Research Policy 42 (2013) 1515–1530

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Co-authorship networks and research impact: A social capital perspective

Eldon Y. Li[a,1], Chien Hsiang Liao[a,2], Hsiuju Rebecca Yen[b,*]

[a] Department of Management Information Systems, National Chengchi University, No. 64, Sec. 2, Zhi-nan Road, Wenshan, Taipei 11605, Taiwan
[b] Institute of Service Science, National Tsing Hua University, No. 101, Sec. 2, Kuang-Fu Road, Hsinchu 30013, Taiwan

ARTICLE INFO

Article history:
Received 14 May 2012
Received in revised form 21 May 2013
Accepted 24 June 2013
Available online 29 July 2013

Keywords:
Social capital
Research impact
Social network analysis
Research collaboration
Team exploration
Network centrality

ABSTRACT

The impact of research work is related to a scholar's reputation and future promotions. Greater research impact not only inspires scholars to continue their research, but also increases the possibility of a larger research budget from sponsors. Given the importance of research impact, this study proposes that utilizing social capital embedded in a social structure is an effective way to achieve more research impact. The contribution of this study is to define six indicators of social capital (degree centrality, closeness centrality, betweenness centrality, prolific co-author count, team exploration, and publishing tenure) and investigate how these indicators interact and affect citations for publications. A total of 137 Information Systems scholars from the Social Science Citation Index database were selected to test the hypothesized relationships. The results show that betweenness centrality plays the most important role in taking advantage of non-redundant resources in a co-authorship network, thereby significantly affecting citations for publications. In addition, we found that prolific co-author count, team exploration, and publishing tenure all have indirect effects on citation count. Specifically, co-authoring with prolific scholars helps researchers develop centralities and, in turn, generate higher numbers of citations. Researchers with longer publishing tenure tend to have higher degree centrality. When they collaborate more with different scholars, they achieve more closeness and betweenness centralities, but risk being distrusted by prolific scholars and losing chances to co-author with them. Finally, implications of findings and recommendations for future research are discussed.

1. Introduction

For academic scholars, maintaining high levels of research productivity is essential to their careers. After a long and arduous research process, scholars commonly expect to publish their findings and have some degree of impact on the knowledge community. Greater research impact brings citations to and establishes the reputation of a scholar. That reputation not only provides a scholar with opportunities for sponsored programs (grants) but also inspires the scholar to continue his or her research efforts. However, each person has his or her own limited cognitive capabilities and bounded rationality (Simon, 1976). To cross the boundary, it is better for a scholar to conduct research in collaboration with other scholars. Such research collaboration allows scholars to work together and achieve a common goal by sharing research workloads (Hauptman, 2005), specific expertise or particular skills (Soderbaum, 2001), and equipment or resources (Bammer, 2008).

Studies have shown that research collaboration can bring co-authors greater research productivity (Katz and Martin, 1997; Lee and Bozeman, 2005) and research impact (Gazni and Didegah, 2011; Sooryamoorthy, 2009). Whereas co-authorship is a form of collaboration in which collaborators publish their research outcomes through paper or electronic media, not all collaborators publish an article together (Katz and Martin, 1997). That is, co-authorship is an "explicit product" of scientific collaboration (He et al., 2011, 2012). Whenever a scholar publishes a co-authored article, he or she has created an individual co-authorship network. The co-authorship of an article reveals only those scholars who made direct contributions to the content of the article. It depicts the one-to-many relationships of a scholar with his or her co-authors. When individual co-authorship networks are threaded together based on the co-authors, they form a large network, which is the collective of the individual co-authorships (Ding, 2011; Liu et al., 2005; Lu and Feng, 2009; Otte and Rousseau, 2002). This network exhibits many-to-many relationships among scholars; with numbers of them being co-authors of co-authors who indirectly contributed their knowledge to published articles. Such an interconnected chain of relationships constitutes a social network in which valuable

* Corresponding author. Tel.: +886 3 516 2146; fax: +886 3 562 3770.
E-mail addresses: eli@nccu.edu.tw (E.Y. Li), jeffen@gmail.com (C.H. Liao), hjyen@mx.nthu.edu.tw (H.R. Yen).
[1] Tel.: +886 2 8661 8082; fax: +886 2 8661 1384.
[2] Tel.: +886 2 847 2429.

0048-7333/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.respol.2013.06.012

resources are shared in the forms of information, understanding, and knowledge through the conduct of social interactions. This network can provide members with collectively owned capital – known as social capital (Nahapiet and Ghoshal, 1998). This capital has been proven to positively influence knowledge creation (McFadyen and Cannella, 2004), knowledge transfer (Inkpen and Tsang, 2005; Walter et al., 2007), and knowledge contributions (Wasko and Faraj, 2005). Through social interactions, members in a collective can benefit from social capital and widen their horizons of understanding and, in turn, achieve better outcomes (Abbasi et al., 2011; Liao, 2011; Yan and Ding, 2009).

According Nahapiet and Ghoshal (1998), there are three dimensions of social capital: structural, relational, and cognitive, each of which will be discussed in detail in the next section. In this study, these three dimensions of social capital are referred to respectively as structural, relational, and cognitive capital. Past studies have applied social network analysis (SNA) to explain the dynamics of co-authorship networks (e.g., Acedo et al., 2006; Lu and Feng, 2009; Otte and Rousseau, 2002; Yan and Ding, 2009). However, they considered only the structural facet from social capital theory, overlooking the other two dimensions: relational and cognitive capitals (Inkpen and Tsang, 2005; Nahapiet and Ghoshal, 1998).

In reviewing the burgeoning literature on the topic, much evidence exists supporting the importance of social capital (e.g., Inkpen and Tsang, 2005; Wasko and Faraj, 2005). Despite the great interest exhibited by various researchers in the interrelationships among the three dimensions of social capital (e.g., Nahapiet and Ghoshal, 1998; Tsai and Ghoshal, 1998), prior studies have largely focused on the consequences of these dimensions independently without considering how they interact (Robert et al., 2008; Wasko and Faraj, 2005). Those studying the interrelationships generally treat structural capital as the predictor of relational and cognitive capitals (Liao and Welsch, 2005; Tsai and Ghoshal, 1998). Notwithstanding that the literature sheds light on the resources that can be derived from social-capital dimensions, it pays little attention to how people are proactive in changing and extending their social capital. Consider, in the context of a co-authorship network, that an author who does not occupy an advantageous position may try to increase his or her structural aspect of social capital by expanding his or her circle of social contacts. How, then, does an author change his or her social interactions and acquire a more desirable position within a larger co-authorship network? Clearly, the literature has hitherto devoted great attention to the consequences of structural capital but provides little insight into how this capital can be enhanced by relational and cognitive capitals. To fill the void in the literature, this study extends the understanding of prior studies from a more comprehensive perspective by applying social capital theory to co-authorship networks and examines the associations among a scholar's different dimensions of social capital and their effects on the research impact of the scholar. The objectives of this study are:

- Define the indicators of a scholar's social capital in a co-authorship network.
- Examine the effects of the indicators of social capital on the research impact of a scholar.
- Explore the impact of relational capital on structural capital.
- Investigate the effect of cognitive capital on structural capital.
- Assess the influence of cognitive capital on relational capital.

2. Background

2.1. Research collaboration, social capital, and research impact

Generally speaking, research impact is a recorded or otherwise auditable occasion of influence from research on actors in academia, business, government, or civil society (LSE Public Policy Group, 2011). In academia, research impact is commonly regarded as the extent to which a scholar's work has been used by other researchers (Bornmann et al., 2008). A popular objective measure of research impact is the citation count provided by ISI's Web of Knowledge (Thomson Reuters, 2011). It has been validated and widely used in the natural and social sciences for evaluating the research contributions of articles, journals, institutions, and individuals (Brown and Gardner, 1985). Nevertheless, the citations in the Web of Knowledge include those from other authors and the authors themselves. The latter are self-citations that must be excluded when evaluating research impact. In essence, the citation count without self-citations can be used as a surrogate for research impact that indicates the extent to which a scholar's article influences other scholars (Liao, 2011).

Past studies have shown that research collaboration produces higher research impact than a single researcher in terms of number of publications (Katz and Martin, 1997; Lee and Bozeman, 2005) and citations (Gazni and Didegah, 2011; Sooryamoorthy, 2009). This is probably because a single researcher cannot effectively mobilize the resources necessary for conducting research (Kling and McKim, 2000). Through research collaboration, a scholar can share his or her resources, such as equipment, workload, expertise, and knowledge, with other scholars (Abramo et al., 2011; Katz and Hicks, 1997; Lee and Bozeman, 2005). Such resources, which are embedded in personal ties and useful for the development of individuals, are regarded as "social capital" (Tsai and Ghoshal, 1998). The social relationships, norms, and values attached to social capital determine the performance of individuals, groups, and organizations that are parts of a socially or economically connected network (Okoli and Oh, 2007). Such networks normally provide participants with opportunities for finding social support, exchanging social capital (including financial resources, goods, or services), and exploring and employing knowledge transfer (Lea et al., 2006). As a result, social capital has been broadly defined as the benefit that actors derive from their social relationships or network (Burt, 1992; Coleman, 1988).

Nahapiet and Ghoshal (1998) propose three dimensions of social capital that facilitate the development of intellectual capital: structural, relational, and cognitive. Each of these dimensions constitutes an aspect of the social structure and facilitates combining and exchange of knowledge among individuals within that structure (Wasko and Faraj, 2005). Several studies suggest that social capital theory provides valuable perspectives for understanding how participants leverage resources or knowledge by gaining value or advantages from social structure (Okoli and Oh, 2007; Tsai and Ghoshal, 1998; Walter et al., 2007). In the same vein, this study adopts the three dimensions of social capital to identify various ways by which a scholar obtains his or her resources or knowledge from social structure in a co-authorship network. These dimensions of social capital are discussed in the next three sections.

2.2. Structural capital of a co-authorship network

Structural capital refers to structural embeddedness (Granovetter, 1985), such as the network ties, configuration, and density of connections among individuals. It describes the "impersonal" configuration of linkages between and among people or units and indicates the overall pattern of connections between actors (Nahapiet and Ghoshal, 1998, p. 244), providing information about who you reach and how your reach them (Burt, 1992). In a social network, centrality is an important structural attribute that indicates an actor's formal power or prominence in the network relative to others (Burkhardt and Brass, 1990). If an actor is in a central position in the network, that actor has many connections with other actors and occupies a strategically significant position in the overall structure of the network (Troshani and Doolin, 2007).

According to the social network literature, there are three common measures of centrality: degree, closeness, and betweenness (Borgatti, 2005; Freeman, 1979; Otte and Rousseau, 2002). In this study, we regard them as three different centralities. *Degree centrality* is defined as the number of direct connections that a given actor (or node) has with other actors, without taking into account the strength of connection (i.e., repeating frequency of a connection). In the context of this study, each direct connection is a unique co-authorship. Being a central actor with high degree centrality, a scholar has collaborated with many colleagues (Otte and Rousseau, 2002). *Closeness centrality* is defined as the mean shortest distance by which a given actor is separated from all other nodes in a network (Lu and Feng, 2009). It is measured by the average of the total reciprocal distance of that actor away from each of the other actors in the network. In this network, a message originating in the most central position (i.e., the actor with the highest closeness centrality) would spread throughout the entire network in minimum time (Freeman, 1979). Therefore, closeness centrality is a surrogate measure of an actor's efficiency in communicating with other actors in the network. In the context of a co-authorship network, a scholar with high closeness centrality indicates that he or she could access or obtain needed resources owned by others in the network more efficiently than any other scholar. Finally, *betweenness centrality* is defined as the proportion of the shortest paths between all pairs of nodes that pass through a given actor in the network (Borgatti, 2005). The betweenness centrality of an actor represents that actor's ability to control the flow of resources or information in the network, which enables the actor to broker information and resources to other actors (Freeman, 1979). Thus, an author with high betweenness centrality means he or she plays the role of "middleman" or "bridge" (Lu and Feng, 2009; Otte and Rousseau, 2002) and could gain different resources or information from different groups in the co-authorship network.

