MIS Quarterly

RESEARCH NOTE

CENTRALITY–IS PROFICIENCY ALIGNMENT AND WORKGROUP PERFORMANCE[1]

Gerald C. Kane
Carroll School of Management, Boston College, Chestnut Hill, MA 02467 U.S.A. {gerald.kane@bc.edu}

Stephen P. Borgatti
LINKS Center for Network Analysis of Organizations, Gatton College of Business & Economics,
University of Kentucky, 550 S. Limestone St., Lexington, KY 40506-0034 U.S.A. {sborgatti@uky.edu}

Virtually all of the extensive previous research investigating the effect of information systems proficiency on performance has been conducted at the individual level. Little research has investigated the relationship between IS proficiency and performance at the group level. In this paper, we argue that IS proficiency at the group level may be more than the simple sum or average of the IS proficiency of individual group members. Rather, effective group-level IS proficiency may also be a function of how a group's IS proficiency is distributed across its members. Relying on concepts associated with social network analysis (SNA), we introduce the concept of centrality–IS proficiency alignment. We argue that groups will perform better if their more proficient members are highly central in the group's communication and workflows network. Data from 468 employees in 32 workgroups show that centrality–IS proficiency alignment is significantly and positively related to performance across multiple systems examined individually and with the portfolio of systems examined as a whole. This approach effectively integrates the structural and resource perspectives of SNA, providing a roadmap so that others may follow a similar approach to address broader questions of group-level user–system interactions in the IS literature and more general questions of central resource alignment in the broader organizational literature.

Keywords: Social network analysis, IS proficiency, centrality, multimodal networks, healthcare delivery, performance, collective use, multilevel analysis

Introduction

End-user proficiency is a key factor in determining how effectively organizations can leverage information systems to influence organizational performance outcomes (Evans and Simkin 1989; Nelson 1991; Santhanam and Sein 1994; Yi and Davis 2003). Users who are more proficient with IS will use those systems to work more effectively and efficiently than users who are less proficient (Marcolin et al. 2000; Yoon et al. 1995). Organizations spend considerable time and money improving the IS proficiency of end users through training, so IS researchers have spent much energy and effort discovering more effective training methods (Nelson and Cheney 1987). Most existing research on IS proficiency has been conducted at the individual level, addressing how well a given user interacts with IS to conduct individual-level tasks. Recent work has suggested that IS researchers should move beyond examining the user-system relationship at the individual level to consider the impact of user-systems interactions at the group level (Burton-Jones and Gallivan 2007). A deeper understanding of IS proficiency at the group level is becoming increasingly important as organizations turn toward formal

[1]Mike Morris was the accepting senior editor for this paper. Peter Gray served as the associate editor.

and informal groups working together to perform shared tasks.

Precisely how to conceptualize and measure IS proficiency at the group level, however, is challenging. If group members are relatively homogenous in their IS proficiency, then the answer is simple: The average level of IS proficiency among group members may be a good measure of the IS proficiency of the group as a whole. If group members have equal proficiency, their knowledge is interchangeable and the proficiency distribution in the group will be irrelevant. Nevertheless, such homogeneity in IS proficiency is rare in most organizational environments. Group members are more likely to have heterogeneous levels of IS proficiency, both in degree and kind, that stem from differences in individual characteristics or roles. Research has shown that group-level ability is often more than the simple sum of the abilities of each member (Tziner and Eden 1985).

The interactions between group members are important factors in understanding how group-level performance manifests individual abilities. Thus, it will be important to consider how IS proficiency is distributed in the group to more fully understand the impact IS proficiency will have on group-level performance (see Burton-Jones and Gallivan 2007; Kozlowski and Klein 2000). For instance, certain individuals may occupy more critical positions in the group's communication and workflows, so their IS proficiency may have greater impact on group performance. Group members may help each other use a system, so the IS proficiency of those sought out by others for help may also be an important factor in group-level IS proficiency. Certain group members may also have greater influence than others, and the IS proficiency of these influential users may affect whether and how others use certain systems.

In short, IS proficiency at the group level may operate quite differently than the simple sum or average of individual IS proficiencies. If so, it may be possible to increase the group-level IS proficiency in ways other than through additional training of indivdual group members. Conversely, it may also imply that a group does not necessarily exhibit high levels of IS proficiency at the group level simply because most of its indivdual members have high levels of IS proficiency.

We use concepts from social network analysis (SNA) to characterize how IS proficiency is distributed in a group. SNA is a research paradigm that studies the configuration of nodes and network ties (Borgatti et al. 2009; Kilduff et al. 2006). Important to SNA is *centrality* (Freeman 1979), a concept used to measure a node's importance in, for example, communication or workflow networks, where centrality indicates the importance of each individual in the overall pattern of information flow. We argue that a group's performance is impacted not only by the average level of IS proficiency but also by the distribution of IS proficiency relative to centrality. That is, a group enjoys greater benefits if its more proficient members are highly central. As such, we argue that the alignment between IS proficiency and users' centrality in the group is likely to be positively related to performance at the group level. We introduce a measure called *centrality–proficiency alignment* (CP-Alignment) to measure the centrality of the group's most proficient users.

Using data gathered from a survey of 468 employees in 32 workgroups in the regional division of a large, national health maintenance organization (HMO), we test whether a group's CP-Alignment is positively associated with the group's performance in terms of the overall health of their diabetic patients, identified by organizational leadership as a key performance metric for healthcare groups. Our hypothesis holds across multiple systems, examined both individually and in aggregate, even after controlling for the average levels of IS use and IS proficiency in the group. CP-Alignment is also more reliably associated with performance than these other measures. These results demonstrate that a simple inventory of group capabilities, as in a count or sum of individual IS proficiency, fails to adequately show the group's function as an ensemble. Rather, a group's social structure can be used to exploit available resources (in this case, the IS proficiency of individuals) for the good of the group. This work contributes to the IS literature by developing a measure to study how IS proficiency and, potentially, other IS attributes (e.g., IS trust, IS avoidance) are distributed in a group. The work contributes to the social network literature by effectively melding Burt's (1992) structural perspective with Lin's (1982) resource theory, two major streams in the network literature (Borgatti and Foster 2003).

IS Proficiency and Organizational Performance

Considerable IS literature research has focused on users' ability to apply technology to maximize performance on specific job tasks (Chan and Storey 1996; Evans and Simkin 1989; Kang and Santhanam 2003; Nelson 1991; Santhanam and Sein 1994). IS proficiency represents a key factor for determining how effectively people leverage IS (Marcolin et al. 2000); it influences organizational performance outcomes because proficient users maximize IS features and functions to enhance their work (Jasperson et al. 2005; Marcolin et al. 2000). More efficient users can use systems to conduct their tasks more effectively (Kang and Santhanam 2003; Nelson 1991; Santhanam and Sein 1994; Yi and Davis 2003; Yoon et al. 1995).

Research has shown that high-proficiency and low-proficiency users interact differently with IS. High-proficiency users understand IS *conceptually* (Compeau and Higgins 1995; Compeau et al. 1999; Santhanam and Sein 1994). They grasp a system's overall structure, function, goals, and abilities; they connect a system's functions with task requirements and thus apply a system to conduct tasks in ways that diverge from previous experience. Low-proficiency users, in contrast, understand IS *procedurally* (Compeau and Higgins 1995; Compeau et al. 1999; Santhanam and Sein 1994); they know how to perform system functions but lack understanding of how functions contribute to overall system logic.

How might these fundamentally different ways of interacting with a system influence individual performance? First, research has shown that users with a conceptual understanding of a system are less likely to make mistakes when using IS (Santhanam and Sein 1994). They are better able to recognize when particular data, interactions, or results fail to fit with their understanding of how a system should function. Fewer interaction errors positively impact performance by eliminating redundancy; users are less likely to need to correct errors or redo tasks. A conceptual understanding could also positively impact performance by lowering chances that undetected errors would significantly and negatively affect performance. For instance, data that were incorrectly entered could lead users to make incorrect decisions. Thus, a small error could cause a much greater negative impact.

Second, users with a conceptual understanding of a system can apply it to unfamiliar tasks and to a wider variety of tasks (Robey and Sahay 1996), so that they perform better in more turbulent and diverse settings. The ability to apply IS to varied tasks not only influences individuals' performance directly, but using a system for unfamiliar tasks can also further increase their IS proficiency as they learn from their efforts (Carroll and Mack 1985). Low proficiency users, with their limited procedural understanding, can apply IS to fewer and more limited task situations, which limits a system's performance benefits. Unfamiliar tasks or the need to rely on others for help would also disrupt their performance, so that they would expend more effort in doing their work (if they could do it at all). Low-proficiency users are also less likely to learn from their continued interactions with IS if they apply it only in familiar and predicable ways (Carroll and Mack 1985). Thus, high-proficiency users should use IS more efficiently in variable task conditions.

