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Network Position and Exploratory Knowledge Creation: Evidence from US IT Clusters

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Abstract

In This study, I explore the effects of structures of technological alliance networks on firms' exploratory knowledge creation. The research is built upon the connections between social network, organizational learning, and organizational ambidexterity theories. Firms pursue knowledge creation opportunities by forming technological alliances, but no consensus has been reached regarding the optimum strategy of alliance formation activities, i.e., whether the return of knowledge creation always increases in tandem with numbers of alliances or it diminishes at some point due to various factors such as costs of maintaining ties and capabilities of absorb information and knowledge generated from alliances.

The study sheds light on the controversy of whether the relationship between network structures and knowledge creation is positive or curvilinear by distinguishing different orientations of knowledge creation activities, which entail different network structures and strategies. More specifically, by extracting exploratory knowledge creation from the overall knowledge creation activities, the relationship between basic network position features and exploration is more focused and accurate.

Empirical investigation, which uses hand-collected data of alliance activities and patent application behaviors of 67 firms in several IT clusters in US, proves the curvilinear relationship between alliance network centrality and exploratory knowledge creation. Results of the study help to address the conflicts of networks' effects on knowledge creation with new evidence from knowledge intensive industries, and provided insights on organizational learning and firm innovation strategies.

Key words: Exploratory knowledge creation, social network structures, centrality, innovation strategy

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1. Introduction

1.1 Academic Context

In the current era, there is consensus among both practitioners and scholars that knowledge is crucial for gaining organizational competitive advantages and improving organizational innovation performance (Senge, 1990; March, 1991; Zander & Kogut, 1995; Argote & Miron-Spektor, 2011). Knowledge, be it in the form of explicit knowledge such as simple information stream, routines and procedures in daily organizational operations, or tacit knowledge such as individual ideas, know-how and expertise, is often embedded in sophisticated social contexts and influenced by many factors (Polanyi, 1966).

Therefore, the way of gaining knowledge is often neither easy nor forthright, as many questions and obstacles stand between the initial sparkles of ideas, knowledge and the final performance (Yu, Fang, & Ling, 2004). Questions such as how to identify knowledge source, share and interpret knowledge across different individuals, and how to absorb, use and retain knowledge acquired within and across organizational boundaries, and turn it into more concrete performance are some of the most essential considerations when organizations try to transfer knowledge into organizational performance.

To gain knowledge, organizations invest many efforts, capital and time in learning. Those continuous investments, practices, initiatives of change and development in organizations that target at acquiring and changing knowledge are defined as organizational learning (Argote & Miron-Spektor, 2011).

The academic body of organizational learning helps understand the essence of knowledge in organizations and shows momentous strategic implications, especially in the context of fierce competitions of technology imitation, accelerating speed of knowledge renewal and innovation cycles.

Many scholars and practitioners studied the topic from different aspects through the years, thus abundant and significant theories have been established (e.g., Argyris & Schon, 1978; Senge, 1990; Crossan, Lane, & White, 1999), models and different stages and processes of organizational learning have been categorized (Nonaka & Takeuchi, 1995; Nevis, DiBella, & Gould, 1995), different types or approaches of organizational learning have been introduced (March, 1991; Tushman & O'Reilly, 1996), corresponding strategies of effective learning have been proposed (Burt, 1992; Reagans & McEvily, 2003), and various factors that could affect organizational learning or its processes have been analyzed (e.g., Hansen, 1999; Edmondson, 1999; Bandura, 2000; Bock & Kim, 2002; Cabrera & Cabrera, 2002; Cross & Cummings, 2004; Miron-Spektor, Erez, & Naveh, 2011).

Among all the theories concerning organizational learning, one factor has shown its prominence in the last few decades, that is, the social network (Phelps, Heidl, & Wadhwa, 2012). A network is a set of nodes representing actors and the set of ties representing relationship between the nodes (Brass et al., 2004). The logic of the fast-growing research interests between social network, knowledge and learning lies in the accurate demonstration of how friends or colleagues socialize and interact, how our organizations, communities or even societies work and cooperate, and how networks influence individuals' perceptions, views, and ultimately, actions (Nahapiet & Ghoshal, 1998).

More specifically, learning in organizations is an intricate systematic process, and each step of organizational learning entails all organizational members to collaborate and interact in order to create knowledge (David & Fahey, 2000). In this knowledge creation process, social interactions, conflicts, social reconciliation are often the priorities in organizational design and reform, such as setting up teams or projects of research and development, incorporating of the knowledge of acquired firms to current knowledge pool, or strategic alliancing with another firm for its knowledge source (Levin & Cross, 2004).

Once knowledge is created in social networks, to extract, share, and transfer it to diverse individuals and units across organizational boundaries call for different structures and different strategies (Coleman, 1988; Burt, 1992; Hansen, 1999; Reagans, Zuckerman, & McEvily, 2004). Communicating the different ideas, needs, and concerns of different parties during the knowledge sharing process is often delicate and sensitive because sometimes it means risks and loss from the gaming theory or assumption of self-interest (Blau, 1964; Wasko & Faraj, 2000). But those risks could be mitigated when trust and affection are involved (Szulanski, Cappetta, & Jensen, 2004; Chowdhury, 2005). Trust and reciprocity are, to a large extend, influenced by individuals' social environment (Levin & Cross, 2004; Edmondson, 1999).

After sharing and collaboration, knowledge needs to be incorporated into organizational frameworks, and diffused to the whole organization before finally becomes the performance (Nonaka & Takeuchi, 1995). In this knowledge adoption and retention stage, high level of cooperation of multiple units and organizations are required as well. There are too many examples of how firms fail not due to lack of knowledge and technology, but due to miscommunication and conflicts between internal departments, or between external key stakeholders. To ensure the smooth transfer from knowledge and learning to innovation performance, making good use of the networks plays a pivotal role.

Despite all those studies' efforts devoted to social networks, there are still many unexplored aspects and conflicted evidences of the relations between learning and networks.

For instance, some claim that it is more beneficial to maintain intimate relationships with limited individuals because knowledge sharing is a delicate process and require trust and psychological safety to reduce behaviors of opportunism (Bian, 1997; Edmondson, 1999; Levin & Cross, 2004), while others propose that weaker social relationships, such as acquaintances, have the advantages of having access of more diverse and useful information. And in the situation of learning, various sources of information and networks with open and diverse knowledge increase the possibilities of learning and sharing novel knowledge, explore beyond boundaries, and obtain information embedded in sparse social connections (Granovetter, 1973; Burt, 1992).

Also, it is proved that organizational learning could benefit financial performance and innovation performance, but these benefits are not without costs. Maintaining social ties calls for attention, energy, and other investments (Hansen, 1999; Reagans & McEvily, 2003). Therefore, such cost-benefit analysis could yield controversial results.

Another aspect of observed mixed results and controversies is the omission of different types of organizational learning (Phelps, 2010). Although there is consensus that no network structure is universally beneficial (Adler & Kwon, 2002), contingencies of how to accord different network structures with different types of knowledge and learning are still not thoroughly discovered.

Organizational learning could be categorized into two fundamentally different activities, one being taking risks and exploring new resources and possibilities, the other one being refining productivity of current products and procedure efficiency, and exploiting the established domain (March, 1991; Birkinshaw & Gupta, 2013).

But most previous studies of social networks fail to distinguish these two types of learning (Phelps, 2010). Among the few studies assigning appropriate network structures to exploration and exploitation, the results are mixed, while empirical evidences are scarce and limited.

For instance, the roles of weak ties and strong ties are controversial (Tiwana, 2008; Peng & Wu, 2013). Between moderate level of density and highly dense networks, which is the optimal structure of innovation performance for both types of learning (Lazer & Friedman, 2007; Fang, Lee, & Schilling, 2010). The debate has been ongoing regarding the effectiveness of centralized networks and decentralized ones on organizational learning (Guan & Liu, 2016). Some scholars carry out empirical studies to analyze the relation between networks and exploration or exploitation, but the samples have different characteristics such as variation in industries or industrial cluster, therefore yield mixed results (Gilsing et al., 2008; Phelps; 2010).

1.2 Research Question

To address these limitations and controversies, this study will follow the mindset aforementioned and carry out an empirical study to investigate the influence of network structure on organizational learning.

The focus of structural property in this study is one fundamentally important position index: network centrality. Centrality has drawn various attentions in different levels of studies, from interpersonal relationships to interorganizational network. The results of these studies are robust yet conflicted with each other at many levels.

Further scrutiny into this network feature, by extricating exploration and exploitation learning, would shed more light on these conflicts.

The basic prediction under inspection in this study is that social network structures in strategic alliances influence organizational learning. This study will empirically analyze specific network structures and performance of exploration embedded in several mature and well-established industrial clusters, and analyze the influences of alliance network structure at interorganizational level on firm knowledge creation, measured by its innovation products, patents, one of the most frequently used methods to analyze knowledge creation performance (Phelps et al., 2012).

1.3 Contribution

This study contributes to the academic body of organizational learning, social network analysis, and organizational ambidexterity in several aspects.

First, by focusing on network position, this study provides empirical evidence of the relationship between social networks and organizational learning. Social networks have been regarded as a promising direction of how to carry out better organizational learning, but studies concerning relationship between networks and knowledge creation are far less frequent than studies focusing on effects of networks on knowledge sharing, and their results are more conflicted and limited. This research scrutinizes further the influences of social networks on the input stage of knowledge and learning, i.e., knowledge creation, and reconciles the diverged theories, shedding light on the mixed results by differentiating approaches of learning. i.e., exploration and exploitation.

Second, comparing to previous empirical studies addressing influences of networks on exploration and exploitation respectively, this study collects data from more recent samples in high-tech industries, expands the sampling scope to both public and private firms, and proves the conceptual propositions by scholars that moderate level of network centrality is optimal for exploration.

This study also provides managerial insight for firms leverage different innovation strategies. Firms could create knowledge from both internal and external sources, such as internal R&D, acquisitions, and strategic alliances. And because firms' resources and capital are not unlimited, the choices of appropriate strategies are always among top priorities of mangers minds. The results of the current study help to estimate the performance of alliance formation on knowledge creation, and therefore provide a practical tool to assess benefits and costs of different approaches of knowledge creation.

1.4 Outline

This study contains six chapters. Chapter two is the literature review constructed in a logically relevant way. Basic concepts, constructs, and previous studies are described and critically demonstrated in this chapter. Chapter three incorporates conceptual framework and methodology, in which the main hypotheses of the current study, which are evolved from summarizing the defects and limitations of previous studies, will be proposed, variables and samples would be elaborated more specifically, and the work of empirical research is illustrated in detail. Chapter four presents the results of the current study along with interpretations of results. Chapter five is the discussion, where the main findings are discussed, results are interpreted, and limitations are demonstrated, with future research suggestions proposed. Chapter six includes the main conclusion of the study.

2. Literature Review

2.1 Knowledge and Learning

Research on knowledge shows its prominent in the last few decades, and during the development of academic body, many different propositions and definitions are introduced to analyze and research the topic.

Although in the practical knowledge management activities, most of the time the terms knowledge and information are regarded as the same, many scholars note the distinctions between these two concepts (Huber, 1991; Alavi & Leidner, 2001). A popular definition is that knowledge is grounded around information, justified and characterized by individual views and perspectives (Nonaka, 1994). Scholars propose a comprehensive notion of knowledge that rather than merely a flow of information, knowledge includes also expertise and know-how held by different levels of organizational members from persons, units to the entire organizations (Bartol & Srivastava, 2002).

Early research has established that knowledge includes explicit knowledge and tacit knowledge (Polanyi, 1966). Explicit knowledge (or codified knowledge) refers to common practices, procedures and actions that could be expressed or codified in knowledge systems and that could be shared straightforwardly (Zander & Kogut, 1995). Tacit knowledge refers to non-codifiable knowledge with particular experience or rooted in social activities. Therefore, understanding of tacit knowledge and transferring it across organizations are not as easy as its explicit counterpart (Kogut & Zander, 1992). These two dimensions of knowledge are also different in that explicit knowledge is easy to transfer in formal organizational systems, while tacit knowledge is an ongoing process (Nonaka, 1994).

Knowledge at organizational level, similar as individual knowledge, is often cited as both in the form of the stock and in the prospective of the process (Argote & Miron-Spektor, 2011). In other words, knowledge repositories vary in organizations, including both explicit knowledge which can be codified as information, practices and routines, and implicit knowledge which is more difficult to articulate, e.g., organizational experience.

It is common sense that to gain knowledge, one needs to learn. As noted by Kolb (1976), learning is a process generating knowledge by transforming experience. Originally, learning refers to the activity of individuals gaining of knowledge and expertise (Kim, 1993).

Organizational learning first derived from the individual learning when scholars reveal that organizations engage learning activities the same way as individuals. Organizations also transform past experience to handle new tasks in new circumstances. Scholars point out that only individual learning is not sufficient for organizational success and sustained competitive advantages, and organizational learning is more intricate than an amplification of all individual learning (Kim, 1993). Organizational learning takes place from the bottom level up to the top level, including inter-dependent activities of individual level learning, group teamwork, and organizational innovation (Crossan et al., 1999).

2.2 Organizational Learning

The definition of organizational learning varies according to diverse stand points scholars take. Prior definition is that organizational learning is a procedure of detecting failure and mistakes of organizations and redesigning organizational systems (Argyris & Schon, 1978). Pedler, Burgoyne, and Boydell (1991) argue that organizational learning is a process of organizational reform by stimulating individuals to learn. According to Nevis and colleagues (1995), organizational learning refers to the progress of performance improvement derived from making use of successful practice and knowledge accumulated in the past. Chen and Ma (2000) define organizational learning as a crucial component of organizational innovation, and by learning, organizations could continuously change and adapt to the fast-changing environment.

These theories take a systematic view and consider activities to cope with strategic change and changing business environment as learning (Kogut & Zander, 1992). And they highlight the organizational level actions and the relationships between organizations and environment. Thus, the systematic view bears the limitations that concepts of organizational learning and organizational change are essentially interrelated and sometimes confused (Yu, Fang, & Ling, 2004).

The other approach of organizational learning study is the social interaction perspective. This view, rather than taking organizations as a whole system, emphasizes the interpersonal and other types of social relations both within and outside organizations. Senge (1990) proposes that a learning organization includes five disciplines, including personal mastery, mental model, team learning, share vision and system thinking.

Aligned with the latter view are some more recent definitions. Crossan and colleagues (1999) define organizational learning as social processes from intuition to institution of knowledge of individual, team, and organizational level. Argote and Miron-Spektor (2011) also point out that organizational learning is an organizational change in knowledge when organizations gains experience. And organizational learning is entrenched in organizational environment which includes the social relations.

