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The role of partner diversity in collaborative knowledge creation –A study in the Victorian biotechnology industry

Adel Moslehi
Monash University, Adel.Moslehi@monash.edu

Henry Linger
Monash University, Henry.Linger@monash.edu

Kerry Tanner
Monash University, Kerry.Tanner@monash.edu

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The role of exploration/exploitation knowledge process in collaborative knowledge creation

Adel Moslehi, Adel.Moslehi@monash.edu
Henry Linger, Henry.Linger@monash.edu
Kerry Tanner, Kerry.Tanner@monash.edu
Monash University, Faculty of Information Technology

Abstract

There is increasing research on knowledge networks as sources to acquire and access knowledge. While this literature mainly has focused on the contribution of network structure characteristics, existing reviews show that the current literature has produced seemingly contradictory results and a growing body of research highlights the need for contingency approaches. Based on a thorough literature review, this research focused on knowledge process as one of the contingencies; this has also been considered as a measure for the knowledge exploration process. Hence two hypotheses were formulated and tested by studying the patent co-authorship networks of biotechnology firms in Victoria, Australia. Using social network analysis and moderated multiple regressions, our research positively confirmed the relationship between knowledge processes and network structure. Also based on the interaction analysis, two interesting inter-relations are discussed. Finally the implications of the findings and the potential to contribute to understanding prior contradictory results are discussed.

Keywords

Knowledge networks, exploration, exploitation, social network analysis

INTRODUCTION

In a rapidly changing era, organizations need to create knowledge to be innovative in order to survive. Some scholars like Gupta (2006), have considered knowledge to be the very raison d'être of inter-organizational partnerships. Inter-organizational partnerships consist of networks of relationships which can be used as means of knowledge creation. These networks as sources to acquire and access knowledge have been called knowledge networks (k-networks) (Cross, Parker and Borgatti 2002; Kane and Alavi 2008). These networks operate in every organization and are not limited to network-type organizations, matrix organizations, or team-based organizations (Allee 2000). These networks also can be classified as internal and external (Birkinshaw and Hagstrom 2000, cited by Škerlavaj, Song and Lee (2010)). External or inter-organizational k-networks comprise relationships that a firm has with its customers, suppliers, peers and other external stakeholders (Škerlavaj et al. 2010). A k-network includes individuals and collections of individuals, such as groups, departments, organizations, and agencies.

Our review of the research highlights how different theories, level of analysis, and themes produce seemingly contradictory results (as reported by Phelps, Heidl and Wadhwa (2012) in terms of the network characteristics that are relevant to knowledge creation. One of these constructs is knowledge process. Given that organizational knowledge is mainly communicated and created through collaboration with partners within k-networks, studying partner diversity as an aspect of the process of knowledge creation in the inter-organizational k-network is of interest. To explain the relations between k-network structure and knowledge creation, our research explores the question of how the interaction of knowledge process and k-network structure contributes to knowledge creation in knowledge-based industries. To address gaps in the literature, our study has identified knowledge process as a mediating factor that can contribute to understanding the contradictory results of the existing literature.

The rest of the paper is structured as follows. First we position of our research within the k-network literature by clarifying the dimensions of this research, which leads to the literature review and also the proposed hypothesis about the role of knowledge process on knowledge creation. Next, the Australian biotechnology industry as the setting of the research is introduced and then social network analysis (SNA) and moderated multiple regressions (MMR) as the research approach is described. Finally the results are presented and discussed, followed by the conclusion.

SELECTED NETWORK THEORIES FROM THE K-NETWORK PERSPECTIVE

Given the two main streams of social capital research reviewed by Borgatti and Foster (2003), in this section the main theories on social capital are discussed, from the k-network perspective. We argue that these theories have produced conflicting results and that there is a need for research that goes beyond these categories.

