Coauthorship Dynamics and Knowledge Capital: The Patterns of Cross-Disciplinary Collaboration in Information Systems Research

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ABSTRACT: From the social network perspective, this study explores the ontological structure of knowledge sharing activities engaged in by researchers in the field of information systems (IS) over the past three decades. We construct a knowledge network based on coauthorship patterns extracted from four major journals in the IS field in order to analyze the distinctive characteristics of each subfield and to assess the amount of internal and external knowledge exchange that has taken place among IS researchers. This study also tests the role of different types of social capital that influence the academic impact of researchers. Our results indicate that the proportion of coauthored IS articles in the four journals has doubled over the past 25 years, from merely 40 percent in 1978 to over 80 percent in 2002. However, a significant variation exists in terms of the shape, density, and centralization of knowledge exchange networks across the four subfields of IS—namely, behavioral science, organizational science, computer science, and economic science. For example, the behavioral science

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subgroup, in terms of internal cohesion among researchers, tends to develop the most dense collaborative relationships, whereas the computer science subgroup is the most fragmented. Moreover, external collaboration across these subfields appears to be limited and severely unbalanced. Across the four subfields, on average, less than 20 percent of the research collaboration ties involved researchers from different subdisciplines. Finally, the regression analysis reveals that knowledge capital derived from a network rich in structural holes has a positive influence on an individual researcher's academic performance.

KEY WORDS AND PHRASES: coauthorship patterns, knowledge capital, ontology of IS research, research impact, social networks, SSIC index, structural holes.

USING A SOCIAL NETWORK APPROACH, this study examines the structure and pattern of knowledge sharing among information systems (IS) researchers across and within reference disciplines in the IS field over the past three decades. A knowledge network is constructed, based on coauthorship patterns extracted from four major IS area journals, to analyze the specific paths through which knowledge sharing has occurred and intellectual capital has been cultivated within the IS field. Due to the highly interdisciplinary nature of the field, which involves an eclectic set of academic reference disciplines including behavioral science, organizational science, computer science, and economics [10, 50], an understanding of the patterns and characteristics of knowledge sharing by IS researchers is of paramount importance in maximizing the use of the repository of intellectual capital within the field. Such an understanding is necessary not only to trace the general cornerstones around which past IS research has evolved but also to build a holistic model by which future IS research can reshape and advance.

The present study investigates the network formation of over 300 "active" IS researchers who have constituted the foundation and predominant force in formulating and advancing the field. Although IS research has dramatically evolved and expanded to include new research areas, no systematic study has been carried out to elucidate coauthorship patterns both within and across different reference disciplines. This study seeks to provide a comprehensive map by which to explore the general archetypes inherent to the knowledge exchange network structure within the IS field. The identification of such network relationships may suggest ways to more effectively utilize intellectual human capital and other resources that presently do not appear to be fully exploited in academic disciplines, including the IS field.

To our knowledge, this is one of the first studies in the management literature that explores, through the use of social network analysis, the ontological structure of knowledge networks in the form of coauthorship patterns. Prior studies have relied on cocitation patterns to address the issue of connectivity or collaboration among scientists (who typically engage in medical science or natural science disciplines such as physics and biology; for detail, see [43, 44]). The cocitation approach is limited, however, in that it largely represents indirect forms of knowledge exchange that occur through the reading of other researchers' published articles, which is generally beyond the other researchers' control or intention. In order to overcome this limitation, in the present study, we define and analyze coauthorship networks that, we believe, depict more direct and intentional forms of knowledge exchange and in which authors engage in actual collaborative activities.

Finally, we empirically identify the amount of knowledge capital embedded in the "ego network"[1] [54] of individual researchers and explore its influence on their academic impact. The results of our study may offer important implications for the IS field, which is becoming increasingly complex and diverse. Specifically, this study addresses the following research questions:

- What are the distinctive characteristics of the various author networks in the IS field?
- In terms of research collaboration, to what extent does knowledge exchange occur in the IS field both within and across its reference disciplines?
- How do the two types of knowledge capital (i.e., network closures and structural holes) accumulate across various reference disciplines? To what extent do they influence a researcher's academic impact as measured by the number of citations received for his or her publications?

Prior Research

PRIOR STUDIES EXPLORED THE INTELLECTUAL development of the IS field based on two types of mechanisms—namely, citation analyses and classification approaches. For example, through the use of bibliographic cocitation analyses, Culnan [24, 25] explores the mainstream research subfields of IS. By identifying the reference disciplines of each subfield, these studies provide a useful framework for understanding the foundation of the larger IS field. Cheon et al. [19] extend and replicate the work of Culnan and Swanson [26] with the inclusion of additional IS journals. Based on citation data from the 1980–1989 period, they found that the management information systems (MIS) discipline is less established than many non-MIS fields. They discovered, however, that MIS had progressed significantly in academic stature.

Over several years of literature evaluation and project refinement, Barki et al. [7, 8] documented over 1,100 relevant key words through which IS researchers can execute efficient literature searches; when used, this structural scheme also offers valuable insight regarding the historical evolution of the IS field. Swanson and Ramiller [50] presented IS research thematics that reflect the diversity of the reference disciplines from which the papers submitted to *Information Systems Research* during its start-up period (1987–92) borrowed their core concepts. In terms of categorizing the main research questions addressed by the submitted manuscripts (e.g., organizational behavior, decision sciences, economics) and exploring the relationships between these categories, Swanson and Ramiller [50] sought to identify the institutional structure of the field, and thereby indirectly uncover the integration of the various IS subdisciplines.

One limitation of Swanson and Ramiller's [50] study, however, is its narrow representation of the IS research field due to the fact that it focuses on only one IS journal. Vessey et al. [52] analyzed the nature of the diversity in IS research by investigating five key research dimensions (i.e., reference discipline, level of analysis, topic, research approach, and research methods). The classification scheme designed by these authors not only offers a comprehensive framework for comprehending and appreciating the scale and scope of diversity in IS research but also provides an in-depth quantitative analytical framework for comparing and contrasting the various IS journals and the reference disciplines found therein.

Despite the differences in their analytical orientations and objectives, both classification and citation studies provide a useful framework for understanding several important aspects of IS research, including intellectual development and the degree of diversity within the field. However, little is known about knowledge sharing dynamics, in terms of coauthorship patterns, within or across various subfields of IS. In addition, neither study approach has paid sufficient attention to conceptual orientation, instead focusing on empirical exploration. We attempt to fill these gaps by conducting a theory-driven analysis of coauthorship patterns among IS researchers, which may, ultimately, reveal the dynamics of intellectual exchange among them.