Past studies have adopted the number of social interaction ties, or degree centrality, as a surrogate of structural capital to examine its effect on knowledge contributions (Wasko and Faraj, 2005), combining and exchange of resource (Tsai and Ghoshal, 1998), and citation counts (Liao, 2011), among others. Recently, Abbasi et al. (2011) measured all three facets of centrality to assess their impact on research performance. Based on the definitions and measurement methods of the three centralities, each seems to capture a distinct aspect of an actor's role in a social network. Therefore, we apply all three centralities to measure different facets of structural capital in a co-authorship network.

Since the three centralities are measuring the same construct (i.e., structural capital), they are expected to have moderate correlations with each other (Cattell, 1965; Nunnally, 1978). Table 1 exhibits the correlations reported in several studies (e.g., Abbasi et al., 2011; Brass and Burkhardt, 1993; Cho et al., 2007; Ding et al., 2009; Geletkanycz et al., 2001; Hou et al., 2008; Leydesdorff, 2007; Yan and Ding, 2009). Indeed, half of the reported correlations are at the moderate level between .3 and .7. However, some paired measures exhibit a fluctuating pattern, being high in one study and low in another. That is, a scholar with a lot of ties (i.e., high degree centrality) may or may not have a central or broker position (i.e., high closeness or betweenness centrality), and vice versa. A similar inconsistency applies to the association between closeness and betweenness centralities. This may be attributed to the differences in research contexts, data sources, and sample sizes of the studies. Apparently, the distinctive aspects and fluctuating associations of the three centralities have prevented past studies from predicting any causality and interrelationships among them. As such, we do not assume any causality among the three centralities in this study.

2.3. Relational capital of a co-authorship network

Relational capital refers to the assets people create and leverage through ongoing personal relationships, and with which they change behaviors and fulfill social motives, such as sociability, approval, and prestige (Coleman, 1988; Nahapiet and Ghoshal, 1998). It exists when members have a strong identification with the collective, trust others within the collective, perceive an obligation to participate in the collective, and recognize and abide by its cooperative norms (Wasko and Faraj, 2005). Therefore, past studies have operationalized relational capital as trust, commitment, and reciprocity within the collective (Tsai and Ghoshal, 1998; Wasko and Faraj, 2005). According to social exchange theory, people tend to repeat an action when they are fairly rewarded for their actions (Homans, 1958); that is, a long-term relationship (or trust) is sustained by the fairness of exchanges (Murphy et al., 2007). In the context of a co-authorship network, when two authors trust each other, they are more willing to collaborate and share resources without worrying that they will be taken advantage of by their counterpart. Therefore, when trust exists, meaningful communication begins (Hazleton and Kennan, 2000) and combining or exchange of resources happens (Tsai and Ghoshal, 1998). In this case, it is important to assess whether any trust exists between two scholars. More specifically, Moorman et al. (1993) indicated that behavioral intention is a critical facet of the trust concept because, if someone believes a partner is trustworthy, he or she will intend to collaborate with that partner again. In this vein, a plausible way of measuring trust among scholars is to examine whether they had repeated co-authorships. Only when they co-authored two or more

Table 1
Correlations of degree, closeness, and betweenness centralities.

Correlation source	Degree centrality and closeness centrality	Degree centrality and betweenness centrality	Closeness centrality and betweenness centrality
Abbasi et al. (2011), $N = 1809$[a]	.247**	.406**	.162**
Brass and Burkhardt (1993), $N = 75$[b]	.46**	.13	.87**
Cho et al. (2007), $N = 31$[b]	.645** (time 1)	.452* (time 1)	.316 (time 1)
	.641** (time 2)	.269 (time 2)	.406 (time 2)
Ding et al. (2009), $N = 108$[a]	.771**	.980**	.745**
Geletkanycz et al. (2001), $N = 460$[b]	.86*	.94*	.80*
Hou et al. (2008), $N = 125$[b]	.461**	.685**	.406**
Leydesdorff (2007), $N = 7379$[b]	.651**	.509**	.210**
Yan and Ding (2009), $N = 10,579$[a]	.201**	.656**	.194**
This study, $N = 137$[b]	.176*	.302**	.436**

[a] Spearman rank correlation.
[b] Pearson correlation.
* $p < .05$ (2-tailed).
** $p < .01$ (2-tailed).

times have they demonstrated a trustworthy relationship and the willingness to share resources.

Furthermore, the level of one's relational capital in a co-authorship network is relative in nature and depends largely on the richness of resources resulting from trustworthy relationships. That is, if the co-author of a scholar possesses rich resources, the relational capital of that scholar will be enhanced, assuming a trustworthy relationship exists. In a research community, prolific scholars are usually well-known and possess a large volume of valuable resources. They are the important sources of relational capital. Having trustworthy relationships with prolific scholars is an effective way of developing relational capital. Therefore, we use the number of prolific scholars with whom a person has repeated co-authorships (hereafter called "prolific co-author count") as the indicator of relational capital in this study.

2.4. Cognitive capital of a co-authorship network

Cognitive capital refers to those resources an individual develops over time as he or she interacts with others sharing understanding and expertise; learning the skills, knowledge, and specialized discourse; and forming the norms of practices within the collective (Wasko and Faraj, 2005). Engaging in a meaningful exchange of knowledge requires at least some level of shared understanding between parties, such as a shared language and vocabulary (Nahapiet and Ghoshal, 1998), expertise and longer tenure in the shared practice (Wasko and Faraj, 2005), and a shared vision (Tsai and Ghoshal, 1998). In this regard, socialization theory (Moreland and Levine, 1982) serves as a key theoretical basis for understanding the development of cognitive capital through team composition and publishing tenure. Socialization refers to "the process by which persons acquired the knowledge, skills, and dispositions that makes them more or less able members of society" (Brim and Wheeler, 1966, p. 3). Although prior studies on socialization have primarily considered assimilation of newcomers (e.g., doctoral students) to the academic community (Weidman et al., 2001; Weidman and Stein, 2003), it is equally important for scholars to enhance their knowledge of related disciplines and revisit the norms and values of scholarly practice through continuous socialization during their careers. In the context of a co-authorship network, the co-authors may not come from the same discipline. They might develop their cognitive capital from their own disciplines before they become co-authors. Different disciplines have their own shared visions, traditions, codes, languages, knowledge, interpretations, systems of meanings, social networks, and collectively owned social capital. Each operates as a research community that consists of a large number of scholars contributing resources and sharing social capital; and a scholar may be a member of several research communities at the same time. In contrast, a co-authorship network is a much smaller community wherein an author can acquire cognitive capital (shared understanding and expertise) through interactions with network members from one or more disciplines. As time goes by and tenure in the discipline increases, the author can accumulate more cognitive capital and further share it with new co-authors. Therefore, the tenure of a scholar in a discipline is useful for that scholar in promoting his or her shared language, understanding, and expertise of the discipline in a co-authorship network. That is, a scholar with longer tenure is likely to attain more cognitive capital through better understanding of how his or her expertise is relevant to knowledge in the discipline and, thus, is better able to apply the knowledge (Wasko and Faraj, 2005). In this vein, we use length of tenure publishing in a discipline (hereafter called "publishing tenure") as an indicator of cognitive capital.

Another way to accumulate cognitive capital is from team composition of co-authors. As interest in organizational learning and competitive dynamics grew in the 1990s, composition of organizational members became the fundamental ambidexterity in organizational adaptation (Miller et al., 2006). March (1991) introduced the concept of exploration and exploitation to represent the dichotomy of organizational-learning orientations. While exploration leans toward discovery, risk-taking, and innovation, exploitation emphasizes efficiency, refinement, and productivity. Organizational research usually applies this dichotomy to indicate the degree of diversity among team members (Lavie and Rosenkopf, 2006; Perretti and Negro, 2006). In an organization, different members usually have their own specific expertise and knowledge that, collectively, affects the final outcome of organizational performance (Lavie and Rosenkopf, 2006; Wadhwa and Kotha, 2006). These organizational members can be classified into two types: newcomers and old-timers. Newcomers, who are more likely to contribute new knowledge, tend to foster exploration because they can provide a fresh perspective for a team and a novel interpretation of problems, thus generating creative solutions (Perretti and Negro, 2006; Reichers, 1987). In contrast, old-timers, who are more familiar with knowledge already reflected in their organization, tend to enhance exploitation. They are also more adapted to the team's norms and values because they have had more time to observe, accept, and adopt the team's predominant norms and values. Teams with many experienced members have better communication and, thereby, are more likely to fulfill their goals (Taylor and Greve, 2006). Therefore, mixing and matching different members to form new configurations (i.e., balancing exploration and exploitation) are important decisions when designing teams (Chen, 2005; Perretti and Negro, 2006).

In the context of a co-authorship network, member diversity represents a "micro-organizational setting" consistent with March's (1991) dichotomy of exploration and exploitation (Perretti and Negro, 2006). In this context, exploration refers to co-authorships with different scholars, while exploitation means co-authorships with the same scholars. Both exploration and exploitation of team composition enable co-authors to obtain cognitive capital (i.e., shared understanding and expertise), but in very different scopes. While exploration extends shared understanding and applies new knowledge of the discipline to an enlarging collective, exploitation deepens shared understanding and known knowledge within the same collective. The former strategy helps a scholar acquire a broader perspective of the discipline and expand the network size; whereas the latter confines the scholar in a narrower perspective and a smaller group. For the purpose of expanding the sources of cognitive capital, a scholar should adopt an exploration strategy and co-author with new scholars. Based on the discourse above, we use the degree of exploration in team composition (hereafter called "team exploration") as another indicator of cognitive capital.

3. Research model and hypotheses

3.1. Research model

Social capital is the value a scholar derives from integrating social relations in the forms of preferential treatment, cooperation between individuals and groups, shared knowledge, and resources from peers. It helps the scholar break the barrier of individual bounded rationality (i.e., cognitive capability) and further improves his or her research impact. As social relations of a scholar change over time, social capital also evolves and the three dimensions of social capital affect and reinforce each other iteratively. Indeed, Nahapiet and Ghoshal (1998, p. 243) were the first to recognize the interactions between different dimensions of social capital, and stated that, "although we separate these three dimensions analytically, we recognize that many of the features we describe are highly interrelated.” For instance, Tsai and Ghoshal (1998) demonstrated that structural capital, manifesting as network ties, positively affects both relational capital (as trust and trustworthiness) and cognitive capital (as shared vision) in the context of intrafirm networks. Strong social interaction permits members to know and understand each other, share resources and expertise, and earn trust from other members in the network.

Relational and cognitive capitals should also affect structural capital. First, relational trust and commitment are characterized by an individual’s intrinsic motivation to persist in a long-term relationship. This motivation directs one to engage in continuous social interactions with trustworthy members, thus enhancing the strength of structural capital. Therefore, relational capital affects and reinforces structural capital. Second, shared understanding and expertise in a discipline can bridge the communication gap between members in the same discipline and helps attract new members into the co-authorship network, thus strengthening the structural capital of a scholar. As such, cognitive capital also affects and reinforces structural capital. Strictly speaking, structural capital refers to the impersonal overall pattern (or shape and size) of social connections between actors (Nahapiet and Ghoshal, 1998); it provides only the start-up resource upon which relational and cognitive capitals can thrive. The actual resources accumulated for relational and cognitive capitals, given the same structural pattern, depend largely and collectively on the cognitive efforts and proactive behaviors of the individual actors, namely, understanding the peers and the system, trusting and helping each other, expanding and nurturing relations, and sharing knowledge and resources.

Taking a co-evolution perspective, in the first phase, being in better structural positions (i.e., having more structural capital) increases the possibility of extending current shared understanding among more peers in the discipline (i.e., more cognitive capital) and strengthening trustworthy relationships with co-authors (i.e., more relational capital). Then, in the second phase, having more shared understanding and trustworthy relationships will most likely help scholars expand social connections with additional scholars and improve their structural positions in the network. As this evolution process continues, individuals with insufficient structural capital are likely to improve their social networks by investing in their relational and cognitive capitals. In this vein, it is of paramount importance to understand the causality from relational and cognitive capitals to structural capital. Surprisingly, there is a scarcity of research looking into this causality. Therefore, we propose such causality in our research model, overlooking the conventional direction from structural capital to relational and cognitive capitals. Nevertheless, the goal of this proposed model is not to substitute but to complement current understanding regarding the interactions among the dimensions of social capital.