Network position research: The research on effects of network position on knowledge creation mainly considers central position as a positive factor for knowledge creation (Ahuja 2000; Baum, Calabrese and Silverman 2000; Soh, Mahmood and Mitchell 2004). However, there are other studies that show central position may have a weak positive influence (Stuart 2000; Whittington, Owen-Smith and Powell 2009) or even no influence on knowledge creation among biotechnology firms (Owen-Smith and Powell 2004). To explain these conflicting results, some scholars discussed contingent factors including depth and diversity of knowledge (Wadhwa and Kotha 2006; Rothaermel and Alexandre 2009) and partner diversity (Baum et al. 2000).

Closed network vs. sparse network research: The main related concept in this perspective of network research is density, which is addressed in several ways. One is the concept of ego density or network efficiency (Borgatti, Everett and Freeman 2002; Rodan and Galunic 2004) which, given the level of analysis and the theme discussed before, is of interest in this research. Having a dense or sparse ego network has its own merits and flaws. In an inter-organizational context, weak ties serve as a bridge to new opportunities, connecting firms separated by a structural hole which otherwise would not be accessible to each other (Tiwana 2008; Operti and Carnabuci 2011; McEvily, Jaffee and Tortoriello 2012). On the other hand, other studies highlighted the role of dense ego-networks of a firm on its knowledge creation, knowledge integration, and adoption of new ideas (Soh 2003; Schilling and Phelps 2007; Yu, Gilbert and Oviatt 2011). To solve the seemingly contradictory effects, again a contingency approach was proposed and partner diversity (Beckman and Haunschild 2002) was discussed in this literature.

THEORETICAL CONSTRUCTS AND THE RESEARCH HYPOTHESES

This research reviewed the literature on both streams of social capital research. From this analysis knowledge process seemed important to explain knowledge creation within k-networks. In fact, several contingent factors were found in our literature review. This paper, however, has focused on the role of process as one of the important constructs mentioned in previous k-networks research.

In network research, surprisingly there are few studies that have been focused on the role of process, although the importance of the concept has been emphasized (e.g. Tiwana 2008). Likewise, there are very few examples in previous empirical studies in k-network research, particularly at the inter-organizational level that have focused on the knowledge process of the network (Table 1).

Table 1 Research on content of inter-organizational k-networks in two main streams of social network research

Construct	Network position research	Sparse vs. Closed network research
Process	Negative role of reliance on partners’ knowledge (Wadhwa and Kotha 2006; Rothaermel and Alexandre 2009), partner diversity (Baum et al. 2000)	partner diversity (Beckman and Haunschild 2002), Types of Partner (Vasudeva, Zaheer and Hernandez 2012), quality of partner (Demirkan and Demirkan 2012)

In Table 1, the second row shows partner diversity as a contingent factor in both streams of k-network research. By introducing the theoretical background of this construct from two different perspectives, we explain why we have dubbed this row as “knowledge process”.

Partner diversity as an attribute of networks

Role theory (Gross, Mason and McEachern 1958) as a broad school of thought in social science, is used to theorize the way that different actors behave in social networks (Tichy, Tushman and Fombrun 1979). Tichy et al. (1979) defined several possible roles that a firm may play, and mentioned that these roles are highly reliant on whom the firm is linked to. From this perspective, the critical role of partner and partnership become important to the extent that all the network has to offer comes through such partnerships. From the network partner perspective in inter-organizational k-network research, which sometimes is called the nodal perspective (Phelps et al., 2012), there are some studies that have highlighted the role of partners on the performance of firms (Still and Strang 2009; Demirkan, Deeds and Demirkan 2012).

