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Casting the Net: A Multimodal Network Perspective on User-System Interactions

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Information systems (IS) researchers have typically examined the user-system relationship as an isolated dyad between a single, independent user and an individual, freestanding information system. We argue that this conceptualization does not adequately represent most organizations today, in which multiple users interact with multiple information systems within a group. Relying heavily on the theory and methods behind social network analysis, we introduce the concept of *multimodal networks* to assess both users and information systems as equivalent nodes in a single social network. This perspective allows us to examine the influence of information systems on organizational outcomes as a function of all of the user-system and interpersonal interactions in a group. We explore two different possible mechanisms for this influence: (1) direct user-system interactions by aggregating the strength of all the dyadic user-system interactions in a group, and (2) indirect user-system interactions by assessing the centrality of the information systems within the social network. We survey approximately 600 individuals in 40 healthcare groups to test whether either or both of these mechanisms are associated with two types of organizational performance outcomes—efficiency and quality of care. We find that the centrality of the information systems within the network is significantly and positively associated with both efficiency and quality outcomes, but that the average strength of the user-system interactions is not. Implications are that managers and researchers should examine the wider multimodal network of multiple users and multiple systems when assessing the role of IS in organizations in relation to organizational performance outcomes.

Key words: IS use; social networks; multimodal networks; centrality; performance; group-level; indirect use; information use
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Introduction

Information systems (IS) can be used as valuable tools to support organizational work in knowledge-intensive settings. IS enable individuals to store and access vast amounts of codified knowledge, to search and retrieve that knowledge, to combine and create new knowledge, and to apply that knowledge to organizational problems in new ways (Alavi and Leidner 2001, Davenport and Grover 2001, Sambamurthy and Subramani 2005). IS research has recognized, however, that the mere presence of IS in an organization is not sufficient to influence performance outcomes. Whether and how people actually interact with the IS at their disposal is a critical factor for understanding their influence in organizations (DeLone and McLean 1992, Devaraj and Kohli 2003, Kim et al. 2005). IS researchers have traditionally studied the ways in which individuals' own use of information systems affect performance outcomes, but this conceptualization of direct user-system interaction does not illuminate the many forms of indirect impacts these technologies may have. Organizations increasingly rely on virtual and colocated groups comprised of multiple individuals to work together on organizational tasks, and these groups typically depend on more than one information system to support their work. Thus, whereas most IS research continues to conceptualize user-system interactions as a *dyad* (a single user interacting with a single information system) most organizations actually function as a *network* (multiple users interacting with multiple information systems).

Understanding how user-system interactions influence group-level performance outcomes in a networked setting of multiple people and multiple information systems is a nontrivial problem. On one hand, the answer may be simple. Group-level interactions between multiple people and multiple information systems may be an aggregation of the dyadic user-system interactions traditionally examined in IS research. On the other hand, the answer might not be so simple. Multiple people interacting with each other and with multiple information systems could result in complex structures of interpersonal and user-system interactions. These network structures, overlooked in a traditional dyadic conceptualization of user-system interactions, may be important for producing a more complete understanding of the impact of IS on organizational outcomes.

This paper investigates the influence of IS on group-level organizational performance outcomes in multiuser, multisystem groups. We investigate two different possible mechanisms for its influence. First, we test whether the impact of an information system on organizational performance outcomes is a function of *direct use*. We aggregate the strength of all the dyadic user-system interactions in a group to assess its relationship to a group's performance outcomes. Second, we test whether the impact of an information system on organizational performance outcomes is also related to its *indirect use*, the network of interpersonal interactions that mediate information transfer between information systems and all members of the group, users and nonusers alike. We draw upon social network analysis to assess the relational structures associated with indirect use in terms of a node's centrality, described later in this paper. The characteristics attributed to a node's centrality strongly parallel the intended role of the information system in organizations, and should serve as an effective approach to assess the broader structure of interpersonal and user-system interactions in a network.