Fig. 1 summarizes our proposed model regarding the associations among the three dimensions of social capital and their influence on research impact. In this model, the dimension of relational capital consists of one indicator: prolific co-author count. The dimension of structural capital contains three indicators: degree, closeness, and betweenness centralities. The third dimension is cognitive capital, which consists of two indicators: team exploration and publishing tenure. Finally, the dependent variable of research impact is on the right side, which is assessed by citation count (excluding self-citations).

3.2. Associations between structural capital and research impact

Prior studies have illustrated that scholars may increase research impact from co-authorship using the three centrality measures of structural capital. More specifically, Yan and Ding (2009) applied the three measures and PageRank (which is a variant of eigenvector centrality) to co-authorship networks and examined their correlations with citation count. The results showed the four measures are significantly correlated with citation count. Abbasi et al. (2011) conducted a similar study and applied the normalized version of the three measures, as well as eigenvector centrality, average tie strength, and efficiency of co-authorship network. They found that degree centrality has a significant positive effect on research performance as measured by g-index, but closeness and betweenness centralities do not. Liao (2011) examined the impact of degree centrality on research performance (measured by journal impact factor, citation count, and research award). He also revealed that degree centrality has a significant positive effect on research performance.

In a social network, a person who is directly linked with many others (i.e., high degree centrality) is likely to be in the mainstream of information flow within the network (Freeman, 1979). Indeed, Chi et al. (2007) address interactive firm behaviors in e-business and suggest that degree centrality reflects a firm’s direct engagement in various collaborative operations and access to external assets of connected partners, such as technology, money, and managerial skills. High degree centrality can lead to greater volume and speed of resource flows. In the context of a co-authorship network, a scholar with high degree centrality means he or she is highly connected with other colleagues; therefore, the scholar can benefit

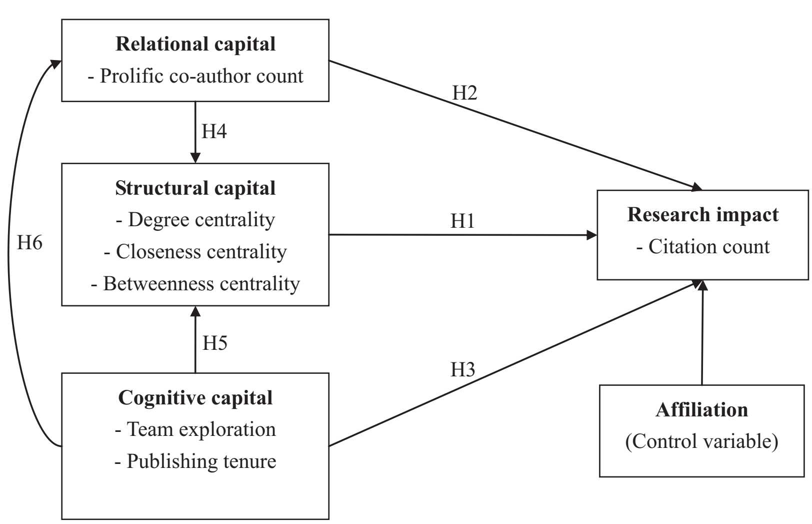

Fig. 1. Conceptual framework.

from structural capital and receive more information, knowledge, and resources. The impact of these benefits is likely to be reflected in improved quality of publications. Hence those publications would garner more citations from other scholars. Another rationale is that he or she is more likely to attract citations from other scholars due to having a central position in the social structure (i.e., high centrality). Because of this centrality, his or her publications are more likely to be cited by other scholars who work on related research topics and who are directly or indirectly linked in his or her co-authorship network. Thus, we predict that scholars who are highly connected with other members (i.e., high degree centrality) in a co-authorship network can benefit from structural capital, which in turn leads to higher research impact as measured by citation count.

H1a. Scholars with higher degree centrality in a co-authorship network have higher citation count.

Closeness centrality means an actor is related to all others through a small number of paths (Otte and Rousseau, 2002), and it depicts the mean distance of the actor's node from all other nodes (Lu and Feng, 2009). A central actor controls either resources or information and possesses a status that makes him or her capable of influencing the behaviors of others in the network (Liu et al., 2005). In the context of a co-authorship network, a scholar with high closeness centrality means that he or she can reach all scholars in the network faster than anyone else. Taking advantage of high closeness centrality, he or she can acquire needed resources more efficiently and improve the quality of his or her publications. Since publication quality increases citations count, as noted in H1a, we predict that scholars who are closer to other members (i.e., high closeness centrality) in a co-authorship network can access more structural capital, which in turn leads to more citations for their publications.

H1b. Scholars with higher closeness centrality in a co-authorship network have higher citation count.

Betweenness centrality represents the position in the network that controls resources or information passed from one actor (or group) to another (Freeman, 1979). It reflects an actor's relative position in spanning the structural holes in a network. A structural hole between two clusters in a network does not mean that actors in the two clusters are unaware of one another. It simply means they are so focused on their own activities that they have paid little attention to the activities in the other cluster. A structural hole indicates that clusters on the two sides of the hole operate with different knowledge flows. Individuals who bridge these holes attain an advantageous position that yields information and control benefits (Abbasi et al., 2011; Burt, 1992). Thus, an actor with high betweenness centrality is likely to obtain rich knowledge that is non-redundant but, rather, additive (Chi et al., 2007). Consequently, we predict that scholars having high betweenness centrality can enhance their research by taking advantage of non-redundant knowledge and resources. This will improve their publication quality and, in turn, lead to higher citation count.

H1c. Scholars with higher betweenness centrality have higher citation count.

3.3. Association between relational capital and research impact

Based on the literature of relational capital, a trustworthy relationship is an important asset because it enables an actor to integrate and leverage resources accessible from the relationship. Prior studies have revealed that the work of prominent scholars, such as Nobel Prize laureates, tends to receive wide attention and high numbers of citations (Brown and Gardner, 1985; Inhaber and Przednowek, 1976). Based on this finding, we believe that when actors establish trustworthy relationships with prominent scholars and collaborate on research, their co-authored articles will attract more citations because the articles tend to be regarded as high-quality work – the so-called "halo effect." Because prolific scholars are prominent in their disciplines, we predict that scholars who have more trustworthy relationships with prolific scholars and co-author more with them will benefit from larger relational capital that, in turn, leads to more citations for publications.

H2. Scholars with higher prolific co-author counts have higher citation count.

3.4. Associations between cognitive capital and research impact

As mentioned earlier, member diversity in team composition (i.e., exploration and exploitation) facilitates accumulation of cognitive capital. We believe that exploration is more helpful in producing competitive cognitive capital than exploitation because it can bring different or new understanding for the collective. Teams with members who share diverse knowledge generate new combinations of knowledge by incorporating distinct knowledge areas (Wadhwa and Kotha, 2006) thereby engendering higher levels of team creativity and increase the quality of group decision-making (De Dreu and West, 2001). That is, high team exploration may enhance the quality of scholars' research publications through novelty and insights; thereby, they may receive more citations from other scholars. Another rationale is that teams with diverse memberships bring forth varied research issues and enrich their perspectives, leading to more attention and citations from other scholars. Accordingly, we predict that scholars who co-author with more diverse members in a co-authorship network (i.e., higher team exploration) will accumulate larger cognitive capital and increase publication quality, which in turn leads to more citations for their publications.

H3a. Scholars with higher team exploration have higher citation count.

Furthermore, scholars with longer publishing tenure are likely to have better understanding of, and expertise in, their disciplines and know how to apply that knowledge to research investigations. They are better able to select interesting topics, apply appropriate methodologies, and judge the quality of research outputs. Empirical studies have shown that experience (or tenure) correlates strongly with performance in individual learning (Pajares and Miller, 1994; Potosky, 2002) and organizational management (Wood and Bandura, 1989). In this vein, the tenure an individual has accumulated in the discipline may influence the final outcome of research collaboration. In the context of a co-authorship network, senior scholars might achieve greater research impact than junior scholars because they have much more experience and cognitive capital with which to conduct high-quality research. We, therefore, predict that scholars with longer publishing tenure will accumulate larger cognitive capital and increase publication quality, which in turn leads to more citations for their publications.

H3b. Scholars with longer publishing tenure have higher citation count.

3.5. Association between relational capital and structural capital

Prior studies have shown that relational trust and commitment is essential to continuous social interactions (Huang et al., 2009; Kreijns et al., 2003). In a co-authorship network, nurturing trustworthy relationships or co-authoring more with prolific scholars will increase the likelihood of social interactions and ties with other different scholars, leading to higher structural capital and changes in degree, closeness, and betweenness centralities (Freeman, 1979; Otte and Rousseau, 2002). Furthermore, when a scholar establishes repeated co-authorships with prolific scholars, he or she can get acquainted with other scholars or research groups in the network through referrals from these prolific co-authors. This increases the individual's chances of collaborating with different scholars and helps him or her shift into advantageous positions in the network by linking with many scholars (i.e., degree centrality), directly or indirectly connecting with more scholars in the other research groups (i.e., closeness centrality), or spanning more holes between research groups (i.e., betweenness centrality). Consequently, it enhances the three centralities of the scholar. Therefore, we postulate:

H4a. Scholars with higher prolific co-author counts have higher degree centrality.

H4b. Scholars with higher prolific co-author counts have higher closeness centrality.

H4c. Scholars with higher prolific co-author counts have higher betweenness centrality.

3.6. Associations between cognitive capital and structural capital

Members in an organization with shared understanding and expertise (i.e., cognitive capital) are more likely to take collective actions (Donnellon et al., 1986) and engage in more social interactions (Rogoff, 1990). Therefore, we predict that cognitive capital will elicit an actor's willingness to embrace social interaction in a co-authorship network. Specifically, when a scholar collaborates with different co-authors (i.e., explorative team composition), he or she is more likely to engage in brainstorming and gain a shared understanding, knowledge, and expertise from them. Most importantly, such extended understanding and expertise can enhance his or her reputation in the discipline, thereby increasing the potential for expanding social relationships with additional scholars. If social relationships change, the level of structural capital will certainly change. In essence, scholars adopting a higher degree of team exploration may see positive changes in their structural capital (i.e., centralities) because they are more likely to expand their networks and include new members. Hence, we postulate:

H5a. Scholars with higher team exploration have higher degree centrality.

H5b. Scholars with higher team exploration have higher closeness centrality.

H5c. Scholars with higher team exploration have higher betweenness centrality.

Similarly, publishing tenure helps scholars produce shared understanding and expertise, as well as engage in meaningful exchanges of knowledge with other scholars in the discipline. This will improve the quality of social interactions and increase the likelihood of research collaboration. For example, a senior scholar with long publishing tenure is regarded as having a high level of shared understanding and expertise. During that tenure, he or she had more opportunities to meet with other scholars at social gatherings or academic conferences and establish social relationships with them. This is very likely to bring the scholar greater respect and an enhanced reputation, thereby attracting research collaboration from other scholars who undertake studies related to his or her research streams. Just as changing social relationships will shift the level of structural capital for a scholar, longer publishing tenure will also positively affect the span of social relationships and increase the scholar's structural capital in the network. Therefore, we postulate:

H5d. Scholars with longer publishing tenure have higher degree centrality.

H5e. Scholars with longer publishing tenure have higher closeness centrality.

H5f. Scholars with longer publishing tenure have higher betweenness centrality.