However, among all these aspects of partners, only diversity of partners is represented in both streams of network position research and sparse vs. closed network research (Baum et al. 2000; Beckman and Haunschild 2002; Wadhwa and Kotha 2006; Rothaermel and Alexandre 2009; Vasudeva et al. 2012). These studies highlighted the role of partner diversity, albeit implicitly. In network position research, Baum et al. (2000) concluded that having a central position in a k-network, can create inefficient configurations which not only may return “less diverse information and capabilities for greater cost than a smaller non-redundant set” (p: 274), but may also prevent a firm from acquiring new knowledge since the firm is limited to a few identical partners. However, they did not test their idea empirically. By testing the firm’s technology sourcing, Rothaermel and Alexandre (2009) and Wadhwa and Kotha (2006) found that strong reliance on a partner as a source of technology can have negative performance implications. Within the stream of sparse vs. closed network research, Beckman and Haunschild (2002), showed that partner diversity of a firm strengthens the firm's learning, probably because of having timelier access to more diverse information. However, they did not measure density of their networks so it is not clear to what extent these relations are due to having a sparse network, as shown by Baum et al. (2000). Similarly Vasudeva et al. (2012) and Bae and Gargiulo (2004) found that reliance on a limited number of partners for a firm may decrease organizational profitability from its alliances, although if the firm is embedded in a closed network structure (i.e. high-density ego-network) it may have a better return from its alliances. The summary of findings in these two streams shows that having diverse partners may increase access to more diverse knowledge required for knowledge creation. The key point here is that partner diversity helps an organization to not be too dependent on a limited number of partners with limited knowledge. In other words, having diverse partners gives firms more freedom and opportunity to substitute their partners whenever required, hence firms are able to create more knowledge through their partners.

Partner diversity as a knowledge process

In inter-organizational k-network research, partner-diversity has been considered as a knowledge process attribute (Lavie and Rosenkopf 2006; Tiwana 2008; Rothaermel and Alexandre 2009). The literature refers to diversity of partners as a representation of the exploration vs. exploitation knowledge process (March 1991; Lavie and Rosenkopf 2006). The knowledge process may aim at either enhancing exploitation by focusing on existing knowledge which is acquired, transferred and used in other similar situations, or exploration which is creating new knowledge by sharing and synthesizing of knowledge (March and Levinthal 1993). Moreover, as March and Levinthal (1993) mentioned, companies need both exploration and exploitation in order to survive in the long-term. But there is often a trade-off between the two approaches due to constraints on resources and the firm's strategic orientation (Bierly, Damanpour and Santoro 2009). Finding an ambidexterity between these two processes has also been discussed as a major challenge of creating new products (Atuahene-Gima 2005; Rothaermel and Alexandre 2009; Kim, Song and Nerkar 2011). Although the importance of balance is discussed in their work, the role of network structure as the context of knowledge creation is not addressed. Tiwana (2008), however, showed that having simultaneously strong ties and bridging ties will provide access to a diverse array of specialized knowledge on the one hand, and provide the ability to convey complex ideas to diverse partners on the other hand.

Partner diversity in terms of the exploration vs. exploitation process was mentioned by Lavie and Rosenkopf (2006). Addressing the exploration/exploitation literature at the inter-organizational level, Beckman, Haunschild and Phillips (2004), Verspagen and Duysters (2004), and Baum, Rowley, Shipilov and Chuang (2005) present recurrent alliances between organizations as a form of exploitation, and alliances formed with new partners are considered exploration. In this regard, having a diverse range of partners is a sign of an exploration knowledge process, while having few partners for a firm shows the firm's tendency towards an exploitation process. Lavie and Rosenkopf (2006) dubbed partner diversity as structural exploration/exploitation. Hence we propose:

H1: The exploration/exploitation knowledge process of an actor will not be associated with the knowledge creation of the actor.

H2: In a k-network, the effect of exploration/exploitation knowledge process of actors on knowledge creation is mediated by the k-network structure of the actor.

RESEARCH METHOD

In this section, first the k-network is defined in the context of the Victorian biotechnology industry, and then the research design and data collection are explained.