IS Proficiency at the Group Level

Most of the research on the performance impact of IS proficiency has been conducted at the individual level. In many organizations, however, tasks are increasingly conducted and evaluated in formal and informal workgroups that employ multiple IS. People often work with others to interact with IS to perform group-level tasks, but little research has investigated how IS proficiency is related to performance at the group level. Previous individual-level research implies that groups with highly proficient members should perform better than groups with lower individual proficiency. It could follow, therefore, that average IS proficiency level of group members will be associated with group performance.

While this supposition may be true, a simple averaging of individual level proficiency may mask considerable underlying heterogeneity in proficiency, as group members are likely to possess very different levels of IS proficiency. In multiperson, multisystem groups, each member is likely to use each system with higher and lower levels of proficiency depending on the specific systems they use most (Bhattacherjee and Prekumar 2004). Differences in IS proficiency may result from users' personal characteristics (e.g., personality traits, demographics). For instance, the literature related to the diffusion of technology innovation suggests that populations consist of early and late adopters, categories that are rooted partially in individual characteristics (Wejnert 2002). Differences in IS proficiency may also come from role characteristics. Roles may be formal: for instance, an analyst may use one set of systems and an administrative assistant may use another, even though they work together to perform group-level tasks. Roles may also be informal: as groups work together over time, they may establish patterns of working together. If certain members are sought out more than others for help in using particular systems, those helpers will develop even deeper proficiencies and, consequently, are sought out ever more frequently (Hollingshead 1998; Wegner 1987). Thus, multisystem groups are extremely unlikely to develop homogenous levels of IS proficiency with all systems.

Because heterogeneity of IS proficiency in groups is a virtual certainty, it is important to consider how IS proficiency is distributed in the group, as the distribution of proficiency may be as or more important than average levels (Burton-Jones and Gallivan 2007; Kozlowski and Klein 2000). The interactions between group members' skills and abilities are often an important factor in determining how these abilities lead to group performance (Tziner and Eden 1985). Certain distributions, therefore, may be more advantageous than others for group performance. For example, suppose two groups have the same average proficiency, but in one the highly proficient users are high status and willing and able to share their expertise, while in the other the top users are inaccessible or difficult to deal with. It seems reasonable to suggest that the first group will do a better job of making use of its members' proficiencies.

The underlying principle here is that, to maximize the group's ability to capitalize on its collective proficiency, the members with the greatest proficiency should be located conveniently for others to access their help. In short, they should be highly central (Freeman 1979) in the communication network. More specifically, they should have high eigenvector centrality (Bonacich 1972), an aspect of centrality that considers the centrality of the people to whom they are connected. A person's eigenvector centrality in the network is a function of having connections with others who are well connected in the network. Eigenvector centrality has been associated with power and influence (Baum et al. 2005; Roy and Bonacich 1988) as well as information access (Borgatti 2005; Rodan and Galunic 2004). Thus, individuals with high eigenvector centrality strongly affect the groups they are part of, both because they are well positioned to diffuse information and practices (Borgatti 1995) and because centrality can confer status, making it more likely that others will adopt the concepts and practices of the central person. Group performance should, therefore, be improved if the most central members of the group are the more proficient IS users.

Centrality–Proficiency Alignment

Again, we refer to alignment between centrality and proficiency within a group as *centrality–proficiency alignment*, or CP-Alignment. We conceptualize CP-Alignment as a continuum ranging from strong positive alignment to strong negative alignment. A strong positive alignment exists between node centrality and proficiency when the most proficient users tend to be the most central. A strong negative alignment exists between centrality and proficiency when the more proficient users tend to be the most marginal.

High CP-Alignment can affect group performance in several ways. First, central people may more directly contribute to a group's performance in terms of the work they produce. People who are central in a social network occupy a more important position within the knowledge flows and work flows of a group (Borgatti and Cross 2003; Brass 1981, 1984). Returning to the literature on individual level proficiency, higher IS proficiency will be associated with higher individual performance, and higher individual performance of key group members will have greater effects on group performance.

Second, central people may indirectly contribute to group performance in terms of their ability to support others. Group members may turn to other members for advice on using a system (Sykes et al. 2009) or ask other members to use a system on their behalf (Kraemer et al. 1993). People will turn for help and advice to those with whom they are connected, so more central people are more likely to be approached for help. If these people also have high proficiency, the help they provide is likely to be more valuable. Central users, whether by virtue of offering help to a greater variety of users or simply by being in a better position to observe how other users interact with a system, may also better understand how others use that system. The knowledge of how others interact with a system may enable central users to provide better help on specific problems, as central users would better understand the contexts in which help was needed. Furthermore, obtaining IT help is often not an individual or even interpersonal challenge but rather a collective one that requires the involvement and resources of all group members (Rasmussen et al. 2006). If the high-IS proficiency people are more central in the network, they will be more aware of the network resources available and better able to marshal those resources to address collective problems.

Third, high proficiency users may influence how other group members use IS. A group's social network is an important source of information and attitudes regarding IS (Burkhardt and Brass 1990; Kane and Labianca 2011; Rice and Aydin 1991), and eigenvector centrality is associated with greater network influence (Bonacich 1972). Certain "master users," typically not the formal leaders of the group, often exert considerable influence over whether and how their peers use IS (Spitler 2005). Similarly, high-proficiency family members often influence the degree to which other members of the family group adopt and use IS (Kiesler et al. 2000). If the high-proficiency users are central in the group's social network, they will be better positioned to influence the group in ways that promote effective IS use. People in workgroups are also more likely to use the IS if they perceive that coworkers have been well-trained to use it (Gallivan et al. 2005). The actions and behaviors of central group members are typically more visible than the behavior of other members, so highly proficient central members may model effective use behaviors and give others the confidence to use a system themselves.

In other words—whether the result of individuals' greater direct impact on the group's work, of their ability to better help others when needed, or of their informal influence that encourages others to adopt and use IS effectively—the alignment of IS proficiency with eigenvector centrality within a group should be positively related to the group's performance. We state this formally as Hypothesis 1.

H1. *A group's centrality–IS proficiency will relate positively to its performance.*

Research Method and Setting

We developed a survey and administered it to 514 members of 32 healthcare groups in the regional division of Health Providers in early 2005. This standard sociometric instrument provided respondents with a roster of group members and the five systems that HealthProviders identified as most critical for outcomes across all groups. Respondents rated the frequency and depth of their interaction with other members of the group and their levels of use and general proficiency with each IS. The survey prompted good response rates (n = 468, 91 percent), with no significant differences in the response rates of doctors, nurses, or support staff. All groups had at least an 80 percent response rate, an important threshold for the type of whole network analysis conducted here (Oh et al. 2004; Sparrowe et al. 2001).

The independent variable is CP-Alignment. To construct this group-level measure, we first measured individual-level IS proficiency and eigenvector centrality.

IS Proficiency. Both the leadership and employees of Health Providers reported that five systems are critical for providing effective patient care (see Table 1). They declined to select the most important ones or to weigh their relative importance; they indicated that each is an independent application; each requires a different password; and each is equally essential for providing effective care.

The individual IS proficiency scores reflected a three-item scale based on the effort-expectancy construct (Venkatesh et al. 2003), which integrates the ease of use (Moore and Benbasat 1991), perceived ease of use (Davis 1989), and complexity (Thompson et al. 1991) constructs (see Table 2). We consulted with HealthProviders' senior leadership and concluded that we could not use the original 12-item scale for our purposes. Consistent with previous research (Venkatesh et al. 2003), we selected instead a small sample of items from the original scale based on feedback solicited during the pretests and in conjunction with HealthProviders' senior leadership. We also pretested the scale before administering the full survey. The items loaded appropriately on the construct, resulting in a Cronbach's alpha of .93.[2] Respondents also assessed their IS proficiency with the five systems on seven-point scales.

Eigenvector Centrality. The calculation of the individual centrality scores relied on the collected network data. Respondents rated the frequency (1–6) and depth (1–6) of their interactions with each person in their group and the frequency (1–6) and functionality (1–6) of their interactions with each of the systems (see Table 3). The responses pertaining to interactions with individuals were summed to create a measure of interpersonal tie strength; the responses regarding interactions with systems were summed to create a measure of IS use. Asymmetric ties were then symmetrized using the minimum method (Borgatti et al. 2002), in which the strength of tie between two nodes A and B was assigned the smaller of the strength of tie from A to B and from B to A. This method is standard in SNA (Hansen 1999; Mardsen and Campbell 1984), especially in previous studies of multimodal networks (Kane and Alavi 2008).