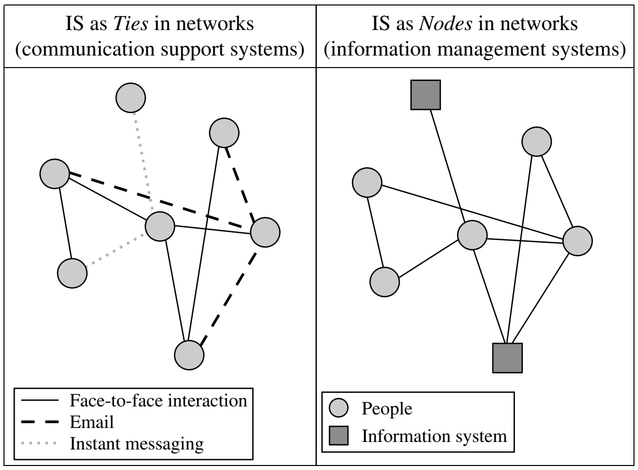
We find that the centrality of the IS within the network is significantly related to organizational performance outcomes, but the simple aggregation of dyadic user-system interactions is not. The impact of information systems on organizational performance outcomes in a multiuser, multisystem group, therefore, is more complex than simply the sum of direct user-system interactions that comprise it. It depends instead on the network structures that emerge when the user-user and user-system relationships are integrated as a whole network. These findings suggest that IS researchers should move away from an exclusively dyadic conceptualization of direct user-system interactions and begin to explore the interplay between digital and social networks.

Integrating Digital and Social Networks

We employ social network analysis as a framework for understanding user-system interactions in a multiuser, multisystem group. We adopt the concept *multimodal network*, defined as the collection of people and IS used to share information within an organization, to refer to this setting (Monge and Contractor 2003). The term *multimodal* refers to two types of nodes—people and information systems—treated equivalently within a single network. Organizations can employ two general categories of IS to support knowledge-intensive work—communication support systems and information management systems (Goodman and Darr 1998, Hansen et al. 1999, Robey et al. 2000). Communication support systems—such as email, instant messaging, and videoconferencing—are primarily used as digital channels to transfer information between a source and a recipient. Information management technologies—such as knowledge bases and knowledge warehouses—are freestanding repositories that store, process, and organize knowledge.[1]

[1] These technologies differ in some key ways. Whereas knowledge shared via communication support systems are usually intended for a specific other, knowledge shared via information management systems are usually not shared with a specific recipient in mind. Rather, it is usually shared with the understanding that a number of a given knowledge network members might utilize the knowledge contributed at a later time, including the very person who contributed it. Another difference is whether the information system adds value to the knowledge-sharing process. In communication support systems, the technology adds little, if any, additional value to the transmitted knowledge beyond moving it efficiently from one location to another. In information management systems, however, the system often combines, synthesizes, and organizes the knowledge contained in it, adding value to that knowledge.

Figure 1 Information Systems in Social Networks



This difference has important implications for examining these systems from a social network perspective (Figure 1). Communication support systems are best conceptualized as *electronic ties* in networks, connecting two human nodes. Research in this area has analyzed the interpersonal social networks that occur across communication support technologies (Ahuja and Carley 1999, Ahuja et al. 2003, Wasko and Faraj 2005). Information management systems, however, are best conceptualized as *electronic nodes* in networks. Because information management systems are capable of acting as independent entities, acting and interacting with other nodes in a network in powerful, automatic, and sometimes autonomous ways, it is important to account for their unique role in information networks independently and explicitly (Carley 2002, Monge and Contractor 2003). Previous research has suggested that humans and nonhumans can be integrated as equivalent nodes into a single network (Callon et al. 1986, Latour 1987). The multimodal network concept presented in this paper focuses exclusively on the role of information management technologies as a node in the network.