Patent co-authorship networks as k-networks in the Victorian biotechnology industry:

Australia has a relatively strong position in pharmaceuticals and biotechnology in the Asia-Pacific region (Ernst and Young 2011) and Victoria is among the leading states within Australia, since it is characterised by a large human health subsector, which involves more than 75 per cent of the biotechnology companies located in the country (Allen Consulting Group 2010). In this industry, there are different types of actors, including public research organizations like universities, pharmaceutical-bio companies[1], government agencies, hospitals, or even individual innovators.

Our research focuses on patent co-authorship networks (Cantner and Graf 2006) of this industry. These co-authorship networks are characterized by legally binding contracts and licensing to protect the intellectual property of exclusive partners, and are very common in knowledge-intensive industries like biotechnology

1 There are differences in bio technology firms and pharmaceutical firms, however such differences were not important in this research.

(Walker, Kogut and Shan 1997). In this industry, patenting can be used to represent knowledge creation (Wadhwa and Kotha 2006). However, there are some limitations with counting patents to understand knowledge creation. Firstly, the industry type influences product patent propensity (Arundel and Kabla 1998). To avoid this issue, it is recommended to collect data from a single industry (Ahuja 2000). Secondly, the full range of each firm's knowledge creation will not be captured by patents. Some knowledge may not be patentable but still have economic value (Arundel and Kabla 1998). However patents have been shown to be an important mechanism in the biotechnology industry (Plum and Hassink 2011).

Research design:

Participants were all the Victorian biotechnology actors who had published at least one patent in IP Australia (AusPat2), from 2001-2010. We intended to collect data from the whole network. To do so, we used a snowball sampling approach to get the list of all 126 Victoria-based actors, of which 69 were participating in the network. To analyse the data, we used social network analysis (SNA) and moderated multiple regressions (MMR). In our research, the primary aim of using UCINET6 (Borgatti et al. 2002) as an SNA software package was to understand the pattern of relationships between biotechnology actors, while MMR (Irwin and McClelland 2001) was employed to analyse interaction effects between the constructs. Using SPSS 20, our research applied MMR which included a negative binomial multiple regression analysis—as an extension of the Poisson multivariate regression analysis, followed by the interaction analysis (West and Aiken 1991; Dalal and Zickar 2012).

Constructs are exploration index or partner diversity (process), centrality and ego-network density (structure). To calculate the exploration index of actors, we used the Herfindahl index and Simpson's diversity index, which have been used in a variety of fields, including k-network research (Demirkan and Demirkan 2012). More specifically, the exploration index is defined by the proportion of particular partners in the ego network of a firm, among the total number of all collaborating partners of the firm. There are also several measures (methods) to calculate centrality like degree, eigenvector, closeness, and betweenness centrality. The degree of an actor in a given network is calculated by total number of ties shared by the focal actor with other members of the network. In this research, all these measures were calculated by UCINET6. To calculate ego-network density in a weighted network where the value or frequency of the partnerships is considered for measuring the density of the ego network, there are four approaches: arithmetic mean, geometric mean, maximum and minimum (Opsahl and Panzarasa 2009). The maximum and minimum approaches do not seem appropriate in this research. Among the two others, geometric mean is measured by using tnet in R[3] in this research.

Validity:

To understand the role of interplay among all the k-network constructs including the size and type with knowledge creation, we used a negative binomial as an extension of the Poisson multivariate regression analysis by SPSS 20. Since the dependent variable is a counted variable (number of patents), linear regression is not appropriate in modelling such data, mainly because the assumptions of homoscedastic or normally distributed errors are violated as supported by the Koenker test (Koenker and Bassett Jr 1982) for Heteroscedasticity. Our data showed that Chi-Square=14.361 and significance level of Chi-square was .0062 (which is less than .05).