Table 1 Comparison of Different Views of Organizational Learning

	Systemic view	Interaction view
Function of Organization	information-processing machine	knowledge-creating entity
Definition	process of detecting malfunction of organizations, rebuilding organizational theories in use and correcting mistakes	organizational change in terms of organizational knowledge as organizations obtain experience
Ultimate Goal	Adaption to environment	Creating, using, and retaining knowledge
Mechanism	Interaction between organization and environment	Interaction between organization, members, and environment
Orientation	Routine-based, history-dependent, and target-oriented	Innovation oriented and social oriented
Level of study	Mainly organizational level	Multilevel: from individual to inter-organizational level
Examples	Argyris and Schon (1978)	Senge (1990)
	Levitt and March (1988)	Kim (1993)
	Pedler, Burgoyne, and Boydell (1991)	Crossan, Lane, and White (1999)
	Huber (1991)	Edmondson (1999)
	Kogut and Zander (1992)	Nonaka and Takeuchi (1995)
	Nevis, DiBella, and Gould (1995)	Miller, Zhao, and Calantone (2006)
	Chen and Ma (2000)	Argote and Miron-Spektor (2011)

Source: author’s creation.

Scholars have built many models to analyze processes of organizational learning.

Argyris and Schon (1978) propose that organizational learning includes several processes: discovery, invention and production, and generalization. Learning activities begin with detecting problems, malfunctions, and opportunities in organizations, cited as discovery process. Next, in the invention and production process, organizations generate solutions based on the outcomes of the first step, and implement knowledge produced from the process. And then by output step of generalization, organizations could benefit from previous learning efforts and retain knowledge in organizational boundaries.

This model is a highly generalized conceptual framework, and it lacks the illustration of on-going cyclical feature, which represent the organizational knowledge renewal and the continuous learning efforts of organizational learning processes of creation, learning, transferring and retention. Also, it emphasizes on the organizational level does not take into consideration individual level innovation, and group level teamwork, or interdependence between individual and organizational learning (Kim, 1993).

Several models have been developed to address these limitations. More emphases are given to the on-going loops of organizational learning and relations between learning of different levels in organizations.

Building on the model of Argyris and Schon (1978), Huber (1991) adds the process of organizational memory, which illustrates the inventory of knowledge.

Kim (1993) proposes that individual mental models and shared mental models interact with each other in cooperation between organizational members, and thus these interactions link individual learning and organizational learning. Mental models refer to deep images that characterize view of world that interprets new situations by borrowing experience from past (Senge, 1990; Kim, 1993).

Crossan and colleagues (1999) propose that organizational learning include a series of activities: it starts with intuiting that produces knowledge at interpersonal level; then knowledge is transferred and turned into shared experiences by processes of interpreting and integrating; finally, by institutionalizing, knowledge and experience become part of organizational knowledge systems.

Similarly, Nevis and colleagues (1995) introduce a three-stage model of organizational learning including knowledge acquisition, knowledge sharing, and knowledge utilization. By these processes, organizations generate knowledge, share knowledge among different organizational members, integrate knowledge into organizations, and apply it to new contexts when necessary.

Argote and Miron-Spektor (2011) also propose that organizational learning is composed of three processes: knowledge creation, knowledge transfer and knowledge retention. Although organizational learning is categorized as several processes, it does not necessarily mean that they are isolate. In fact, most of the time these processes are interconnected or overlapped, and there is no obvious transit from one process to another.

Table 2 Models of Processes of Organizational Learning

	Input	Learning		Outcome	
Argyris and Schon (1978)	discovery	invention	production	generalization	
Huber (1991)	Knowledge Acquisition	Information Distribution	Information Interpretation	Organizational Memory	
Nevis, DiBella, and Gould (1995)	knowledge acquisition	knowledge sharing		knowledge utilization	
Nonaka (1994)	socialization	externalization	combination	internalization	
Crossan et al. (1999)	intuiting	interpreting	integrating	institutionalizing	
Chen and Ma (2000)	discovery	invention	production	generalization	Feedback
Argote and Miron-Spektor (2011)	knowledge creation	knowledge transfer		knowledge retention	

Source: author's creation.

The comparison of these models indicates that scholars have reached a consensus that organizational learning starts with single tipping points that could generate novel knowledge, then spread across organizations into collective learning behaviors, and finally retain knowledge in organizational systems. This study will draw on the recent framework proposed by Argote and Miron-Spektor (2011), the three-process model of knowledge creation, knowledge transfer, and knowledge retention, because it has incorporated the prior theories and developed a concise model to illustrate the on-going activities in organizational learning. In the following parts of this section, each process of organizational learning will be discussed.

2.2.1 Knowledge Creation

Knowledge creation could be defined as the process that units generate new knowledge (Argote & Miron-Spektor, 2011). And as the first step of organizational learning, it has attracted much attention ever since Nonaka addressed the notion and analyzed it by introducing the example of Japanese firms and illustrating the implication of innovation of this process (Nonaka & Takeuchi, 1995).

According to Nonaka and Takeuchi (1995), knowledge creation includes four modes of knowledge conversions, i.e., socialization, externalization, combination and internalization. These modes are interconnected to form the foundation in the spiral process of organizational knowledge creation. Knowledge creation starts with socialization, which refers to the interaction of tacit knowledge through experience between members; the next step is externalization, meaning that by discussion and knowledge sharing, tacit knowledge becomes explicit knowledge such as organizational experiences, practices and routines; subsequently explicit knowledge needs to be exchanged by formal mechanisms and along with reconfiguring of established information flows, the process being cited as combination; and eventually the internalization means that members learn the knowledge from these processes, transfer it into their own individual tacit knowledge, and diffuse it to the whole organization.

Even though scholars grant different names and develop various conceptualizations for this process, they convey the same essence and exemplify the importance of this process. For instance, knowledge creation process is cited as a process of discovery by Argyris and Schon (1978); it is referred to as intuiting process in the organizational learning framework developed by Crossan and colleagues (1999); and Nevis and colleagues (1995) present this stage as knowledge acquisition.

Knowledge creation is influenced by many interrelated factors, including: environmental factors, individual characteristics, and motivational factors. Environmental factors include dynamics context, e.g., rapid technologic change, short product life cycles, diversity in terms of mental models, and organizational climates for risks and teamwork, ego social networks of individuals which is beneficial for searching for relevant information to generate knowledge upon (Cross et al., 2001; Smith, Collins, & Clark, 2005), and contingent work which reduces firm’s cost and increase flexibility and thus provide competitive advantages (Matusik & Hill, 1998). Individual characteristics include existing knowledge stocks of individuals and innovation capabilities (Smith et al., 2005). Motivational factors include effective organizational atmosphere such as care and trust (Von Krogh, 1998), and autonomy which encourages individuals and groups to generate knowledge from experience and share this experience for exploration (Nonaka & Takeushi, 1995), and accordingly less autonomy for lower degree of exploration (McGrath, 2001).

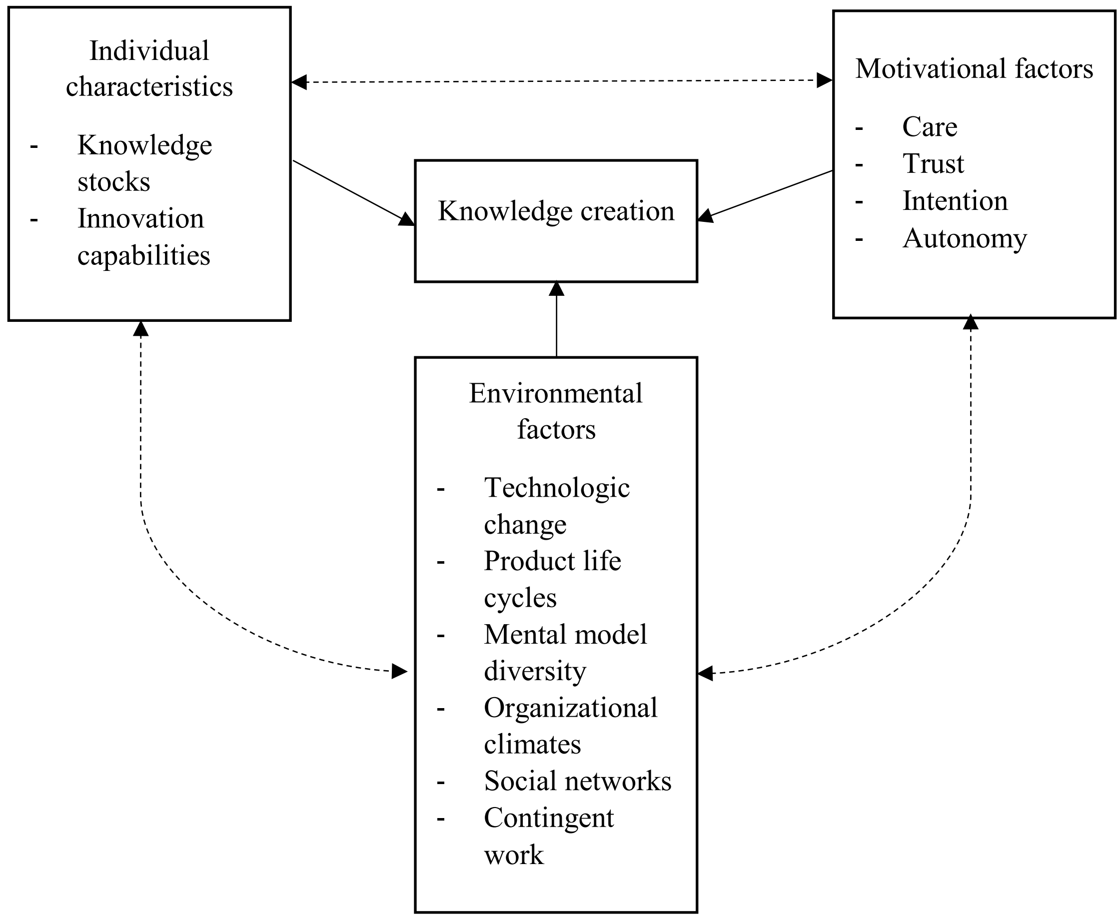

Figure 1 Influential factors of Knowledge Creation

Source: author's creation.

2.2.2 Knowledge Sharing

One simple definition of knowledge sharing is the diffusion process of the outcome of learning (Nevis et al., 1995). Another generally accepted definition is solving problems and developing new solutions by combining and cooperating knowledge, experience, and expertise from different sources and different individuals (Cummings, 2004).

Different terms and expressions have been used to describe the process, such as knowledge invention and production (Argyris & Schon, 1978), information distribution (Huber, 1991), team learning and share vision (Senge, 1990), knowledge sharing (Nevis et al., 1995), externalization (Nonaka & Takeuchi, 1995), interpreting and integrating (Crossan et al., 1999), knowledge transfer (Argote & Miron-Spektor, 2011), the central message these terms convey is that sharing activities of individuals are the link between individual learning and organizational learning.

Many factors influence knowledge sharing such as technologies, characters of knowledge, environmental factors, individual characteristics, and motivational factors (Bock & Kim, 2002; Ipe, 2003; Lin, & Lee, 2006; Wang & Noe, 2010).

Technological systems play an important role in transmitting knowledge across organizations, for instance, organizational knowledge database and manual of knowledge transfer have been adopted widely to facilitate knowledge sharing (Lin & Lee, 2006). And characters of knowledge (whether knowledge is codified or tacit) affect the efforts and energy devoted to knowledge sharing (Hansen, 1999; Reagans & McEvily, 2003). Environmental factors refer to social environment, cultural features of organizational life, and contexts inside and outside organizations (Cabrera & Cabrera, 2002; Cross & Cummings, 2004; Lin & Lee, 2006). Individual characteristics include personal experience, self-efficacy, and personality traits (Bandura, 2000; Cabrera, Collins, & Salgado, 2006; Matzler et al., 2008). Motivational factors include trust embedded in social relationships and leader–member exchange, etc. (Bock & Kim, 2002; Chowdhury, 2005, Quigley et al., 2007; Levin et al., 2010).

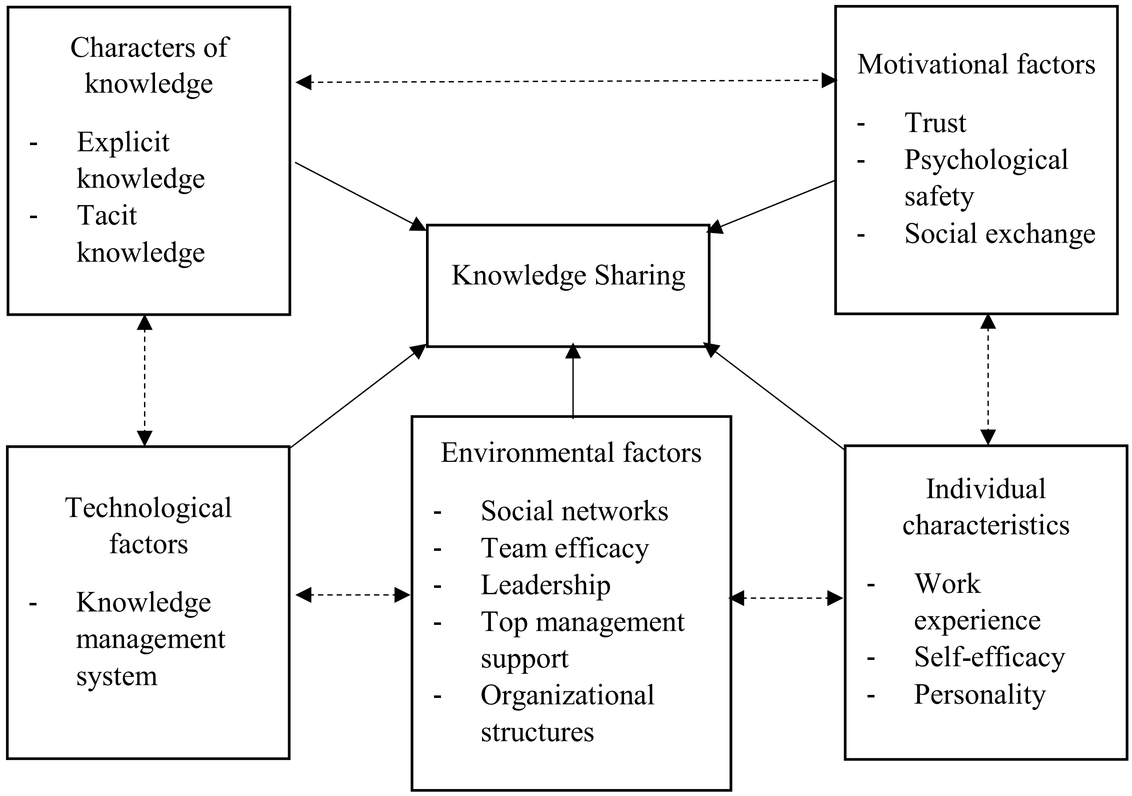

Figure 2 Influential factors of Knowledge Sharing

Source: adaptation from Wang & Noe, 2010.