The Multidisciplinary Nature of the IS Field

IS IS A MULTIDISCIPLINARY SCIENTIFIC FIELD comprising various academic reference domains [5, 10, 38, 50]. Keen described IS as "a fusion of behavioral, technical and managerial issues" [38, p. 10]. Several researchers (i.e., [26, 50]) have proposed an array of classification models that reflect the diverse fields of study within the IS discipline. Building on Swanson and Ramiller [50] and Vessey et al. [52], we identify four reference disciplines from which IS researchers have borrowed theories—namely, behavioral science, organizational science, computer science, and economic science. We have outlined some of the major topics that have been studied extensively in each of these subfields to illustrate the level of diversity within and across them (Table 1).

Traditionally, behavioral IS researchers have addressed questions fundamental to individual users' attitudes, behavior, acceptance, and self-efficacy in conjunction with the development and use of IS. Organizational IS researchers, in contrast, are concerned with the sociological, organizational, strategic, and managerial issues surrounding the planning, development, implementation, and evaluation of IS. Nonetheless, there are many similarities between these two fields in terms of research questions and methods. Computer science IS researchers tend to focus on the technical design of IS [50]. Typical questions pursued by researchers in the computer science stream involve the engineering aspects of software design, work flow analysis, data mining, artificial intelligence, and so on. Finally, economics IS researchers generally deal with the economic efficiency of IS and analyze the quantitative aspects of business profitability accruing from IS [50]. In recent years, however, the focus of the economic research stream has been greatly expanded to include more macro-level or market-related issues, such as network externality in relation to information technol-

Table 1. A Taxonomy of IS Research

	Formality	
Level	Low	High
Macro	Organizational science • IT and social and organizational change. • IT and strategic advantages. • IT and organizational culture issues. • Impact of IT on organization design. • Firm-level IS planning and implementation. • Firm-level knowledge management. • IT outsourcing. • Application of new technology to organizational effectiveness.	Economic science • Economics of IS. • Econometric analysis of the business value of IT. • Electronic market analysis, online auctions. • Network economics. • Economics of software versioning. • Efficiency of electronic markets. • Analytical economic modeling, game theory, and applications of industrial organization.
Micro	Behavioral science • Cognitive psychology-related experimental studies in IT. • User acceptance of IT. • End-user computing. • Media richness. • Technology-mediated teams. • Individual IT adoption and diffusion. • Computer self-efficacy. • Influence of technology-mediated communication on individual users. • Behavioral aspects of human–computer interaction.	Computer science • Work flow management. • Design of intelligent agents/expert systems. • Technical aspects of software engineering. • Technical sides of system design and engineering. • Data base/data warehouse and mining. • Use of formal logics for system development. • Fuzzy logics, graph theory.

Note: This list is not intended to be exhaustive or comprehensive.

ogy (IT) adoption [14], the economic efficiency of bundling information goods [4], and the market efficiency of e-commerce [15, 21].

In order to study the structural differences inherent in each reference discipline, we have developed a 2×2 matrix based on two criteria: the level at which the research is carried out and the degree of formality required to represent or convey knowledge (see Table 1). The identification of the different aspects of the subfields is an essential prerequisite to the exploration of the systematic differences in network formation, knowledge flow, and social capital across the various reference disciplines. The vertical axis of the matrix shown in Table 1 denotes the unit of analysis—namely, micro-level (individuals, groups) or macro-level (firms, interorganizations, markets)—while the horizontal axis denotes the degree of formality required for knowledge representation in the subfield. Although other factors undoubtedly exist, we believe that these two dimensions play dominant roles in either enabling or constraining knowledge exchange and network formation across the various subfields of IS.

We propose that the unit of analysis may influence the likelihood and magnitude of external research collaboration (knowledge exchange across, and not within, the subnetwork). The unit of analysis separates behavioral science and computer science from organizational science and economic science. Behavioral researchers and computer scientists have traditionally engaged in extensive knowledge sharing and research collaboration because of their complementary relationships. For example, system development requires an understanding of the behavior of system users, and vice versa. As described earlier, researchers in behavioral science and computer science both tend to focus primarily on micro-level issues concerning individual users and computer systems/algorithms, respectively; for example, many behavioral science researchers have placed an emphasis on user attitudes, participation, adoption, and cognitive absorption. Similarly, many computer science researchers have paid attention to micro-units such as computer/system/software algorithm concepts and problem-solving concepts, while rarely examining organizational concepts, societal concepts, or disciplinary issues [47]. Human–computer interaction is one area in which researchers from these two fields have engaged in extensive collaboration. Organizational and economics researchers, in contrast, typically focus on (inter)organizational rather than individual-level issues related to IS; there is, for example, an extensive body of organizational IS literature that deals with the impact of IT on organizational strategy, culture, structure, and competitive advantage. Economics researchers, in comparison, have concentrated their attention on issues such as the economic (or market) value of IT investments, the business value of interorganizational systems, and the efficiency of electronic markets.

In regard to the second dimension of the matrix, formality, the economic science and computer science disciplines tend to place emphasis on theoretical development and use more formal types of language, such as mathematical equations and algorithms, to develop research ideas and transmit output. These formal types of language, which are necessary to express theories or results, may inhibit research collaboration with people in other subfields. In contrast, both the behavioral and organizational science groups are typically less reliant on formal representation of knowledge through analytical models and tools. Compared to the economic science and computer science disciplines, these two subgroups are more open and integrate more diverse research orientations and methods. The behavioral and organizational sciences embrace theory development as well as theory testing, and permit researchers to employ both quantitative and qualitative research methods. Flexibility in research orientation and methods in these two fields may promote a high level of specialization or division of labor, one of the primary facilitators of research collaboration and knowledge exchange [39]. We thus expect to observe more research collaboration and coauthorship between these two subfields. Therefore, we hypothesize different levels of research collaboration among the four subdisciplines as follows:

H1a: Because of similarity in research orientation and degree of formality of knowledge representation, behavioral and organizational science reference disciplines will show a high degree of research collaboration in the form of coauthorship.

H1b: Because of similarity in research orientation and degree of formality of knowledge representation, economics and computer science reference disciplines will show a high degree of research collaboration in the form of coauthorship.

H2a: Because of similarity in level of analysis, behavioral and computer science reference disciplines will show a high degree of research collaboration in the form of coauthorship.

H2b: Because of similarity in level of analysis, organizational science and economics will show a high degree of research collaboration in the form of coauthorship.

Two Forms of Social Capital: Network Closure Versus Structural Holes

According to Bourdieu and Wacquant, social capital is "the sum of the resources, actual or virtual, that accrue to an individual or a group by virtue of possessing a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" [13, p. 119]. In contrast to the view established by traditional economists, prominent sociologists such as Burt [16, 17], Coleman [22], and Granovetter [33] assert that variance or inequality in the success of individuals cannot be explained solely by their personal attributes, but is more significantly determined by the extent of social capital accumulated in their respective networks.