Capturing Direct Use Through User-System Tie Strength

IS researchers have long recognized that the influence of information systems on organizational outcomes depends greatly on the degree to which users directly interact with the systems available to them (Devaraj and Kohli 2003, Hansen and Haas 2001, Kim and Malhotra 2005). The more that individuals use the information systems available to them, the greater organizational performance impact those systems are likely to have. Direct user-system interactions are typically described along two dimensions: frequency and depth of interaction.

Frequency of interaction describes how often an individual interacts with an information system at his or her disposal. The more frequently an individual interacts with an information system, the more that system influences organizational performance outcomes (Deveraj and Kohli 2003). Frequent interaction means that the system will be better able to provide real-time information for the individual or for others who may use the system. It also means that the individual will have to conduct fewer additional tasks to support its usage (e.g., writing information down for later entry). If an individual does not interact with an information system at all (the lowest possible frequency), the system is not likely to impact the tasks it was designed to support. Doll and Torkzadeh (1998) argue that frequency of interaction is "a pivotal construct in the system-to-value chain that links upstream research on the causes of system success with downstream research on the organizational impacts of information technology" (p. 171).

People will vary in how much of the functionality available in an information system they will use, an aspect of direct user-system interactions that we will call *depth of interaction* (Griffith 1999, Jasperson et al. 2005). Some users may interact with systems only for the most basic tasks, whereas other users may employ a substantial degree of functionality in the system (Hiltz and Turoff 1981, Kay and Thomas 1995). Individuals who interact with the systems more deeply can leverage more of the capabilities of the information system to support their knowledge tasks. Depth of interaction is theorized to be a measure of technology in use, capturing how much an individual adapts a technology to meet the unique tasks and requirements that the user must address (Desanctis and Poole 1994, Orlikowski 1992). Individuals who interact with a system deeply are more likely to employ the features of the system that are most relevant for their task requirements, further improving performance outcomes.

User-system interaction, therefore, is a combination of both its frequency and depth of interaction. IS research has not sufficiently explored how frequency and depth of interaction relate to one another in a multiperson, multisystem setting (Lamb and Kling 2003, Vertegaal 2003). Social network literature offers some guidance in this instance. The concept of *tie strength*, commonly defined as a sum of the frequency and depth of direct interactions between two nodes, has long been used to study information transfer in multiperson groups (Hansen 1999, Mardsen and Campbell 1984). Borrowing from this concept, we introduce the term *user-system tie strength* to assess the direct interactions of multiple users with multiple information systems in a group.

Average tie strength between nodes has long been associated with performance outcomes in knowledge-intensive settings, but the precise nature of this relationship has been the source of great debate (Borgatti and Foster 2003, Raider and Krackhardt 2002).[2] Some argue that high average tie strength in a network leads to superior outcomes, because it yields richer and more in-depth information-sharing relationships (Coleman 1988, Krackhardt 1992, Walker et al. 1997). Others argue that low tie strength is superior because these ties require less energy to maintain and can facilitate a greater breadth of information exchange (Burt 1992, Granovetter 1973). Researchers have found that the influence of tie strength on performance outcomes depends on two important moderating factors: the network context and the type of knowledge-sharing tasks.

The *network context* suggests that the performance impact of average tie strength depends on whether the ties occur within groups or across groups (Reagans and McEvily 2003, Reagans and Zuckerman 2001). Higher tie strength is associated with greater performance outcomes when they occur *within* a group because they enable the group to function more reliably as a whole. Higher average tie strength leads to richer information transfer, greater trust between nodes, better transitive memory, and redundant channels that leads to more reliable communication (Borgatti and Cross 2003, Brass 1995, Raider and Krackhardt 2002). These arguments have parallels in the IS literature. Higher user-system tie strength is associated with richer information transfer between user and system (Jasperson et al. 2005). It is associated with a greater trust between user and system (McKnight et al. 2002). High average user-system tie strength within a group would allow individuals to be more aware of where to find needed information in the systems (Alavi and Tiwana 2003). It would also be associated with the ability of other users to conduct necessary tasks in the system if one user is unable to use the system. Because this study explores how to account for the use of information systems *within* organizational groups, the above arguments would suggest that higher average user-system tie strength would lead to improved performance outcomes.