2.2.3 Knowledge Retention

Knowledge retention is the output process of organizational learning (Yu, Fang, & Ling, 2004). Knowledge gained and transferred in the previous two processes is used, implemented, and adopted by other individuals or units in organizations. Through this process, knowledge is used, transferred into performance, and retained in organizations by exertions of building organization's memory and efforts of slowing down the speed of knowledge decays (Argote & Miron-Spektor, 2011).

Knowledge retention, similar as the previous two processes, is quoted as different terms. Argyris and Schon (1978) refer this process as generalization, because knowledge discovered and produced needs to be generalized towards the whole organizations and across numerous boundaries to become knowledge of organizations, finally showing its effect on performance, and saving as inventory of knowledge for future use. It is also cited as internalization (Nonaka & Takeuchi, 1995), institutionalizing (Crossan et al., 1999), utilization (Nevis et al., 1995), and knowledge adoption (Phelps et al., 2012).

Research on knowledge retention typically focuses on how to effectively reuse knowledge and how knowledge decays along with organizational change and evolution (Argote & Miron-Spektor, 2011). Factors that influence knowledge retention include loss of knowledge reservoirs and sources such as turnover and retirement, different types of knowledge, and social network structures. For instance, the adoption would be accelerated if knowledge sources occupy central positions (Nerkar & Paruchuri, 2005), and loss of knowledge would be more detrimental if it is caused by key actors who bridge the structural holes (Burt, 1992).

2.3 Social Networks and Organizational Learning

2.3.1 Social Networks

A social network is composed of a number of individuals and a set of ties representing social relationships between actors (Brass et al., 2004). It has been developed for more than half a century to illustrate the essence of society and has been introduced into the organization study for more than 20 years.

Relationship between organizational learning and social networks has been an increasing research interest in the last few decades. Social network analysis is prominent in studies of learning field for its precise illustration of social relationships of individuals and practical organizational design and change implication it provides (Nahapiet & Ghoshal, 1998).

Social network studies yield abundant results on the topic of organizational learning (see Phelps et al., 2012 for a review). Those studies span in a wide range, from individual relationship level up to interorganizational alliance network level. And they examined various network characteristics such as strengths of ties (e.g., Levin & Cross, 2004), ego network properties (e.g., Reagans & McEvily, 2003), whole network structures (e.g., Tsai, 2002), position of actors in networks (e.g., Owen-Smith & Powell, 2004), and notably, properties of knowledge (e.g., Hansen, 2001; Reagans & McEvily, 2003). Most of the studies focus on one of the three organizational learning processes.

The largest proportion of these studies examined the relationship between knowledge sharing and networks. This inclination is due to the complicity and delicate features of this process. Knowledge sharing is highly social oriented and calls for cooperation and interactions between individuals. To promote effective knowledge sharing, organizations and individuals involved need to pay extra attention to knowledge properties, characteristics of individuals or units from both knowledge source and knowledge recipient, and relationships between parties. Aligned with this understanding, it is no surprise that most research efforts are on knowledge sharing (see Wang & Noe, 2010 for a review). Slightly inferior to the research enthusiasm of knowledge sharing is the research efforts on knowledge creation. And the least explored process is knowledge retention (Phelps et al., 2012).

In the following part, studies concerning each process across different levels will be reviewed and compared, and special attention would be paid to the relationships between inter-firm alliance networks and organizational learning.

2.3.2 Social Networks and Knowledge Creation

Knowledge creation is the first step of organizational learning. According to knowledge-based theory, many efforts of organizations target at coordinating knowledge residing in organizational members and applying it by different mechanisms (Grant, 1996). And these mechanisms include managing the social networks to promote knowledge creation in organizations because knowledge is generated by teamwork and day-to-day interactions of members (Cross et al., 2001; Smith et al., 2005). Therefore, scholars provide different propositions and suggestions to encourage effective knowledge creation.

At the interpersonal level, it is argued that knowledge creation is positively related to structural holes (the social hole when two groups do not share a tie and the network is diverse and open) because individuals could constantly bring more novel and diversified ideas into the networks and thus generate new knowledge by building on these information flows (McFadyen, Semadeni, & Cannella, 2009). It is also proved that at intraorganizational level, high density of networks within the team and high network diversity outside the team are not contradictory with each other, and both factors account for knowledge creation and innovation (Reagans & Zuckerman, 2001). Studies also yield conflicting results on effects of these two features on knowledge creation at interorganizational level. Some evidence shows that bridging ties and structural holes are helpful for knowledge creation (McEvily & Zaheer, 1999), while others claim that higher level of structural holes is negatively related to innovation in collaborations (Ahuja, 2000).

The topic of how nodes' positions in networks affect knowledge creation also attracts much attention. Power comes along with possessing the central location in the networks. Such central locations not only access the knowledge potentials and control information in knowledge sharing process, but also provides the possibilities of combining and converting information passing by into novel knowledge (Burt, 2004).

At the interpersonal level, although individuals with high centrality have aforementioned advantages, these advantages come not without costs. For instance, developing and maintaining ties and the numbers of strong ties one can keep is limited. And efforts devoted in maintaining these ties might diminish return of knowledge creation (McFadyen & Cannella, 2004). In intraorganizational networks, centrality is considered as positive enhancer of knowledge creation (Tsai, 2001). However, as units vary in their capabilities to absorb and replicate knowledge transferred from other units, to generate knowledge by taking advantages of centrality, the absorptive capacity is also a necessary condition (Cohen & Levinthal, 1990; Tsai, 2001). At interorganizational level, results of network position are mixed. Some research shows that centrality positively affect innovation in geographically dispersed alliance networks (Owen-Smith & Powell, 2004), while others claim that relying exclusively technology sourcing and cooperation with alliance partners would result in a disadvantage of losing knowledge created, and therefore the diminishing returns as amount of knowledge source rises (Rothaermel & Alexandre, 2009).

2.3.3 Social Networks and Knowledge Sharing

Right from the early stage of social network studies, it has been argued that we could make use of different features of our social resources to help to share knowledge.

However, many claims remain controversial for a long time. At individual level, Granovetter's (1973) weak ties strength theory proposes that wide range of social networks and sparse social ties have the benefit of non-redundant information when individuals tried to seek information and explore beyond familiar local networks. This proposal is followed by structural holes theory, which states that by bridging social disconnection between groups (cited as structural holes), organizations could benefit from more social connections, and gain social capital that could bring competitive advantages (Burt, 1992). Reagans, Zuckerman and McEvily (2004) also find out that interaction within non-redundant networks could improve productivity and gather more diverse knowledge and thus bring out innovation and creativity.

On the contrary, Coleman (1988) proposes that dense and cohesive networks would enhance harmonization and trust, and therefore promote knowledge sharing. Several empirical studies tested this proposal and supported the claim. For instance, in the research of social networks among hotel managers, scholars reveal that managers form alliance even with competitors to share client resources to improve performance (Ingram and Roberts, 2000). Strong ties also help to create the trust environment and promote teamwork of members (Levin & Cross, 2004).

These two opposite theories reach balance and reconciliation when Reagans and McEvily (2003) introduce the contingency view of both range (represents the level of structural holes and sparse ties) and cohesion (indicates the closeness of actors in the network) and their effects on knowledge sharing. They find that both these two structural features positively affect knowledge sharing. And social cohesion affects incentive and efforts of individuals to invest in sharing knowledge with others and network range increases individual's ability to sharing complex knowledge to others.

At the intraorganziational level, Reagans and Zuckerman (2001) find that corporate R&D Teams with high level of network density among members would help to foster better coordination of the team, and teams with greater variation across demographic categories would enhance its capability of information transfer and learning. Also, strong ties across different units are proven to promote effective knowledge sharing (Hansen, 1999).

At the interorganizational level, the effects of structural holes and network closure are often contradictory as well. Some studies show that high level of network closure of interorganizational collaboration would be helpful for knowledge diffusion (Lawrence, Hardy, & Phillips, 2002), while other research finds evidence of the benefits of structural holes on accessing new information and ideas (McEvily & Zaheer, 1999). Most of the studies addressing tie strengths and knowledge sharing provide evidence for hypothesis that strong ties are beneficial for knowledge sharing and information flow (Tiwana, 2008).

The other network structure attracts attentions from scholars is the network position. Actors who hold the central location in networks are often perceived as individuals with power, and are easier to generate leadership from centrality. And therefore, information flow is coordinated (and some cases, controlled) by individuals with high centrality (Balkundi & Kilduff, 2006). Studies investigating the effects of network position also span across different levels of organizations.

At the interpersonal level, it is argued that individuals located in central positions have accesses to both more ties and more diverse information (Burt, 2004). At the intraorganizational level, research evidence is consistent with results from interpersonal level. More central units and departments have more and diversified sources of knowledge across the whole organization, and therefore affect the effectiveness of knowledge transfer (Tsai, 2001). At the interorganizational level, it is argued that alliances provide the advantages of accessing knowledge (Grant & Baden-Fuller, 2004), and central nodes in physically spread alliance networks could be more influential in knowledge sharing activities (Owen-Smith & Powell, 2004).

2.3.4 Social Networks and Knowledge Retention

Unlike the previous two processes of organizational learning, topics of knowledge retention, such as how networks affect implementation of knowledge across different boundaries, how to adopt and use knowledge acquired, and how to retain knowledge in reservoirs of various networks in organizations with least deterioration, are less studied (Argote & Miron-Spektor, 2011; Phelps et al., 2012).

Some studies suggest that knowledge adoption and implementation are more successful when knowledge is created by individuals possessing central position in networks. This is because high centrality is associated with access to more sources of information and knowledge and high quality of innovation (Nerkar & Paruchuri, 2005). At the interorganizational level, strong ties with prior strategic alliances contribute to integrate information and knowledge into innovation (Tiwana, 2008), and under situation of high level of market uncertainty, firms tend to reinforce their networks, and choose to maintain established ties (Beckman, Haunschild, & Phillips, 2004).

Table 3 Summary of Studies of Relationships between Social Networks and Organizational Learning

		Organizational learning processes		
		Knowledge creation	Knowledge sharing	Knowledge retention
	Interpersonal level	Conflicts: Positive or curvilinear relationship between centrality and knowledge creation	Consensuses: Positive relationship between centrality and knowledge sharing	Consensuses: Positive relationship between centrality and knowledge retention
Network position	Intraorganizational level	Consensuses: Positive relationship between centrality and knowledge creation	Consensuses: Positive relationship between centrality and knowledge sharing	
	Interorganizational level	Conflicts: Positive or negative relationship between centrality and knowledge creation	Consensuses: Positive relationship between centrality and knowledge sharing	

Table 3 (continued)

		Organizational learning processes		
		Knowledge creation	Knowledge sharing	Knowledge retention
	Interpersonal level	Consensuses: Positive relationship between structural holes and knowledge creation	Conflicts: Positive or negative relationship between structural holes and knowledge sharing	
Ego network structure	Intraorganizational level	Conflicts: Debate of benefits of dense within-unit networks and network diversity outside unit	Consensuses: Positive relationship between dense network and knowledge sharing	
	Interorganizational level	Conflicts: Positive or negative relationship between structural holes and knowledge creation	Conflicts: Debate of benefits of structural holes and network closure	Consensuses: Positive relationship between stablished relations with alliances and knowledge retention

Source: adaptation from Phelps et al., 2012

2.4 Limitations of Previous Studies

Many studies concerning the relationships between social network and organizational learning yield conflicted results.

For instance, the debates between strengths of weak ties and strong ties (Granovetter, 1973; Bian, 1997; Tiwana, 2008), and the long existing conflicts of benefits of structural holes and network density (the extend of how close of actors in networks and the network is dense and more closed) (Burt, 1992; Reagans & McEvily, 2003).

Also, although numerous studies have indicated organizational learning is related to both financial performance and innovation performance, whether certain network structures continue to improve these performances or the effects decline at some point, i.e., an inverted-U relationship, are still highly controversial (Lazer & Friedman, 2007; Phelps, 2010). Some scholars suggest that what comes along with increasing benefits are costs (sometimes even higher increasing rate), and these costs exist for many typical estimated beneficial structures, such as high density (Lazer & Friedman, 2007) and high centrality (McFadyen & Cannella, 2004). Actors have to invest time and energy to maintain those ties (Reagans & McEvily, 2003), to reciprocate (Hansen, 1999), and to have the corresponding absorptive capacity to adopt and use this information and knowledge. (Cohen & Levinthal, 1990; Tsai, 2001).

Another aspect of observed mixed results and controversies is the omission of different types of organizational learning (Phelps, 2010). Although there is consensus that no network structure is universally beneficial (Adler & Kwon, 2002), contingencies of how to accord different network structures with different types of knowledge, learning, and innovation are still not thoroughly discovered.

In the seminar work by March (1991), organizational learning includes two different types of activities; the first one is exploration, which means searching new resources, experimentation, and taking risks, etc., and the other type is exploitation which indicates efforts in improving efficiency, refinement, and productivity in the existing domain (Birkinshaw & Gupta, 2013). These two seemingly contradictory learning orientations entail different (and sometimes even contrary) strategies, structures of organizations, and organizational contexts (Duncan, 1976; Gibson & Birkinshaw, 2004; O'Reilly & Tushman, 2008).

In the next part, the definitions of these two types of organizational learning will be introduced and different theories around exploration and exploitation will be discussed in detail.

2.5 Exploration and Exploitation

Although the seminar work of March (1991) is titled as “Exploration and Exploitation in Organizational Learning”, it draws more attention in the field of organizational ambidexterity (OA) than in organizational learning. However, this is deemed almost natural, given that March does not provide specific instructions of how to promote effective organizational learning, instead the theory illustrates the fundamental incompatibilities between exploration and exploitation, which provides the theoretical gravitas for research on OA (Birkinshaw & Gupta, 2013).

Ambidexterity, at the origin, means the capacity to be skilled on both hands, and it has been introduced into organizational studies to illustrate organizational capability of doing things equally well. The generally accepted definition of OA is proposed by Tushman and O'Reilly (1996): the ability of pursue incremental (exploitative) and discontinuous (explorative) innovation simultaneously. It emphasizes the capability of resolving tensions between these two apparently competing activities under given structures and resources.