The concept of social capital is used to explain the notion of knowledge capital. When researchers collaborate on projects, a significant amount of knowledge sharing occurs. During research collaboration, this flow of knowledge becomes a stock of knowledge, which mutually benefits the researchers in their future projects [28]. According to Walker et al., "a social network structure is a vehicle for inducing cooperation through the development of social capital" [53, p. 110].

Despite a general consensus on the important role played by social capital in an individual's success or organizational performance, there are two schools of thought regarding the mechanisms by which social capital is created and mobilized. The *network closure* view maintains that social capital is created by a network of strongly interconnected relationships, whereas the *structural hole* theory posits that social capital is produced through a loosely coupled network in which actors can broker connections between otherwise disconnected segments [16]. These two perspectives offer drastically different prescriptions for developing and maintaining social capital. Below, we develop hypotheses that link these two forms of social capital with academic performance of individual researchers.

Network Closure and Academic Performance

Based on the strong tie assumption, some pioneering researchers of social capital, such as Coleman [22], asserted that dense or closed networks in which nodes are highly connected to each other are the essential means of creating and maintaining social capital [41]. The network closure perspective has therefore focused on the strength of relationships and density of the social network, with the view that social capital is more effectively generated within rather than between network segments.

More specifically, the network closure view holds that a closely knit network characterized by numerous ties connecting the actors provides them with several substantive benefits—namely, knowledge sharing, complementarity [1], reduced opportunism, and well-coordinated conflict resolution [31]. Berg et al. [11] demonstrated that a dense or cohesive network with many direct and indirect ties results in an extensive amount of knowledge sharing among members. Arora and Gambardella [3] found that members of a dense network tend to be well acquainted with their partners' particular strengths and weaknesses, which efficiently facilitates complementary collaboration. Given that knowledge sharing and complementarity of skills and backgrounds are critical aspects of academic collaboration, a cohesive network formation is expected to enhance each individual's academic performance.

In addition, opportunistic behavior (i.e., shirking, lack of collaboration) is less likely to occur among the members of a strongly connected network due to established trust and norms. Any researcher who attempts to behave opportunistically or violate the norms will be sanctioned, which will negatively affect his or her future academic performance. Finally, members of a dense network will be better able than their sparse-network counterparts to smoothly resolve conflicts among themselves [31, 34]. Researchers collaborating on a project often have different views and ideas, and therefore go through a resolution process. Prior research (e.g., [34, 53]) has shown that, due to intense collaboration, the members of a dense network have a greater tendency to find mutually satisfactory solutions in which their differences converge.

H3a: Social capital derived from network closures positively influences a researcher's academic performance.

Structural Holes and Academic Performance

Strong bonds between research partners are often productive and efficient from the collaboration and cooperation perspectives. Nonetheless, dangers may exist in strong relations. For example, such relations may cause researchers to be trapped in their own network [31] or to suffer from a lack of fresh knowledge [41]. Researchers who forge strong ties over an extended period of time may experience *a cognitive lock-in* [51] and *relational inertia* [31], which prevent them from accepting new ideas and forming new ties.

Addressing these potential drawbacks of network closure, the structural hole view advocated by Burt [16] and others places an emphasis on the position of the actor within the network, rather than on the strength and density of the actor's relations.

Structural holes refer to "disconnections between nodes" or "a relationship of non-redundancy between two contacts" [16, p. 18]. Drawing from the notion of the strength of weak ties [33], the structural hole theory asserts that the value of social capital can be maximized only when created with minimal redundancies (i.e., overlapping sources of information) and maximal brokering opportunities. Several empirical studies have shown that social capital produced by structural holes affects employees' job performance more positively than social capital generated by closely knit networks [41]. Top management's boundary-spanning activities result in high company performance [32]. Similarly, structural holes were found to be significantly associated with a higher innovation rate [1, 49] and faster revenue growth [9].

The specific informational benefits produced by structural holes include access, timing, and referrals [16, 17]. Loosely coupled networks rich in structural holes enable individual actors to access fresh insights and obtain innovative ideas that are crucial ingredients in the production of original research. Academic communities can greatly benefit from new ideas and insights provided by external researchers who might often think differently from, and have other perspectives than, those within groups characterized by strong bonds. Boundary spanners, linking pins, and knowledge routers may play a significant role in the theoretical and empirical advancement of their academic disciplines through the introduction of innovative ideas, questions, and research methods.

Consequently, bridges or structural holes are necessary building blocks for the optimal construction or configuration of a network in which new information accumulates and informational redundancies are minimized [16]. According to this view, the diversity and uniqueness of information are crucial aspects of social capital, which can be created only in a network rich in structural holes [31]. For this reason, a loosely coupled network may provide researchers with a structural platform that enables them to interact dynamically with many other researchers and to gain new knowledge and insight.

> *H3b: Social capital derived from structural holes positively influences a researcher's academic performance.*

Researchers may be thus become more influential by accumulating both types of knowledge capital. They can deepen their knowledge bases in specific domains by preserving relationships with their coauthors. They can also widen their intellectual research scope by obtaining new resources through knowledge-brokering or boundary-spanning activities.

Research Method

To address our research questions, we examined coauthorship networks established by IS researchers over the past three decades. In this study, we operationally defined the construct of knowledge networks as the coauthoring of journal articles. It is clear that many other forms of knowledge sharing exist among scholars (e.g., conference presentations, reviewing of papers, informal conversations) and that a substantial amount of research col-

Table 2. Initial Sample of Journal Articles

	ISR	*JMIS*	*MISQ*	*MS*	
Periods	1980–2002	1984–2002	1977–2002	1977–2002	Total
Total number of authors	567	1,288	1,258	298	3,411
Sole authorship	42	134	182	26	384
	(17)	(23)	(30)	(19)	(24)
Two authors	135	245	274	66	720
	(54)	(43)	(45)	(49)	(46)
Three authors	54	140	124	31	349
	(21)	(24)	(20)	(23)	(22)
More than three	21	55	33	11	120
authors	(8)	(10)	(5)	(8)	(8)
Total number of articles	252	574	613	134	1,573

Note: Numbers in parentheses indicate percentage of each coauthorship pattern.

laboration fails to produce publications. In this regard, therefore, the coauthorship of journal articles reflects only part of the broad phenomenon of successful knowledge sharing in academia. Nevertheless, the coauthoring of journal articles may be an objective indicator of intensive, serious, and relatively long-term collaboration among researchers who are highly committed to the relationships.