We entered these data into UCINet (Borgatti et al. 2002), which was used to calculate individual eigenvector centrality scores.[3] Eigenvector centrality is a node centrality in which nodes are scored more highly depending on their connections to well-connected nodes. It is a recursive measure in which a node's centrality is proportional to the sum of centralities of the nodes to which they are connected, weighted by the strength of connection (Bonacich, 1972). Formally, eigenvector centrality is the principal eigenvector of the network data matrix A, where a_{ij} gives the strength of the tie from node i to node j. An eigenvector $\mathbf{x}$ satisfies the recursive equation $\lambda\mathbf{x} = A\mathbf{x}$, where λ is the eigenvalue associated with eigenvector $\mathbf{x}$. The principal eigenvector is the one with the largest λ. The equation effectively says that a node's centrality is proportional to the sum of centralities of its contacts.

CP-Alignment. The alignment between IS proficiency and centrality for a given group was defined as the Pearson correlation coefficient between members' IS proficiency and their eigenvector centrality in the interaction network. This use of correlations is well-known in SNA and other social science literatures. For example, in SNA, the best-regarded measure of the degree of homophily in a group consists of a correlation between two dyadic variables, one indicating the tie strength

[2]The validity measures are relevant only for the user–system dyad, consistent with the proposed conceptualization of IS proficiency. Consistency of these measures within a user, system, or network is neither assumed nor expected.

[3]The five separate centrality scores calculated for each member of the network included all group members and one system. Introducing each system independently and calculating different centrality scores in relation to each avoided methodological challenges related to multimodal networks (i.e., systems cannot report about each other) but also accounted for the unique way each system was integrated into the group's workflows.

Table 1. Description of IS Used by Each Healthcare Group

Sys #	System	Description
1	Scheduling	Manages appointments, patient flow, and patient contact/benefits information.
2	Lab	Doctors order lab tests through this system, which then traces the sample through the lab and send the results electronically to the doctor's inbox.
3	Radiology	Schedules radiology tests. The radiologist analyzes the results and inputs diagnosis.
4	Medical Abstract	Synthesizes doctor diagnoses, treatment recommendations, and pharmacy information for past 10 patient interactions. This knowledge augments the full medical record or replaces it if a full record is unavailable.
5	Conferencing	Distributes results of recent medical research and implications of the findings for healthcare practice.

Table 2. Items Used in the IS Proficiency Construct

IS Proficiency. Respondents replied to each question for each system used on a seven-point Likert scale (*Strongly Agree—Strongly Disagree*), adapted from Venkatesh et al. (2003):

1. I find this system easy to use.
2. I am skillful at using this system.
3. (RC) Using this system takes too much time from my normal duties.

Table 3. Questions Used in Sociometric Survey

Interpersonal Interactions. Respondents replied to each question for each person in the group (social network roster method). Anchors are in parentheses. Questions adapted from Burt (1992).

1. On average, how often do you interact with this person? (Never, Rarely, Monthly, Weekly, Daily, A few times per day, Hourly or more)
2. How close is your working relationship with this person? (Very Close, Close, Somewhat Close, Somewhat Distant, Distant, Very Distant)

User–System Interactions. Respondents replied to each question for each system in the group (adapted from social network roster method). Anchors are in parentheses. Questions adapted from Burt (1992).

1. On average, how often do you interact with this system? (Never, Rarely, Monthly, Weekly, Daily, A few times per day, Hourly or more)
2. I use all of the functionality available in this system. (Strongly Agree, Agree, Somewhat Agree, Somewhat Disagree, Disagree, Strongly Disagree)

between each pair of nodes and the other indicating whether they share a given node attribute such as race or gender (Ibarra 1992). Once homophily is measured for each group, one can then use this variable to test a group-level hypothesis. For example, Krackhardt and Stern (1988) argued that under conditions of environmental turbulence, groups with high homophily will perform poorly compared with groups that have lower homophily.

Similarly, the core-peripheriness (Borgatti and Everett 2000) of a network is measured as a correlation between tie strength and joint centrality (i.e., a network has high core-peripheriness if, for all pairs of nodes, central nodes tend to have strong ties with each other, while peripheral nodes tend to have only weak ties with each other). Cross and Cummings (2003) used this correlation as an independent variable to predict the performance of work groups in a Fortune 500 telecommunications firm. Another application of a correlation as an independent variable in the network literature is in studies that predict the performance of a manager as a function of the accuracy of their perceptions of the social network of their subordinates. In these studies, the accuracy for each manager was measured as the correlation between their view of the network and the "truth," a composite constructed from the subordinates' responses. Krackhardt (1990) found that when the correlation between a manager's perceptions and the truth was high, the manager was seen as more powerful.

The practice of using correlations as independent variables is also well known outside the network literature. For example, in the person–organization fit literature (Caldwell and O'Reilly 1990; Chatman 1989), a "fit" score is calculated for each respondent by correlating the study participant's answers on a series of questions to their organization's profile along the same dimensions. The fit variable is then used in a regression to predict outcomes such as job satisfaction (Chatman 1991; Elfenbein and O'Reilly 2007).

The practice is also consistent with multilevel modeling (Bryck and Raudenbush 2001; Snijders and Bosker 1999), in which group-level regressions involve variables whose values are the regression coefficients from individual-level regressions conducted separately within each group. For example, a study of 10,000 students in 100 schools might regress children's grades on parents' income separately for each school, obtaining 100 regression coefficients for income. These beta coefficients then become a variable in a school-level regression in which the beta coefficients are related to other school-level variables, such as quality of the school cafeteria (e.g., higher betas are seen in schools with poor nutrition, because kids with richer parents get better nutrition at home). Of course, regression betas are simply unstandardized partial correlation coefficients. In a regression $Y = b0 + b1X + e$, if X and Y are standardized, the parameter b1 will be precisely the correlation between X and Y.

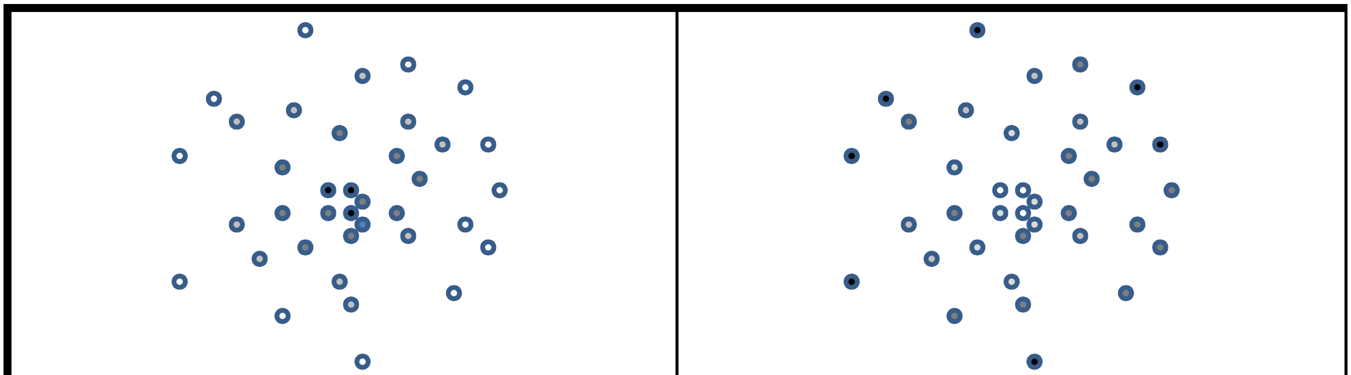
In our application, a positive correlation coefficient indicates that proficiency is distributed through the network such that the more proficient users are also the most central (see Figure 1a). This enabled the expertise of the high-proficiency users to benefit the most users. A zero value indicated that proficiency is distributed randomly with respect to centrality, so that the probability of a high proficiency user being at the network core is no better than chance. Finally, a negative value for a given group indicated that the more proficient users tend to be on the group margins, which represents potential underutilization of knowledge resources (see Figure 1b). Note that the restricted range (-1 to +1) of a correlation value poses no problem in our regressions because we use the correlation as an independent variable.

Because group members used various systems differently, IS proficiency scores are system-specific. Thus, we calculated five different scores of CP-Alignment for each group, one for each system used. We then averaged the IS proficiency score of each user for each system and developed a sixth CP-Alignment score as an omnibus measure of CP-Alignment. Understandably, considerable collinearity occurs between these six measures of CP-Alignment and the average IS use and IS proficiency control variables, so we examined each measure independently.