Therefore the linear regression model is not recommended for our data so the model is tested by using negative binomial regression analysis. Moreover, since we used a single data source to measure both dependent and independent variables, there would be a risk of common-method bias (CMB). However, CMB was not deemed a problem for this analysis (Podsakoff, MacKenzie, Lee and Podsakoff 2003), as the test of Harman's single-factor shows (Variance = .480 < .5). Another assumption in conducting a multi regression analysis is about non-multicollinearity. To check this, here the common test of Tolerance or Variance Inflation Factors (VIF) was used for each variable. In our VIF test, values of between 1.39 and 3.34 were obtained. According to the common rule VIF should be less than 10. To be consistent with the literature (Rodan and Galunic 2004), for this analysis we used 0.05 significance level. Finally to check for interactions of constructs we used normalized variables in order to avoid the problematic β weight. A detailed discussion of that can be found in Irwin and McClelland (2001).

RESULTS:

The descriptive statistics and the correlations between the variables for the 69 cooperative biotechnology actors are provided in Table 2. In statistical terms, knowledge creation (i.e. number of published patents) is the dependent variable, and independent variables are exploration index, degree centrality and ego-network density.

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2 http://www.ipaustralia.gov.au/auspat/index.htm

3 http://toreopsahl.com/tnet/software/

Table 2 Descriptive analysis of all variables and interactions

Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1. Patent Number	8.90	13.98	1							
2. Degree Centrality normal	8.99	11.89	.368**	1						
3. Valued-Density	.51	0.45	-.306*	.492**	1					
4. Exploration Index	0.53	0.29	.144	.863**	.560**	1				
5.Valued-Density *centrality	0.18	0.64	-.043	-.369**	-.605**	-.346**	1			
6.Valued-Density* Exploration	.60	0.83	-.451**	-.360**	-.194	-.277*	.669**	1		
7. Centrality*Exploration	0.56	1.01	.059	.010	-.354**	-.155	.558**	.455**	1	
8.Centrality * Valued-Density *exploration	-.21	.73	.059	.628**	.557**	.641**	-.180	-.356**	-.170	1
Valid N (listwise) 69	**. Correlation is significant at the 0.01 level (2-tailed)				*. Correlation is significant at the 0.05 level (2-tailed).					

The results of the binomial regression analysis to explain role of process on knowledge creation of the actors in the Victorian biotechnology industry are also reported in Table 3. There are several models that have been tested (Table 3) to check for the possible interactions (mediation) of process and structure (both centrality and density). The summary of the all tests are reported in Table 3. Size and types of actors were also considered as control variables. Table 3, however, does not show the results of tests for the size and type simply because of the space limitation and because none of size and type variables were significant in these models.

Table 3 Binominal regression models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Degree norm-Centrality			.059** (.012)	.054** (.014)	.64** (.014)	.139** (.034)	.058** (.015)	.064** (.0162)
Valued-Density	-1.52** (.3640)	-1.55 (.412)	-.988** (.3088)	-1.16** (.349)			-.998† (361)	-1.10* (.384)
Exploration Index	2.32** (.580)	1.112 (.705)			-1.018 (.654)	-2.892* (.993)	.042 (.769)	-.363 (.900)
Centrality*Valued Density				-.334 (.290)				
Valed Density* Exploration		-.79** (.212)						
Centrality*Exploration						-.889* (.317)		
Centrality * Valued-Density *exploration								.284 (.308)
Likelihood Ratio Chi-Square	23.729	38.386	43.401	44.749	35.784	45.771	43.40	44.229
Goodness of Fit-Bayesian Information Criterion (BIC)	436.104	425.682	416.433	419.319	424..05	418.297	420.664	424.073
Model Degree of freedom	2	3	2	3	2	3	3	4
Prob.> Chi-Square	.000	.000	.000	.000	.000	.000	.000	.000
Valid N (listwise) 69	**. Correlation is significant at the 0.01 level (2-tailed)				*. Correlation is significant at the 0.05 level (2-tailed).			

The results support both hypotheses (Table 4). Here the question is how the interaction of process and structure affects knowledge creation. To answer this question in our research, the MMR includes binominal multiple regression analysis and then the interaction analysis (West and Aiken 1991; Irwin and McClelland 2001).