The *task type* also predicts whether high or low tie strength will be associated with improved performance outcomes. Higher tie strength is associated with performance benefits in relation to knowledge *exploitation* tasks, in which existing information is applied to clearly defined organizational situations (March 1991, Rowley et al. 2000). As nodes interact more frequently with one another, higher tie strength allows two nodes to develop a shared language that results in more efficient interactions (Carlson and Zmud 1999, Nahapiet and Ghoshal 1998). Although information systems can be used to support both exploration and exploitation tasks, the information management systems examined in this study are most often associated with knowledge *exploitation* tasks (Kane and Alavi 2007). Information management systems transfer and synthesize existing organizational knowledge, making it available to employees when needed (Carlile and Rebentisch 2003). Stronger user-system ties can enhance the efficacy of these systems within the group (Majchrzak et al. 2004, Markus 2001). Higher tie strength yields robust and efficient information sharing, which are better for dealing with the known requirements exploitation tasks.

These arguments should not be interpreted to mean that low user-system tie strength might not be important in other settings, particularly when they occur across groups and for knowledge exploration tasks.

[2] In networks that employ valued ties, such as in this analysis, average tie strength is also equivalent with *network density*. We retain the use of the tie strength terminology here to distinguish more clearly between user-system and user-user ties, but the theoretical arguments presented here apply to both concepts.

When maintained across groups, weak ties are particularly helpful for dealing with knowledge exploration tasks in which task requirements are not well known in advance, because they provide greater access to resources not found in the group (Hansen 2002). Performance advantages associated with lower tie strength are also found in relation to knowledge exploration tasks. These tasks tend to be more heavily associated with communication support systems (Constant et al. 1996, Kane and Alavi 2007, Pickering and King 1995), information technologies not addressed in this study. Nevertheless, because the concept of multimodal networks forwarded by this paper focuses exclusively on within-group interactions involving information management systems, previous research would suggest that average user-system tie strength should be positively associated with outcomes in our research setting.

Hypothesis 1 (H1). *Average tie strength between users and systems in a multimodal network will be positively related to organizational performance outcomes.*

Capturing Indirect Use Through IS Centrality

Recent research, however, has suggested that the influence of IS on organizational outcomes may involve more than just the direct interactions between users and information systems. Information is valuable to the degree that it can be transferred to an applicable situation (Choudhury and Sampler 1997, Grant 1996). Information can be transferred from a system to those who need it through mechanisms other than direct use. As users interact with each other and with nonusers to conduct work-related tasks, they can also use their interpersonal relationships to transfer information to, from, or about the information systems with which they interact (Lamb and Kling 2003). The use of interpersonal interactions to augment direct IS use has been previously identified in the IS literature as both indirect use (Kraemer et al. 1993) and information use (Burton-Jones and Straub 2006). For the purposes of this paper, we will refer to these interactions as *indirect use*. Little research has investigated how these indirect use relationships in a group may influence the organizational performance impact of information systems.

Interpersonal relationships can be a critically important channel for transferring information to, from, and about information systems in a multiuser, multisystem group. For instance, a manager might ask an employee for information, and the employee might use an information system to create or find the information to provide to the manager. The manager benefits from the use of the system, even though he or she never interacts with the system directly. In this case, the effectiveness with which information in the system can be transferred to the manager is a function of both the user-system relationship (the employee's interaction with the system) and the interpersonal relationship (the manager's interaction with the employee).

