forms for midstream supply chain.

Suitable forms of organization	Sequential and cycling stages			
	Science & policy decision-making community	Renewable energy Industry	Local resident community	F (or K)
Sequential KM function Cluster mean	1.76[a] (2,3)[b]	1.97 (1)	1.72 (1)	2.93[c] $p < 0.104$
Central KM function Cluster mean	2.34	2.39	2.41	10.37 $p < 0.051$
Project-decentralized KM task force Cluster mean	3.87 (3)	4.04 (3)	2.78 (1,2)	11.46 $p < 0.043$
Functionally located KM cells Cluster mean	2.89 (3)	2.96 (3)	4.53 (1,2)	13.39 $p < 0.032$
Matrix KM function Cluster mean	1.26 (3)	1.82 (3)	2.23 (1,2)	3.78 $p < 0.113$

[a] *Note*: Mean based on 5-point Likert scale comparing the data collected in the end of 2013.
[b] *Note*: Numbers in parentheses indicate the cluster groups from which this cluster is significantly different at $\alpha = 0.05$ according to the Bonferroni, post-hoc pairwise comparison procedures.
[c] *Note*: F and corresponding p-values based on ANOVA test.

first tier of the knowledge flow, the centralized KM structure located at the highest level offers the strongest guidance and alignment among strategic policy and KM initiatives, the best co-ordination and communication of KM activities, and the clearest understanding of responsibilities for participants. Tier one provides an overview of needs and distributes knowledge about similar problem-solving activities from firm to firm, from one to one, and from project to project expeditiously. However, reviews at the beginning of each project may disconnect with the operational reality of previous projects. In the second tier of the knowledge flow, project-decentralized KM task forces driven by operational and strategic needs enable the pragmatic testing of the contributions of the KM initiatives. Tier two enhances inter-functional knowledge sharing and transfers implicit knowledge and explicit knowledge, from project to project and from firm to firm. Meanwhile, it also faces the risk of project isolation. In tier three of the knowledge flow, the functionally located KM cells transfer knowledge of specific expertise within engineering functions. Nevertheless, it lacks effective incentives for inter-functional knowledge distribution, which hinders the coordination of different knowledge management [20].

In light of the above, the hierarchical structure of suitable organization forms for KM should be dynamically adjusted according to actual interactive learning environment regarding different sectors or different levels of supply chain in a practical industry. Rapid changes of technological, market, social, and legal environments are characteristics of new emerging markets, such as the renewable energy industry in China. To summarize, functions about the centralized KM structure should be reinforced in the upstream supply chain of the renewable energy industry, functions about project-decentralized KM task forces should be intensified in the midstream supply chain, and functions about the functionally located KM cells should be emphasized in the downstream supply chain.

In this study, the subjective judgments are assumed to be discrete and certain. However, in real practice, the judgment may

Table 5
Suitable organization forms for downstream supply chain.

Suitable forms of organization	Sequential and cycling stages			
	Science & policy decision-making community	Renewable energy Industry	Local resident community	F (or K)
Sequential KM function Cluster mean	2.32[a] (2,3)[b]	1.87 (1,3)	2.52 (2)	4.23[c] $p < 0.091$
Central KM function Cluster mean	2.49	2.53	2.62	10.52 $p < 0.052$
Project-decentralized KM task force Cluster mean	4.47 (2,3)	3.04 (1)	3.16 (1)	12.64 $p < 0.042$
Functionally located KM cells Cluster mean	2.46 (2,3)	3.32 (1)	3.56 (1)	14.39 $p < 0.038$
Matrix KM function Cluster mean	1.29 (2,3)	1.92 (1)	2.43 (1)	3.64 $p < 0.108$

[a] *Note*: Mean based on 5-point Likert scale comparing the data collected in the end of 2013.
[b] *Note*: Numbers in parentheses indicate the cluster groups from which this cluster is significantly different at $\alpha = 0.05$ according to the Bonferroni, post-hoc pairwise comparison procedures.
[c] *Note*: F and corresponding p-values based on ANOVA test.