Dependent Variable

The dependent variable represented a key performance outcome, chronic care, which was arguably the most important metric for evaluating healthcare groups. Acting consistently with empirical data from the healthcare industry (Thorpe et al. 2004), HealthProviders focused its regional effort on chronic care, the largest source of increasing costs. Patients with chronic diseases such as diabetes are often the most difficult to treat because they require consistent care during multiple successive appointments over time. To operationalize chronic care, we used a dichotomous variable of diabetes control that measures whether a diabetic patient's long-term blood sugar level remains within recommended guidelines.[4] In this effort, the organization critically needed its information system to allow the group to perform ongoing monitoring of the patient's condition (lab system), to offer consistent care over time (medical abstract system), to conduct outreach for patients who missed recommended tests (scheduling system), to monitor HealthProviders educational and support services (conferencing system), and to follow up in assessing complications (radiology system). Patients certainly were responsible for much of their own care, but the primary care group was responsible for supporting patients by giving them the right information at the right time.

[4]Data were obtained for all 9,950 patients in the region diagnosed with diabetes. The "gold standard" for diabetes control is the HbA1C test, which captures long-term average blood sugar levels. This dichotomous variable indicates whether a particular patient's HbA1C level is above 9, or "under control," according to common medical practice.



1a. Positive Alignment (Darker nodes, corresponding to IS proficiency, are more central)

1b. Negative Alignment (Darker nodes, corresponding to IS proficiency, are on the periphery)

Figure 1. CP-Alignment

Control Variables

In addition to gathering key independent variables through a survey, we obtained other metrics from existing organizational records to use as control variables, as Table 4 details. The models controlled for the characteristics of the patient, doctor, or group that might influence the group's ability to provide chronic care. First, at the patient level, specialists outside the primary care setting conducted the eye exam, cholesterol screening, and nephropathy screening, which may indirectly affect diabetes control. These variables also served as proxies for the extent to which the patient participates in managing the disease. Insurance plan accounted for the type of care (HMO or PPO) the patient receives from Health Providers, because different business relationships may influence the services the patient chooses. Patient risk assessed whether the patient had another underlying medical condition that may affect the ability to control diabetes.

Second, the analysis controlled for the characteristics of the individual doctor designated as the patient's primary care provider. Although the group works together to provide care and the patient may make an appointment with any doctor in the group, HealthProviders assigned each diabetic patient to a primary doctor who was responsible for ensuring that the patient received appropriate care and intervention. Thus, certain characteristics of the primary doctor may affect the overall ability to provide chronic care. Organizational tenure captured the doctor's familiarity with HealthProviders' systems and processes. Race was included because of its strong effects on healthcare delivery (Ryn 2002). Studies of IS proficiency often use gender as a control, as we did here (Venkatesh and Morris 2000).

Third, the models controlled for group characteristics, including the size of the group, its various demographic characteristics, and the type of care mainly provided (although all groups provide primary care). The models also controlled for the characteristics defined at the doctor level: gender composition, racial composition, and average tenure. Aspects of the user–system interactions further controlled for the alternative explanation that network structure, separate from the configuration of IS proficiency, produced the results. To ensure that performance differences did not result because some groups used the IS more frequently or deeply than others, we controlled for IS use by calculating how frequently and deeply members used particular systems. The models also controlled for network centralization to ensure that the social network structure did not lead to performance differences. As a representation of dispersion in the centralities of the various nodes, centralization tested whether the network was dominated by a few highly central nodes, with remaining nodes in peripheral positions (Freeman 1979). Finally, to test the relationship of CP-Alignment with more traditional constructs, we included the group members' average IS proficiency.

Data Analysis

To ensure accuracy, an independent research assistant audited the data, which were entered into Excel and then imported into the statistical package R for analysis. Appendices A and B provide the descriptive statistics and a correlation matrix, respectively. Clustering the patients in groups violated the independence of errors assumptions of regressions. To correct for this multilevel clustering of data, we employed a

Table 4. Control Variables

	Variable	Type	Definition
Patient Level	Eye Exam	Dichotomous	Has the patient received an eye exam in the past year? (1 = *yes*, 0 = *no*)
	Cholesterol Screening	Dichotomous	Has the patient's cholesterol been checked in the past year? (1 = *yes*, 0 = *no*)
	Nephropathy Screening	Dichotomous	Has the patient's kidney function been checked in the past year? (1 = *yes*, 0 = *no*)
	Insurance Plan	Dichotomous	Is the patient's insurance plan an HMO (0) or a point-of-service product (1)?
	Patient Risk	Dichotomous	Does the patient have other health factors complicating their diabetes control (i.e. heart disease)? (1 = *yes*, 0 = *no*)
Doctor Level	Dr. Gender	Dichotomous	Doctor is male or female (1 = *male*, 0 = *female*).
	Dr. Tenure	Continuous	Length of time doctor has been employed at HealthProviders (years).
	Dr. Race	Dichotomous	Whether the doctor is a minority (1 = *white*, 0 = *minority*)
Group Level	Group Type	Dichotomous	Whether a group is an Internal Medicine (base category, *n* = 23) or Pediatric (*n* = 9) Group
	N Group	Continuous	The number of employees in the group.
	Racial Composition	Percentage	Percentage of the group that is white (vs. minority).
	Average Tenure	Continuous	On average, how long group members have been employed at Health Providers (years).
	Gender Composition	Percentage	Percentage of a group's employees who are male.
	IS Use	Continuous	The average frequency and depth with which group members use the IS available to them.
	Average IS Proficiency	Continuous	The average levels of IS proficiency possessed by members of the group.
	Network Centralization	Continuous	The disparity in eigenvector centralities between nodes.

Huber-White robust variance/covariance matrix and a logistic regression model. The Huber-White approach is based on the assumption that the error terms were correlated within groups but not across groups. It was appropriate because the dependent variables are at the patient level, but the primary independent variables of interest are specified at the group level. Various researchers recommend that 10 groups provide a sufficient sample size (Snijders and Bosker 1999) or that 30 groups are better for studies of group-level coefficients (Hox 2002). The data exceeded both standards.

Results

Table 5 presents the model results, operationalized according to whether a diabetic patient's blood sugar levels remain within clinically acceptable levels. Models 1–5 represent the effects for each system individually, and Model 6 reflects the results when the data for all five systems are averaged. In support of H1, the CP-Alignment effect was significant and positively associated with quality of chronic care in all models, even when controlling for average proficiency levels. This means that, on average, a group performed better when its high-proficiency members were well connected rather than peripherally located.

Interestingly, with alignment controlled, we observed little effect of simple average proficiency. For four of the five systems, the effect of average proficiency when controlling for alignment was nonsignificant at the 0.05 level, while for the remaining system the effect was negative. This suggests that when groups act as a team, as in a transactive knowledge system (Borgatti and Cross 2003; Hollingshead 1998; Moreland et al. 1996), it is not necessary for every member to