3.7. Associations between cognitive capital and relational capital

In line with the research findings by Tsai and Ghoshal (1998), we propose that cognitive capital will positively affect relational capital based on socialization theory and social exchange theory as discussed in the Background section. The former theory explains how socialization helps a scholar build social ties and create cognitive capital, while the latter explains how social exchange fosters trusting relationships and engenders relational capital for the scholar. In the context of a co-authorship network, opportunities for socialization reside in academic activities when they interact with different co-authors. Research in organizational behavior shows that top management's socialization activities can span corporate boundaries and lead to higher firm performance (Geletkanycz and Hambrick, 1997). Adding new external contacts not only conveys information about the environment and its changing contingencies, but also shapes frames of reference through which individuals understand the external context. In this vein, while existing co-authors provide scholars with opportunities for socialization, new co-authors allow the scholars to maximize their learning and complement their knowledge of up-to-date practices. Likewise, scholars with long publishing tenures are more likely than junior scholars to be familiar with the academic norms and values shared in the discipline due to having had more socialization with journal editorial boards and reviewers. Accumulated collective values and norms, which are the major manifestations of cognitive capital, facilitate conditions for scholars to develop repeated co-authorships (i.e., trusting relationships) with prolific co-authors. When team members hold similar values, they tend to draw common interpretations, grasp compatible perceptions, and ultimately reach effective decisions (Cannon-Bowers and Salas, 2001), encouraging team members to continue the collaboration. Also, as noted by Ouchi (1980, p. 138), "common values and beliefs provide the harmony of interests that erases the possibility of opportunistic behavior." Taken together, we argue that cognitive capital manifested as team exploration and publishing tenure should positively affect relational capital. Hence, we make the following hypotheses:

H6a. Scholars with higher team exploration have higher prolific co-author counts.

H6b. Scholars with longer publishing tenure have higher prolific co-author counts.

4. Methodology

4.1. Data collection

All data for this study were collected and derived from the Social Science Citation Index (SSCI) database provided by ISI's Web of Knowledge. In order to identify the effects of social capital on citation count, we take into consideration the time lag effect of citations after an article is published because the citations for an article is usually low during the first few years after its debut. In our data collection design, social capital data for a scholar are computed from the articles he or she published during the 5-year period between 1999 and 2003. Then the citation data for an article are collected five years after the article was published. For example, if an article was published in 2003, citation data from 2008

Table 2
Citation window of articles.

Publication year	Citation window (4 years)
1999	2004–2007
2000	2005–2008
2001	2006–2009
2002	2007–2010
2003	2008–2011

and beyond are retrieved. Past research suggests that a meaningful bibliometric study should have a fixed citation window of at least 3 years in length (van Raan, 2006). We, therefore, adopt a 4-year citation window. For prolific co-author count, we select those who published three or more research articles from 1999 to 2003 in premier Information Systems (IS) journals as prolific scholars. The rationale is that, if a scholar can published a top journal article on average every two years or less, he or she is qualified as being prolific. The citation windows for these publishing years are provided in Table 2. Specifically, we examine the social capital of a co-authorship network created between 1999 and 2003, and investigate its influence on citations during the period between 2004 and 2011. The time periods of independent variables and dependent variable do not overlap. This fixed-lag and fixed-window approach to citation count may overlook the immediate research impact derived by a high-quality article during the first 5 years. Yet, it allows us to avoid the timing problem and ensure that past social capital affects future citations.

Regarding premier IS journals, the selection procedure is as follows. First, we select six recent studies in the literature (Ferratt et al., 2007; Katerattanakul et al., 2003; Lowry et al., 2004; Mylonopoulos and Theoharakis, 2001; Peffers and Ya, 2003; Rainer and Miller, 2005) that provide rankings of IS-related journals since 2000. Second, we exclude journals not reported in three or more of the six studies because they lack enough evidence of quality. Third, we calculate the mean ranking for each journal as shown in Table 3. Fourth, we exclude those journals that are not "pure" IS journals, according to the grouping method used by Rainer and Miller (2005). Finally, we select the top five pure IS journals, including *MIS Quarterly* (*MISQ*), *Information Systems Research* (*ISR*), *Journal of Management Information Systems* (*JMIS*), *Information & Management* (*I&M*), and *Decision Support Systems* (*DSS*). Note that *Communications of the ACM (CACM)*, *Management Science (MS)*, *Decision Sciences (DS)*, and *Harvard Business Review (HBR)* are excluded because they are not "pure" IS journals.

From the total 704 articles published in these five premier IS journals during 1999–2003, we identify 1169 unique authors who published one or more articles. Among them are 101 prolific scholars who published 3 or more articles during the same period, as shown in Table 4. Regarding the 1068 scholars who are non-prolific, we only consider those who published two or more articles ($N = 140$) for the purpose of measuring relational capital, because those who published one article ($N = 928$) invariably have zero as the value of relational capital according to the selection criterion in this study. Including these 928 zeros in the dataset will result in a severely skewed distribution of relational capital and create significant bias in model estimation (Gu and Wu, 2003; Hair et al., 1998). Moreover, those who published two articles but did not co-author twice with any prolific scholar ($N = 104$) also have a nil value of relational capital, leaving only 36 non-prolific scholars who are usable subjects. Similar to the 101 prolific scholars, these 36 scholars may or may not have co-authored with the same prolific scholars twice, thus the values of their relational capital may or may not be zero. Therefore, we analyze our research model using a total of 137 subjects (i.e., 101 prolific and 36 non-prolific scholars).

4.2. Measurement

To assess the structural capital of a co-authorship network, prior studies applied social network analysis (SNA) to measure centralities (e.g., Acedo et al., 2006; Lu and Feng, 2009; Otte and Rousseau, 2002; Yan and Ding, 2009). SNA is the mapping and measuring of relationships and flows among people, groups, organizations, computers, or other information or knowledge processing entities. It

Table 3
Prior journal ranking studies from 2001 to 2007.

Journals	[A]	[B]	[C]	[D]	[E]	[F]	Mean rank	Rank of means
MISQ	1	1	2	1	1	2	1.33	1
ISR	3	2	3	2	3	1	2.33	2
CACM	2	3	1	5	2		2.6	3
JMIS	4		6	3	5	4	4.4	4
MS	5		7	4	4		5	5
DS	8		5	6	7		6.5	6
HBR	7		4	15	6		8	7
I&M	10	14	9	9	12	9	10.5	8
DSS	9	20	11	7	8	8	10.5	9
EJIS	11	14	8	11	13	10	11.17	10
ACM T	13	10	18	10	9		12	11
CAIS	18		10		23	6	14.25	12
SMR	12		17		16		15	13
IEEE TSE		5	24	22	10		15.25	14
Database	14		14		30	5	15.75	15
JAIS	30		20	12		3	16.25	16
OS	15		22	14			17	17
ISJ	16	17	23	13			17.25	18
ACM CS	24	12	16		20		18	19
JSIS	20	22		18	28	7	19	20
IEEE Computer	19	16	19	25	19		19.6	21
ASQ	21		15		24		20	22

Prior studies: [A]: Mylonopoulos and Theoharakis (2001); [B]: Katerattanakul et al. (2003); [C]: Peffers and Ya (2003); [D]: Lowry et al. (2004); [E]: Rainer and Miller (2005); and [F]: Ferratt et al. (2007).
Journal abbreviations:
MS, Management Science; DS, Decision Sciences; HBR, Harvard Business Review; EJIS, European Journal of Information Systems; ACM T, ACM Transactions; CAIS, Communications of the AIS; SMR, Sloan Management Review; IEEE TSE, IEEE Transactions on Software Engineering; JAIS, Journal of the Association for Information Systems; OS: Organization Science; ISJ, Information Systems Journal; ACM CS, ACM Computing Surveys; JSIS, Journal of Strategic Information Systems; ASQ, Administrative Science Quarterly.

Table 4
Publication counts of scholars selected from premier IS journals (1999–2003).

Scholar	MISQ	ISR	JMIS	I&M	DSS	Scholar	MISQ	ISR	JMIS	I&M	DSS
Benbasat, I	5	4	3	0	1	Lee, H	0	1	0	4	1
Jiang, JJ	1	0	2	9	0	Lyytinen, K	2	1	1	0	0
Klein, G	1	0	2	9	0	Marakas, GM	1	2	0	1	0
Kauffman, RJ	1	2	6	0	0	Marsden, JR	0	0	2	0	2
Whinston, AB	0	4	1	0	4	Massey, AP	1	0	2	0	1
Grover, V	1	1	3	3	0	Montoya-Weiss, MM	1	0	2	0	1
Sambamurthy, V	4	3	1	0	0	Rai, A	1	1	0	2	0
Zmud, RW	6	1	1	0	0	Reich, BH	2	1	1	0	0
Agarwal, R	5	2	0	0	0	Sabherwal, R	0	2	1	1	0
Chau, PYK	0	0	2	4	1	Santhanam, R	1	1	1	0	1
Dennis, AR	1	2	2	0	1	Sethi, V	0	1	0	3	0
Kumar, A	0	3	2	0	1	Watson, HJ	2	0	0	1	1
Tam, KY	0	1	4	1	0	Wixom, BH	2	0	1	1	0
Wei, KK	2	1	0	2	1	Wu, DJ	0	0	2	0	2
Ba, SL	2	1	0	0	2	Zhao, JL	0	1	1	0	2
Basu, A	0	3	0	0	2	Aiken, M	0	0	0	3	0
Clemons, EK	0	0	5	0	0	Benaroch, M	1	1	1	0	0
Gupta, A	0	2	2	0	1	Bendoly, E	0	0	0	1	2
Hu, PJH	0	0	2	2	1	Blanning, RW	0	2	0	0	1
Keil, M	3	0	2	0	0	Byrd, TA	0	0	1	2	0
Lee, S	0	0	0	4	1	Chatterjee, D	2	0	1	0	0
Markus, ML	3	1	1	0	0	Davis, FD	1	1	1	0	0
Nunamaker, JF	0	0	5	0	0	Davison, R	1	0	0	1	1
Purao, S	0	1	2	1	1	Dehning, B	1	0	0	2	0
Straub, DW	2	2	0	1	0	Devaraj, S	0	1	2	0	0
Tan, BCY	1	1	0	2	1	George, JF	1	0	0	0	2
Barki, H	1	2	1	0	0	Goodhue, DL	1	0	0	2	0
Bhattacherjee, A	1	0	2	0	1	Hardgrave, BC	0	0	2	1	0
Chen, HC	0	0	2	0	2	Hiltz, SR	0	0	2	0	1
Gallupe, RB	0	2	1	1	0	Hitt, LM	0	2	1	0	0
Han, I	0	0	0	3	1	Holsapple, CW	0	0	0	1	2
Irani, Z	0	0	1	3	0	Huff, SL	1	1	0	1	0
Karahanna, E	2	0	0	1	1	Jain, HK	0	0	1	1	1
Kim, YG	0	0	1	2	1	Kwok, RCW	0	0	1	1	1
Kohli, R	0	1	1	1	1	Lai, VS	0	0	0	2	1
Lee, AS	2	1	0	1	0	Lederer, AL	0	0	1	1	1
Lee, B	0	1	1	0	1	Ross, JW	2	0	1	0	0
Lee, YW	0	0	2	1	0	Salisbury, WD	0	1	0	1	1
Lim, KH	1	1	1	0	0	Strong, DM	0	0	1	2	0
Love, PED	0	0	1	2	0	Sussman, SW	0	2	0	1	0
Majchrzak, A	3	0	0	0	0	Thong, JYL	0	0	3	0	0
Malhotra, A	3	0	0	0	0	van der Aalst, WMP	0	1	2	0	0
McHaney, R	0	0	0	3	0	Venkatesh, V	2	1	0	0	0
Menon, NM	0	1	1	0	1	Walsham, G	2	1	0	0	0
Mukhopadhyay, T	0	2	1	0	0	Watson, RT	0	1	0	0	2
Nazareth, DL	0	0	1	1	1	Weill, P	3	0	0	0	0
Pakath, R	0	0	0	1	2	Wheeler, BC	2	1	0	0	0
Palvia, PC	0	0	0	3	0	Wu, IL	0	0	0	2	1
Raghunathan, S	0	1	1	0	1	Yoo, Y	1	2	0	0	0
Rice, RE	1	0	1	1	0	Zhuge, H	0	0	0	3	0
Riemenschneider, CK	0	0	1	2	0						

has been used in sociology, anthropology, information systems, organizational behavior, and many other disciplines (Liebowitz, 2005). This study uses the SNA software – UCINET (Borgatti et al., 1999) to calculate the three measures of degree, closeness, and betweenness centralities. More specifically, it derives these measures as follows. First, there are 101 prolific scholars selected in this study and they published a total of 308 articles in premier IS journals. Based on the collaborative relations in these 308 articles, 330 peripheral co-authors (i.e., those who are not prolific scholars) are identified. The 36 non-prolific scholars selected in the last section belong to this peripheral group. The relationships among these 431 scholars (i.e., 101 prolific scholars and 330 peripheral co-authors) form a social network for analysis. Second, this study develops a program to create a relation matrix (431×431) as input data in UCINET. Each cell of the relation matrix represents the number of collaborations between any two given scholars. Finally, the normalized degree, closeness, and betweenness centralities of the 137 target scholars are calculated by dividing the original value of degree centrality by $(N-1)$, that of closeness centrality by $1/(N-1)$, and that of betweenness centrality by $(N-1)(N-2)/2$, where $N = 431$ (Freeman, 1979).