Sample

Many subdisciplines in management, psychology, engineering, economics, and other academic fields attend to issues related to IS. In the present study, we focus our attention only on IS researchers in the domain of management, and we further concentrate on articles published in four major outlets of academic IS studies: *Information Systems Research (ISR), Journal of Management Information Systems (JMIS), Management Science (MS),* and *MIS Quarterly (MISQ).*[2] These journals have been consistently top-ranked according to the Association for Information Systems (www.isworld.org). For *Management Science,* we included only IS-related articles.[3] We began by archiving all articles appearing in these four journals over the past thirty years, through the use of electronic library data resources (JSTOR and ABI) as well as hard copies. As reported in Table 2, we identified a total of 1,573 articles written by 3,411 authors. Approximately 75 percent of the articles are credited to multiple authors. Of the 1,189 coauthored articles, 1,063 (90 percent) were written by either two or three authors. Figure 1 reveals that the proportion of coauthored articles in these journals has increased steadily over time.

To pursue our research questions regarding the distinct network characteristics of various IS subdisciplines and the patterns of network connections across various subnetworks, we created subgroups of authors representing each subdiscipline. To this

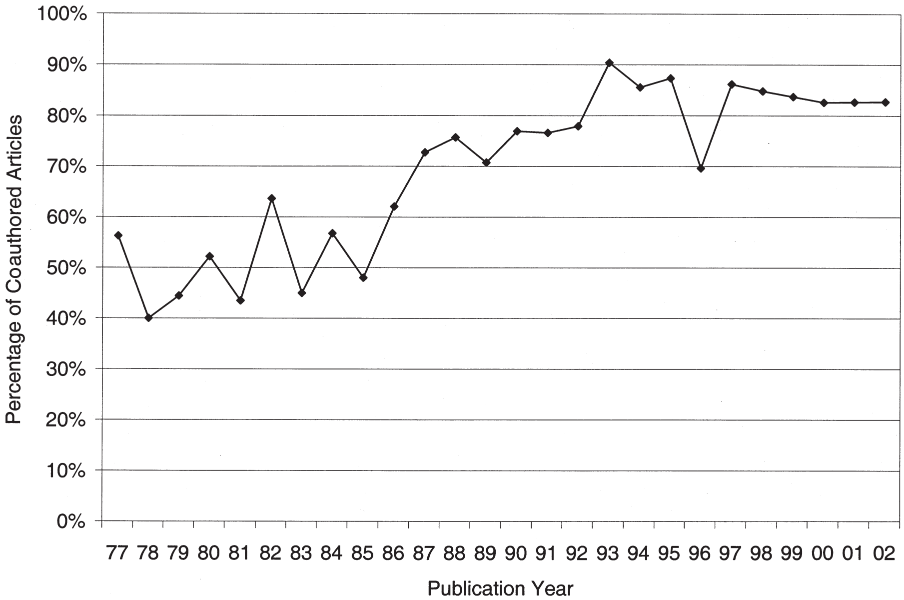

Figure 1. Proportion of Coauthored IS Articles Between 1977 and 2002 Included in the Current Data

end, we identified authors who had published more than three articles in the four journals composing our data set. We labeled these individuals as key authors who might have played a significant role in shaping the research literature. Note that the cutoff point of three publications is an arbitrary criterion that was employed to develop a representative sample from the current data that was neither too limiting nor too inclusive. This procedure generated a list of 316 authors, approximately 20.5 percent of the initial sample. The final sample for subgroup analysis included peripheral authors who published articles with these 316 key authors but had a total of less than three articles published. Together, the key authors and peripheral authors compose the analysis sample (n = 1,010).

In this sample, the 1,010 authors were linked by 1,967 actor-by-actor ties. The value assigned to each tie represents the number of research collaborations between the same two authors appearing in the present data. For the purpose of network analysis, the actor-by-actor coauthorship matrix is symmetrized and transformed into an undirected relationship matrix (or *adjacency matrix* in network terms).

Identifying Subgroups

As elaborated earlier, based on classification frameworks proposed by previous studies [50], we identified four main areas of IS research (behavioral science, organizational science, computer science, and economic science). Note that this classification is not intended to be exhaustive but, rather, to represent the major research fields in IS. To identify the members of these four subgroups, the first author of the current study analyzed the published research of all 316 key authors and carefully assigned each of them to one of the four research areas based on the content of their published works.[4] The majority of the key authors belong to either the behavioral or the organizational group (134 and 112 authors, or 42.4 percent and 35.4 percent, respectively) (Table 3). The technical and economics groups could be considered minorities, representing 13.0 percent and 9.2 percent of the key authors identified, respectively. Table 3 also shows the average number of years elapsed since the key authors earned their Ph.D. degrees and the total number of publications for each subgroup. These key authors were used to create a coauthorship or collaboration network, which also includes peripheral authors who published one or two articles together with the key authors identified in this study.

Variables

H3a and H3b posit the effects of individual researchers' knowledge capital on their academic performance. To test these hypotheses, we constructed a set of variables, as summarized in Table 4. The dependent variable was academic impact as measured by the number of citations received for each key author's published articles included in our data. Citation counts have often been used as a proxy for quality of research [42] or academic impact, referring to a given author's degree of influence in academia [27]. We collected the data using the Social Science Citation Index (SSCI) provided by the Institute for Scientific Information. The SSCI offers weekly updated records of publication and citation extracted from its database of over 1,700 of the world's leading scholarly social science journals.[5] Due to its multidisciplinary coverage and high-quality content, the SSCI has been widely used in the social sciences as a reliable source of citation patterns (e.g., [23, 27, 42]). The SSCI provides current and past records of publications of our key authors as well as citation counts for their articles. Using this database, we obtained citation counts for each article and summed the counts for all the articles written by a given author.

As the independent variables, network closure and structural holes are the indices representing the two contrasting aspects of knowledge capital that we predict will affect academic performance. Density of ego network was used to gauge the degree of network closure of each key author's collaboration network [12]. When a researcher's ego network is dense, his or her coworkers are more likely to be connected to each other, resulting in a closely knit collaboration network. The second knowledge capital index was based on the notion of structural holes, which was computed by the equation presented in Table 4. Burt [16] operationalized structural holes as a reverse function of network constraints, which indicates the degree of redundancy of one's ego network: when network constraint is low, the ego network is less redundant, and thus there exists a greater number of structural holes within the network, a situation that provides greater opportunities for researchers to obtain unique information or other resources and to broker exchange relationships. With low network constraint, researchers are more likely to have flexible collaborative relationships and thus are less likely to experience a "cognitive lock-in" [51].

Table 3. Sample Characteristics of the Four Subgroups of IS Researchers

	Behavioral science	Organizational science	Computer science	Economic science	Entire sample
Number of key authors	134	112	41	29	316
Years since Ph.D.	17.68	18.78	18.87	14.21	17.86
Average number of publications included in the present data	5.91	5.39	4.20	6.34	5.55
Number of peripheral authors	343	257	117	100	694*
Size of total network (key + peripheral authors)	477	369	158	129	1,010*

* The total number of peripheral authors is smaller than the sum of those in the four subgroups because some peripheral authors appeared in more than one subgroup by working with key authors associated with different subgroups.