Table 5. Model Results

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	B	SE	B	SE	B	SE	B	SE	B	SE	B	SE
Intercept	-2.17**	(0.83)	-3.61***	(0.48)	1.42	(1.10)	-0.80	(0.77)	-1.67***	(0.52)	-1.32+	(0.70)
Eye Exam	1.14***	(0.10)	1.14***	(0.10)	1.14***	(0.10)	1.15***	(0.10)	1.14***	(0.10)	1.14***	(0.10)
Cholesterol Screening	2.05***	(0.09)	2.05***	(0.09)	2.04***	(0.09)	2.03***	(0.09)	2.05***	(0.09)	2.05***	(0.09)
Nephrology Screening	0.79***	(0.08)	0.80***	(0.08)	0.78***	(0.08)	0.78***	(0.08)	0.80***	(0.08)	0.80***	(0.08)
Insurance Plan	0.73***	(0.08)	0.73***	(0.08)	0.73***	(0.08)	0.73***	(0.08)	0.73***	(0.08)	0.73***	(0.08)
Patient Risk	0.43***	(0.13)	0.42***	(0.13)	0.42***	(0.13)	0.41***	(0.13)	0.43***	(0.13)	0.43***	(0.13)
Dr. Gender	-0.06	(0.07)	-0.03	(0.07)	-0.02+	(0.07)	0.00	(0.06)	-0.05	(0.07)	-0.04	(0.06)
Dr. Race	0.00	(0.08)	0.00	(0.09)	0.06	(0.09)	0.01	(0.09)	-0.03	(0.08)	-0.01	(0.08)
Dr. Tenure	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)	-0.01	(0.01)	0.00	(0.01)	0.00	(0.01)
n Group	0.01	(0.01)	0.00	(0.01)	-0.01	(0.01)	0.00	(0.01)	0.01***	(0.00)	0.00	(0.00)
Group Type	0.82+	(0.47)	0.63	(0.43)	0.99+	(0.56)	0.76	(0.58)	0.90*	(0.46)	0.82+	(0.44)
Racial Composition	1.14***	(0.15)	1.15***	(0.10)	1.54***	(0.15)	1.24***	(0.18)	1.15***	(0.10)	1.32***	(0.09)
Gender Composition	-1.05+	(0.57)	-1.12+	(0.62)	-0.26	(0.61)	-0.50	(0.74)	-1.27***	(0.36)	-0.87*	(0.38)
Average Tenure	-0.11***	(0.02)	-0.08***	(0.03)	-0.15***	(0.03)	-0.11***	(0.02)	-0.11***	(0.02)	-0.12***	(0.02)
Network Centralization	0.00	(0.01)	0.01	(0.01)	-0.02	(0.01)	0.01	(0.01)	-0.01	(0.01)	-0.01	(0.00)
IS Use (S1)	0.00	(0.04)										
Avg. IS Prof (S1)	0.07	(0.14)										
Cent-Prof Alignment (S1)	0.39***	(0.08)										
IS Use (S2)			0.08+	(0.04)								
Avg. IS Prof (S2)			0.22+	(0.12)								
Cent-Prof Alignment (S2)			0.45*	(0.18)								
IS Use (S3)					0.10***	(0.02)						
Avg. IS Prof (S3)					-0.66***	(0.20)						
Cent-Prof Alignment (S3)					0.53***	(0.12)						
IS Use (S4)							-0.15	(0.13)				
Avg. IS Prof (S4)							0.09	(0.22)				
Cent-Prof Alignment (S4)							0.24*	(0.12)				
IS Use (S5)									0.04+	(0.02)		
Avg. IS Prof (S5)									-0.07	(0.08)		
Cent-Prof Alignment (S5)									0.39***	(0.04)		
IS Use (Avg.)											0.08+	(0.04)
Avg. IS Prof (Avg.)											-0.25+	(0.14)
Cent-Prof Alignment (Avg.)											0.88***	(0.09)
Hosmer and Lemeshow Test	.690		.170		.887		.324		.513		.756	
R^2	.19		.19		.20		.19		.20		.20	

Notes: N = 9950, Huber-White Robust Sandwich Estimators.
+$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$.

have IS proficiency; it is enough that a few well-connected individuals do. Effectively, network ties substitute for direct IS proficiency.

Furthermore, if CP-Alignment was omitted from the aggregate model (results not shown), average IS proficiency level was negative and significant at the 0.05 level. Failing to account for the CP-Alignment, therefore, could lead the researcher to erroneously conclude that lower overall proficiency leads to superior performance when lower aggregate IS proficiency may actually result from superior coordination and more effective distribution of IS proficiency in the group. The correlation matrix supported this interpretation somewhat: average levels of IS proficiency and CP-Alignment were negatively correlated (-.143, $p < .01$). Note that a single system (radiology) drives most of the negative average IS proficiency scores, so the aggregate result may have something to do with the features of this system. Regardless, the observation still holds that average IS proficiency levels alone are insufficient for examining the effects of group-level IS proficiency on performance.

Discussion

In this paper, we introduce the concept of centrality–IS proficiency alignment (CP-Alignment) as a factor of group performance. We argue that groups can leverage variance in user IS proficiency if they are structured so that those who have high proficiency are located in the center of the social space, where others may easily view and access their skills. We also offer a method of measuring this alignment condition.

Our key contribution in developing and testing the CP-Alignment construct is showing that a simple inventory of group capabilities by totaling the sum of the individual capabilities is insufficient to understand the function of the group as an ensemble. That is, important group properties depend crucially on the structure and configuration of resources (Kowzlovski and Klein, 2000). In this paper, we not only offer the new group-level construct of CP-Alignment as a theoretical concept, but also present a simple and effective way to measure it.

More generally, our contribution is to elucidate the way a group's social structure is used to exploit available resources (in this case, the IS skills of individuals) for the good of the group. We essentially posit that social networks—unlike sets of unconnected individuals—provide a mechanism for the emergence of group-level capabilities that are more than the sum of the members' capabilities. Social networks can be seen as constituting transactive knowledge systems (Borgatti and Cross 2003; Hollingshead 1998; Moreland et al. 1996) that enable appropriately configured groups to exploit their members' expertise. In a sense, such systems can be seen as providing group members with a virtual kind of human capital where they do not have to know something directly as long as they have ties to those that do. Thus, we reveal that social ties provide individual and group benefits in the effective utilization of IS. We hope that our theoretical and methodological contributions will encourage other researchers to explore how the distribution of similar traits and resources (e.g., IS trust, IS avoidance) affect how groups interact with IS in other settings.

We also contribute to social network analysis. As noted earlier, the network analysis literature is already familiar with the general concept of using correlation as an independent variable. However, to our knowledge, researchers have yet to propose the property of centrality–resource alignment, which could be useful in many contexts. For example, in the context of networks and HIV (Morris 1997), a correlation between centrality and high-risk behavior would provide a better index of community risk than simply averaging individual risk behavior, because it harms the community more if the more central nodes in the sexual network are engaging in the riskiest behaviors. More generally, in the network diffusion literature (Valente 1995), a negative correlation between centrality and openness to innovation should translate to slower diffusion rates because the early adopters are more marginal and therefore impact fewer people directly. In the network social capital literature (Coleman 1988; Putnam 1995), the correlation between individual centrality and possession of resources could provide an index of group-level social capital—specifically, the group's ability to access and exploit its resources. Thus, centrality–resource alignment effectively melds Burt's (1992) structural perspective with Lin's (1982) resource theory, two major streams in the network literature (Borgatti and Foster 2003).

Managerial Implications

Understanding the configuration of user–system interactions also promises benefits for managers. A manager who understands how CP-Alignment relates to group performance can focus on appropriate improvements in IS proficiency. Organizations often apply a strategy that targets particular users for increased training, creating so-called superusers who are available to help others (Karuppan and Karuppan 2008). According to our study, the effectiveness of such an approach depends partially on the position of superusers in the group's social network. If the superusers are situated centrally, the group is likely to make the expertise widely available. If the superusers are peripheral, individual training gains are less likely to benefit others or to affect group-level performance outcomes.

We also suggest that improving the impact of group-level IS proficiency may not require improving the IS proficiency of any one individual. Rather, network structures can be altered to create more effective configurations that make better use of individuals' IS proficiency and, consequently, improve group-level proficiency. Organizational researchers note ways managers might reconfigure network structures, from actively adding or removing group members (Cross and Prusak 2002) to changing the network's functioning "generative rules," such as incentive structures or administrative routines (Kogut 2000).

Limitations and Further Research

This study's limitations should be considered carefully. First, multiple systems affected the dependent variable of interest, but no theoretical or empirical rationale exists for weighting the role of multiple systems. Therefore, we have examined systems independently and in aggregate to control for alternative explanations; better methods clearly are needed to address multisystem environments. Some systems (e.g., radiology) have an inordinate effect on certain outcomes (e.g., average IS proficiency), but they could be identified only *post hoc*.

Second, we took a snapshot of the network structure at a single time point. The network structure was generally stable over the data collection period, but this approach offers little insight into how or why particular configurations might arise. The role of network dynamics and evolution are not well researched in relation to SNA, and other methods may be better suited to such questions.

Third, this study relied on respondents' perceptions of both the nature of their social relationships and their IS proficiency. Such perceptual approaches are an inherent weakness in sociometric instruments for SNA because perceptions might differ considerably from reality. However, this approach also enabled an exploration of both the frequency and the depth of user–system and interpersonal relationships, rich metrics that are often difficult to establish with objective, secondary data.

Conclusion

Despite these limitations, this study makes important contributions to research and practice. In this paper, we find that the CP-Alignment of a group is positively related to performance outcomes, even after controlling for average levels of IS use, IS proficiency, and interpersonal interactions. It is not enough to know the group members' average proficiency with a system; it is also important to recognize how this proficiency is distributed across the group's social network. This paper represents a first step toward a deeper understanding of how the configurations of user–system interactions influence performance at multiple organizational levels. We hope that other researchers build on and extend the approach outlined here.