To examine relational capital for each of the 137 scholars, this study analyzes the graphic output of UCINET and derives the prolific co-author counts of individual scholars. The graph depicts the relations among the prolific scholars, excluding their peripheral co-authors (see Fig. 2). Furthermore, because trustworthiness among co-authors is an important attribute of relational capital, we include only those authors who co-authored at least twice, thinking that they must trust each other enough to collaborate again. For example, in Fig. 2, the relational capital of "Straub, DW" is one because he co-authors with one prolific scholar (i.e., "Karahanna, E") two or more times in the network, excluding "Watson, RT" and "Boudreau, MC" with whom he co-authors only once. Note that the prolific co-author counts of the scholars displayed on the left side of Fig. 2 (i.e., "Bhattacherjee, A", "Kim, YG", etc.) are all zeros in this dataset.

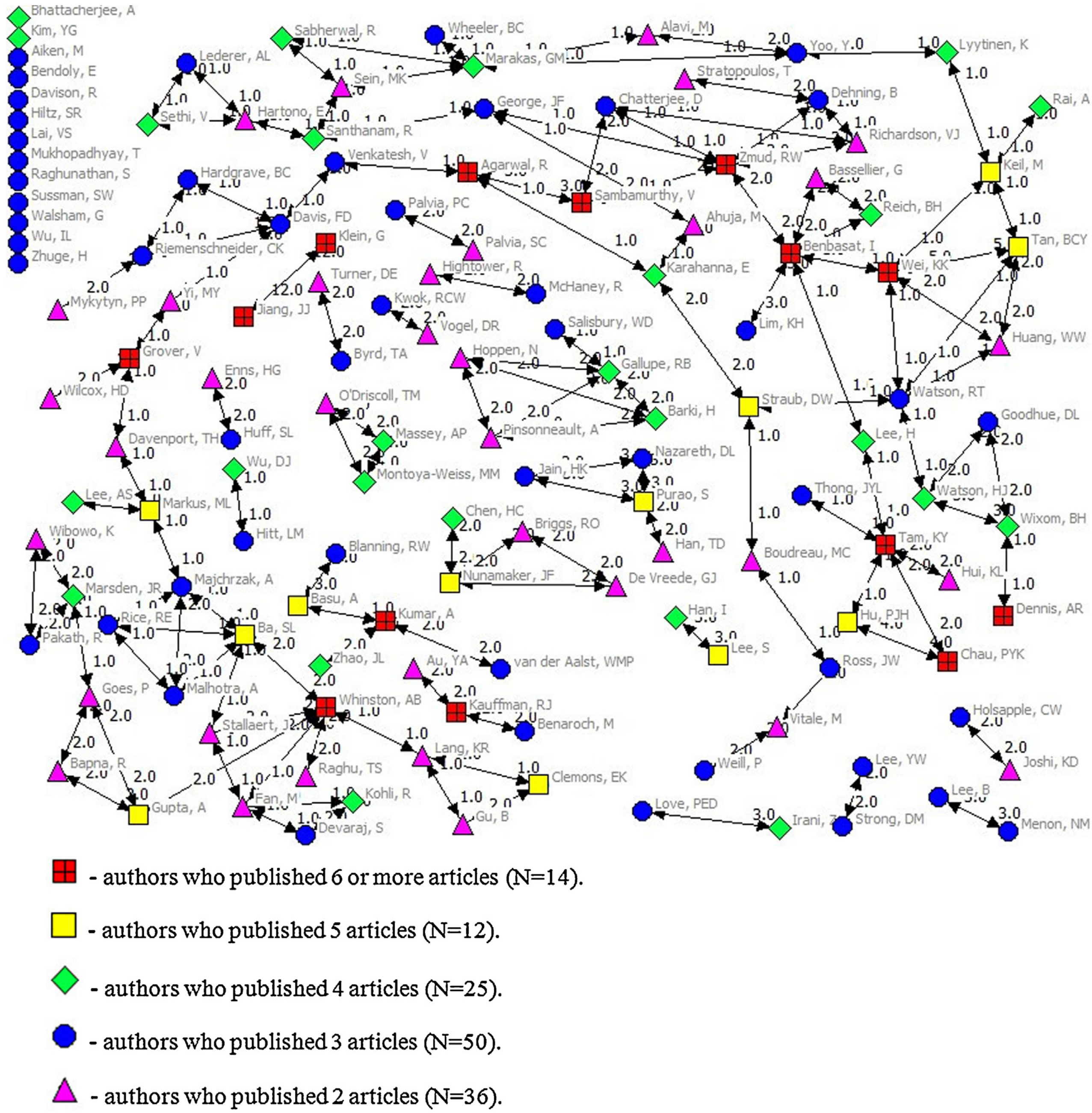

Fig. 2. The collaborative relations of 101 prolific and 36 non-prolific scholars.

To measure member diversity of team composition (i.e., explorative versus exploitative), this study develops a collaboration diversity index (CDI), as indicated in Eq. (1), where $\sum \text{coauthor}_i - \sum \text{duplicate}_i$ stands for the total of non-duplicated, unique co-authors and $\sum \text{relation}_i$ refers to total collaborative relations of all published journal articles. When the value of CDI is equal to 1, team composition is completely explorative; that is, the number of non-duplicated co-authors equals the number of collaborative relations, meaning that scholars collaborate with different co-authors on each article. In contrast, a value near zero indicates extreme exploitation; that is, the total number of collaborative relations is much higher than the total number of non-duplicated co-authors, meaning scholars collaborate with the same co-authors. When a scholar did not co-author with anyone, the value is zero, indicating full exploitation. Therefore, the range of this index is from zero to one, showing a spectrum of member diversity in team composition. Table 5 shows an example in which author *A* published 12 articles and had 11 collaborative relations with 5 unique co-authors. Following Eq. (1), the value of CDI for author *A* is .455.

$$\text{Collaboration diversity index} = \frac{\sum \text{coauthor}_i - \sum \text{duplicate}_i}{\sum \text{relation}_i}$$

$$i = 1, 2, \ldots n \quad \text{article} \tag{1}$$

Publishing tenure is measured as the time between 2011 and the year the scholar first published an article in the IS discipline, which addresses the cognitive capital he or she accumulated. This variable is derived from the SSCI database. For example, if a scholar published his or her first IS-related article in 1978, the value for publishing tenure would be 33.

Table 5
An example of calculating collaboration diversity index of Author A.

Article no.	Author list	Relation of A	Co-authors	Duplicate
1	A, B	AB	B	–
2	A	–	–	–
3	A, B	AB	B	Yes
4	B, A	AB	B	Yes
5	A	–	–	–
6	A, C	AC	C	–
7	C, A	AC	C	Yes
8	B, A, D	AB & AD	B D	Yes
9	C, A	AC	C	Yes
10	A	–	–	–
11	E, A, F	AE & AF	E F	–
12	A, B	AB	B	Yes
Total		11	11	6

Collaboration diversity index = (11 − 6)/11 = 5/11 = .455.

Citation count is also collected from the SSCI database, as it provides not only records of an author and his or her publications, but also the citations for each publication (Oh et al., 2005). However, the citation data in the SSCI database include self-citations, which render a biased estimate for research impact of an article (Nederhof, 2006). To avoid this bias, we manually tally the citations without self-citations for each article, using the 4-year windows in Table 2. Any citations coming from an author or co-authors of an article are regarded as self-citations and excluded from the citation count of the article. Specifically, the citation count of a scholar is derived by aggregating the citations of all the articles published during 1999–2003 in the 5 premier journals by that scholar and subtracting the total number of self-citations.

A control variable in this study is the affiliations of the 137 target scholars. Long et al. (1998) found that the status of academic affiliation has a positive association with research productivity in terms of the number of publications in top journals and citations for publications. Thus, we incorporate affiliation into our model as a control variable. Following the approach by Long et al. (1998), the status of academic affiliation is determined by an overall ranking for each institution as well as status rankings (i.e., high, middle, and low status). However, we found that some authors' affiliations are not classified by Long et al., such as University of Notre Dame, University of Hong Kong, and National University of Singapore. These affiliations are classified into the category of "others." In addition, some scholars switched their affiliations during the 1999–2003 period, thus we choose the last one as his or her affiliation. Because the status of academic affiliation is on a nominal scale, it is treated as a dummy variable in this study.

5. Analyses and results

Descriptive statistics, the values of variance inflation factor (VIF), and the correlation matrix of estimated variables are illustrated in Table 6. All VIF values are less than the common threshold of 5.0, indicating there is no significant multicollinearity among these variables. We further confirm that the bias from self-citations is significant by testing the difference in the means of citation counts with and without self-citations (t = 7.621; p < .001). Therefore, this study uses citation count without self-citations as the dependent variable.

To test the hypothesized associations, we consider two approaches to estimating the parameters of a structural equation model (SEM), namely, the covariance-based approach and component-based (or variance-based) approach (Fornell et al., 1990). While the covariance-based approach uses the solution process for simultaneous equations to find the estimates, the component-based approach performs a multiple regression analysis independently for each endogenous variable with a re-sampling estimation process (Hair et al., 2012). As suggested by Hair et al. (2011, p. 140), covariance-based SEM, exemplified by software such as LISREL and EQS, should be used if the research objective is theory testing and confirmation. In contrast, if the research objective is prediction and theory development, then the appropriate method is variance-based SEM, such as partial least squares (PLS). Because the aim of this study is to predict the influence of social capital theory on research impact, using the PLS approach is appropriate. Moreover, the PLS procedure is able to model latent constructs under conditions of non-normality and small to medium sample sizes (Chin et al., 2003). However, with smaller ratios of sample size to number of indicators, the known bias in PLS for overestimating measurement loadings and underestimating structural paths among constructs may occur (Chin et al., 2003). Thus, a general rule is that the ratio should never fall below 5–1. Strictly speaking, the desired level of the ratio is between 15 and 20 observations for each independent variable (Hair et al., 1998). There are 137 observations and six independent variables in this study, so the ratio is 22.8–1 which is above the desired level, thus indicating there is little concern of small-sample bias. To examine the specific effect of each indicator, this study first conducts path analysis for all variables (see Fig. 3). Overall, one of the three dimensions of structural capital, betweenness centrality, positively affects citations for publications (H1a: β = −.009, p > .05; H1b: β = −.077, p > .05; H1c: β = .685, p < .001), so H1 is partially supported. However, the direct effects of relational capital (prolific co-author count) and cognitive capital (team exploration and publishing tenure) on citation count are not significant (H2: β = .037, p > .05; H3a: β = .062, p > .05; H3b: β = .015, p > .05), indicating that neither H2 nor H3 is supported.

For relational capital, the results show that expanding trustworthy relationships with prolific colleagues is beneficial for improving structural capital, thus H4a (β = .492, p < .001), H4b (β = .353, p < .01), and H4c (β = .269, p < .05) are supported. For cognitive capital, team exploration is not significantly associated with degree centrality (H5a: β = .273, p > .05), while other hypothesized associations (i.e., team exploration with closeness and betweenness centralities) are significant (H5b: β = .566, p < .001; H5c: β = .456,

Table 6
Descriptive statistics, VIF, and correlation matrix (N = 137).

ID		Mean	S.D.	VIF	1	2	3	4	5	6
1	Degree centrality	.122	.078	1.429	1					
2	Closeness centrality	.383	.137	1.416	.176*	1				
3	Betweenness centrality	1.886	3.644	1.428	.302**	.436**	1			
4	Prolific co-author count	.73	.723	2.215	.328**	−.014	−.021	1		
5	Exploration CDI	.775	.207	2.309	−.009	.335**	.298*	−.647**	1	
6	Publishing tenure	17.72	7.162	1.177	.353**	.065	.202*	.038	.126	1
7	Citation count	109.58	165.1	N/A	.200*	.260**	.665**	−.019	.217*	.153

* p < .05 (2-tailed).
** p < .01 (2-tailed).