Exploration is often connected with flexibility, adaptability, responsiveness, trials, searching for new resources, taking risks of entrepreneurship, carrying out experimentation that could be beneficial to organizations potentially (Birkinshaw & Gupta, 2013). While exploitation is often addressed together with efficiency, alignment, integration, refinement of established routines, more efficient production, and improvement of productivity by various means (O'Reilly & Tushman, 2013).

Different scholars and schools of thoughts hold different views towards the interaction and interplay between these two kinds of activities. The application of OA has both theoretical and empirical evidence support in various fields including international business, organizational studies, strategy alliance formation and so on (Simsek, 2009). Some most important debates remaining unreconciled for a long time in OA include: are exploration and exploitation two ends of a continuum or logically independent from each other? Is it more beneficial to maintain a balance between exploration and exploitation for the same unit or it is better to specialized in one kind of activities due to resource restraints and unit capabilities?

Attempts to resolve those controversies lead to different streams of OA.

Sequential ambidexterity, which appears early in research, indicates that organizations shift their structures over time to meet with strategies of certain moment, and it is the categorized as the first type of OA (Duncan, 1976). From the perspective of industry life cycle, organizations face different challenges in different stages of the cycle. For instance, in the introduction and growth stage, new and unique products are produced, and radical innovation and creative strategy are entailed. However, in the subsequent stages, economies of scale would show the value and improving productivity and efficiency take the prominent position in the strategy design. Many case analyses prove that firms shifting their structures over time survived, and those do not, disappeared. But those cases fail to show how ambidexterity occurs, what the antecedents are, and why some organizations succeed, while some others tried, but failed anyway (Adler, Goldoftas, & Levine, 1999; House & Price, 2009).

Simultaneous ambidexterity proposes an alternative way of interpreting the ambidexterity. It suggests that the exploration-exploitation trade-off is achieved by attaching different roles to separate subunits (with different competencies, practices, and cultures) in organizations (O'Reilly & Tushman, 2008). The key to benefit from ambidexterity is to assign different roles to different units and to detect and grasp the opportunities in different activities performed by units. This, naturally, entails excellent leadership, control, and communication mechanism (Jansen et al, 2008). Following this line of logic, the key tasks for OA are organizational design. However, one possible defect of this stream is whether the organizations possess the capabilities to assign those tasks to different units, whether they have the resources to do so (Cao, Gedajlovic, & Zhang, 2009). Consider the loop of failures organizations might face: firms have limited resources to assign certain activities to certain units, and therefore they are not able to achieve OA, thus not able to benefit from it, and this result in poor performance, and less resources due to poor performance. Therefore, this stream of OA is more valuable under certain conditions: firms with more resources and larger scales (Lin, Yang, & Demirkan, 2007).

If the poor performance of firms is entirely a loop of failures and there is no other explanation and suggestions from the theory, one would challenge whether OA is a useful framework or another cover story of "how our company succeed".

The other interpretation of OA, namely contextual ambidexterity, is targeting at challenging this loop indicated by simultaneous ambidexterity. Gibson and Birkinshaw (2004) propose that different roles are not necessary to be assigned to different units. In their argument, simultaneously aligning and adapting are possible on the individual level, and by supportive and encouraging organizational contexts, individuals could shift between exploration and exploitation (Adler et al., 1999). From this perspective, cultures, norms, and positive and encouraging contexts are the key to achieve OA (Wang & Rafiq, 2014; Khazanchi, Lewis, & Boyer, 2007).

Although there are discrepancies among these three types of OA, it does not mean they are contradictory to each other. They are more likely to complement each other under different environments and contexts (O'Reilly & Tushman, 2013).

More specifically, under stable environment, or in traditional industries, where the innovation paces are relatively slow, and product life cycle are longer, organizations could afford to change strategies and their structures of exploration or exploitation over time, sequential ambidexterity is more feasible. While in highly competing environment with high level of uncertainty, for instance, information technology industry, the fierce completion calls for quick responses and planning ahead of time and ahead of competitive rivalries. In this sense, simultaneous ambidexterity shows its great value. In industries where adaptions and customization is highly prized, contextual ambidexterity would be valuable since it allows individuals to shift their roles and to take initiatives to better satisfy the customer needs and get feedback from local markets (Benner & Tushman, 2003).

Contextual ambidexterity and simultaneous ambidexterity involve different level of organizations, although ambidexterity itself is a multilevel construct (Simsek, 2009; Birkinshaw & Gupta, 2013). Aligning with the definition emphases on individual level (contextual ambidexterity), unit level and firm level (simultaneous ambidexterity), empirical studies of OA span from individual to interfirm level (Junni et al., 2013).

Table 4 Summary of Different Views of Organizational Ambidexterity

	Sequential Ambidexterity	Simultaneous Ambidexterity	Contextual Ambidexterity
Approach to achieve ambidexterity	Changing and shifting strategic goals between exploration and exploitation when facing different challenges over time	Designing proper structures to allow different units in organizations to engage in exploration and exploitation respectively	Building cultures, working contexts, and environments that allow organizational members to shift and change between exploration and exploitation
Contexts	Stable environment	Intensive competition	Turbulent environment
Level of study	Interorganizational	Intra and interorganizational	Individual
Level of resources required	Low	High	Low
Limitations	How sequential ambidexterity occurred and doubt of its effectiveness	Requires high level of resources, capabilities, and leadership support	The assumption of all individuals possessing necessary capabilities

Source: adaptation from O'Reilly & Tushman, 2013

In the field of organizational learning, emphases are different from traditional OA studies reviewed above. The difference lies in the ultimate purpose of learning: knowledge (Argote & Miron-Spektor, 2011). Despite the huge investment in designing sophisticated knowledge systems and shifting roles and strategies emphases of different units or over time, many organizations find it hard to benefit from it (Babcock, 2004). This is due to the two aspects of the challenges of organizational change: both in formal and in informal structure. Formal structure refers to organizational structure established by formal design and control, while informal structure includes community of practices, social networks structure, etc. (Brown & Duguid, 2001; Tiwana, 2010).

To gain knowledge, only formal structural design and assign different roles to different units is not enough. Informal and formal structures of organizations sometimes differ from each other (Balkundi & Kilduff, 2006), and they could affect knowledge creation, sharing and retention in different manners (Jansen, Van Den Bosch, & Volberda, 2006; Gulati & Puranam, 2009). And in organizational learning processes, social interactions play a pivot role (Miller, Zhao, & Calantone, 2006). Successful and effective organizational changes always contain the human process and ultimately change organizational culture and shared value (Cummings & Worley, 2014). And making use of different structures of social networks is more socially accepted to achieve these goals, because organizational change invokes resistance and risks. Although it might be more feasible and cost efficient to achieve the same goal by forming and aligning network structures, rather than the formal organizational structures, social networks are less discussed in OA studies (Auh & Menguc, 2005; Lavie & Rosenkopf, 2006; Raisch et al., 2009).

Among these scarce studies, scholars already show that not only the formal organizational structure is the antecedents of OA, external and internal networks play a role here as well (Lee, Lee, & Lee, 2003; Lazer & Friedman, 2007; Gilsing et al., 2008; Im & Rai, 2008). In the next part, studies addressing the relationships between social networks and exploration and exploitation will be reviewed.

2.6 Exploration, Exploitation, and Social Networks

Scholars propose different approaches of using ties, preferable network positions, and network structures to foster OA, but the results for empirical study are mixed. In this section, relevant research concerning social networks and tension of exploration and exploitation is reviewed and then the studies of the fit between social networks OA, limitations of these studies, and conflicting results will be discussed.

2.6.1 Organizational Structures of Exploration and Exploitation

In the study by Perretti and Negro (2006), it is argued that lower and higher status actors in teams, and simpler and more complex organizational structures are positively related to exploration, while the middle members and medium level of structure complexity are negatively related to exploration. While this study records the long-time change of formal organizational change, it does not indicate whether in the flatter networks the behaviors of actors and relationships would show a similar trend. By forming and aligning network structures, rather than the formal organizational structures, it might be more feasible and cost efficient to achieve the learning goal.

Fang, Lee, and Schilling (2010) prove that moderate level of cross-group linking would be the best structure to achieve the balance between exploration and exploitation from the structural design perspective. However, this study is carried out as formal organizational structural design simulation experiment, which is not the least social resistant way. As is acknowledged widely, organizational change invokes resistance and risks, while semi-isolated subgroups could be measured in social network analysis by index of cohesion, subgroup index and openness.

2.6.2 Effects of Social Networks

Gilsing and colleagues (2008) analyze the combined effects of embeddedness i.e., network position, density and technological distance, on exploration performance. But this study is carried out among several industries, and importance of exploration products, e.g., patents, vary from industry to industry. Further investigation of samples of firms that provide similar products and services is necessary.

Tiwana (2008) discusses strong and bridging ties play complementary roles when it comes to the balance of exploration and exploitation: weak and bridging ties provide access to diverse and collect information and innovation opportunities existed among the scarcely distributed external networks, and strong ties help to integrate knowledge acquired from different sources into organizations. Lavie, Kang, and Rosenkopf (2011) also propose that balancing exploration and exploitation across domains with different network ties could generate better performance. While Peng and Wu (2013) claim that creating diverse ties in global production networks would help achieve ambidexterity when organizations aiming for upgrading in global production networks.

Lazer and Friedman (2007) compare different networks in their performance of exploration and exploitation. The network with linear structure results in better long-term performance and enable exploration. On the contrary, the network with highest density (each member is connected with any other actors) performs better in transferring information in short term, and thus stimulate exploitation. This study also manifests a curvilinear relationship between connectedness and performance, and this inverted-U relationship has been proved by several studies of networks or organizational structure (Uotila et al., 2009; Fang et al., 2010).

Phelps (2010) empirically proves that within a single industry, network structure influence exploratory innovation. But the sample in this study is not in same local networks and these firms are not located in same geographic location and industrial cluster, and thus different conditions of industry commons (Pisano & Shih, 2009), and this might cause the differences in their structures and innovation strategies and performance. Empirical evidence shows that in different modes of clusters, network characteristics are significantly different (Turkina, Van Assche, & Kali, 2016).

These studies, which examine the effects of social networks on exploration and exploitation reviewed above, yield mixed results, and have some limitations that require further analysis. Therefore, built on the methodologies and theoretical grounds of prior studies, empirical research will be designed and tested in the following sections to address these limitations.

3. Conceptual Framework and Methodology

3.1 Conceptual Framework

This study is targeting at complementing the limitations of previous research of how social network structure affect organizational learning by distinguishing different types of learning. The theoretical grounds this study build on are social network theories and organizational learning theories.

Social network theories describe the social structures as networks constituted by individuals (cited as notes) and relationships (cited as ties). They provide a useful and straightforward illustration of how social interaction happens, transmits, and evolves, and thus are convenient tools to visualize and analyze the social environment of groups, units, organizations, communities, and societies (Wasserman & Faust, 1994). Interorganizational level studies of social networks have been established and matured in the previous studies (Ahuja, 2000; Burt, 2004). And, there are several studies carried out at the interorganizational level specifically targeting at effects of networks on exploration or exploitation (e.g., Owen-Smith & Powell, 2004; Gilsing et al., 2008; Phelps, 2010), therefore it is legit and viable to use social network theories to analyze the interorganizational alliance networks in this study.

Organizational learning traditionally has two streams of views of learning, and each of these two views holds different assumptions and requires different mechanisms to learn. The first one, systemic view, regards organizations as information-processing machine and it exist as an entity to interact with and adapt to environment. The other view, interaction view, regards the goal of organizations as to create knowledge, use and retain knowledge to remain competitive, and this goal is realized by interaction between organizations, members and environment (Nonaka & Toyama, 2003). The latter view is social oriented and takes social environment into consideration while the former view lacks the ability to analyze these social aspects of organizations.

In this study, the theoretical ground of organizational learning will be the social interaction view and specifically, the social relationships of strategic alliances and their effects on learning performance.

To better analyze the organizational learning activities, scholars simplify and categorize them into several processes. This study will build on the process categorization by Argote and Miron-Spektor (2011) that organizational learning includes three processes: knowledge creation, knowledge transfer, knowledge retention. And emphasis of the study will be postured on the first process, i.e., knowledge creation, by analyzing the innovation performance of organizations. In the previous chapter, factors that could influence knowledge creation have been reviewed, and among them the factor of social network is the pertinent one, which will be under scrutiny in this study.

Organizational learning could be categorized as two types of activities, exploration and exploitation (March, 1991). And based on the different features, assumptions, and actions entailed by these two types of learning, scholars provide several theories to address the tension between exploration and exploitation (Birkinshaw & Gupta, 2013). Organizational ambidexterity (OA) is developed under this consideration. And different types of OA are proposed, i.e., sequential ambidexterity, simultaneous ambidexterity, contextual ambidexterity. These theories apply to different level of study and different environment under examination (Benner & Tushman, 2003).

In the current study, the research setting is IT industry which is featured as highly competitive and knowledge-intensive. And according to the general application criteria of different types of ambidexterity, simultaneous ambidexterity applies to this case, that is, in industry such as the current IT industry, firms need to response quickly and the industry environment is highly competitive. This study will be carried out at firm level, therefore it is viable to assume simultaneous ambidexterity view: firms can shift their innovation orientation according to their strategic emphases.

In the operationalization of OA, different scholars take different views of how to measure OA according to whether they conceptualize exploration and exploitation as distributed at different ends of a continuum or as independent from each other. Some studies tend to measure exploration and exploitation separately, i.e., combination perspective (Auh & Menguc, 2005; Phelps, 2010), while others measure them as continuum in which one serves as successive activities of the other, and measure them as relative degrees of innovation orientation, i.e., balance perspective (Lavie, Stettner, & Tushman, 2010).

In this study, the first perspective will be adopted to align with the level of study (interorganizational study) and assumption of the OA in simultaneous ambidexterity, because combination perspective assumes firms has resources and can achieve high level of each activities separately, and the focus will be exploration.

To summarize, the conceptual framework of this study is constructed on social network theories, more specifically, structure of interorganizational alliance networks, and organizational learning with emphasis on knowledge creation of exploration innovation. In the following parts of this chapter, hypotheses of the relationships between network structure organizational learning will be proposed, and measurements of variables will be offered as well.

3.2 Key Hypothesis

Among the network structure analyses, centrality is one of the earliest and widely used conceptual tools, because it is very useful for identifying the most important and powerful actors in networks (Wasserman & Faust, 1994; Scott, 2000; Everett & Borgatti, 2005).