Acknowledgments

The authors would like to thank Mike Morris (senior editor) and Peter Gray (associate editor) for their work at delivering a timely and constructive review process. Their efforts helped bring out the best in our work, and we are truly appreciative. Additionally, we would like to thank Scott Soltis for his outstanding help and insight in developing certain aspects of the literature review. We would also like to thank Maryam Alavi, Dan Brass, Rob Fichman, Joe Labianca, and Sam Ransbotham for their support at various stages of the project. This material is based upon work supported by the National Science Foundation under Grant No. (0953285).

References

Baum, J. A. C., Rowley, T. J., Shipilov, A. V., and Chuang, Y. T. 2005. "Dancing with Strangers: Aspiration Performance and the Search for Underwriting Syndicate Partners," *Administrative Science Quarterly* (50:4), pp. 536-575.

Bhattacherjee, A., and Premkumar, G. 2004. "Understanding Changes in Belief and Attitude Toward Information Technology Usage: A Theoretical Model and Longitudinal Test," *MIS Quarterly* (28:2), pp. 229-254.

Bonacich, P. 1972. "Factoring and Weighting Approaches to Status Scores and Clique Identification," *Journal of Mathematical Sociology* (2), pp. 113-120.

Borgatti, S. P. 1995. "Centrality and AIDS," *Connections* (18:1), pp. 112-114.

Borgatti, S. P. 2005. "Centrality and Network Flow," *Social Networks* (27), pp. 55-71.

Borgatti, S. P., and Cross, R. 2003. "A Relational View of Information Seeking and Learning in Social Networks," *Management Science* (49:4), pp. 432-445.

Borgatti, S. P., and Everett, M. G. 2000. "Models of Core/Periphery Structures," *Social Networks* (21:4), pp. 375-395.

Borgatti, S. P., Everett, M. G., and Freeman, L. C. 20002. "UCINET for Windows: Software for Social Network Analysis.," Analytic Technologies., Harvard, MA.

Borgatti, S. P., and Foster, P. C. 2003. "The Network Paradigm in Organizational Research: A Review and Typology," *Journal of Management* (29:6), pp. 991-1013.

Borgatti, S. P., Mehra, A., Brass, D. J., and Labianca, G. 2009. "Network Analysis in the Social Sciences," *Science* (323:5916), pp. 892-895.

Brass, D. J. 1981. "Structural Relationships, Job Characteristics, and Worker Satisfaction and Performance," *Administrative Science Quarterly* (26), pp. 331-348.

Brass, D. J. 1984. "Being in the Right Place: A Structural Analysis of Individual Influence in an Organization.," *Administrative Science Quarterly* (29:4), pp. 518-539.

Bryck, A. S., and Raudenbush, S. W. 2001. *Hierarchical Linear Models: Applications and Data Analysis Methods*, Newbury Park, CA: Sage Publicatoins.

Burkhardt, M. E., and 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), pp. 104-127.

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

Burton-Jones, A., and Gallivan, M. J. 2007. "Toward a Deeper Understanding of System Usage in Organizations: A Multilevel Perspective," *MIS Quarterly* (31:4), pp. 657-679.

Caldwell, D., and O'Reilly, C. 1990. "Measuring Person–Job Fit Using a Profile Comparison Process," *Journal of Applied Psychology* (75), pp. 648-657.

Carroll, J. M., and Mack, R. L. 1985. "Metaphor, Computing Systems, and Active Learning," *International Journal of Man–Machine Studies* (22), pp. 39-57.

Chan, Y. E., and Storey, V. C. 1996. "The Use of Spreadsheets in Organizations: Determinants and Consequences," *Information & Management* (31:3), pp. 119-134.

Chatman, J. 1989. "Improving Interactional Organizational Research: A Model of Person–Organization Fit," *Academy of Management Review* (14:3), pp. 333-349.

Chatman, J. A. 1991. "Matching People and Organizations—Selection and Socialization in Public Accounting Firms," *Administrative Science Quarterly* (36:3), pp. 459-484.

Coleman, J. S. 1988. "Social Capital in the Creation of Human Capital," *American Journal of Sociology* (94), pp. 95-120.

Compeau, D. R., and Higgins, C. A. 1995. "Application of Social Cognitive Theory to Training for Computer Skills," *Information Systems Research* (6:2), pp. 118-143.

Compeau, D. R., Higgins, C. A., and Huff, S. 1999. "Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study," *MIS Quarterly* (23:2), pp. 145-158.

Cross, R., and Cummings, J. N. 2004. "Tie and Network Correlates of Individual Performance in Knowledge-Intensive Work," *Academy of Management Journal* (47:6), pp. 928-937.

Cross, R., and Prusak, L. 2002. "The People Who Make Organizations Go—Or Stop," *Harvard Business Review* (80:6), pp. 104-112.

Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* (13:3), pp. 319-340.

Elfenbein, H. A., and O'Reilly, C. A. 2007. "Fitting In: The Effects of Relational Demography and Person–Organization Fit on Group Process and Performance," *Group and Organization Management* (32), pp. 109-142.

Evans, G. E., and Simkin, M. G. 1989. "What Best Predicts Computer Proficiency," *Communications of the ACM* (32:11), pp. 1322-1327.

Freeman, L. 1979. "Centrality in Social Networks: Conceptual Clarification," *Social Networks* (1), pp. 215-239.

Gallivan, M. J., Spitler, V. K., and Koufaris, M. 2005. "Does Information Technology Training Really Matter? A Social Information Processing Analysis of Coworkers' Influence on IT Usage in the Workplace," *Journal of Management Information Systems* (22:1), pp. 153-192.

Hansen, M. T. 1999. "The Search–Transfer Problem: The Role of Weak Ties in Sharing Knowledge Across Organization Subunits," *Administrative Science Quarterly* (44:1), pp. 82-111.

Hollingshead, A. 1998. "Retrieval Processes in Transactive Memory Systems," *Journal of Personality and Social Psychology* (74:3), pp. 659-671.

Hox, J. J. 2002. *Multilevel Analysis: Techniques and Applications*, Mahwah, NJ: Lawrence Erlbaum Associates.

Ibarra, H. 1992. "Homophily and Differential Returns— Sex-Differences in Network Structure and Access in an Advertising Firm," *Administrative Science Quarterly* (37:3), pp. 422-447.

Jasperson, J. S., Carter, P. E., and Zmud, R. W. 2005. "A Comprehensive Conceptualization of Post-Adoptive Behaviors Associated with Information Technology Enabled Work Systems," *MIS Quarterly* (29:3), pp. 525-557.

Kane, G. C., and Alavi, M. 2008. "Casting the Net: A Multimodal Network Perspective on User–System Interactions," *Information Systems Research* (19:3), pp. 253-272.

Kane, G. C., and Labianca, G. 2011. "IS Avoidance in Healthcare Groups: A Multilevel Investigation," *Information Systems* (22:3), pp. 504-522.

Kang, D., and Santhanam, R. 2003. "A Longitudinal Field Study of Training Practices in a Collaborative Application Environment," *Journal of Management Information Systems* (20:3), pp. 257-281.

Karuppan, C. M., and Karuppan, M. 2008. "Resilience of Super Users' Mental Models of Enterprise-Wide Systems," *European Journal of Information Systems* (17), pp. 29-46.

Kiesler, S., Zdaniuk, B., Lundmark, V., and Kraut, R. 2000. "Troubles with the Internet: The Dynamics of Help at Home," *Human-Computer Interaction* (15), pp. 323-351.

Kilduff, M., Tsai, W., and Hanke, R. 2006. "A Paradigm Too Far? A Dynamic Stability Reconsideration of the Social Network Research Program," *Academy of Management Review* (31:4), pp. 1031-1048.

Kogut, B. 2000. "The Network as Knowledge: Generative Rules and the Emergence of Structure," *Strategic Management Journal* (21:3), pp. 405-425.

Kozlowski, S. W. J., and Klein, K. J. 2000. "A Multilevel Approach to Theory and Research in Organizations," in *Multilevel Theory, Research, and Methods in Organizations,* K. J. Klein and S. W. J. Kozlowski (eds.), San Francisco: Jossey-Bass, pp. 3-90.

Krackhardt, D. 1990. "Assessing the Political Landscape – Structure, Cognition, and Power in Organizations," *Administrative Science Quarterly* (35:2), pp. 342-369.

Krackhardt, D., and Stern, R. N. 1988. "Informal Networks and Organizational Crises: An Experimental Simulation," *Social Psychology Quarterly* (51:2), pp. 123-140.

Kraemer, K. L., Danziger, J. N., Dunkle, D. E., and King, J. L. 1993. "The Usefulness of Computer-Based Information to Public Managers," *MIS Quarterly* (17:2), pp. 129-148.