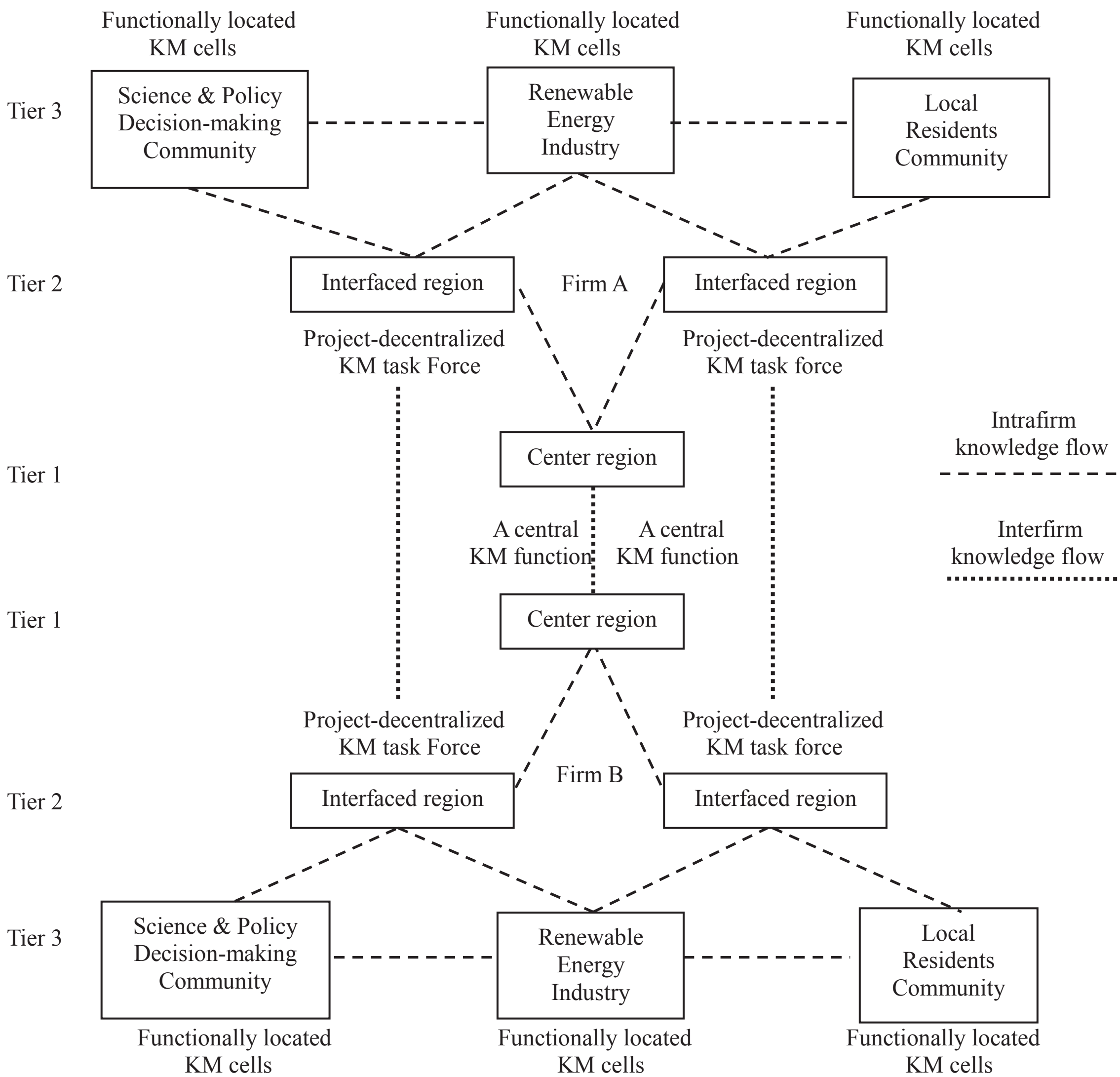

Fig. 1. Suitable forms for interactive learning within firms in a social network.

contain vagueness, and the responses from the participants may be uncertain. Therefore, fuzzy statistics may need to be applied, and this can be a future research direction. In addition, AHP (analytical hierarchical process) has been known to be a good decision making methodology which can consider both qualitative and quantitative attributes of a problem. The integration of AHP with fuzzy set theory has been applied in some renewable energy studies to deal with uncertainties. For example, Chen et al. [39] proposed a fuzzy AHP approach associated with benefits, opportunities, costs and risks for selecting suitable solar-wind power generation system. Dehghanian et al. [40] applied fuzzy AHP to identify the most critical component types of distribution power systems for maintenance scheduling. Razi Kazemi and Dehghanian [41] proposed a fuzzy AHP approach for the optimal placement of RTUs (remote terminal units) for data acquisition and control in a power distribution system. Therefore, the adoption of fuzzy AHP to evaluate suitable organization forms for knowledge management in the renewable energy industry can be proposed in the future.

In addition, multivariable statistics analysis, such as cluster analysis and factor analysis, can be employed by big data analytics. The results obtained from big data analytics can provide a stronger decision-making power, a deeper discovery power, a more optimal procedure power, and a more precise analysis power at the same time [42]. However, when employing big data analytics, big data with characteristics of volume, velocity, variety and veracity must be satisfied, and a research methodology including analytic visualizations, data mining algorithm, predictive analytic capabilities, semantic engines, and data quality and master data management must be considered [43]. In addition, overall handling procedures consisting of data collection, preprocess, statistics and analysis, and data mining must be carefully processed [42]. In order to have big data analytics, an operational mechanism, a constructional standard, a sharing platform, and a specialized team must be built up [44]. Though it is still hard to have big data analytics for expert-related questionnaire, it is the target for the authors to build up such a comprehensive capability and to tackle the problem by big data analytics in the near future.

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