Centrality refers to the extent to which an actor is connected to other actors in the network, and it is represented by the number of ties this actor involved (Wasserman & Faust, 1994). In a network, an actor could have both direct ties and indirect ties, and actor is considered locally central if he or she is surrounded by many direct ties in immediate network, and it is considered global central if it is strategic important in the whole structure of the network. And these two centrality indexes have different measurements in empirical studies such as degree centrality and closeness centrality (Scott, 2000).

In the case of organizational learning, studies have shown that central position affect learning across different levels in organizations, but many of these studies yield conflicted results.

Many studies manifest the positive effects of centrality. Possessing the central location of the network can generate leadership and power and bring out the advantages of accessing more diverse information and knowledge for individuals (Burt, 2004; Balkundi & Kilduff, 2006). Centrality can also ease the knowledge transfer process across units at intraorganizational level (Tsai, 2001) and help implement knowledge acquired and transferred in previous processes (Nerkar & Paruchuri, 2005). And at the interorganizational level, firm's innovation performance is affected by the number of relationships with collaboration network partners (Ahuja, 2000).

On the other hand, some studies also find that it is not always positive relationships between centrality and organizational learning. At the individual level, McFadyen and Cannella (2004) argue that advantages of social ties come along with costs. This is because individuals' time, energy, and resources are limited, and therefore the number of ties that individuals' can maintain as effective aide to knowledge creation is limited. They empirically prove the curvilinear relationship between centrality and knowledge creation by analyzing the scientific work of scientists in biomedical field and find that as the number of ties increases to a certain point, the performance of knowledge creation will decrease.

In their study, McFadyen and Cannella (2004) only consider the direct ties because knowledge creation calls for direct social interaction, and often depends on recombination and exchange of tacit knowledge. While in other studies, scholars also examined the effects of different types of ties and individuals in different positions in the network in terms of whether they are central or in peripheral position. Perry-

Smith (2006) argues that centrality alone does not affect individual creativity, but that central individuals with large number of social relationships from outside organizational boundaries are proven less creative than those with fewer outside ties. And the situation is different when individuals possess the peripheral position, and in this case, individual creativity is proven to be higher when actors have more outside ties.

At interorganizational level, research suggests that organizational ambidexterity of internal versus external technology sourcing should be achieved, and over dependence on either type of sourcing partners can pose negative effect on performance (Rothaermel & Alexandre, 2009). And centrality plays more influential role when the network is more physically spread, because in the same area where networks are dense and organizations are geographically close to each other, information flow and knowledge exchange is easier and more intensive than those of geographically dispersed networks (Owen-Smith & Powell, 2004).

From these results of previous studies, no consensus of the relationship between centrality and knowledge organizational learning has been achieved, and further analysis of these conflicts is needed.

The first effort of further investigating relationships between social networks and organizational learning would be separating learning processes and scrutinizing them respectively. Not much is known about mechanisms of network structures change along with the organizational learning processes move forward. It is logic to assume different processes entail different network features because they have different purposes, for instance, knowledge creation might depend on the sparse and non-redundant networks to collect novel knowledge and diverse information, while knowledge retention, as the output stage of organizational learning, targets at implement knowledge into the organizational system and slowing down the knowledge decaying rate (Argote & Miron-Spektor, 2011). It is possible that the less external ties involved in the process, and the more centralized the networks are, the faster and more effective the process will be. Therefore, the investigation of how networks influence each of these different processes is necessary.

Another possible reason for these discrepancies is the omission of innovation type, i.e., exploration or exploitation (Phelps, 2010). Most of these studies see innovation (or knowledge created, performance, creativity) as one unified outcome of firms, and use either subjective (e.g., scales or interviews) or objective measurements (e.g., impact factor of scientific work or count of patents). However, taking exploration-exploitation view into consideration, it is doubtful whether the overall knowledge created could reflect the real situation in different orientations of innovation.

Exploration is targeting at pursuing new knowledge and searching for new possibilities (March, 1991), and it often generates risks of no significant return of efforts and energy devoted in these activities in short term (Levinthal & March, 1993). And thus, it would be possible that a certain portion of knowledge created is the result of exploration, and the other portion is out of exploitation. And these activities clearly need different network structures to support (Gilsing et al., 2008; Phelps, 2010). Scholars argue that central actors are exposed to more diverse information and are more familiar with the whole picture of the network, and therefore they are more confident in facing risks (Perry-Smith, 2006; Gilsing et al., 2008). As the number of ties increases, firms are expected to be more confident and specialized in dealing with risks in exploration.

Similar with the situation of individuals, firms could also face the costs of maintaining too many alliance relationships because firms also possess limited resources and need absorptive capacity to make use knowledge embedded in alliance relationships. However, this possibility by no means indicates that the mechanisms of interpersonal level is readily transferable to higher level of organizations (Phelps et al., 2012). It is suggested in prior studies that overreliance on external partners for knowledge creation is also a risk to performance (Rothaermel & Alexandre, 2009), but more empirical evidence should be provided to show how the relationship changes and the specific curve of the relationship.

Therefore, following the two aspects of possible solution of limitations of prior studies, this study proposes the following line of reasoning. It is possible that with the increase of number of ties firms maintain, the effectiveness of knowledge creation of these ties would decrease because although much knowledge is made available through alliances, firms are not able to make good use of it or turn it into exploratory knowledge because resource constrains. And thus, a negative effect of too many ties could be argued. Therefore, the following hypothesis is proposed:

Centrality has a curvilinear (inverted-U) relationship with exploratory knowledge creation.

3.3 Research Setting

In this study, the IT industry was chosen as the research setting. Three reasons were behind this choice. First, IT industry is considered as one of the most innovative and knowledge-intensive sector, and technological innovation is well-suited in the priority of strategy of many firms in IT industry (Stuart, 2000; Cockburn & MacGarvie, 2011). These features suggest that IT industry would be a suitable investigation object in the study of innovation and knowledge creation.

Second, IT firms consistently file patents and new knowledge created was well documented. Therefore, the use of patent count as the measure of knowledge creation in this study would be feasible. According to *U.S. Cluster Mapping Project*, from year 2003 to 2013, for a consecutive ten-year period, IT industry represented the largest share of U.S. utility patents awarded (more than 30% of all patents awarded each year were from IT industry).

Third, IT industry is composed of firms with heterogeneous structures and features, from small and medium-sized enterprises (SMEs) to multinational corporations (MNCs), and from local private studios to publicly listed firms. Furthermore, collaboration in the form of strategic alliance are very common in IT industry, and firms rely heavily on alliance to create knowledge (Stuart, 2000). Therefore, the sample of the study would not be limited to public firms and MNCs and would generate a sufficient variation of the variables.

3.4 Sample and Data

The research data set for this study was the alliance formation and patent application activities of firms in 7 information technology and analytical instruments industrial clusters (IT clusters) across United States. These clusters were selected by the criteria developed in *the U.S. Cluster Mapping Project,* which provides comprehensive data and tools to research regional concentration of related industries in U.S. And business activities related to IT clusters include electronic components, computers and peripherals, semiconductors, software publishers, software reproducing, process and laboratory instruments, medical apparatus, and audio and video equipment.

Initially, 199 firms from 7 clusters were selected with references of their local engagement and activities. Then the alliance formation activities during the period of 2011-2014 and patent application activities of those firms during 2012-2015 were documented. And then the firms that had record of both activities were selected, and finally resulted in a sample of 67 firms located in these clusters.

The alliance formation activities were monitored over a 4-year range, from 2011 to 2014. Among the sample of 67 firms, 47 public firms were counted, and 20 private firms were counted. Alliance information was collected from multiple sources including annual reports of firms, news release from company websites, and news articles and database such as Factiva and Lexis-Nexis. Overall, the search documented 1393 alliances over four years.

Following previous studies, the dependent variable of this research, the exploratory knowledge creation, is developed by patent counts of firms (Ahuja, 2000; Gilsing et al., 2008; Phelps, 2010). All firms in the sample of the current study have physical existence in industrial clusters in United States despite where their headquarters are located, therefore the data of patents is retrieved from database of The United States Patent and Trademark Office (USPTO). US patent system is reputable of its effective protection of intellectual property, its standardized and rigorous application and publication procedures (Phelps, 2010), and single country patent counting method insures the patent consistency and comparability for both US firms and international firms could be maintained (Ahuja, 2000).

The number of alliance formed during the period 2011-2014 was listed, and then the patent application behaviors (2012-2015, respectively) were recorded to estimate the effects of alliances on subsequent exploratory knowledge creation behaviors. And patent application of each year in this study was assumed as independent from each other, therefore overall 268 samples were included in the study, and 216 valid alliances were observed.

Information of firm features was collected through multiple sources, which include annual reports, news release, *Orbis, LexisNexis Corporate Affiliations, and SEC filings*.

3.5 Measurement

3.5.1 Dependent Variable

Exploratory knowledge creation. Scholars develop two distinguished streams of measurements to capture the essence of organizational knowledge created by learning (Easterby-Smith, Crossan, & Nicolini, 2000). First type of measurement is qualitative measurement of cognitive change, for instance the learning effectiveness (desired outcomes or specific operational knowledge developed) perceived by individuals after learning process (McGrath, 2001), benefits of new skills, technologies, and capabilities in interorganizational learning perceived and assessed by senior analysts of firms (Lane & Lubatkin, 1998). The other measurement focuses on quantitative organizational performance change, such as new products, services, and patent stock (Ahuja, 2000; Alcacer & Gittelman, 2006; Gilsing et al., 2008; Phelps, 2010).

Among those measures, patent counting prevails in recently studies because it is a valid indicator of knowledge creation (Schilling, 2015), and various approaches of patent count have been proposed and developed to analyze knowledge creation in previous studies, such as number of patents (Ahuja, 2000), citations (Alcacer & Gittelman, 2006; Phelps, 2010), and patent classifications (Gilsing et al., 2008; Wang et al., 2014).

In this study, the patent classification approach was adopted for two reasons. First, the interorganizational level focus of the current study calls for a measurement that could capture the knowledge stock from the organizational level, and the fact that many multinational firms in the sample are devoted into various domains indicates the possible risks that individuals in organizations might not be aware of all the technologies and knowledge changes during the time frame of the study, therefore the self-evaluated cognitive change was not selected as the principal measurement approach. Second, among different types of patent counts, classification approach was adopted in the current study because different classes in US patent system are categorized by technological principles (Phelps, 2010), and they represent the knowledge elements related to the patents, and thus the changes in patent classification indicate the changes in knowledge creation of firms (Wang et al., 2014).

The first step of developing the measurement was to document patent International Patent Classification numbers (IPC, 4 Characters for each class) of all patents of a firm in each year, because each patent has been assigned to at least one class, this step would generate a list of classes of the firm's knowledge in that year. Then the class list of all the patents of the firm in previous 5 years was created by adding up all the classes of patents a firm had. Several studies have proved that 5-year window is considered appropriate as the timeframe for depreciation of knowledge, i.e., knowledge normally loses its value after 5 years (Katila & Ahuja, 2002; Gilsing et al., 2008), and knowledge created without repetition in several prior years would be considered as new knowledge or novel innovation (Phelps, 2010).

Then the comparison of those two lists was carried out. New classes appeared in the list of a given year but not appeared in the list of prior 5-year list would be considered as exploratory knowledge classes. And then a sum of counts of those new classes of each firm would act as the index of exploratory knowledge creation of a given year. The knowledge creation activities were documented in this way for year 2012, 2013, 2014, 2015, respectively.

3.5.2 Explanatory Variable

Centrality. To measure network centrality, information of technological alliance formation of each firm during year 2011-2014 was recorded. And to ensure the emphasis of the current research, knowledge creation, not all alliance activities were included in the sample, for instance, original equipment manufacturer (OEM) partners and alliances who focus on the production part of the value chain, and licensing and reseller partners were excluded because the knowledge exchange during those processes is limited.

Centrality represents the relative connectedness of an actor. In this study, the index of degree centrality was applied because it measures the number of direct ties an actor possesses. According to McFadyen and Cannella (2004), direct ties play crucial roles in knowledge creation because knowledge exchange happens in these direct relationships.

By scanning multiple information sources published in annual reports, news releases from company websites, and news archives in search engines, technological alliance information was collected and listed by time. The starting time of alliances was assumed as the time of announcement or actual date mentioned in news articles. It should be noted that MNCs sometimes announce alliance formation without specifying the units or departments concerned in the alliances, and SMEs also tend to announce only names and cooperation level with MNCs for branding purposes. Therefore, in the operationalization of the alliance ties, the data was aggregated to the firm level, for instance, if a firm headquartered in Europe formed a research center at one of the industrial clusters in the dataset, and it had the joint technological development agreement with a local firm without specific project target, the alliance then was considered between the MNCs and the local firm with references of database of *Orbis* and *LexisNexis Corporate Affiliations*.

3.5.3 Control Variables

Several firm-level and industry-level variables were introduced to minimize the effects of factors other than the exploratory variable.

At the firm level, 6 control variables were included. As the simultaneous ambidexterity view was adopted in the current research, and the assumption of simultaneous ambidexterity is that firms have the capabilities and resources to shift their knowledge creation orientation between exploration and exploitation, therefore the elimination of potential effects of firms' capital, resources, and scale was necessary.

Ownership structure. Public firms and privately owned firms differ in their capacities of raising capital, requirements of financial disclosure, and shareholders' composition. This difference could affect the financial resources available for firms to engage in exploratory innovation because exploration entails continuous investments and trials and experiments, and on the other hand, financial returns generated by prior exploitation bring out new resources in short term, and might reinforce itself among different alternatives of learning (Katila & Ahuja, 2002). Therefore, a control variable was developed in which privately owned firms were indicated by number "0" and public firms were indicated by number "1".

International experience. MNCs have wider accesses to knowledge in different regions, more experience of cooperating with different strategic partners both in national market and international market. This international experience could bring the higher possibilities of combining diverse knowledge and exploring new technological domains. Meanwhile, MNCs suffer from coordination and communication problems compared to SMEs, and knowledge creation activities might be negatively affected by those problems (Phelps, 2010). In the study, a binary variable was developed to indicate whether a firm has at least one alliance that is different from a firm's origin country during the observation years (indicated by number "1") or only work with alliances in domestic environment (indicated by number "0").

Firm age. With growing, firms are likely to gain experience in certain domains, and face the situation of "the success trap", i.e., capabilities and competitiveness are developed through activities within domains, and short-term outcomes are generated, and thus opportunities to explore outside their domains are lost (Levinthal & March, 1993). While younger firms, without constraints of previous experience and knowledge stock produced by prior exploitation, are generally considered as more exploratory (Gilsing et al., 2008). And this variable was indicated by the number of years from the time a firm was incorporated.