Table 4 Results about the hypotheses

Hypotheses	Result	Details
H1	Not rejected	Process has no direct association with knowledge creation (ρ=.144, α=.238)
H2	Not rejected	Process is supported negatively by density and centrality (Model 2-6)

Density and Process: Beyond the influence of each density and process (Model 1), the interaction between them was associated with knowledge creation. In Model 1, exploration shows positive significant effects on knowledge creation (β=2.32, α=.005); however density shows significant negative effects (β=-1.52, α=.000). However the combination of these two associated negatively with knowledge creation (β=-.797, α=.000). According to this multiple regression analysis, it is clear that the interaction of density and exploration is significantly associated with knowledge creation; however the exploration process has no impact on its own (H1). To explain the possible interactions (Figure 1), for actors with low density ego-networks, increasing diverse partners (exploration process) results in more patents (R=.40). Even for actors with medium density ego-networks, there is a positive association between exploration and knowledge creation in terms of patents. However, when actors are located in a high-density network, increasing exploration resulted in lower knowledge creation (R=-.40). According to the scatter-plot of density and knowledge creation for three groups of low, medium and high exploration, density regardless of exploration process of actors always showed significant negative correlation with knowledge creation. However, the impact for actors with low diverse partners (low exploration process) was very weak (R for low, medium and high exploration groups were as follows .09, -.30, and -.52). This was supported by the multi-regression analysis result as well since density remained significant even after the mediator factor of exploration was added (Table 4, Model 2).

A Spearman correlation coefficient analysis between density and exploration revealed moderate positive correlation (ρ=.560, α=.000). This meant that actors who were located in k-networks with a certain level of ego-network density, also tended to possess more diverse partners. In other words, considering the interaction analysis, we can see that focusing on exploration for actors with low dense networks may facilitate more knowledge creation, however probably it would not be the case for the actors in dense networks. In summary, these results show that focusing on exploration may lead to higher patents only for actors with low density networks. This association is still positive till the actors reach a medium level of density (mean of geo-metric valued density=.526). Then in contrast for the actors with high dense ego-network, pursuing exploration may result in lower patents.

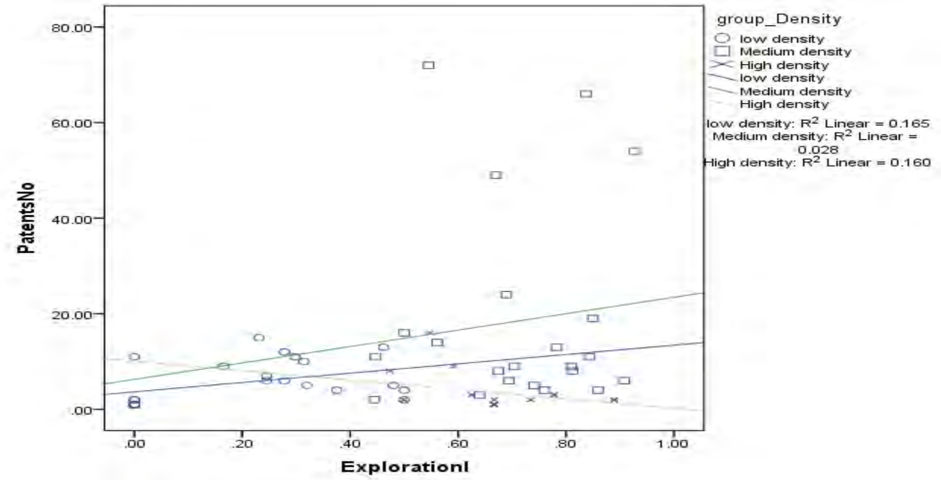

Figure 1 The Correlation between patent number and exploration index based on the three groups of density