Table 4. Description of Variables

	Variables	Description	Measurement
Dependent variable	Academic performance	The level of each key author's academic success indicated by his or her influence on others' research.	The sum of the number of citations received by all the articles written by a key author (www.isinet.com/products/citation/ssci/).
Independent variable (knowledge capital predictors)	Network closure	The extent to which one's own network is well connected, resulting in close, cohesive relationships.	The proportion of the actual number of ties over all possible ties that could be present: [(actual ties present in the network)/(potential ties that could be linked in the network)] * 100.
	Structural hole	The extent to which one's ego network is not redundant and thus provides more opportunities for brokering or playing the role of the "linking-pin" among actors and various subnetworks.	Structural hole = 1 minus the degree of network constraints. This index is computed based on the three inputs (size, density, and hierarchy). Formula: $1 - C_{ij} = 1 - (P_{ij} + \Sigma_q P_{iq} P_{qj})^2$, for $q \neq i, j$, where P_{ij} is the proportion of i's relation invested in contact j. The total in parentheses indicates the proportion of i's relations that are directly or indirectly invested in connection with contact j [16].
Control variables	Seniority	The seniority of a given author.	Number of years elapsed since earning Ph.D..
	Leadership	The tendency of being a leader (first author) in research collaboration.	The proportion of first-authored articles among all coauthored articles.

To control for potential influences of extraneous variables on academic performance that might have implications for an author's social capital in a research network, we included two control variables in our hypothesis testing: seniority of the researcher and the tendency to play a leadership role in research collaboration [30, 48]. Intuitively, we might assume that senior researchers have more research experience and a relatively larger amount of resources at their disposal (funding, research assistants, etc.) than do junior members. Moreover, senior researchers have had time to expose themselves to the research community, which may promote their academic impact as measured by citation counts. In addition, according to the literature on coauthorship [30, 48], when authors assume a leadership role, it may indicate that they possess critical resources (e.g., the ability to generate research ideas, conduct research, manage the publication process) that attract colleagues and enable them to play a central role in collaborative research [36]. Specifically, researchers who consistently take a leadership position that is characterized by a significant demand for resources are more likely to have extensive network connections and occupy a central position in the research network. We use authorship order as a surrogate indicator of leadership in research collaboration. However, it is not always clear how the authorship order protocol (i.e., the order in which authors' names appear in publication) is determined; many researchers use the level of contribution as a basis of the order protocol, but, occasionally, names are simply listed in alphabetical order. Nevertheless, because of the potential effect of name order on academic performance as well as the frequent use of level of contribution as the basis for name order, we include it as a control variable.

Results

Comparison of the Subnetwork Characteristics

THE MAIN ANALYTIC STRATEGY WE EMPLOYED to compare subnetworks was network analysis with UCINET VI [12]. Before testing the hypotheses regarding external collaboration among the four subareas of IS, we compared their basic network characteristics in order to reveal whether different forms of collaboration network were generated by subdisciplines with differing knowledge creation traditions. The results of this comparative analysis are shown in Table 5.

Network centralization refers to the extent to which network-related values are unequally distributed among actors (e.g., power centralization in organizations). In a highly centralized network, for instance, it is likely that a single actor (or small group of actors) is highly connected relative to others (e.g., star network, see [54]). Conceptually, highly centralized networks form *scale-free* network structures [6] in which the connectivity of nodes shows uneven distribution of ties. In terms of degree of each actor (i.e., number of ties held by each actor), the behavioral science (15.53 percent) and economic science (19.92 percent) subnetworks were more centralized than the other two. In terms of betweenness of actors (i.e., number of relationships uniquely mediated by the focal actor), the economic science and organizational science subnetworks show

Table 5. Network Characteristics

	Behavioral science	Organizational science	Computer science	Economic science	Entire group
Degree-based network centralization (percent)	15.5	7.3	7.5	19.9	8.4
Betweenness-based network centralization (percent)	16.1	29.4	4.4	36.3	21.4
Overall clustering coefficient	1.43	0.85	0.30	0.91	1.23
Number of components	14	20	19	6	20
Fragmentation index	0.31	0.49	0.86	0.38	0.16
Average density of ego network	51.1	44.0	27.9	42.9	45.5

Notes: Due to space limitations, we did not include the specific computational details of the network measures; see [54] for greater detail.

Table 6. Comparison of External Ties Per Researcher from Four Subnetworks

	Behavioral science subnetwork	Organizational science subnetwork	Computer science subnetwork	Economic science subnetwork
Behavioral researchers ($N = 134$)	6.16 (5.57)	0.72 (0.92)	0.22 (0.57)	0.04 (0.21)
Organizational researchers ($N = 112$)	0.87 (1.40)	4.34 (3.50)	0.14 (0.48)	0.16 (0.56)
Computer science researchers ($N = 41$)	0.71 (1.17)	0.44 (0.84)	3.61 (2.57)	0.17 (0.50)
Economics researchers ($N = 29$)	0.21 (0.41)	0.59 (1.05)	0.24 (0.51)	5.59 (4.52)
F-value(3, 312)	54.19***	67.29***	127.56***	131.98***

Notes: Numbers in parentheses are standard deviations; *** $p < 0.001$.

greater centralization than the other two, with the lowest centralization observed in the computer science subnetwork.

The four subnetworks also possess distinctive characteristics in terms of their internal cohesion or connectivity among actors. Overall clustering coefficients indicate that researchers in the behavioral science subnetwork tend to develop the most dense collaborative relationships, suggesting that collaborators in a behavioral science researcher's network who are directly or indirectly linked to the target researcher tend to be connected to one another without his or her mediation. In contrast, the computer science subnetwork is characterized by sparser relationships among researchers. The results of component analysis, in which subgroups of connected actors (components) are identified, indicate that the computer science subnetwork is the most fragmented (fragmentation index = 0.857). Moreover, while the computer science subnetwork is the smallest of the four, it possesses more network components than the other larger subnetworks. As explained earlier, the average density of the ego networks is the number of ties among alters—that is, directly or indirectly connected research collaborators in the present context—expressed as a proportion of the actual ties present among all possible ties. As presented in Table 6, collaborators of behavioral science researchers are more likely to be connected to each other (51 percent) than those of computer science researchers (28 percent).

Overall, the comparison of the four subnetworks indicates that (1) the behavioral science subnetwork shows moderate centralization and the greatest connectivity; (2) the organizational science subnetwork is moderately centralized and connected; (3) the computer science subnetwork is highly decentralized and highly fragmented; and (4) the economic science group is highly centralized and moderately fragmented.