Firm size. Firm size could affect innovation and knowledge creation in different ways. Large firms are likely to have more financial resources to invest in exploration activities which generally produce less short-term return than exploitation (Levinthal & March, 1993). While it is also possible that with increase of size, firms' expertise, products, and services are developed around similar domains, which could lead to the emphasis of exploitation and neglection of exploration. The natural log of number of employees was used to measure the size of a firm. Due to the data availability of the sample firms, which included both large scale public firms and small and private firms, the number of employees did not strictly match alliance formation activities each year, and the number served as an approximation of average firm size during the observation period.

R&D intensity. Knowledge could be created from both internal and external approaches. While alliances and acquisitions represent the efforts of seeking knowledge outside organizations, R&D expenditures indicate the commitment level in knowledge creation within organizational boundaries (Ahuja, 2000; Lee & Lieberman, 2010). The R&D intensity was measured by firm's R&D expense relative to its operating revenue. This measure was also an approximation of average R&D intensity level and did not strictly correspond to the actual of each year due to data availability.

Industry classification. Although all the firms in the sample of the study physically located in IT industries, those firms varied in their core business domain. Firms from different industries might vary in propensity of patent application. To minimize the variation between different industries, the NAICS 2012 Core Code (2 digits) of each firm was recorded. And overall the firms were in 9 sector groups, and each group was assigned to a category.

Cluster Strength. The research sample of current study spans across several industrial clusters in US and those clusters vary in size and geographic locations. Clusters provide industrial commons, which include various capabilities in a bounded location such as advanced materials supply and technologies, manufacturing competencies, and R&D expertise (Pisano & Shih, 2009). And they also foster the knowledge exchange and information flow, which is highly correlated to knowledge creation, and therefore network structure is more prominent when firms are physically spread (Owen-Smith & Powell, 2004). Therefore, to minimize the effects of clusters on knowledge creation, the location quotient measurement was used. Location quotient represents the level of specialization of a given cluster compared to the nationwide average and is often used as the indicator of cluster strength (Delgado, Porter, & Stern, 2010). It is the result of dividing the share of a certain industry's employment in a cluster by its share in nationwide average. All clusters selected in the study had average location quotients higher than 1, which indicated they were strong clusters.

Table 5 Variable Descriptions

Variable Name	Explanation	Mean	SD	Min.	Max.
Dependent variable					
Exploratory knowledge creation	Number of new patent classes that appeared in a firm's IPC class list in each year but did not appeared in the list of previous 5 years' patent list	6.14	6.365	0	31
Explanatory variable					
Centrality	The number of alliance formed by a firm in each year during 2011-2014	6.63	5.869	1	35
Control variables					
Ownership structure	Dummy variable set to one if a firm is a publicly listed, and default = private firm	.70	.458	0	1
International experience	Dummy variable set to one if a firm has at least one alliance that is different from its origin country, and default = a firm has no international alliance	.90	.306	0	1
Firm age	The number of years from the time a firm was incorporated	25.09	28.843	0	164
Firm size	Natural log of number of employees	9.7029	1.7351	4.32	12.76
R&D intensity	Firm's R&D expense relative to its operating revenue	13.2608	9.3730	0	63.77
Industry classification	Dummy variable set to one if the NAICS 2012 Core code of a firm starts with 45, and default = firms with NAICS 2012 Core code that starts with 33	.0149	.12148	0	1

Table 5 (Continued)

Variable name	Explanation	Mean	SD	Min.	Max.
Industry classification	Dummy variable set to one if the NAICS 2012 Core code of a firm starts with 51, and default = firms with NAICS 2012 Core code that starts with 33	.0746	.26328	0	1
	Dummy variable set to one if the NAICS 2012 Core code of a firm starts with 53, and default = firms with NAICS 2012 Core code that starts with 33	.0149	.12148	0	1
	Dummy variable set to one if the NAICS 2012 Core code of a firm starts with 54, and default = firms with NAICS 2012 Core code that starts with 33	.1343	.34164	0	1
	Dummy variable set to one if the NAICS 2012 Core code of a firm starts with 56, and default = firms with NAICS 2012 Core code that starts with 33	.0149	.12148	0	1
	Dummy variable set to one if the NAICS 2012 Core code of a firm starts with 32, and default = firms with NAICS 2012 Core code that starts with 33	.0149	.12148	0	1
	Dummy variable set to one if the NAICS 2012 Core code of a firm starts with 52, and default = firms with NAICS 2012 Core code that starts with 33	.0149	.12148	0	1
	Dummy variable set to one if the NAICS 2012 Core code of a firm starts with 42, and default = firms with NAICS 2012 Core code that starts with 33	.0149	.12148	0	1
Cluster strength	The location quotients of IT clusters which the sample firms located in	2.8265	.86045	.97	3.45

Table 6 Correlation Matrix

	1	2	3	4	5	6	7	8
1. Exploratory knowledge creation								
2. Centrality	.313**							
3. Centrality^2	.236**	.924**						
4. Ownership structure	.234**	.178**	.142*					
5. International experience	.163*	.192**	.112	.204**				
6. Firm age	.236**	.211**	.132	.156*	.088			
7. Firm size	.346**	.373**	.309**	.217**	.089	.348**		
8. R&D intensity	-.321**	-.139	-.086	-.006	.165*	-.196**	-.391**	
9. Cluster strength	.167*	.239**	.186**	.398**	.300**	.152*	.194**	.178**

Notes: *p < 0.05; **p < 0.01. Correlations for industry classification and year dummies suppressed.

Table 7 Results of Linear Regression Analysis of Exploratory Knowledge Creation

Variable	Model 1	Model 2	Model 3
Constant	2.003 (5.236)	5.811 (5.209)	-13.517 (5.180)
Control variables			
Ownership Structure	.130 (1.168) **	.120 (1.136) *	.124 (1.130) **
International experience	.029 (3.955)	-.006 (3.897)	-.017 (3.895)
Firm age	.106 (.014)	.093 (.014)	.070 (.014)
Cluster strength	.013 (.592)	-.005 (.577)	-.007 (.584)
Firm size	.117 (.307)	.033 (.314)	.033 (.312)
R&D intensity	-.295 (.050) ***	-.287 (.049) ***	-.273 (.049) ***
Industry classification dummies included	Yes	Yes	Yes
Year dummies included	Yes	Yes	Yes
Explanatory variable			
Centrality		.230 (.074) ***	.509 (.187) ***
Centrality^2			-.291 (.007) *
Number of organizations	67	67	67
Number of observations	189	189	189
R^2	.308	.347	.355

Notes: standard errors are in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

Industrial classification and year dummy variables are included in the regressions but are not reported in the table.

4. Results

Table 5 presents the descriptive statistics of 216 observations included in the sample. Table 6 provides the correlations between the variables.

Table 7 reports the results of the linear regression analysis. Model 1 only includes all the control variables, and model 2 introduces the explanatory variable of the study. Model 3 includes both explanatory variable and its squared term to test the curvilinear relationship. No multicollinearity problem was observed because the variance inflation factor (VIF) for all variables in model 1, model 2 and model 3 were below ten.

Among the control variables, relationships between ownership structure and exploratory knowledge creation are significant. And the positive relationship indicates that compared with private firms, public firms have better performance in exploratory knowledge creation. This is aligned with the assumption that public firms are better at raising financial resources to engage in exploration activities. It should be noted that R&D intensity shows a negative relationship with dependent variable. The negative relationship might be caused by the fact that R&D intensity in this study was measured by the total expenditures relative to its total operating revenue, and exact proportions of internal R&D activities, such as investing in new labs and research centers, and external R&D efforts, such as technologic alliances, was not accessible in this case, and it was possible that internal R&D took the majority of investment thus the R&D intensity measure actually reflected the internal R&D level, which was assumed as more exploitation oriented than external knowledge creation activities rather than exploration (Lee & Lieberman, 2010).

the hypothesis of the study predicts that centrality has a curvilinear effect on exploratory knowledge creation. And the results support the hypothesis. In model 3 from table 7, the positive coefficient between centrality and exploratory knowledge creation, and negative coefficient for the squared term indicate a curvilinear relationship.

5. Discussion

The current study aimed at addressing the limitations of previous studies related to organizational learning and social networks. In the process of organizational learning, social network structures play different roles at different levels of organizations. Centrality, one of the most frequently researched structure features, has drown many attentions while raised many controversies at the same time. In the knowledge sharing process, centrality is viewed as positive factor, while in the process of knowledge creation, conflicted results have been observed across different levels of study (Tsai, 2001; McFadyen & Cannella, 2004; Rothaermel & Alexandre, 2009).

Possible explanation for these conflicts is that prior studies overlook the fact that innovation and knowledge creation include different types of activities and therefore need to align with different strategies and network structures. Exploratory knowledge creation entails searching for new information, and therefore it is assumed that engaging in more network ties is beneficial because network partners have knowledge that could be obtained by alliance formation activities, while on the contrary, exploitation activities target at increasing efficiency and refining the established knowledge stock, therefore increasing ties might not be an effective approach. Therefore, it is necessary to separate exploration and exploitation and test effects of social network structures on these two activities respectively.

This study addressed the limitation by building linkages between organizational learning, organizational ambidexterity, and network theories. And the effects of the cost of network ties were also noted and considered in the hypothesis, which predicted that centrality has a curvilinear relationship with exploratory knowledge creation.

The results drawn from 67 firms across several IT clusters are consistent with the hypothesis. With the increase in the number of alliance ties firms maintain, the return of exploratory knowledge creation first increase and then diminish, showing an inverted-U curve.

This study has both academic and managerial implications.

First, it contributes to the organizational learning literature. Organizational learning is a complex system that would benefit firms' performance. Prior research dedicated to the relationships between innovation and networks often manifests conflicts. One possible solution is to separate the innovation into different processes and study the interaction between learning behaviors and networks because knowledge creation, sharing, and retention call for different strategies and structures of networks. For instance, many prior studies focus on the social networks' knowledge sharing and information transmitting ability, and abundant empirical evidence has been produced to support the propositions that social network structures could affect knowledge sharing. Centrality has been well studied and basic consensus has been reached that it is beneficial for knowledge sharing.

While with regards to knowledge creation process, although social networks analysis has been proposed as a promising research direction in knowledge creation studies (Simsek, 2009; Argote & Miron-Spektor, 2011), empirical studies are rare, many aspects of the topic remain unresolved, and no consensus has been achieved whether it is universally true that more ties a firm has, the more successful the knowledge creation will be.

The conflicts of effects of centrality on knowledge creation exist for a long time, and many studies showed different conclusions on the topic at different study levels (Phelps et al., 2012). One reason is assumed as omission of differentiation between exploration and exploitation. Once these two types of activities are separated from each other, the observation should be more accurate and the effects are expected to be more specific. Even among the studies that differentiate the exploration and exploitation, samples of these studies vary in industry and firm types, and thus generate different results. There is no consensus whether the curvilinear relationship exist between network structures and different types of innovation and knowledge creation (e.g., Gilsing et al., 2008; Phelps, 2010).

This study analyzed the network structure of centrality at the interorganizational level, documented firm alliance formation activities and knowledge creation behaviors, and supported the proposition of curvilinear relationships between social networks and knowledge creation.

Second, this study used a carefully designed approach to capture the exploratory knowledge creation performance of firms from IT industry using updated firm information in high-tech and knowledge intensive industries (firms from different IT clusters across US) and different types of sample firms (both public firms and private firms). Prior studies mainly focus on publicly listed firms or MNCs, while private firms and SMEs are somewhat neglected (Gilsing et al., 2008; Phelps, 2010). In the current study, ownership structure, firm size, firm age, and international experience of the firms vary and the appropriate sample ensures the generalizability of the study. And the result of the study provides new empirical evidence for the topic, and advocate the proposition of effects of centrality on exploration.

Third, the result of the study contributes to organizational ambidexterity literature. One challenge in balancing exploitation and exploration is to access and integrate knowledge both within and outside organizational boundaries, the optimal strategies to take on this challenge are not clear (Raisch et al., 2009). In this study, alliances were viewed as an approach of external knowledge sources that could benefit the subsequent exploration, and the performance of exploration at different levels of alliance numbers was compared and analyzed, and the theoretical proposition addressed by OA scholars that a moderate level of network centrality is optimal, was tested and supported (Simsek, 2009).

This study also has managerial implication for organizational learning and innovation strategy. Firms could create knowledge in variety of approaches, for instance, internally, firms could invest more on research and development activities, and externally, acquisition is a direct and fast way to acquire and bring in knowledge that complementary to firms' current knowledge pool. Research suggested that acquisitions within primary business domain of a firm are adopted as exploitation enhancer, while outside the knowledge fields and distant from firms' current operating domains, acquisitions are more exploration oriented (Lee & Lieberman, 2010). This study considered another approach of forming technology alliance, and proved that technology alliances, as an alternative approach to create knowledge, affect the subsequent innovation and knowledge creation. Therefore, for managers of organizations that target at exploratory innovation, they could have a different choice when taking various factors such as costs, ownership structures, and knowledge diversity embedded in external knowledge sources into consideration because these features in alliances are generally different from those of acquisitions. Moreover, when engaging in alliance formation, managers will benefit from the principle that maintaining as many alliances as possible does not guarantee better knowledge creation performance, and that the optimum strategy is the moderate numbers of alliances.

It should be noted that this study has some limitations too.

The level of the current study is at interorganizational level, therefore, the research design only considered formal alliance formation activities, and did not incorporate any information of units' or individuals' interactions among alliances. It is assumed that with the number of alliance increase, the positive effects will diminish, but more specific information embedded in those alliances was not documented, such as informal relationships between firms (e.g., social ties between top management teams across firms), individuals' conflicts occurred in initial teamwork, costs of reconciling those conflicts, knowledge sharing behaviors, knowledge element contribution level in a patent by a certain alliance, and proportion of patent application activities that are purely inspired by alliances' knowledge (Phelps, 2010). Also, in the study, for the operationalization purpose, it was assumed that alliances firms formed were homogeneous and they all contribute to knowledge creation equally, while in reality this is often not true, firms usually have some preferences and emphases regarding cooperating with alliance partners. Thus, the effects proven in the study should be considered as tentative because further alliance interaction evidence needs to be collected to justify the causal relationship (Schilling, 2015).