Process and Centrality: Another significant interaction is among process and centrality, as is shown in Models 5-6. Centrality and process, and the interaction of them are associated with knowledge creation. First in Model 5, exploration had no significant effects on patents (α=.120); however centrality showed weak positive significance (β=.064, α=.000). Nevertheless in Model 6 when the interaction factor was added, all of them became significant. Although exploration had negative impact, therefore the combination of these two associated negatively with knowledge creation (β=-.889, α=.005) and the model improved as BIC decreased (Table 4) however not very significantly. To test the interaction analysis (Figure 2), all actors were categorised based on exploration index into three groups of low, medium and high exploration. According to the scatter-plot of centrality and knowledge creation for three groups of low, medium and high exploration, the results show that centrality regardless of exploration process of actors always showed significant positive correlation with knowledge creation. However the impact for actors with low diverse partners (low exploration process) was weak (R=.32 compared to actors with medium (R=.91) and high exploration (.83) groups. This was supported in the multi-regression analysis as well, since density remained significant even after adding the mediator factor of exploration. Also exploration had a mixed positive and negative association with knowledge creation. This is why the effect of this variable in Model 5 is not significant. More precisely, for peripheral actors (low central), increasing diverse partners (exploration process) resulted in more knowledge creation (R=.14). However for firms with medium central position, there was a negative association between exploration and knowledge creation (R=-.54). Likewise, when very central actors focused on higher exploration process, this resulted in a lower number of patents (R=-.26). This means that focusing on exploration may lead to higher knowledge creation only for actors with a peripheral position in the k-network. In contrast, for the actors with a more central position, pursuing exploration may result in lower knowledge creation.

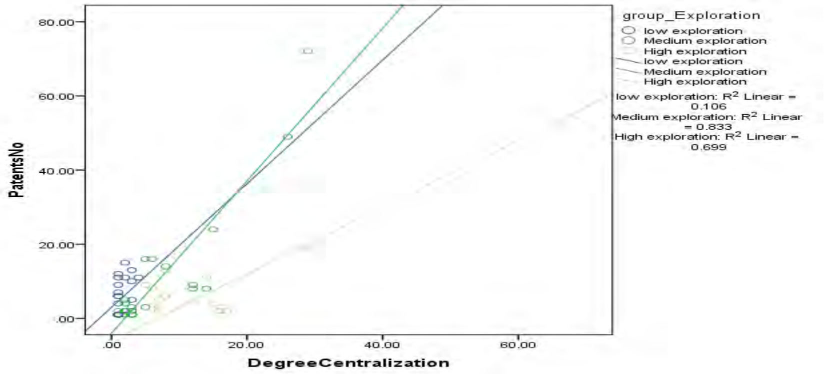

Figure 2 The Correlation between patent number and centrality based on the three groups of exploration

A Spearman correlation coefficient analysis between centrality and exploration revealed a very strong positive correlation (ρ=.863, α=.000). Actors who possessed a more central position in the k-network showed more intention for exploring new partners. Adding this to the interaction analysis, we can see that actors with high central position cannot expect to increase their knowledge creation by contracting with new partners. It means for these actors that it would be better if they kept their relations with their current partners. In summary, focusing on exploration may lead to higher knowledge creation only for actors with a peripheral position in the k-network. In contrast, for the actors with a more central position, pursuing exploration may result in lower knowledge creation.

DISCUSSION

This research addressed two hypotheses through an empirical study to understand the role of exploration/exploitation knowledge processes on collaborative knowledge creation. In this regard, we analysed the interaction role of partner diversity and the k-network structure.