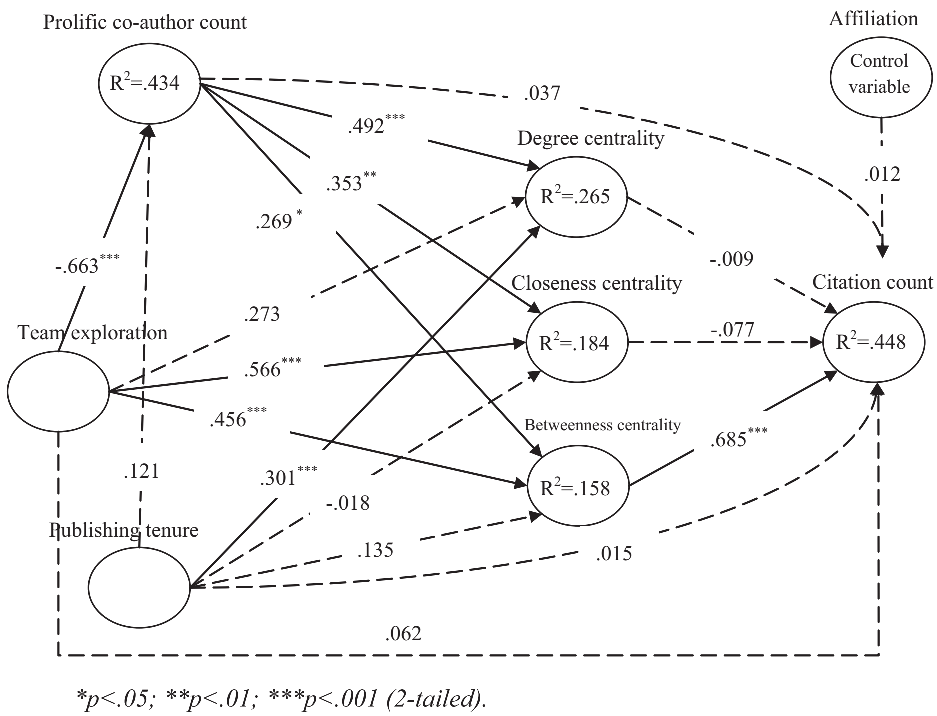

Fig. 3. Tests for the hypothesized associations ($N = 137$).

$p < .001$). Contrary to the results of team exploration, longer publishing tenure is favorable for developing degree centrality in the network (H5d: $\beta = .301$, $p < .001$), but its effects on closeness centrality (H5e: $\beta = -.018$, $p > .05$) and betweenness centrality (H5f: $\beta = .135$, $p > .05$) are not significant. With respect to the impact of cognitive capital on relational capital, the result is contrary to our expectation; publishing tenure is not significantly associated with prolific co-author count (H6b: $\beta = .121$, $p > .05$), whereas team exploration affects significantly but negatively this count (H6a: $\beta = -.663$, $p < .001$).

In order to assess the effect size of a particular independent variable on a dependent variable, the squared multiple (or multiple partial) correlation (R^2) is used to calculate Cohen's f^2 (1992). The formula of effect size (f^2) is as follows.

$$\text{Cohen's } f^2 = \frac{R^2_{\text{full}} - R^2_{\text{reduced}}}{1 - R^2_{\text{full}}}$$

where R^2_{full} is the value of R^2 from the least-square model that includes all independent variables; R^2_{reduced} is the value from that includes all but one particular set of independent variables.

According to Cohen (1992), an effect size of $.02 \le f^2 < .15$ is small; $.15 \le f^2 < .35$ is medium; and $f^2 \ge .35$ is large. Table 7 reveals the effect sizes of all significant hypothesized associations. It is confirmed that betweenness centrality has a large effect size ($f^2 = .589$) on citation count, while prolific co-author count and publishing tenure have medium ($f^2 = .186$) and small ($f^2 = .118$) effect sizes, respectively, on degree centrality. Likewise, team exploration and prolific co-author count have medium ($f^2 = .219$) and small ($f^2 = .087$) effect sizes, respectively, on closeness centrality. Moreover, team exploration has a large effect size on prolific co-author count ($f^2 = .765$). For the betweenness centrality, the effect sizes are small exerted by both team exploration ($f^2 = .138$) and prolific co-author count ($f^2 = .049$). Although some independent variables exert small effect sizes, the β values indicate that their effects are important, but to a lesser extent.

6. Discussion and implications

This study is the first to examine the effects of social capital on research impact using the three dimensions in social capital theory. The effects from each dimension are discussed below.

Table 7
Effect sizes of significant hypothesized associations.

Hypothesis	β	Cohen's f^2	Effect size[a]
H1c: Betweenness centrality → citation count	.685***	.589	Large
H4a: Prolific co-author count → degree centrality	.492***	.186	Medium
H4b: Prolific co-author count → closeness centrality	.353**	.087	Small
H4c: Prolific co-author count → betweenness centrality	.269*	.049	Small
H5b: Team exploration → closeness centrality	.566***	.219	Medium
H5c: Team exploration → betweenness centrality	.456***	.138	Small
H5d: Publishing tenure → degree centrality	.301***	.118	Small
H6a: Team exploration → prolific co-author count	−.663***	.765	Large

[a] The overall effect sizes $f^2 \ge .02$, .15, or .35 are regarded as small, moderate, and large effects, respectively.
[*] $p < .05$ (2-tailed).
[**] $p < .01$ (2-tailed).
[***] $p < .001$ (2-tailed).

6.1. The effects of structural capital

For the effects of structural capital, this study found that betweenness centrality positively affects citation count and has the largest beta coefficient and a large effect size ($f^2 = .589$), but degree and closeness centralities do not have any significant effect. This finding for betweenness centrality is consistent with the study by Yan and Ding (2009). It reveals that spanning the structural holes is critical in the context of a co-authorship network. That is, acquiring non-redundant resources from other research groups is much more important than just obtaining needed resources from neighboring peers since it renders a competitive advantage based on the resource-based view (Peteraf, 2006). According to this finding, we suggest that research institutions should encourage research activities that involve co-authorship with different scholars from different research groups or centers, or even different disciplines (Leydesdorff, 2007). One possible measure is to give more performance evaluation points or more research funding to scholars with such co-authorships. Institutions with limited funding may offer small seed grants to initiate inter-group research projects and subsequently enlarge these grants based on their inter-group research performance.

Contrary to our expectations, degree and closeness centralities do not lead to higher citation count. Although the finding about closeness centrality is consistent with the study of Abbasi et al. (2011), we suspect a suppressor effect might exist because the zero-order correlations are significant between betweenness centrality and closeness centrality, as well as betweenness centrality and citation count. A suppressor variable is a variable that has a significant zero-order correlation with the dependent variable, but is also correlated with one or more predictor variables (Wasko and Faraj, 2005). When one of predictor variables has a negative weight on the dependent variable in path model, this situation is called negative suppression (Maassen and Bakker, 2001). Suppression particularly occurs when the beta coefficient of the initial predictor reverses sign, whereas the beta coefficient for the suppressor variable increases relative to its initial validity coefficient (Conger, 1974). A classical examination of suppressor effect is based on a comparison between zero-order correlations and path coefficients following the Conger's definition (see Hicks and Patrick, 2006; Maassen and Bakker, 2001). Accordingly, we found that two independent variables, namely, closeness centrality ($r = .260$) and betweenness centrality ($r = .665$), exhibit positive zero-order associations with dependent variable (citation count). Including both closeness and betweenness centralities in the PLS model, however, resulted in a reversal of the sign for closeness centrality ($\beta = -.077$) and an increase in the validity coefficient of betweenness centrality ($\beta = .685$). This additional analysis confirms our suspicion about the suppression effect in this model. Previous study by Abbasi et al. (2011) reported the association between these two centralities and the g-index that seems to exhibit a similar suppressor effect. Since the omission of any suppressor will lead to either an underestimation or an overestimation of the relationships between independent and criterion variables (Cohen and Cohen, 1983), future research should avoid using merely zero-order correlations to estimate the effects of centralities on research impact and analyze the joint effects of all three centralities in an estimation model.

6.2. The effects of relational capital

Despite the results showing no direct effect of relational capital on citation count, it exerts positive and significant influence on the three centralities. Since betweenness centrality has a significant and positive effect on citation count, relational capital, consequently, has an indirect effect on citation count through betweenness centrality, but with a small effect size ($f^2 = .049$). This suggests that co-authoring with prolific scholars may not produce a halo effect for the authors who are also prominent researchers in the field. In other words, while one prominent author projects a positive signal on the quality of published article, the addition of more prominent co-authors can only marginally increase the signaling effect. Nevertheless, co-authoring with prolific scholars may help individual authors strengthen their positions in the network because it is more likely for them to gain connections with authors who are newly entering the network through these prolific co-authors than through their regular colleagues (Moody, 2004). This enables the authors to expand their networks and increase the opportunities for disseminating their work in the networks. Thus, relational capital benefits individual authors' citation counts indirectly through its effects on structural capital.

According to this finding, we should encourage researchers to expand their relationships with prolific scholars, although it is easier said than done. One plausible way to increase the likelihood for researchers to become acquainted with prolific scholars could be through participation in international conferences or symposiums featuring these prolific scholars. In addition, research institutions could actively identify prolific scholars in the target discipline and invite them to join multiyear research projects funded by grant agencies, such as National Science Foundation in the U.S., National Science Council in Taiwan, and Framework Programme in the European Union, among others. This will expand the relationships between their faculty members and the prolific scholars, thereby increasing their relational capital.

6.3. The effects of cognitive capital

Consistent with the finding of relational capital, cognitive capital also has no direct effect on citation count. Neither team exploration nor publishing tenure affects citation count. The finding about team exploration is consistent with that of Liao (2011). Moreover, prior study shows that collaboration with more scholars helps researchers to share workloads, but it also increases communication and coordination costs when they work together (see Lee and Bozeman, 2005). It implies that expanding relationships with other scholars might decrease the quality of work and impede the research impact. This dissipating effect is very likely a consequence of having access to many non-redundant ties (different co-authors), which requires researchers to deal with a higher volume of more diverse information. Such access consumes time and resources that cannot be allocated to absorbing and integrating already-obtained novel insights (Gilsing et al., 2008). Accordingly, we suspect that the association between team exploration and research impact might level off at a certain threshold, which explains the insignificant effect of team exploration. To explore the possible curvilinearity of the association between team exploration and citation count, we conducted an additional test using PLS and found that neither team exploration ($\beta = .784$, $t = 1.582$, $p > .05$) nor its square ($\beta = -.622$, $t = 1.192$, $p > .05$) has a significant effect on citation count. Therefore, there is no significant curvilinearity in the association between team exploration and citation count. Regarding the other constructs, we also tested the possible existence of curvilinear associations between them and citation count. Specifically, no significant curvilinearity was found for prolific co-author count (i.e., relational capital), degree and closeness centralities (i.e., structural capital), or publishing tenure (i.e., cognitive capital).

Moreover, team exploration is positively associated with closeness and betweenness centralities with medium ($f^2 = .219$) and small ($f^2 = .138$) effect sizes, respectively. This interesting finding suggests that if researchers collaborate with different colleagues, it will help them link with people from other research groups, meaning they can more efficiently acquire needed resources from other groups in the network. Therefore, research institutions should encourage their faculty members to co-author with different scholars because it helps to expand the collaboration networks of their members. They should value not only single-authorship but also co-authorship during the process of performance evaluation. As for degree centrality, the finding shows that it is not significantly influenced by team exploration. Through the same curvilinear test, we found using PLS that the association between team exploration and degree centrality has a curvilinear pattern; team exploration has positive effect on degree centrality ($\beta = 1.173$, $t = 2.668$, $p < .01$), while its square has negative impact on degree centrality ($\beta = -1.201$, $t = 2.733$, $p < .01$). That is, high team exploration might hinder the development of degree centrality. Therefore, we suggest that future researchers who seek to co-author with new scholars should be aware of the possibility of losing their old partners. Too much effort in managing too many new partners is very likely to irritate and turn away the old partners. Maintaining an appropriate degree of team exploration might be a good approach to optimize the three centralities in structural capital.