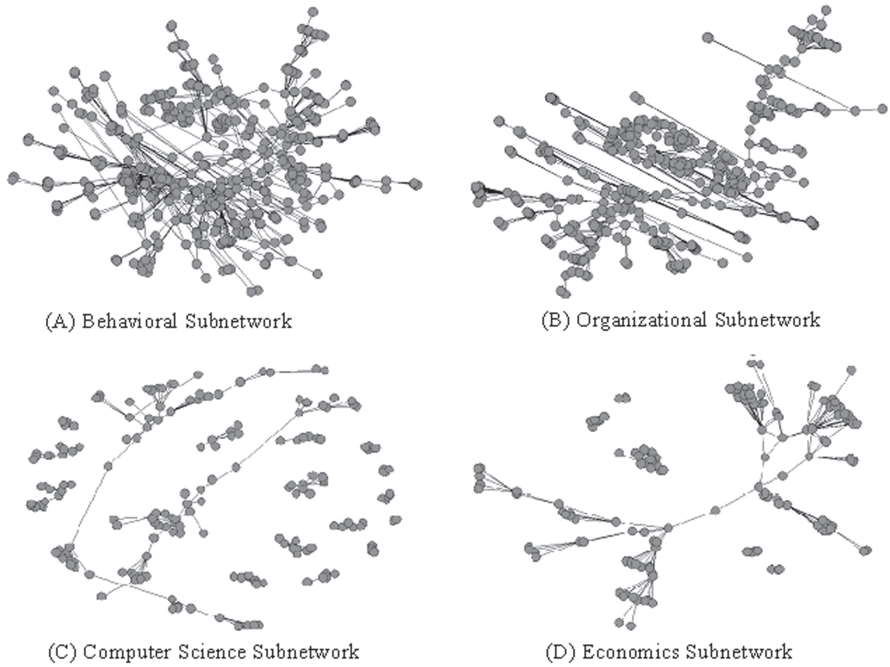

Figure 2. Network Diagrams of Four Subnetworks

The network diagrams shown in Figure 2 illustrate these differences by visually depicting the distinct collaboration patterns of the four subnetworks. The large number of actors within these networks (particularly in the behavioral science and organizational science subnetworks) makes it difficult to interpret the relational patterns involving individual actors. Nevertheless, these diagrams clearly illustrate that the behavioral science subnetwork is the most dense and centralized network (see diagram A in Figure 2), whereas the computer science subnetwork is the sparsest and the most fragmented (diagram C). The economic science subnetwork is also highly fragmented, but organized around a small number of central actors (i.e., "stars"), indicating a high level of centrality. Finally, as depicted in diagram B in Figure 2, the organizational science researchers were relatively well connected with numerous central actors. All in all, these various network characteristics and diagrams show that the four subnetworks have distinct network properties, which suggest that they may exhibit different knowledge exchange patterns.

Research Collaboration Across Subnetworks

One of the main purposes of this study is to explore the extent to which researchers in different IS research domains collaborate externally. Based on the unit of analysis and level of formality associated with each subgroup of researchers, we hypothesized that researchers from subgroups that are similar on those two dimensions would col-

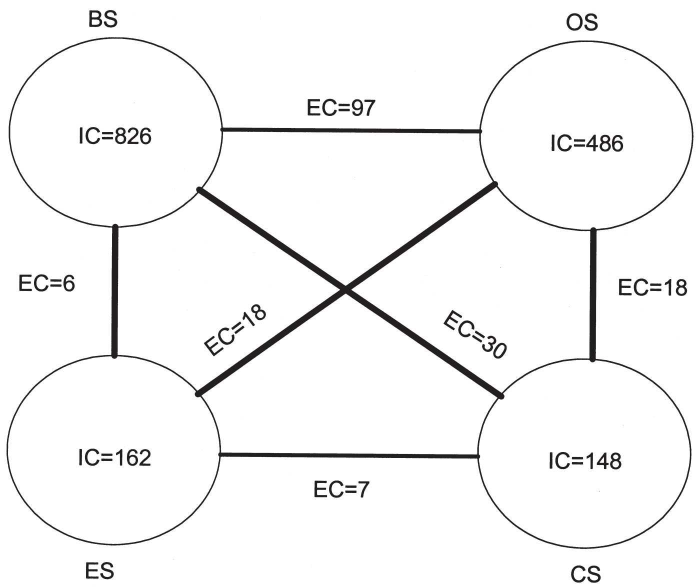

Figure 3. Internal and External Collaborations of Four Subnetworks of IS Research.
Notes: IC—number of internal collaborations; EC—number of external collaborations; BS— behavioral science; OS—organizational science; ES—economic science, CS—computer science.

laborate more frequently than those from subgroups that are different. Figure 3 provides detailed descriptions of the ways in which researchers in each subnetwork collaborate with those in each of the other three subnetworks.

Interestingly, the computer science subnetwork, which was the sparsest and most fragmented network of the four, shows the highest level of external collaboration. In fact, the proportion of external ties for the computer science subnetwork (27.1 percent) was substantially higher than those for the behavioral science and economic science subnetworks (13.9 percent and 16.1 percent, respectively), both of which were dense and highly centralized. In the case of the organizational science subnetwork, which exhibited a moderate level of fragmentation, the proportion of external collaboration was also located between the extremes of the other subnetworks (21.5 percent). This contrasting pattern effectively resonates the idea of "tension" between loose versus tight coupling of actors within a system, in which members of a cohesive, well-connected, or hierarchically organized system tend to be more committed to internal relations at the expense of potentially more beneficial external exchanges of ideas and other resources [20]. In the present data, computer science researchers seemed to compose a less cohesive, and therefore less constraining, exchange network, which effectively offers greater freedom and resources (e.g., time, energy) that allow them to more easily span the boundaries of academic disciplines.

Our hypotheses regarding differentiated levels of external collaboration among the four subnetworks were tested at the individual level because the sizes of the four subnetworks were significantly different, making it difficult to compare the total number of external collaborations at the network level. Table 6 presents the actor-level frequencies of internal and external collaboration ties for each of the four subnetworks. The diagonal of Table 6 shows the internal collaboration that occurs among researchers from the same discipline. A series of pairwise t-tests indicated that behavioral science and economic science researchers exhibited a greater number of internal collaboration ties than computer science researchers (all $p < 0.05$). The difference between behavioral science and organizational science subnetworks was also significant ($p < 0.05$).

H1a posits that behavioral science and organizational science researchers may collaborate often because of their similarity in terms of research orientation and low formality. Table 6 shows that external collaboration between behavioral science and organizational science was indeed the most frequent, significantly higher than any of the other types of external collaboration (all $p < 0.001$), even after controlling for the size of the corresponding networks. Accordingly, H1a is supported by the present data. H1b proposes frequent collaboration between computer science and economic science researchers. As shown in Table 6, interaction between computer science and economic science was the least frequent form of external collaboration for both computer science and economic science researchers (the difference was significant only with computer science researchers at $p < 0.10$). Hence, the data did not support H1b.