Lin, N. 1982. "Social Resources and Instrumental Action," in *Social Structure and Network Analysis,* P. Mardsen and N. Lin (eds.), Beverly Hills, CA: Sage Publications, pp. 131-145.

Marcolin, B. L., Compeau, D. R., Munro, M. C., and Huff, S. L. 2000. "Assessing User Competence: Conceptualization and Measurement," *Information Systems Research* (11:1), pp. 37-60.

Mardsen, P. V., and Campbell, K. E. 1984. "Measuring Tie Strength," *Social Forces* (63), pp. 482-501.

Moreland, R., Argote, L., and Kirhsnan, R. 1996. "Socially Shared Cognition at Work: Transactive Memory and Group Performance," in *What's Social About Social Cognition*, J. Nye and A. Brower (eds.), Thousand Oaks, CA: Sage Publications, pp. 57-85.

Moore, G. C., and Benbasat, I. 1991. "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation," in *Information Systems Research* (2:3), pp. 192-222.

Morris, M. 1997. "Sexual Networks and HIV," *AIDS* (11), pp. S209-S216.

Nelson, R. R. 1991. "Educational Needs as Perceived by IS and End-User Personnel: A Survey of Knowledge and Skill Requirements," *MIS Quarterly* (15:4), pp. 503-525

Nelson, R. R., and Cheney, P. H. 1987. "Training End Users: An Exploratory Study," *MIS Quarterly* (11:4), pp. 547-559.

Oh, H. S., Chung, M. H., and Labianca, G. 2004. "Group Social Capital and Group Effectiveness: The Role of Informal Socializing Ties," *Academy of Management Journal* (47:6), pp. 860-875.

Putnam, R. D. 1995. "Bowling Alone: America's Declining Social Capital," *Journal of Democracy* (6:1), pp. 65-78.

Rasmussen, H., Haggerty, N., and Compeau, D. 2006. "Marshalling Support: How Computer Users Negotiate Technical Problems," in *Proceedings of 5th Annual Workshop on HCI Research*, Milwaukee, WI, December 9, pp. 45-49.

Rice, R. E., and Aydin, C. 1991. "Attitudes Toward New Organizational Technology—Network Proximity as a Mechanism for Social Information Processing," *Administrative Science Quarterly* (36:2), pp. 219-244.

Robey, D., and Sahay, S. 1996. "Transforming Work Through Information Technology: A Comparative Case Study of Geographic Information Systems in County Government," *Information Systems Research* (7:1), pp. 93-110.

Rodan, S., and Galunic, C. 2004. "More than Network Structure: How Knowledge Heterogeneity Influences Managerial Performance and Innovativeness," *Strategic Management Journal* (25:6), pp. 541-562.

Roy, W. G., and Bonacich, P. 1988. "Interlocking Directorates and Communities of Interest Among American Railroad Companies, 1905," *American Sociological Review* (53:3), pp. 368-379.

Ryn, M. V. 2002. "Research on the Provider Contribution to Race/Ethnicity Disparities in Medical Care," *Medical Care* (40:1), pp. 140-151.

Santhanam, R., and Sein, M. K. 1994. "Improving End-User Proficiency—Effects of Conceptual Training and Nature of Interaction," *Information Systems Research* (5:4), pp. 378-399.

Snijders, T. A. B., and Bosker, R. 1999. *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*, Thousand Oaks, CA: Sage Publications.

Sparrowe, R. T., Liden, R. C., Wayne, S. J., and Kraimer, M. L. 2001. "Social Networks and the Performance of Individuals and Groups," *Academy of Management Journal* (44:2), pp. 316-325.

Spitler, V. K. 2005. "Learning to Use IT in the Workplace: Mechanisms and Masters," *Journal of Organizational and End User Computing* (17), pp. 1-25.

Sykes, T. A., Venkatesh, V., and Gosain, S. 2009. "Model of Acceptance with Peer Support: A Social Network Perspective to Understand Employees' System Use," *MIS Quarterly* (33:2), pp. 371-393.

Thompson, R. L., Higgins, C. A., and Howell, J. M. 1991. "Personal Computing: Toward a Conceptual Model of Utilization," *MIS Quarterly* (15:1), pp. 125-143.

Thorpe, K. E., Florence, C. S., and Joski, P. 2004. "Which Medical Conditions Account for the Rise in Health Care Spending?," Health Affairs—Web Exclusive, pp. W4-437–W4-445 (http://content.healthaffairs.org/cgi/reprint/hlthaff.w4.437v1.pdf).

Tziner, A., and Eden, D. 1985. "Effects of Crew Composition on Crew Performance: Does the Whole Equal the Sum of Its Parts?," *Journal of Applied Psychology* (70), pp. 85-93.

Valente, T. W. 1985. *Network Models of the Diffusion of Innovations*, Cresskill, NJ: Hampton Press.

Venkatesh, V., and Morris, M. G. 2000. "Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior," *MIS Quarterly* (24:1), pp. 115-139.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. 2003. "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3), pp. 425-478.

Wegner, D. M. 1987. "Transactive Memory: A Contemporary Analysis of the Group Mind," in *Theories of Group Behavior,* B. Mullen and G. G. Goethals (eds.), New York: Springer-Verlag, pp. 185-208.

Wejnert, B. 2002. "Integrating Models of Diffusion of Innovations: A Conceptual Framework," *Annual Review of Sociology* (28), pp. 297-306.

Yi, M. Y., and Davis, F. D. 2003. "Developing and Validating an Observational Learning Model of Computer Software Training and Skill Acquisition," *Information Systems Research* (14:2), pp. 146-169.

Yoon, Y. H., Guimaraes, T., and O'Neal, Q. 1995. "Exploring the Factors Associated with Expert Systems Success," *MIS Quarterly* (19:1), pp. 83-106.

About the Authors

Gerald C. (Jerry) Kane is an assistant professor of Information Systems at Boston College's Carroll School of Management. His research interests include exploring the role of information systems in social networks, organizational applications and implications of social media, and the use of IT in healthcare organizations. Jerry is a recent recipient of a CAREER Award from the National Science Foundation, for research on using social media to manage knowledge. His published research has appeared or is forthcoming in such journals as *MIS Quarterly*, *Information Systems Research*, *Organization Science*, *ACM Transactions on MIS*, *Marketing Science*, and *Harvard Business Review*, among others. Jerry received his Ph.D. from the Goizueta Business School of Emory University and his M.B.A. in Computer Information Systems from Georgia State University. Prior to his career as an academic, he was ordained as a clergyperson in the United Methodist Church.

Stephen P. Borgatti is the Paul Chellgren Chair of Management at the Gatton College of Business and Economics at the University of

Kentucky. He received his Ph.D. in Mathematical Social Science from the University of California, Irvine, in 1989. His research interests include social networks and knowledge management. He is a coauthor of the UCINET software package for social network analysis, and a past president of INSNA, the professional association for social network researchers. He has received the Simmel Award from INSNA for contributions to the field. His work has appeared in *Science*, *Social Networks*, and a variety of management journals, including *Organization Science* and *Academy of Management Review*.

Appendix A

Descriptive Statistics

		N	Minimum	Maximum	Mean	Std. Dev.
	Chronic Care	9950	0 (n = 3389)	1 (n = 6561)	0.66	0.47
D.V.	Eye Exam	9950	0 (n = 8116)	1 (n = 1834)	0.18	0.39
	Cholesterol Screening	9950	0 (n = 571)	1 (n = 9379)	0.94	0.23
	Nephrology Screening	9950	0 (n = 3256)	1 (n = 6694)	0.67	0.47
	Insurance Type	9950	0 (n = 8048)	1 (n = 1902)	0.19	0.39
	Patient Risk	9950	0 (n = 9739)	1 (n = 211)	0.02	0.14
Dr. Level	Dr. Tenure	80	0.81	24.04	7.89	4.59
	Dr. Race	80	0 (n = 22)	1 (n = 58)	0.28	0.41
	Dr. Gender	80	0 (n = 52)	1 (n = 28)	0.65	0.48
Group Level	Group Type	32	0 (n = 24)	1 (n = 8)	0.00	0.03
	Number in Group	32	8	26	16.06	4.44
	Average Tenure	32	3.41	11.82	6.25	1.34
	Racial Composition	32	0.00	0.80	0.25	0.25
	Gender Composition	32	0.09	0.29	0.18	0.05
	Network Centralization	32	4.61	52.22	11.70	9.34
Systems	IS Use (S1)	32	7.27	11.17	9.31	1.04
	IS Use (S2)	32	6.20	10.87	9.21	0.86
	IS Use (S3)	32	5.25	10.13	8.09	1.11
	IS Use (S4)	32	6.67	10.75	8.84	0.83
	IS Use (S5)	32	6.56	10.83	8.46	1.08
	IS Use (Avg.)	32	7.47	9.97	8.78	0.66
	IS Proficiency (S1)	32	4.67	6.27	5.52	0.42
	IS Proficiency (S2)	32	4.37	6.03	5.08	0.44
	IS Proficiency (S3)	32	4.58	6.36	5.42	0.38
	IS Proficiency (S4)	32	4.43	6.03	5.15	0.34
	IS Proficiency (S5)	32	4.57	6.36	5.51	0.36
	IS Proficiency (Avg.)	32	4.74	6.14	5.34	0.27
	CP-Alignment (S1)	32	-0.73	0.78	0.31	0.33
	CP-Alignment (S2)	32	-0.32	0.72	0.19	0.28
	CP-Alignment (S3)	32	-0.38	0.77	0.26	0.29
	CP-Alignment (S4)	32	-0.62	0.94	0.16	0.34
	CP-Alignment (S5)	32	-0.64	0.75	0.27	0.30
	CP-Alignment (Avg.)	32	-0.13	0.65	0.24	0.21