This example can be extended to describe more complex relational structures that enable indirect use. The manager might benefit from having a number of different employees available to use a system on his or her behalf, relying on the employee most readily available to transfer information to and from the system or on multiple employees to handle larger tasks. One employee may have developed a specialization with a particular system, and the manager might rely on the individual most able to access a particular type of information in a particular system. The manager might interact with the system personally but augment his or her own direct interactions with indirect use, relying on interpersonal relationships for help using the information systems in complex, unfamiliar, or high cognitive load tasks. Thus, indirect use represents multiple possible ways that individuals rely on interpersonal relationships to deploy information to, from, or about an information system to where it is needed and used.

The concept of indirect use suggests that how effectively a group can leverage an information system to impact performance outcomes is a function of both the direct user-system interactions and the interpersonal relationships maintained by those users to transfer information between the systems and others in the network. Social network analysis offers a mechanism, referred to as centrality, to describe and analyze such complex relational structures that comprise indirect use. Centrality captures how well a particular node is directly and indirectly situated among all other relationships in the network (Brass 1995, Bonacich 1972). High centrality means the node is well-connected to other nodes in the network, and low centrality means the node is not well-connected to other nodes in the network. We refer to the centrality of the IS nodes in the multimodal network as *IS centrality*.

Centrality of a node has been theorized as a measure of the degree to which a network as a whole values the information held by a particular node and seeks access to it (Perry-Smith and Shalley 2003). If a node is perceived by members of the network to possess valuable knowledge, others establish direct relationships with that node in an effort to access the valuable knowledge it possesses. Network members who value the information but, for whatever reason, cannot establish a direct relationship with the node possessing the valued information will establish relationships with those nodes who can provide access to that information. A node whose knowledge is valued by the group as a whole will become more central in the network as a result of other members seeking to access it, directly or indirectly. If an information system is more central in a multimodal network, it will mean that the members of the group as a whole value the information contained by the system. If an information system is less central in a multimodal network, it will mean that the members of the group as a whole does not value to information contained by the system.

Centrality has been shown to yield a number of important benefits for the node itself, including perceived power (Brass 1984), organizational influence (Ibarra 1993), and performance outcomes (Podolny and Baron 1997). These benefits result from the node's ability to use their central position to better identify and leverage the resources available in the network. A central position in the network has also been shown to provide important information benefits for nodes that occupy them, in terms of timing, access, and referral (Burt 1992). *Timing* describes how quickly a node receives information in a network. By virtue of their position, central nodes are likely to receive information more quickly than peripheral nodes, because the central nodes are, on average, closer to all information in the network. *Access* describes the likelihood that a node will be able to find needed information in a network. Because a central node is well connected to other nodes, it is better able to use those relationships to find the information needed within a network. *Referral* describes the likelihood that other nodes in a network will pass information to a node. Members of a network are more likely to pass information to a central node, because they are more likely to know the abilities and interests of that node.

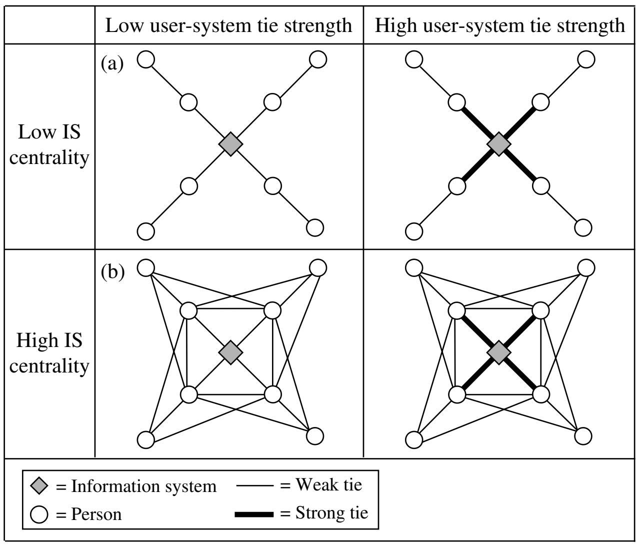
The information benefits of centrality result from the structural position of the node, and not from the characteristics or actions of the node itself. Thus, if an information system is central in the multimodal network, it will also benefit from better timing, access, and referral of information. If information can get to and from an information system more quickly (timing), the information contained by that system and available to the group will be more up to date and accurate. The more easily group members can access the systems to get needed information from or put important information into the system (access), the more reliable the flow of information between the system and the group. If group members know which systems possess the information they need and in which system particular information should be stored (referral), it will mean that the information contained by the systems is of greater relevance to the tasks faced by the group. Thus, IS centrality will be positively related to the accuracy, reliability, and relevance of information contained in a group's information system. Groups that possess more accurate, complete, and relevant information will be able to leverage this resource to improve their performance outcomes (Choudhury and Sampler 1997, Grant 1996). Thus, in knowledge-intensive settings, IS centrality will be positively associated with group-level organizational performance outcomes.