Two possible future research direction could help to address this limitation. First, cross-level studies, which collect data from multiple sources and levels in organizations, could compare activities in alliances including cognitive changes, such as trust building and conflicts, and cooperation between members or units, and thus open the black box of relationship between alliance networks and knowledge creation. Second, a few recent empirical studies suggest that knowledge elements, indicated by patent classes or industrial classifications, related to each other, and could be mapped out as knowledge networks, where nodes of networks are classes that patents belong to, and ties are appearance of two or more classes in one patent. And knowledge networks and collaboration networks (e.g., alliances) are distinct and affect innovation in different ways (Wang et al., 2014; Guan & Liu, 2016). By mapping out the knowledge networks and comparing knowledge networks at multiple levels of actors involved in knowledge creation activities, for instance alliances, units, and individuals, might shed light on actual knowledge contribution of alliances and bring the possibility of uncovering the causal relationships between networks and knowledge creation.

The second limitation of the study is the approach of using patent to generate dependent variable of the study. Knowledge has different properties and features, and it can be categorized as explicit or tacit, and different ties and networks are used to cope with different knowledge properties (Kogut & Zander, 1992; Hansen, 1999; Reagans & McEvily, 2003). In this study, the prediction is that alliances affect subsequent knowledge creation, it is logic to assume that firms draw knowledge elements from alliances and integrate it in exploratory knowledge products, i.e., patents. While patent application indicates the proportion of knowledge that could be codified during the knowledge sharing in the process, it is also possible that exploration efforts of certain knowledge is not represented in patents, for instance concerns of business confidentiality, knowledge leak and spill-over or tacit knowledge that is difficult to assign to patent system (Phelps, 2010; Schilling, 2015).

One possible solution is to combine quantitative measures of learning such as patents with cognitive measures before and after alliance formation (McGrath, 2001). This would entail complementary qualitative study with precise targeting study samples such as departments involved directly in alliances, which could be another promising future direction.

The other limitation of the study is the construction of the explanatory variable. This study follows the proposition provided by McFadyen and Cannella (2004) that knowledge creation is promoted mainly by direct interactions, therefore direct ties are crucial in this process, i.e., the degree centrality should be taken into consideration when studying knowledge creation. However, the fact that degree centrality plays crucial role by no means suggests that other network position indexes have no effect on knowledge creation. For instance, to create knowledge, firms need to gather useful information from multiple sources, and sometimes these sources are located further than one step length in the networks, to gain inspiration of knowledge creation, especially exploratory knowledge creation in high-tech industry, exploring further than immediate ties might be necessary. And in that case, other types of centrality indexes, such as closeness centrality, play certain roles in knowledge creation. To solve this limitation, future study could also incorporate different types of measurements of centrality and test their effects.

6. Conclusion

Knowledge creation process in organizational learning is important for organizations that seek sustained competitive advantages. Social networks have been proven to affect knowledge creation in various ways, among which many claims and propositions are conflicted with each other. It is suspected in this study that knowledge creation is not a unidimensional activity, instead, it includes two types of efforts: exploration and exploitation.

By testing alliance formation activities and patent application behaviors of firms in IT clusters in US, this study empirically prove that network centrality and exploratory knowledge creation have a curvilinear relationship. The results of the study contribute to organizational learning literature and social network academic body by shedding light on controversy of the topic, and provide managerial implication in innovation strategies. The limitations of the current study could be resolved by cross-level studies that incorporate more specific information of interactions of alliances members and knowledge networks of innovation products.

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Appendix 1

Lists of sample firms in the study

Company name	Date of incorporation	State or province (in US or Canada)	Country	Major sector	NAICS 2012 Core code
3M COMPANY	25/06/1929	MN	United States of America	Chemicals, rubber, plastics, non-metallic products	3279
ADVANCED MICRO DEVICES INC	01/05/1969	CA	United States of America	Machinery, equipment, furniture, recycling	3344
AGILENT TECHNOLOGIES INC	04/05/1999	CA	United States of America	Machinery, equipment, furniture, recycling	3345
ALTERA CORP	25/03/1997	CA	United States of America	Machinery, equipment, furniture, recycling	3344
AMERICAN SUPERCONDUCTOR CORP	1987	MA	United States of America	Machinery, equipment, furniture, recycling	3353
APPLE INC.	03/01/1977	CA	United States of America	Machinery, equipment, furniture, recycling	3341
APPLIED MATERIALS INC	18/03/1987	CA	United States of America	Machinery, equipment, furniture, recycling	3332
ARINC INC.	01/01/2013	MD	United States of America	Machinery, equipment, furniture, recycling	3364
ASUSTEK COMPUTER INCORPORATION	1990		Taiwan, China	Machinery, equipment, furniture, recycling	3341
AT&T INC.	05/10/1983	TX	United States of America	Post & telecommunications	5171
ATLATL SOFTWARE	2012	OR	United States	Publishing, printing	3346

			of America		
ATMEL CORP	04/03/1999	CA	United States of America	Machinery, equipment, furniture, recycling	3344
AVAYA INC	19/05/2000	CA	United States of America	Machinery, equipment, furniture, recycling	3342
BAE SYSTEMS PLC	31/12/1979		United Kingdom	Machinery, equipment, furniture, recycling	3364
BROCADE COMMUNICATIONS SYSTEMS INC	11/02/1999	CA	United States of America	Publishing, printing	3346
CHERWELL SOFTWARE INC	2004	CO	United States of America	Other services	5415
CISCO SYSTEMS INC	10/12/1984	CA	United States of America	Machinery, equipment, furniture, recycling	3342
DELL, INC.	22/10/1987	TX	United States of America	Machinery, equipment, furniture, recycling	3341
DYNETICS INC	1974	AL	United States of America	Other services	5417
EBAY INC	13/03/1998	CA	United States of America	Wholesale & retail trade	4539
EMC CORP	23/08/1979	MA	United States of America	Machinery, equipment, furniture, recycling	3341
FACEBOOK, INC.	29/07/2004	CA	United States of America	Other services	5191
FAIRCHILD SEMICONDUCTOR INTERNATIONAL INC	10/03/1997	CA	United States of America	Machinery, equipment, furniture, recycling	3344
FLEXTRONICS LTD.	05/1990		Singapore	Machinery, equipment, furniture, recycling	3344
FREESCALE SEMICONDUCTOR,	03/12/2003	TX	United States of America	Machinery, equipment, furniture, recycling	3344

INC.					
FRONTRANGE SOLUTIONS USA	1988	CO	United States of America	Publishing, printing	3346
FUJITSU LIMITED	1935		Japan	Machinery, equipment, furniture, recycling	3341
GOOGLE INC.	23/07/2015	CA	United States of America	Other services	5191
HITACHI DATA SYSTEMS CORP	1989	CA	United States of America	Wholesale & retail trade	4236
HONEYWELL INTERNATIONAL INC	24/11/1999	NJ	United States of America	Machinery, equipment, furniture, recycling	3363
HP INC.	11/02/1998	CA	United States of America	Machinery, equipment, furniture, recycling	3341
INTERNATIONAL BUSINESS MACHINES CORP	16/06/1911	NY	United States of America	Other services	5415
ICF INTERNATIONAL, INC.	18/04/2006	VA	United States of America	Other services	5416
INTEL CORP	01/03/1989	CA	United States of America	Machinery, equipment, furniture, recycling	3344
INTUIT INC	01/02/1993	CA	United States of America	Publishing, printing	3346
JUNIPER NETWORKS INC	10/09/1997	CA	United States of America	Machinery, equipment, furniture, recycling	3342
KLA TENCOR CORP	09/07/1975	CA	United States of America	Machinery, equipment, furniture, recycling	3344
LEVEL 3 COMMUNICATIONS, INC.	10/12/1985	CO	United States of America	Post & telecommunications	5171

LEXMARK INTERNATIONAL INC	25/05/1990	KY	United States of America	Machinery, equipment, furniture, recycling	3341
LSI CORPORATION	05/12/1986	CA	United States of America	Machinery, equipment, furniture, recycling	3344
MARVELL TECHNOLOGY GROUP LTD	11/01/1995		Bermuda	Machinery, equipment, furniture, recycling	3344
MAXIM INTEGRATED PRODUCTS INC	19/08/1987	CA	United States of America	Machinery, equipment, furniture, recycling	3344
MICROSOFT CORP.	22/09/1993	WA	United States of America	Publishing, printing	3346
NATIONAL INSTRUMENTS CORP	03/05/1994	TX	United States of America	Publishing, printing	3346
NETAPP, INC.	01/11/2001	CA	United States of America	Machinery, equipment, furniture, recycling	3341
NETFLIX, INC.	29/08/1997	CA	United States of America	Other services	5322
NOKIA OYJ	1865		Finland	Machinery, equipment, furniture, recycling	3342
NVIDIA CORP	24/02/1998	CA	United States of America	Machinery, equipment, furniture, recycling	3344
NXP SEMICONDUCTORS N.V.	2006		Netherlands	Machinery, equipment, furniture, recycling	3344
OPERA SOFTWARE ASA	2004		Norway	Other services	5415
ORACLE CORP	09/09/2005	CA	United States of America	Publishing, printing	3346
QUANTA	09/05/1988		Taiwan,	Machinery, equipment,	3341

COMPUTER INC.			China	furniture, recycling	
RED HAT INC	17/09/1998	NC	United States of America	Publishing, printing	3346
SAIC	01/02/2013	VA	United States of America	Other services	5415
SAMSUNG ELECTRONICS CO., LTD.	13/01/1969		Republic of Korea	Machinery, equipment, furniture, recycling	3344
SIEMENS AG	1847		Germany	Machinery, equipment, furniture, recycling	3345
SONY MOBILE COMMUNICATIONS AB	09/2001		Sweden	Other services	5417
SYMANTEC CORP	19/04/1988	CA	United States of America	Publishing, printing	3346
TIBCO SOFTWARE INC	13/11/1996	CA	United States of America	Publishing, printing	3346
VMWARE, INC.	10/02/1998	CA	United States of America	Publishing, printing	3346
WESTERN DIGITAL CORP	26/10/2000	CA	United States of America	Machinery, equipment, furniture, recycling	3341
XILINX INC	05/02/1990	CA	United States of America	Machinery, equipment, furniture, recycling	3344
YAHOO INC	1995	CA	United States of America	Other services	5415
ZEBRA IMAGING INC	1996	TX	United States of America	Other services	5614
ZYNGA INC.	26/10/2007	CA	United States of America	Other services	5182
Mitre Corporation	1958	VA	United States of America	Other services	5417

OptumInsight	1993	MN	United States of America	Other services	5241

Appendix 2

Information Technology and Analytical Instruments Clusters

	Major sub-regions in cluster	Specialization (by year)			
		2011	2012	2013	2014
San Jose	Santa Clara County, CA Alameda County, CA San Francisco County, CA San Mateo County, CA Contra Costa County, CA San Joaquin County, CA Sonoma County, CA Stanislaus County, CA Solano County, CA Monterey County, CA	3.42	3.45	3.41	3.37
Austin	Travis County, TX Williamson County, TX Hays County, TX Bastrop County, TX Burnet County, TX Caldwell County, TX Lee County, TX Milam County, TX Llano County, TX Blanco County, TX	2.96	2.82	3.08	3.33
Charleston	Charleston County, SC Berkeley County, SC Dorchester County, SC Colleton County, SC	0.96	1.02	0.99	1.29
Colorado Springs	El Paso County, CO	1.95	1.93	1.92	1.98

	Fremont County, CO Teller County, CO Kit Carson County, CO Lincoln County, CO Cheyenne County, CO Custer County, CO				
Denver	Denver County, CO Arapahoe County, CO Jefferson County, CO Adams County, CO Boulder County, CO Larimer County, CO Douglas County, CO Weld County, CO Mesa County, CO Broomfield County, CO	1.27	1.14	0.99	1.03
Madison	Dane County, WI Rock County, WI Dubuque County, IA Sauk County, WI Columbia County, WI Grant County, WI Green County, WI Iowa County, WI Jo Daviess County, IL Juneau County, WI	2.32	2.07	2.09	2.17

Appendix 3

Examples of generating the dependent variable of a firm in year 2012 and 2013

First, document the patent classes from 2007 to 2013

Title	Application Date	Assignee/Applicant	IPC Current Full (4 Characters)
Universal data storage system that maintains data across one or more specialized data stores	2013-12-12	Netflix Inc.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	G06F
PREDICTIVE AUTO SCALING ENGINE	2013-10-18	Netflix Inc.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	G06N, H04L
CONFIGURING DNS CLIENTS	2013-09-16	Netflix Inc.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	H04L
Key generation and broadcasting	2013-08-16	NETFLIX INC.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	H04L
DYNAMIC SECURITY TESTING	2013-08-05	Netflix Inc.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	G06F
Media content rankings for discovery of novel content	2013-07-30	Netflix Inc.,Los Gatos,CA,US | NETFLIX.COM INC.,Los Gatos,CA,US	G06F
Progressive deployment and termination of canary instances for software analysis	2013-06-25	NETFLIX INC.,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	G06F, H04L
TARGETED PROMOTION OF ORIGINAL TITLES	2013-06-12	NETFLIX Inc.,Los Gatos,CA,US	H04N
STRATIFIED SAMPLING APPLIED TO A/B TESTS	2013-03-15	NETFLIX INC.,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	G06Q
CACHED EVALUATION OF PATHS THROUGH GRAPH-BASED DATA REPRESENTATION	2013-09-19	NETFLIX INC.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	G06F
EVALUATION OF PATHS THROUGH GRAPH-BASED DATA	2013-09-19	NETFLIX INC.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	H04L

REPRESENTATION			
GENERATION OF PATHS THROUGH GRAPH-BASED DATA REPRESENTATION	2013-09-19	NETFLIX INC.,Los Gatos,CA,US | NETFLIX INC,Los Gatos,CA,US	H04L
Personalized markov chains	2013-03-14	Netflix Inc.,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	G06F, G06N
CRITICAL SYSTEMS INSPECTOR	2013-03-14	NETFLIX INC.,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	G06F
Long term metrics applied to multivariate testing	2013-03-13	NETFLIX Inc.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	G06F, H04L
SEARCHES AND RECOMMENDATIONS USING DISTANCE METRIC ON SPACE OF MEDIA TITLES	2013-03-13	NETFLIX INC.,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	G06F
USING CANARY INSTANCES FOR SOFTWARE ANALYSIS	2013-03-12	NETFLIX INC.,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	G06F
ADAPTIVE ROW SELECTION	2013-01-21	NETFLIX INC.,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	G06F
Site-based server selection	2013-01-07	Netflix Inc.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	G06F, H04L
Proxy application with dynamic filter updating	2013-01-04	Netfilx Inc.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	G06F, H04L
Managing content on an ISP cache	2012-12-10	NETFLIX INC.,Los Gatos,CA,US | NETFLIX Inc,Los Gatos,CA,US	G06F, G06Q, H04L, H04N
Multi-CDN digital content streaming	2012-11-21	NETFLIX INC.,Los Gatos,CA,US | Netflix Inc.,Los Gatos,CA,US	G06F, H04L
PARTITIONING STREAMING MEDIA FILES ON MULTIPLE CONTENT DISTRIBUTION NETWORKS	2012-10-17	NETFLIX INC,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	G06F
SYSTEM AND METHOD FOR MANAGING	2012-10-11	NETFLIX INC.,Los Gatos,CA,US |	G06F