Based on similarity of level of analysis in research, in H2a, we expected a high level of collaboration between the two micro-areas, behavioral science and computer science. For behavioral science researchers, computer science researchers comprise the second-most frequent source of external collaborators, less frequent than organizational science, but more frequent than economic science researchers (both $p < 0.01$). For computer science researchers, behavioral science researchers were the most frequent collaborators, although the difference was significant only with economic science researchers ($p < 0.05$). This finding may be clouded by the small sample size. The present data therefore offer partial support for H2a. Drawing on the same argument, H2b suggests frequent collaboration between the two macro-fields: organizational science and economic science. For the members of the organizational science group, economic science researchers were not frequent collaborators. In contrast, economic science researchers were the most strongly connected with the organizational science group ($p < 0.10$). Therefore, the data provide partial support for H2b.

Network Closure, Structural Holes, and Academic Performance

In H3a and H3b, we predicted that an individual scholar's academic impact is related to the two types of knowledge capital that can accrue from his or her research network: the density or cohesiveness of the research network (knowledge capital from network closure) and the unique position of the researcher in the network (knowledge capital from structural holes). Table 7 shows the results of a regression analysis that tested the effect of the two types of knowledge capital on a researcher's academic performance based on number of citations. The adjusted R-square was 12 percent,

Table 7. Two Sources of Social Capital Predicting Individual Researcher's Academic Impact

	Unstandardized coefficients (B)	Standard error	*t*-value
(Constant)	120.336	34.391	3.499***
Seniority	3.094	1.080	2.866***
Leadership	51.167	30.732	1.665*
Network closure	–0.494	0.502	–0.984
Structural holes	186.782	68.327	2.734***
F-value	9.67 ($p < 0.001$)		
Adjusted *R*-square	0.12		

*** $p < 0.01$; * $p < 0.1$.

indicating that 12 percent of the variance in the researcher's academic impact could be explained by the variables included in the model. The results reveal that seniority is a significant predictor of a researcher's academic impact on other scholars ($p < 0.01$). Although it was only marginal, a researcher's tendency to be the first author (an indicator of leadership) was also related to his or her academic impact ($p < 0.10$).[6] Surprisingly, knowledge capital generated from network closure was not a significant predictor of academic impact ($p > 0.10$). However, supporting the structural hole argument, the index of structural holes was significantly and positively related to academic impact ($p < 0.01$). Overall, the present data support structural holes as a basis of knowledge capital accumulation among researchers (H3b supported), but not network closure (H3a not supported).

Discussion and Implications

THIS PAPER HAS EXAMINED the coauthorship networks of IS researchers through social network analysis. In order to understand the connectivity among researchers and macro-network dynamics in this highly interdisciplinary field, we have paid careful attention to the following issues: (1) temporal changes in collaborative efforts among IS researchers, (2) the network characteristics of each subdiscipline, (3) external collaboration across the four subdisciplines, and (4) the impact of two types of knowledge capital on the academic performance of individual researchers. In this section, we discuss our findings related to these four areas of concern, along with study limitations and potential directions for future studies.

Increasing Research Collaboration Among IS Scholars

Our data, based on more than 1,500 research articles published in four major IS journals over the past three decades, clearly show that coauthorship among IS researchers has steadily increased over time, probably due to many factors, including increased supplies of doctorates,[7] a trend toward more external collaboration, an increasing number of conferences, and advances in communication technologies. This rising trend of coauthorship also seems prevalent in other disciplines [39]. Two points are worth noting in regard to the increasing coauthorship phenomenon. Several researchers [39, 46] have demonstrated that coauthored papers are more likely to be accepted for publication than are sole-authored papers. Because we only dealt with "successful" publications in this study, we cannot validate this argument in the context of the IS research field. Nevertheless, we believe this phenomenon may have also contributed to the increasing number of coauthored publications in top IS journals. Apparently, intellectual collaboration increases the quality of a paper and thus reduces the probability of its rejection. Hudson [37] argues that increased coauthorship in economics is partly due to an increase in quantitative content. The trend toward more quantitative research in IS may also explain the increased frequency of research collaboration.

Distinct Network Characteristics of Subdisciplines

An intriguing phenomenon we observed in this study was the existence of distinctive network characteristics, including connectivity, in each IS subdiscipline. The results of both macro-level (e.g., network centralization, fragmentation) and micro-level (e.g., ego network density) analyses indicate that behavioral and economics researchers are the most tightly connected to each other, while technical researchers are the most loosely coupled. It seems that researchers whose backgrounds are in social science are indeed more "social" than researchers in technical science [39]. Interestingly, however, researchers in the technical subnetwork appear to be more "sociable" with researchers in other networks, showing the highest level of external collaboration (Figure 3). In contrast, the behavioral and economics subnetworks, although dense and cohesive social entities, were relatively low in external collaboration with other subnetworks of IS, isolating them, to a certain extent, within the global network structure of IS researchers.

Varying Degrees of External Collaboration Among Subdisciplines

Diversity in research traditions in terms of research problems, theoretical foundations, and methods are often considered unique features of the IS discipline [10]. Due to similarities in research orientation and methods, the behavioral and organizational research subnetworks are highly connected with each other. In addition, there is a high level of collaboration between behavioral and technical subnetworks, although this trend has been less active recently. Overall, however, external collaboration among researchers in different reference domains appears to be limited and severely unbalanced. Across the four subnetworks, on average, only 17.8 percent of the research collaboration ties involved researchers from different subdisciplines. This dearth of external knowledge exchange could be impeding the development of each subarea as well as the entire IS field. The lowest level of research collaboration is observed between the behavioral and economics subnetworks, followed by the collaboration between the economics and technical subnetworks. This lack of external collaboration between different subfields suggests fertile areas for potential innovative and groundbreaking research topics.

In the management literature, there has been no shortage of organizational theories that emphasize the importance of external connections for reducing organizational inertia (or entropy in the systems perspective), which ultimately threatens the survival of the organization. The list includes major organizational theories such as structural contingency theory [40], population ecology [35], resource dependence theory [45], and social exchange theory [29], to name a few. As another complex system, the survival and advance of academic fields may depend as much on continuous revitalization via interactions with their external environment as those of organizations and industries. Nevertheless, considering the social psychological concept that people are attracted to and more likely to interact with *similar others* [18], the present finding that external socialization is rather uncommon even within the same academic discipline is not surprising at all. To overcome the basic tendency of human beings to develop network connections with similar others (the same academic background in the present context), it would be beneficial to implement systems, policies, or other tools to induce and encourage external connections across various academic fields. Cross-boundary knowledge exchange could provide a crucial mechanism for the advancement of academic fields.