To understand the first hypothesis, which was to see whether or not the exploration process can be associated with knowledge creation, the data showed that there is no link between them. It means that either exploration or exploitation could result in knowledge creation. This idea has also been explored within inter-organizational k-networks in previous research (Li, Vanhaverbeke and Schoenmakers 2008). Although process has no direct association with knowledge creation, we have shown that this element plays a role in explaining the conflicting results, e.g. as reported by Phelps et al. (2012), about the effect of centrality and density on knowledge creation. The immediate effects of the structural elements were confirmed by our study (Model 3). It is important to note that other important factors like trust (Molina-Morales and Martínez-Fernández 2009), and power (Wong, Ho and Lee 2008) were not included in our research, As discussed above, these factors do not address the common constructs explored in this research , as discussed in Table 1.

The second hypothesis, on the mediating role of k-network structure on the contribution of knowledge process to knowledge creation, we explained by using binominal regression analysis followed by interaction analysis. The main findings supported that the interactions among process and structure of k-network is significant and the interactions do not rely significantly on size and type of the actors. These findings can also contribute to existing k-network research in two ways:

1. There are two competing views about the role of ego-network structures, namely closed vs. sparse network. In our research, sparseness or low density of ego-networks shows positive correlation with knowledge creation. Our study showed that focusing on exploration may lead to higher knowledge creation only for actors with a low density network (H2). This association is still positive till the actors reach a medium level of density (mean of geometric valued density=.526). In contrast, for the actors with a high dense ego-network, pursuing exploration may result in lower knoweldge creation. The exploration process also shed more light on the mixed results of the structural hole theory as reported in the literature (Beckman and Haunschild 2002; Phelps 2010; Demirkan and Demirkan 2012). According to this theory, a sparse network with high structural holes is a suitable network for brokering (Burt 2004) and bridging with new partners (exploration process).
2. There is still an open debate on the role of exploration and exploitation on knowledge creation. This research confirmed that focusing on exploration may lead to higher knowledge creation only for actors with a peripheral position in the k-network (H2). In contrast, for the actors with a more central position, pursuing exploration may result in lower knowledge creation. Given the findings for an actor with medium centrality and medium density, increasing the exploration process is expected to produce a mixed result. This could explain that partner diversity helps an organization to not be too dependent on a limited number of partners

with limited knowledge. However, if the actor possesses a central position, the risk of dependency would be decreased, as actors could find needed knowledge because of accessing a central position. This leads to the need for furthur research to include the role of knowledge content in studying the interaction of knowledge process and k-network structure.

CONCLUSION

There is increasing research on knowledge networks as sources to acquire and access knowledge. This paper explored the mediating influence of k-network structure to explain the role of exploration/exploitation knowledge processes on collaborative knowledge creation in k-networks. As a result the interaction role of knowledge network structure and knowledge process was tested and confirmed. In conclusion, this research sought to understand how knowledge process in the Victorian biotechnology industry can be used to produce more knowledge. As there is no single or unified theory of k-networks (e.g. Monge and Contractor 2003), and Galaskiewicz (2007), this research introduced the interaction of knowledge process and structure of k-networks as a new finding that contributes to improve this line of research, particularly within the knowledge creation domain. The research could contribute to resolving contradictions reported in k-network research (Phelps et al. 2012) about the network position and structural hole theory, and exploration/exploitation literature (Li et al. 2008), as mentioned in the discussion section. In practice, the integrative model that addressed the two interactions, discussed above, would provide more intuition for managers to build their k-networks, since in practice a combination of all process, and structural constructs should be considered simultaneously.

All research studies have their own limitations, and this research is not an exception. Although data were collected on the whole Victorian biotechnology industry (126 actors), only 69 actors had participated in the patent k-network. The relatively low number provides some challenges for analysis. There are more techniques required for completing such analysis and always there are some risks for generalizing the results. Also knowledge creation in this research is narrowed to the patent; however the full range of each firm's knowledge creation is not captured by patents. Some knowledge may not be patentable but still have economic value. Likewise, the concept of quality of created knowledge is not captured by counting the number of patents. Therefore this research cannot address the quality of the patents but focuses on whether certain characteristics of k-networks can impact on patents as a measure of knowledge creation.

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