Regarding publishing tenure, this study found it is positively related to degree centrality with a small effect size ($f^2 = .118$). As expected, longer publishing tenure can result in a good reputation and help researchers become well-known scholars or opinion leaders in their co-authorship networks. Further, it may attract their surrounding scholars to collaborate with them. However, publishing tenure does not positively influence closeness and betweenness centralities. That is, long publishing tenure by no means is enough to attract people from other research groups because these groups might already have prominent scholars. Due to competition among prominent scholars, long publishing tenure cannot help a researcher acquire and maintain a central position and bridge between different research groups. According to the positive effect of publishing tenure on degree centrality, we recommend that research institutions consider recruiting senior scholars to take advantage of their influence in co-authorship networks (i.e., high centralities), thereby improving research impact for their faculties' publications.

The finding that publishing tenure and team exploration have complementary effects on structural capital is rather intriguing. Specifically, the former affects degree centrality and the latter influences closeness and betweenness centralities. As a result, we recommend that junior scholars adopt an exploration strategy (i.e., co-authoring with different scholars) for acquiring closeness and betweenness centralities. In contrast, senior scholars could take advantage of their influence in co-authorship networks to disseminate their research outputs and increase their research impact.

Regarding the causality from cognitive capital to relational capital, we found that team exploration is negatively associated with relational trust of prolific scholars, with a large effect size ($f^2 = .765$). Although this result contradicts our expectation, it reveals an important signal that when authors strive to change research partners, it is harmful to develop relational trust because they do not spend enough effort establishing long-term relationships with their co-authors. This finding reveals that team exploration is a doubled-edged sword; it improves closeness and betweenness centralities, but hinders building relational trust. As such, we recommend future researchers maintain a balance of team exploitation and exploration with meaningful effort to nurture relational trust of co-authors. To our surprise, publishing tenure is not significantly related to relational trust of prolific scholars. That is, a senior scholar may have higher shared understanding, code of conduct, and expertise in the research community, but this does not necessarily enable him or her to have trustworthy relationships with more prolific scholars. A plausible explanation is that expanding such trustworthy relationships is more difficult and complex than one commonly expects; it usually takes substantial time and effort to build bonds through social interactions.

Finally, the CDI developed in this study contributes to the extant literature from a new perspective in measuring patterns of co-authorship. Prior studies, especially bibliometric studies, usually examined the research performance of collaborations in terms of co-authorships from different nations (e.g., domestic versus international collaboration), disciplines (e.g., single-discipline versus cross-discipline collaboration), and institutions (Garg and Padhi, 2001; Mattsson et al., 2008; Oh et al., 2005; Rinia et al., 2001). The CDI measurement allows us to examine research performance in terms of member diversity in co-authorships. It will be useful to future researchers in examining the effect of team composition on various research outcomes.

7. Conclusions

This study explains *what* and *why* social capital can be used for scholars in a co-authorship network to improve research impact. More specifically, it defines six indicators with specific characteristic in the network according to the three dimensions in social capital theory, and investigates *how* these indicators interact and affect citation count. Most importantly, it provides future researchers who want to enhance the impact of their publications with several strategies for leveraging social capital. In brief, it found that the three dimensions of social capital directly or indirectly influence citation count. If researchers can analyze their structural positions in the network, surely they can shift into broker positions (i.e., high betweenness centrality) via collaboration with colleagues from different research groups, thereby increasing citation counts. If not, expanding relationships with prolific colleagues might be a good choice as it helps researchers in developing structural capital. Finally, this study found that team exploration contributes to developing closeness and betweenness centralities in structural capital while publishing tenure helps increase degree centrality. This finding suggests that a scholar can identify his or her structural position in the network and formulate a co-authorship strategy according to the future position where he or she wants to be. Nevertheless, one caveat is that collaborating with too many different scholars might put a researcher at risk of being distrusted by prolific scholars and losing chances to co-author with them.

8. Limitations and future research

Although this study offers several implications for research policies, there are four limitations that should be noted. First, this study merely focuses on six indicators based on social capital theory. While the concept of structural capital is very well explained by the three centrality measures, there may be other indicators that better capture the dimensions of relational and cognitive capitals. For relational capital, the duration and frequency of co-authorship may reflect the degree of trust a scholar has with a particular prolific co-author. However, this study estimates a scholar's relational capital by the number of repeated co-authorships with different prolific scholars, rather than the degree of trust with each prolific co-author. Using the co-authorship network in Table 5 as an example and assuming authors *A*, *B*, *C*, and *D* are prolific scholars, if scholar *A* co-authored 5 times in 5 years with prolific scholar *B*, and 3 times with prolific scholar *C* within 2 years, the prolific co-author count of scholar *A* is only "2" (i.e., 2 scholars, ignoring the one-time co-authorship with scholar *D*). In this vein, the prolific co-author counts for Scholars *B* and *C* are both "1". Neither repeated frequency nor repeated duration is considered in the estimation process. Future studies may incorporate these two variables into the measurement of relational capital and examine the extent to which the degree of trust in relationships with prolific scholars affects research impact.

Regarding cognitive capital, the CDI developed in this study merely reflects the number of new members in team composition. Other types of member diversity in terms of different demographic factors, such as nation, ethnicity, institution, and discipline, language, etc., may also affect cognitive capital. Future research could develop a more comprehensive measure of cognitive capital by incorporating these factors.

Second, this study only examines the dynamics of a co-authorship network in the IS discipline using five target journals in the 1999–2003 period. The findings from this dataset may not be generalized to other time periods or disciplines. Future studies could generalize the findings by replicating the study in multiple disciplines with a larger dataset from a longer period. Panel data across different time windows could also be collected to examine how social capital evolves and its effects on research impact over time. As regards the citation window, the 4-year uniform period for each published article might be too short for some disciplines. Because top journals commonly have a cited half-life index of over 10 years, extending this window to 10 years in future studies might improve the accuracy of estimating research impact.

Third, inter-disciplinary research is increasingly in demand in academia. In a co-authorship network, collaborators are not necessarily from the same discipline and some research projects require collaborators with different disciplinary knowledge. This study does not examine issues arising from research activities that involve scholars from different disciplines. Future studies are needed to examine the differences in social capital created by intra-disciplinary versus inter-disciplinary co-authorship networks; and compare the effects on research impact exerted by the social capital from these two types of networks. Fourth, the three dimensions of social capital are highly interrelated, as pointed out by Nahapiet and Ghoshal (1998). In our opinion, they affect and reinforce each other over time. The proposed model herein is a restricted causal model based on cross-sectional data; it does not examine how their interactions evolve over times. Future researchers are encouraged to conduct a longitudinal study to explore how the associations and reciprocal effects change over time. Finally, another variable to consider in future studies is the order of authors, which has been shown to relate positively with citation count (He et al., 2012). Future studies may simply include it as a control variable to mitigate its co-variance with citation count or incorporate it into the measurement of relational capital.

References

Abbasi, A., Altmann, J., Hossain, L., 2011. Identifying the effects of co-authorship networks on the performance of scholars: a correlation and regression analysis of performance measures and social network analysis measures. Journal of Informetrics 5 (4), 594–607.

Abramo, G., D'Angelo, C.A., Solazzi, M., 2011. Are researchers that collaborate more at the international level top performers? An investigation on the Italian university system. Journal of Informetrics 5 (1), 204–213.

Acedo, F.J., Barroso, C., Casanueva, C., Galán, J.L., 2006. Co-authorship in management and organizational studies: an empirical and network analysis. Journal of Management Studies 43 (5), 957–983.

Bammer, G., 2008. Enhancing research collaborations: three key management challenges. Research Policy 37 (5), 875–887.

Borgatti, S.P., 2005. Centrality and network flow. Social Network 27 (1), 55–71.

Borgatti, S.P., Everett, M.G., Freeman, L.C., 1999. UCINET 5.0 Version 1.00. Analytic Technologies, Natick, MA.

Bornmann, L., Mutz, R., Neuhaus, C., Daniel, H-D., 2008. Citation counts for research evaluation: standards of good practice for analyzing bibliometric data and presenting and interpreting results. Ethics in Science and Environmental Politics 8 (1), 93–102.

Brass, D.J., Burkhardt, M.E., 1993. Potential power and power use: an investigation of structure and behavior. Academy of Management Journal 36 (3), 441–470.

Brim, O.G., Wheeler, S., 1966. Socialization After Childhood: Two Essays. Wiley, New York.

Brown, L.D., Gardner, J.C., 1985. Using citation analysis to assess the impact of journals and articles on contemporary accounting research (CAR). Journal of Accounting Research 23 (1), 84–109.

Burkhardt, M.E., Brass, D.J., 1990. Changing patterns or patterns of change? The effects of a change in technology on social network structure and power. Administrative Science Quarterly 35 (1), 104–127.

Burt, R., 1992. Structural Holes: The Social Structure of Competition. Harvard University Press, Cambridge, MA.

Cannon-Bowers, J.A., Salas, E., 2001. Reflections on shared cognition. Journal of Organizational Behavior 22 (2), 195–202.

Cattell, R.B., 1965. The Scientific Analysis of Personality. Penguin Books, New York.

Chen, G., 2005. Newcomer adaptation in teams: multilevel antecedents and outcomes. Academy of Management Journal 48 (1), 101–116.

Chi, L., Holsapple, C.W., Srinivasan, C., 2007. Competitive dynamics in electronic networks: a model and the case of interorganizational systems. International Journal of Electronic Commerce 11 (3), 7–49.

Chin, W.W., Marcolin, B.L., Newsted, P.R., 2003. A partial least squares latent variable modeling approach for measuring interaction effects: results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. Information Systems Research 14 (2), 189–217.

Cho, H., Gay, G., Davidson, B., Ingraffea, A., 2007. Social networks, communication styles, and learning performance in a CSCL community. Computers & Educations 49 (2), 309–329.

Cohen, J., 1992. A power primer. Psychological Bulletin 112 (1), 155–159.

Cohen, J., Cohen, P., 1983. Applied Multiple Regression/Correlation Analysis for the Social Science, 2nd ed. Erlbaum, Hillsdale, NJ.

Coleman, J.S., 1988. Social capital in the creation of human capital. American Journal of Sociology 94 (Suppl.), S95–S120.

Conger, A.J., 1974. A revised definition for suppressor variables: a guide to their identification and interpretation. Educational and Psychological Measurement 34 (1), 35–46.

De Dreu, C.K.W., West, M.A., 2001. Minority dissent and team innovation: the importance of participation in decision making. Journal of Applied Psychology 86 (6), 1191–1201.

Ding, Y., 2011. Scientific collaboration and endorsement: network analysis of coauthorship and citation networks. Journal of Informetrics 5 (1), 187–203.

Ding, Y., Yan, E., Frazho, A., Caverlee, J., 2009. PageRank for ranking authors in co-citation networks. Journal of the American Society for Information Science and Technology 60 (11), 2229–2243.

Donnellon, A., Gray, B., Bougon, M.G., 1986. Communication, meaning, and organized action. Administrative Science Quarterly 31 (1), 43–55.

Ferratt, T.W., Gorman, M.F., Kanet, J.J., Salisbury, W.D., 2007. IS journal quality assessment using the author affiliation index. Communications of the Association for Information Systems 19, 710–724.

Fornell, C., Lorange, P., Roos, J., 1990. The cooperative venture formation process: a latent variable structural modeling approach. Management Science 36 (10), 1246–1255.

Freeman, L.C., 1979. Centrality in social networks: conceptual clarifications. Social Network 1 (3), 215–239.

Garg, K.C., Padhi, P., 2001. A study of collaboration in laser science and technology. Scientometrics 51 (2), 415–427.

Gazni, A., Didegah, F., 2011. Investigating different types of research collaboration and citation impact: a case study of Harvard University's publications. Scientometrics 87 (2), 251–265.

Geletkanycz, M.A., Boyd, B.K., Finkelstein, S., 2001. The strategic value of CEO external directorate networks: implications for CEO compensation. Strategic Management Journal 22 (9), 889–898.

Geletkanycz, M.A., Hambrick, D.C., 1997. The external ties of top executives: implications for strategic choice and performance. Administrative Science Quarterly 42 (4), 654–681.