Appendix B

Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Chronic Care																
2	Eye Exam	0.196**															
3	Cholesterol Screening	0.257**	0.082**														
4	Nephrology Screening	0.214**	0.071**	0.225**													
5	Insurance Type	0.142**	0.112**	0.044**	0.051**												
6	Patient Risk	0.016	-0.003	-0.006	-0.018	-.072**											
7	Dr. Tenure	0.011	0.019	.058**	.060**	.043**	-.034**										
8	Dr. Race	.047**	0.015	.021*	-0.017	.023*	0.019	.116**									
9	Dr. Gender	-0.008	-0.017	0.002	0.008	0.001	-0.01	.256**	.101**								
10	Group Type	-0.017	0.013	-0.013	-0.016	0.009	-0.003	-.022*	.032**	.189**							
11	Number in Group	0	-0.014	-.021*	-0.008	-0.015	-0.004	.024*	.029**	0.001	-.029**						
12	Average Tenure	0.017	-0.003	0.008	0.015	.043**	0.015	.091**	.179**	.207**	.123**	.072**					
13	Racial Composition	.090**	0.006	.028**	-.049**	.061**	.046**	0.013	.473**	.098**	-.059**	.049**	.515**				
14	Gender Composition	-0.009	0.002	-0.003	-.028**	-.023*	-0.017	.100**	.042**	.229**	.243**	0.01	-.125**	.066**			
15	Centralization	-0.01	0.009	-0.003	-.031**	0.01	0.002	-.034**	-.022*	-.148**	-.078**	0.017	-.343**	-.263**	-.237**		
16	IS Use (S1)	-0.011	-0.008	-0.009	-0.002	-.029**	0.002	0.014	.094**	.267**	.253**	-0.018	.218**	.071**	0.002	-.039**	
17	IS Use (S2)	0.008	-0.005	0.018	.039**	-.036**	0.008	0.019	.084**	.219**	.129**	.027**	.289**	.212**	-.099**	-.398**	.771**
18	IS Use (S3)	0.01	0	-.035**	-.060**	-.033**	-0.011	-.078**	.079**	.243**	-.103**	-0.008	.267**	.148**	.242**	-.095**	.555**
19	IS Use (S4)	-0.015	-0.007	0.017	0.019	-0.019	0.014	.184**	.074**	.145**	.175**	-.037**	.120**	-0.013	-.146**	.146**	.836**
20	IS Use (S5)	-0.003	0.007	-.024*	-.074**	.052**	.026**	-.042**	.268**	.096**	.541**	.035**	-.060**	.204**	.290**	.058**	.397**
21	IS Use (Avg.)	-.035**	-0.017	-0.009	.051**	-.042**	-.021*	-.047**	-.125**	.187**	.222**	-.063**	.080**	-.253**	-.203**	.154**	.784**
22	IS Proficiency (S1)	.057**	0	0.019	-0.008	0.009	.023*	-.099**	.257**	.091**	-.156**	.045**	.153**	.469**	-.165**	-.461**	.369**
23	IS Proficiency (S2)	0.015	-0.005	-0.019	-.031**	-.029**	-.027**	-.068**	-.025*	.184**	.085**	.025*	.122**	.112**	.470**	-.227**	-.074**
24	IS Proficiency (S3)	0.019	-0.009	0.017	-.028**	.044**	.043**	.153**	.340**	0.014	-.098**	.022*	.215**	.468**	.076**	-.071**	.244**
25	IS Proficiency (S4)	-0.005	0.009	-.031**	-.066**	.054**	.027**	-.101**	.235**	0.018	.626**	0.015	.175**	.155**	0.011	-.222**	.081**
26	IS Proficiency (S5)	-0.008	-0.018	0	.045**	.039**	0.014	-.050**	.020*	.045**	-.111**	0.007	.402**	.187**	-.366**	-.368**	.378**
27	IS Proficiency (Avg.)	.033**	-0.007	-0.01	-.042**	.044**	.030**	-.087**	.331**	.145**	.194**	.047**	.398**	.539**	.038**	-.545**	.369**
28	CP-Alignment (S1)	0.008	0.002	-.046**	-.051**	-.026**	-.029**	-.257**	-.090**	.095**	-.153**	-.023*	.082**	-.089**	.032**	.041**	-.077**
29	CP-Alignment (S2)	-0.014	0.015	-.039**	-.045**	-0.014	-0.011	-.129**	-.166**	-.100**	.385**	-.030**	-.412**	-.403**	-.099**	-.128**	-.173**
30	CP-Alignment (S3)	-.034**	0.005	-.023*	0	.025*	-0.019	-0.018	-.225**	-.044**	.142**	-.027**	.254**	-.343**	-.197**	.269**	-.250**
31	CP-Alignment (S4)	-0.009	0.014	-0.004	-0.008	-0.018	-0.008	.083**	-.026**	.095**	.268**	.042**	.116**	-.196**	.078**	-.121**	.179**
32	CP-Alignment (S5)	.031**	0.009	-.034**	-.076**	-0.016	-0.015	-.202**	.034**	-0.006	-.328**	-0.01	-0.003	.020*	0.016	.076**	-.282**
33	CP-Alignment (Avg.)	0.001	0.013	-.045**	-.061**	-0.017	-.026*	-.185**	-.120**	.021*	0.005	-0.015	.029**	-.252**	-.035**	.055**	-.200**

		17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
18	IS Use (S3)	.298**															
19	IS Use (S4)	.608**	.230**														
20	IS Use (S5)	.089**	-0.008	.342**													
21	IS Use (Avg.)	.549**	.270**	.616**	.127**												
22	IS Proficiency (S1)	.605**	.152**	.189**	.155**	.157**											
23	IS Proficiency (S2)	-.192**	.413**	-.294**	-.230**	-0.007	-.165**										
24	IS Proficiency (S3)	.067**	.024*	.462**	.513**	-.137**	.259**	-.252**									
25	IS Proficiency (S4)	-.027**	-.123**	.045**	.711**	-.150**	.086**	-.214**	.383**								
26	IS Proficiency (S5)	.448**	-.027**	.296**	.188**	.376**	.555**	-.271**	.326**	.140**							
27	IS Proficiency (Avg.)	.339**	.182**	.223**	.530**	.071**	.675**	.079**	.613**	.585**	.619**						
28	CP-Alignment (S1)	-.243**	.567**	-.405**	-.333**	.059**	-.032**	.630**	-.472**	-.216**	-.199**	-.066**					
29	CP-Alignment (S2)	-.131**	-.091**	-.179**	.066**	-.206**	-.126**	-0.011	-.372**	.364**	-.218**	-.078**	.139**				
30	CP-Alignment (S3)	-.538**	.046**	-.160**	-.163**	-.059**	-.468**	.161**	-.126**	.080**	0.004	-.143**	.336**	.155**			
31	CP-Alignment (S4)	.208**	.317**	.140**	-.044**	-.048**	.061**	-.172**	-.077**	.147**	-.085**	-.027**	-.055**	.319**	.290**		
32	CP-Alignment (S5)	-.333**	.529**	-.502**	-.453**	-.283**	-.031**	.528**	-.364**	-.238**	-.390**	-.144**	.864**	.172**	.269**	.139**	
33	CP-Alignment (Avg.)	-.336**	.486**	-.393**	-.340**	-.168**	-.157**	.431**	-.450**	-.032**	-.298**	-.143**	.807**	.466**	.594**	.438**	.854**