PLAYBACK OF STREAMING DIGITAL CONTENT		NETFLIX INC.,Los Gatos,CA,US	
RELATIONSHIP-BASED SEARCH AND RECOMMENDATIONS	2012-10-04	NETFLIX INC.,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	G06F
SECURITY CREDENTIAL DEPLOYMENT IN CLOUD ENVIRONMENT	2012-09-14	NETFLIX INC.,Los Gatos,CA,US | Zarfoss III James R.,Los Gatos,CA,US | Yuan Yong,Los Gatos,CA,US	H04L, G06F
SPECULATIVE PRE-AUTHORIZATION OF ENCRYPTED DATA STREAMS	2013-03-15	NETFLIX INC,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	H04L
System and method for detecting active streams using a heartbeat and secure stop mechanism	2012-07-13	Netflix Inc.,Los Gatos,CA,US | Zollinger James Mitch,San Jose,CA,US | Pitt Julie Amundson,Livermore,CA,US	H04L
Application Discovery	2013-03-14	NETFLIX INC.,Los Gatos,CA,US | NETFLIX INC.,Los Gatos,CA,US	H04L
API PLATFORM THAT INCLUDES SERVER-EXECUTED CLIENT-BASED CODE	2013-05-09	NETFLIX Inc.,Los Gatos,CA,US | NETFLIX Inc.,Los Gatos,CA,US	H04L
UPSTREAM FAULT DETECTION	2012-04-19	NETFLIX INC.,Los Gatos,CA,US | ORZELL Gregory S.,San Francisco,CA,US | FUNGE John,Sunnyvale,CA,US | CHEN David,San Francisco,CA,US	G06F
Upstream fault detection	2012-04-19	Netflix Inc.,Los Gatos,CA,US | Orzell Gregory S.,San Francisco,CA,US | Funge John,Sunnyvale,CA,US | Chen David,San Francisco,CA,US	G06F
Method and system for improving security and reliability in a networked application environment	2012-04-12	Netflix Inc.,Los Gatos,CA,US | Tseitlin Ariel,Sunnyvale,CA,US | Rapoport Roy,Pacifica,CA,US | Chan Jason,Campbell,CA,US	H04L, G06F
Method and system for reclaiming unused resources in a networked application	2012-04-12	Netflix Inc.,Los Gatos,CA,US | Tseitlin Ariel,Sunnyvale,CA,US |	G06F, H04L

environment		Sadhu Praveen,Sunnyvale,CA,US	
Method and system for evaluating the resiliency of a distributed computing service by inducing a latency	2012-04-12	Netflix Inc.,Los Gatos,CA,US | Tseitlin Ariel,Sunnyvale,CA,US | Sadhu Praveen,Sunnyvale,CA,US | Tonse Sudhir,Fremont,CA,US | Kamath Pradeep,Sunnyvale,CA,US	G06F
Verifying authenticity of playback device	2012-01-06	Netflix Inc.,Los Gatos,CA,US | Zollinger Mitch,San Jose,CA,US | Paun Filip,Menlo Park,CA,US | Kelly Scott G.,Santa Clara,CA,US	H04L
Web server constraint support	2011-12-16	NETFLIX Inc.,Los Gatos,CA,US | Funge John,Sunnyvale,CA,US | Watson Mark,San Francisco,CA,US	G06F, H04L
MEASURING USER QUALITY OF EXPERIENCE FOR A STREAMING MEDIA SERVICE	2011-12-16	NETFLIX INC.,Los Gatos,CA,US | FUNGE John,Sunnyvale,CA,US | WATSON Mark,San Francisco,CA,US | WEI Wei,Fremont,CA,US | CHEN David,San Francisco,CA,US	G06F
STARTUP TIMES OF STREAMING DIGITAL MEDIA PLAYBACK	2011-12-14	NETFLIX CORPORATION,Los Gatos,CA,US | KAISER Christian,San Jose,CA,US | WHITE Jean-Marie,San Jose,CA,US | LAI Yung-Hsiao,Fremont,CA,US	G06F
Internationalization with virtual staging and versioning	2011-08-26	Netflix Inc.,Los Gatos,CA,US | Hunt Neil D.,Los Altos,CA,US | Betz Stephan G.,Soquel,CA,US	G06F
System and method for obfuscation initiation values of a cryptography protocol	2011-07-22	Netflix Inc,Los Gatos,CA,US | Zollinger Mitch,San Jose,CA,US | Paun Filip,Menlo Park,CA,US	H04L
Audio and video streaming for media effects	2011-05-02	Netflix Inc.,Los Gatos,CA,US | Hunt Neil D.,Los Altos,CA,US | Kaiser Christian,San Jose,CA,US	H04N
L-cut stream startup	2011-05-02	Netflix Inc.,Los Gatos,CA,US | Hunt Neil D.,Los Altos,CA,US | Kaiser Christian,San Jose,CA,US	H04N
Recommending digital content based on implicit user identification	2011-04-05	Netflix Inc.,Los Gatos,CA,US | Krishnamurthy Satish Kumar,Los Gatos,CA,US | Funge John,Sunnyvale,CA,US | Hunt Neil D.,Los Altos,CA,US | Yellin Todd	G06F, G06Q

		Scot,Los Gatos,CA,US | Sanders Jonathan Michael,Los Gatos,CA,US	
Content playback APIS using encrypted streams	2011-03-04	Netflix Inc.,Los Gatos,CA,US | Zollinger James Mitch,San Jose,CA,US | Lai Yung-Hsiao,Fremont,CA,US | Park Anthony Neal,San Jose,CA,US | Ronca David Randall,Campbell,CA,US | Kelly Scott Gregory,Santa Clara,CA,US	H04L
Test environment for audio/video playback	2011-02-08	Netflix Inc.,Los Gatos,CA,US | Jiang Ming,Santa Clara,CA,US | Tham Jao,Santa Clara,CA,US | Chitnis Devraj,San Jose,CA,US | Kotwal Gautam,Sunnyvale,CA,US	G06F
Insertion points for streaming video autoplay	2011-01-27	Netflix Inc.,Los Gatos,CA,US | Yellin Todd Scot,Los Gatos,CA,US | Hastings Michael Thomas,San Francisco,CA,US | Purnell-Fisher Thomas,Los Gatos,CA,US | Peters Greg,San Francisco,CA,US	H04N
Variable bit video streams for adaptive streaming	2011-01-21	Netflix Inc.,Los Gatos,CA,US | Hunt Neil D.,Los Altos,CA,US	H04N
Parallel streaming	2013-02-26	NETFLIX Inc.,Los Gatos,CA,US | NETFLIX Inc.,Los Gatos,CA,US	G06F, H04L
Bit rate stream switching	2012-07-05	Netflix Inc.,Los Gatos,CA,US | Wu Chung-Ping,Sunnyvale,CA,US | Kaiser Christian,San Jose,CA,US | Lai Yung-Hsiao,Fremont,CA,US | Zollinger James Mitch,San Jose,CA,US | Ronca David Randall,Campbell,CA,US	H04N, H04L
Parallel video encoding based on complexity analysis	2010-12-10	Netflix Inc.,Los Gatos,CA,US | Ronca David R.,Campbell,CA,US | Kang Steven,Los Angeles,CA,US | Kalluri Rama,Cupertino,CA,US | Katsavounidis Ioannis,Los Angeles,CA,US	H04N
Pre-buffering audio streams	2010-12-09	Netflix Inc.,Los Gatos,CA,US | Funge John,Sunnyvale,CA,US | Peters Greg,San Francisco,CA,US	H04N, H04L

User interface for a remote control device	2010-12-06	Netflix Inc.,Los Gatos,CA,US | Hunt Neil D.,Los Altos,CA,US	G06F, H04N
Variable bit video streams for adaptive streaming	2010-12-06	Netflix Inc.,Los Gatos,CA,US | Hunt Neil D.,Los Altos,CA,US	H04N
Recommending groups of items based on item ranks	2010-10-14	Netflix Inc.,Los Gatos,CA,US | Ciancutti John,Portola Valley,CA,US | Sanders Jonathan Michael,Los Gatos,CA,US | Hunt Neil D.,Los Altos,CA,US | Yellin Todd Scot,Los Gatos,CA,US	G06F
Interest based row selection	2010-06-08	Netflix Inc,Los Gatos,CA,US | Sanders Jonathan Michael,Los Gatos,CA,US	G06F
Dynamic virtual chunking of streaming media content	2010-04-02	Netflix Inc.,Los Gatos,CA,US | Ronca David R.,Campbell,CA,US | Neuenhofen Kay,San Francisco,CA,US | Zollinger James M.,San Jose,CA,US	G06F, H04N
Parallel streaming	2010-03-12	Netflix Inc.,Los Gatos,CA,US | Park Anthony N.,San Jose,CA,US | Hunt Neil D.,Los Altos,CA,US | Wei Wei,Fremont,CA,US	G06F
Data synchronization between a data center environment and a cloud computing environment	2010-02-22	Netflix Inc.,Los Gatos,CA,US	G06F
Client-server signaling in content distribution networks	2010-01-22	Netflix Inc.,Los Gatos,CA,US | Hunt Neil D.,Los Altos,CA,US	G06F
Dynamic randomized controlled testing with consumer electronics devices	2010-01-18	Netflix Inc.,Los Gatos,CA,US | Hunt Neil,Los Altos,CA,US	G06F
Accelerated playback of streaming media	2009-09-09	Netflix Inc.,Los Gatos,CA,US | Chen Eli,San Mateo,CA,US | Peters Greg,San Francisco,CA,US	H04N, H04L
Encoding video streams for adaptive video streaming	2009-08-18	Netflix Inc.,Los Gatos,CA,US	H04N, H04L
Adaptive streaming for digital content distribution	2009-07-24	Netflix Inc.,Los Gatos,CA,US | Park Anthony Neal,San Jose,CA,US | Wei Wei,Fremont,CA,US	H04N

Digital content distribution system and method	2009-07-16	NETFLIX Inc.,Los Gatos,CA,US | Park Anthony Neal,San Jose,CA,US | Hunt Neil D.,Los Altos,CA,US | Wei Wei,Fremont,CA,US	G06F
Activating streaming video in a blu-ray disc player	2009-04-13	Netflix Inc.,Los Gatos,CA,US	H04L
Bit rate stream switching	2009-12-18	NETFLIX INC.,Los Gatos,CA,US | Wu Chung-Ping,Sunnyvale,CA,US | Kaiser Christian,San Jose,CA,US | Lai Yung-Hsiao,Fremont,CA,US | Zollinger James Mitch,San Jose,CA,US | Ronca David Randall,Campbell,CA,US	H04N
On-device multiplexing of streaming media content	2009-12-18	Netflix Inc.,Los Gatos,CA,US | Ronca David Randall,Campbell,CA,US | Wu Chung-Ping,Sunnyvale,CA,US | Lai Yung-Hsiao,Fremont,CA,US	G06F, H04N
Trick play of streaming media	2008-09-05	NETFLIX Inc.,Los Gatos,CA,US	H04N
Processing returned rental items	2008-01-30	Netflix Inc.,Los Gatos,CA,US	G06Q
Rental inventory management	2007-07-06	Netflix Inc.,Los Gatos,CA,US | Rendich Andrew,San Ramon,CA,US | Hunt Neil D.,Mountain View,CA,US | Hastings Reed,Santa Cruz,CA,US	G06Q
User interface and pointing device for a consumer electronics device	2007-03-08	Netflix Inc.,Los Gatos,CA,US | Hastings W. Reed,Santa Cruz,CA,US | Hunt Neil D.,Mountain View,CA,US	G05B
Method of sharing an item rental account	2009-09-14	Netflix Inc.,Los Gatos,CA,US	H04N, G06F, G06K
Approach for estimating user ratings of items	2009-09-18	Netflix Inc.,Los Gatos,CA,US	G06Q

For the dependent variable in 2012:

Step 1 Document the patent classes in 2007-2011

Step 2 Document the patent classes in 2012

Step 3 Compare the IPC number list from step 1 and step 2

IPC 2007-2011	IPC 2012	Comparison
G06F	G06F	Old
H04L	G06Q	Old
H04N	H04L	Old
G06Q	H04N	Old
G05B		
G06K		

No new class appeared in list of the year 2012, therefore, the exploratory knowledge creation in 2012 is measured as 0.

For the dependent variable in 2013:

Step 1 Document the patent classes in 2008-2012

Step 2 Document the patent classes in 2013

Step 3 Compare the IPC number list from step 1 and step 2

IPC 2008-2012	IPC 2013	Comparison
G06Q	G06F	Old
H04N	G06N	New
H04L	H04L	Old
G06F	H04N	Old
G06K	G06Q	Old

The class G06N appeared in list of the year 2013 but did not appear in list of 2008-2012, therefore, the exploratory knowledge creation in 2013 is measured as 1.

Appendix 4

Example of generating the explanatory variable

<table>
<tr><td colspan="2">Alliance</td><td>Date</td></tr>
<tr><td>Intel</td><td>Luxottica Group</td><td>12/03/2014</td></tr>
<tr><td colspan="3">Supporting sources:
https://newsroom.intel.com/news-releases/intel-and-luxottica-group-announce-multiyear-collaboration-for-wearable-tech/
http://www.luxottica.com/en/intel-and-luxottica-group-announce-multiyear-collaboration-wearable-tech
http://www.wsj.com/articles/intel-to-make-smart-eyewear-with-luxottica-1417613001</td></tr>
<tr><td colspan="2">Alliance</td><td>Date</td></tr>
<tr><td>Intel</td><td>Toyota Motor Corporation</td><td>11/ 9/ 2011</td></tr>
<tr><td colspan="3">Supporting sources:
https://newsroom.intel.com/news-releases/intel-toyota-drive-joint-research-on-next-generation-in-vehicle-infotainment-systems/
http://www2.toyota.co.jp/en/news/11/11/1110.html</td></tr>
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