Gilsing, V., Nooteboomb, B., Vanhaverbekec, W., Duystersd, G., Oorda, A.V., 2008. Network embeddedness and the exploration of novel technologies: technological distance, betweenness centrality and density. Research Policy 37 (10), 1717–1731.

Granovetter, M.S., 1985. Economic action and social structure: the problem of embeddedness. American Journal of Sociology 91 (3), 481–510.

Gu, Z., Wu, J.S., 2003. Earnings skewness and analyst forecast bias. Journal of Accounting and Economics 35 (1), 5–29.

Hair, J.F., Anderson, R.E., Tatham, R.L., Black, W.C., 1998. Multivariate Data Analysis, 5th ed. Pearson Education Inc, Boston, MA.

Hair, J.F., Ringle, C.M., Sarstedt, M., 2011. PLS-SEM: indeed a silver bullet. Journal of Marketing Theory and Practice 19 (2), 139–151.

Hair, J.F., Sarstedt, M., Ringle, C.M., Mena, J.A., 2012. An assessment of the use of partial least squares structural equation modeling in marketing research. Journal of the Academy of Marketing Science 40 (3), 414–433.

Hauptman, R., 2005. How to be a successful scholar: publish efficiently. Journal of Scholarly Publishing 36 (2), 115–119.

Hazleton, V., Kennan, W., 2000. Social capital: reconceptualizing the bottom line. Corporate Communications: An International Journal 5 (2), 81–86.

He, B., Ding, Y., Yan, E., 2011. Mining enriched contextual information of scientific collaboration: a meso perspective. Journal of the American Society for Information Science and Technology 62 (5), 831–845.

He, B., Ding, Y., Yan, E., 2012. Mining patterns of author orders in scientific publications. Journal of Informetrics 6 (3), 359–368.

Homans, G.C., 1958. Social behavior as exchange. American Journal of Sociology 63 (6), 597–606.

Hou, H., Kretschmer, H., Liu, Z., 2008. The structure of scientific collaboration networks in Scientometrics. Scientmoetrics 75 (2), 189–202.

Huang, C.C., Lin, T.C., Lin, K.J., 2009. Factors affecting pass-along email intentions (PAEIs): integrating the social capital and social cognition theories. Electronic Commerce Research and Applications 8 (3), 160–169.
Hicks, B.M., Patrick, C.J., 2006. Psychopathy and negative emotionality: analyses of suppressor effects reveal distinct relations with emotional distress, fearfulness, and anger-hostility. Journal of Abnormal Psychology 115 (2), 276–287.
Inhaber, H., Przednowek, K., 1976. Quality of research and the nobel prizes. Social Studies of Science 6 (1), 33–50.
Inkpen, A.C., Tsang, W.K., 2005. Social capital, networks, and knowledge transfer. Academy of Management Review 30 (1), 146–165.
Katerattanakul, P., Han, B., Hong, S., 2003. Objective quality ranking of computing journals. Communications of ACM 46 (10), 111–114.
Katz, J.S., Hicks, D., 1997. How much is a collaboration worth? A calibrated bibliometric model. Scientometrics 40 (3), 541–554.
Katz, J.S., Martin, B.S., 1997. What is research collaboration? Research Policy 26 (1), 1–18.
Kling, R., McKim, G., 2000. Not just a matter of time: field differences and the shaping of electronic media in supporting scientific communication. Journal of the American Society for Information Science and Technology 51 (14), 1306–1320.
Kreijns, K., Kirschner, P.A., Jochems, W., 2003. Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research. Computers in Human Behavior 19 (3), 335–353.
Lavie, D., Rosenkopf, L., 2006. Balancing exploration and exploitation in alliance formation. Academy of Management Journal 49 (4), 797–818.
Lea, B-R., Yu, W-B., Maguluru, N., 2006. Enhancing business networks using social network based virtual communities. Industrial Management & Data Systems 106 (1), 121–138.
Lee, S., Bozeman, B., 2005. The impact of research collaboration on scientific productivity. Social Studies of Science 35 (5), 673–702.
Leydesdorff, L., 2007. Betweenness centrality as an indicator of the interdisciplinarity of scientific journals. Journal of the American Society for Information Science and Technology 58 (9), 1303–1319.
Liao, C.H., 2011. How to improve research quality? Examining the impacts of collaboration intensity and member diversity in collaboration networks. Scientometrics 86 (3), 747–761.
Liao, J., Welsch, H., 2005. Roles of social capital in venture creation: key dimensions and research implications. Journal of Small Business Management 43 (4), 345–362.
Liebowitz, J., 2005. Linking social network analysis with the analytic hierarchy process for knowledge mapping in organizations. Journal of Knowledge Management 9 (1), 76–86.
Liu, X., Bollen, J., Nelson, M.L., van de Sompel, H., 2005. Co-authorship networks in the digital library research community. Information Processing & Management 41 (6), 1462–1480.
Long, R.G., Bowers, W.P., Barnett, T., White, M.C., 1998. Research productivity of graduates in management: effects of academic origin and academic affiliation. Academy of Management Journal 41 (6), 704–714.
Lowry, P.B., Romans, D., Curtis, A., 2004. Global journal prestige and supporting disciplines: a scientometric study of Information Systems journals. Journal of the Association for Information Systems 5 (2), 29–80.
LSE Public Policy Group, 2011. Maximizing the Impacts of Your Research: A Handbook for Social Scientists. London School of Economics, London.
Lu, H., Feng, Y., 2009. A measure of authors' centrality in co-authorship networks based on the distribution of collaborative relationships. Scientometrics 81 (2), 499–511.
Maassen, G.H., Bakker, A.B., 2001. Suppressor variables in path models. Sociological Methods & Research 20 (2), 241–270.
March, J.G., 1991. Exploration and exploitation in organizational learning. Organization Science 2 (1), 71–87.
Mattsson, P., Laget, P., Nilsson, A., 2008. Intra-EU vs. extra-EU scientific co-publication patterns in EU. Scientometrics 75 (3), 555–574.
McFadyen, M.A., Cannella Jr., A.A., 2004. Social capital and knowledge creation: diminishing returns of the number and strength of exchange relationships. Academy of Management Journal 47 (5), 735–746.
Miller, K.D., Zhao, M., Calantone, R.J., 2006. Adding interpersonal learning and tacit knowledge to March's exploration-exploitation model. Academy of Management Journal 49 (4), 709–722.
Moody, J., 2004. The structure of a social science collaboration network: disciplinary cohesion from 1963 to 1999. American Sociological Review 69 (2), 213–238.
Moorman, C., Deshpandé, R., Zaltman, G., 1993. Factors affecting trust in market research relationships. Journal of Marketing 57 (1), 81–101.
Moreland, R.L., Levine, J.M., 1982. Socialization in small groups: temporal changes in individual-group relations. Advances in Experimental Social Psychology 15, 137–192.
Murphy, P., Laczniak, E., Wood, G., 2007. An ethical basis for relationship marketing: a virtue ethics perspective. European Journal of Marketing 41 (1/2), 37–57.
Mylonopoulos, N.A., Theoharakis, V., 2001. Global perceptions of IS journals. Communications of ACM 44 (9), 29–33.
Nahapiet, J., Ghoshal, S., 1998. Social capital, intellectual capital, and the organizational advantage. Academy of Management Review 23 (2), 242–266.
Nederhof, A.J., 2006. Bibliometric monitoring of research performance in the social sciences and the humanities: a review. Scientometrics 66 (1), 81–100.
Nunnally, J.C., 1978. Psychometric Theory, 2nd ed. McGraw-Hill, New York.
Oh, W., Choi, J.N., Kim, K., 2005. Coauthorship dynamics and knowledge capital: the patterns of cross-disciplinary collaboration in information systems research. Journal of Management Information Systems 22 (3), 265–292.
Okoli, C., Oh, W., 2007. Investigating recognition-based performance in an open content community: a social capital perspective. Information & Management 44 (3), 240–252.
Otte, E., Rousseau, R., 2002. Social network analysis: a powerful strategy, also for the information sciences. Journal of Information Science 28 (6), 441–453.
Ouchi, W.G., 1980. Markets, bureaucracies, and clans. Administrative Science Quarterly 25 (1), 129–141.
Pajares, F., Miller, M.D., 1994. Role of self-efficacy and self-concept beliefs in mathematical problem solving: a path analysis. Journal of Educational Psychology 86 (2), 193–203.
Peffers, K., Ya, T., 2003. Identifying and evaluating the universe of outlets for information systems research: ranking the journals. Journal of Information Technology Theory and Application 5 (1), 63–84.
Perretti, F., Negro, G., 2006. Filling empty seats: how status and organizational hierarchies affect exploration versus exploitation in team design. Academy of Management Journal 49 (4), 759–777.
Peteraf, M.F., 2006. The cornerstones of competitive advantage: a resource-based view. Strategic Management Journal 14 (3), 179–191.
Potosky, D., 2002. A field study of computer efficacy beliefs as an outcome of training: the role of computer playfulness, computer knowledge, and performance during training. Computers in Human Behavior 18 (3), 241–255.
Rainer Jr., R.K., Miller, M.D., 2005. Examining differences across journal rankings. Communications of ACM 48 (2), 91–94.
Reichers, A.E., 1987. An interactionist perspective on newcomer socialization rates. Academy of Management Review 12 (2), 278–287.
Rinia, E.J., van Leeuwen, Th.N., van Vuren, H.G., van Raan, A.F.J., 2001. Influence of interdisciplinarity on peer-review and bibliometric evaluations in physics research. Research Policy 30 (3), 357–361.
Robert Jr., L.P., Dennis, A.R., Ahuja, M.K., 2008. Social capital and knowledge integration in digital enabled teams. Information Systems Research 19 (3), 314–334.
Rogoff, B., 1990. Apprenticeship in Thinking: Cognitive Development in Social Context. Oxford University Press, New York, NY.
Simon, H.A., 1976. Administrative Behavior. Free Press, New York.
Soderbaum, F., 2001. Networking and capacity building: the role of regional research networks in Africa. European Journal of Development Research 13 (2), 144–163.
Sooryamoorthy, R., 2009. Do types of collaboration change citation? Collaboration and citation patterns of South African science publications. Scientometrics 81 (1), 177–193.
Taylor, A., Greve, H.R., 2006. Superman or the fantastic four? Knowledge combination and experience in innovative teams. Academy of Management Journal 49 (4), 723–740.
Thomson Reuters, 2011. Journal Citation Reports. Thomson Reuters Publication http://thomsonreuters.com/products_services/science/science_products/a-z/journal_citation_reports/
Troshani, T., Doolin, B., 2007. Innovation diffusion: a stakeholder and social network view. European Journal of Innovation Management 10 (2), 176–200.
Tsai, W., Ghoshal, S., 1998. Social capital and value creation: the role of intrafirm networks. Academy of Management Journal 41 (4), 464–476.
van Raan, A.F.J., 2006. Comparison of the Hirsch-index with standard bibliometric indicators and with peer judgment for 147 chemistry research groups. Scientometrics 67 (3), 491–502.
Wadhwa, A., Kotha, S., 2006. Knowledge creation through external venturing: evidence from the telecommunications equipment manufacturing industry. Academy of Management Journal 49 (4), 819–835.
Walter, J., Lechner, C., Kellermanns, F.W., 2007. Knowledge transfer between and within alliance partners: private versus collective benefits of social capital. Journal of Business Research 60 (7), 698–710.
Wasko, M.M., Faraj, S., 2005. Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. MIS Quarterly 29 (1), 35–57.
Weidman, J.C., Stein, E.L., 2003. Socialization of doctoral students to academic norms. Research in Higher Education 44 (6), 641–656.
Weidman, J.C., Twale, D.J., Stein, E.L., 2001. Socialization of Graduate and Professional Students in Higher Education: A Perilous Passage? Jossey-Bass, San Francisco.
Wood, R., Bandura, A., 1989. Social cognitive theory of organizational management. Academy of Management Review 14 (3), 361–384.
Yan, E., Ding, Y., 2009. Applying centrality measures to impact analysis: a coauthorship network analysis. Journal of the American Society for Information Science and Technology 60 (10), 2107–2118.