Importance of Structural Holes for Academic Impact

Contrary to our prediction, knowledge capital embedded in network closure does not appear to significantly influence a researcher's academic impact. This suggests that researchers who have dense networks are influential within their own network but have a limited impact on others outside their sphere of influence. In contrast, our results indicate that knowledge capital derived from a network rich in structural holes has a positive influence on an individual researcher's academic impact. Influential researchers may effectively mobilize knowledge capital embedded in other research domains through active external collaboration. Due to its significance in academic advancement, the historical evolution of knowledge capital embedded in structural holes deserves additional attention. Figure 4 shows that the amount of both types of knowledge capital (i.e., structural holes and network closure) has increased over time. This figure shows that, prior to reaching the point of critical mass (roughly before 1990), the accumulation of both types of knowledge capital tended to be marginal, despite a steady increase in the number of nodes (i.e., authors). Once such a critical-mass point was reached, however, the rate at which knowledge capital accumulated within the field was far greater than earlier periods,[8] and the knowledge capital related to structural holes in particular began to grow exponentially. Although we are unable to formally verify what has caused this rapid growth, we believe that the active expansion of the field and the increased propensity for researchers to collaborate outside their specialty contributed to this knowledge capital accumulation. Nevertheless, the field could further increase this vital resource by promoting even more external collaboration.

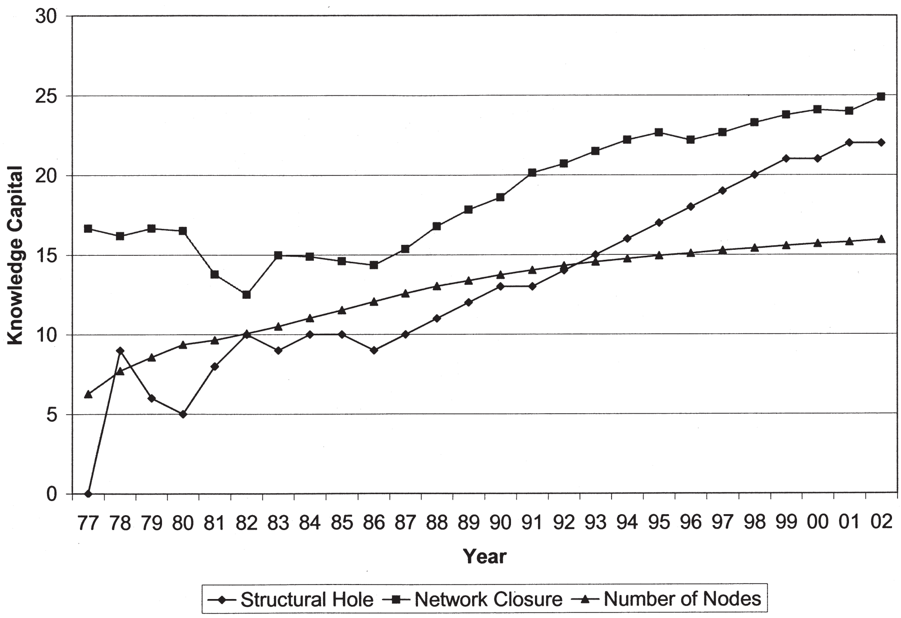

Figure 4. The Evolution of Knowledge Capital in IS Between 1977 and 2002

Limitations and Future Research

ALTHOUGH THIS STUDY SHEDS LIGHT on knowledge sharing patterns among researchers in and between the diverse subfields of IS, the present findings need to be interpreted with caution due to several limitations. As acknowledged earlier, the current data set is based on four major IS journals, thus omitting other scholarly outlets. Building on emerging knowledge data systems, future studies may integrate more comprehensive network data that will reveal a more accurate picture of knowledge sharing and production dynamics among IS researchers.

Another limitation of this study is its focus on documented coauthorship patterns and the order of names in a manuscript's author list. This reliance on published outcomes effectively ignores the complex processes involved in knowledge generation and the idiosyncratic division of labor among different sets of collaborators. For example, some collaborations are based on supervisor–student relationships, whereas others are based on differentiated expertise (e.g., theorists working with programming or data analysis experts). Also, in some cases, contrary to our assumption, researchers may list the names of people involved in alphabetical order rather than in order of importance in terms of contribution to the project. A more in-depth exploration of the interpersonal and task-related processes among research collaborators would be useful for understanding and enhancing the knowledge sharing process among IS researchers.

From the knowledge capital perspective, this study has developed a regression model to predict a researcher's academic performance. The comprehensiveness of the model, however, could be improved further by considering factors not identified in this study. For example, individual factors (e.g., differences in research capabilities and orientations) could play significant roles in explaining variances in academic performance. Although we address this issue from the unique perspective of knowledge networks, it would also be worthwhile to investigate the role of individual differences in creating heterogeneity in academic performance.

Conclusion

Drawing from the perspectives of social networks and social capital, this paper defines and analyzes the coauthorship networks in the field of IS. The author network reveals, at the individual level, *who is connected with whom* in terms of research collaboration. It also depicts the formation and the connectivity of coauthorship patterns both within and across several subfields that presently exist in the highly interdisciplinary research field. An understanding of the ontological structure of knowledge sharing among IS researchers is necessary for maximizing the use of the repository of knowledge capital embedded in the IS field. Given that the size and the characteristics of coauthorship networks are likely to change over time, future research should pay close attention to the evolutionary nature of the IS network. The research framework presented in this study lays some conceptual and methodological foundations for understanding more comprehensive and dynamic knowledge networks in the IS research community, whereas the results of the network analysis suggest a fruitful research collaboration direction that may contribute to the further development of the discipline.

Notes

1. An ego network is a specific kind of social network that consists of a *focal node* (e.g., individuals, firms) and a set of *contacts* or *alters* to whom the ego is directly connected.

2. The analysis would be more comprehensive were all IS journals included. Due to limited resources, we include only these four representative journals. We acknowledge this as one of our limitations. Future research should consider expanding the journal list.

3. We took a rigorous approach in identifying the IS-related articles published in *Management Science.* The first and third authors of this paper each identified the IS articles based on reading of the abstracts. These two authors met and compiled the list together. The identification was very consistent. The articles that were identified by only one author were reviewed carefully. The two authors together read the abstracts and introduction sections of those papers in order to determine their suitability as samples. Through this approach, 134 articles were finally identified as IS articles.

4. We conducted an interrater agreement test with a senior IS researcher who did not participate in this research. The kappa value was 0.84, which is considered very high according to the criterion developed by Altman [2].

5. For further information, refer to www.isinet.com/products/citation/ssci/.

6. As mentioned earlier, due to the ambiguity in the authorship order protocol, this result should be interpreted with some caution. The regression analysis without this variable produced a similar result for the other variables included in the model.

7. Source: www.isworld.org/dissertationdatabase/index.htm.

8. In order to show the two trends in one graph, the scale used for the structural hole–based knowledge capital was adjusted. (The original value was multiplied by 100. The number of nodes was adjusted through a log-transformation.) In terms of trends, the growth rate of structural hole knowledge capital is more noticeable than that of network closure knowledge capital.

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