Hypothesis 2 (H2). *The centrality of the information systems in a multimodal network will be positively related to organizational performance outcomes.*

Two Features, One Network

User-system tie strength and *IS centrality* capture different aspects of the multimodal network. Figure 2 illustrates simplified versions of these structural features to help understand which network features are captured by each measure. In the illustrations below,

Figure 2 Visualizing Network Features



each network only incorporates one information system, and ties are only represented as weak (thin lines) or strong (thick lines). In the actual networks we studied, we examined six information systems and ties valued on a 12-point scale.

User-system tie strength captures the relationships between the direct users and the system in a network. The low-tie-strength condition is represented in our graphs by the four direct users having weak ties with the system, interacting with the system with relatively low frequency and depth. The high-tie-strength condition is represented by the four direct users in the network having strong ties with the system, interacting with the system with relatively high frequency and depth. Thus, our measure of *user-system tie strength* is similar to traditional measures of IS use, with two exceptions. First, drawing directly from the social network measure of tie strength, it incorporates both frequency and depth of interaction as a single measure of user-system interaction. Second, it considers the interactions of all the users of a system and all the systems in the network, rather than examining the relationship between an individual user and a single system.

IS centrality is represented in our figures as the relationship between users and other members of the network. IS centrality represents how the entire group benefits from the information system as a result of indirect use of the system, not just the direct users (Kraemer et al. 1993).[3] The low-IS centrality condition is represented in our graphs by the four direct users having only a single relationship with one other member of the group. This network structure has a relatively low benefit from indirect use, because the users can only transmit the information to one other member of the network and the other members of the network can only rely on one user to interact with the system on their behalf. The high-IS centrality condition is represented in our graphs by the four direct users having a large number of connections with other members of the network. This network structure has relatively high opportunity for indirect use, because each individual has multiple interpersonal channels to transfer information to and from the information system.

The two measures employed in this study capture different aspects of the user-system interactions, and can operate independently from one another. For instance, the low- and high-IS centrality conditions illustrated in Figure 2 demonstrate how *IS centrality* can change without any change in user-system tie strength. Nevertheless, our two measures will be positively correlated with one another because both incorporate the direct user-system ties into its measure. Our data reflect this positive correlation, although it is not high enough to cause problems for our data analysis.

Research Setting and Method

Our research was conducted in a regional division of a national health maintenance organization (HMO), pseudonymously referred to in this paper as HealthProviders. At HealthProviders, healthcare is provided at the level of the healthcare group, a collection of doctors, nurses, and support staff that address the healthcare needs of a fixed panel of patients. Although HealthProviders has developed a robust IS infrastructure to support groups in providing effective healthcare, their ability to provide effective care

[3] It is important to note that *IS centrality* does not only capture indirect use, but it is a global measure that captures both direct and indirect use by incorporating user-system ties to define the direct users in the network. We interpret *IS centrality* as primarily capturing the features of indirect use in this setting because we also include direct user-system tie strength in our analysis.

relies heavily on the ability of group members to interact effectively with each other and with this IS infrastructure. These groups share a number of features that make it an attractive setting to study the effects of multimodal networks.

First, these groups share a common task of delivering healthcare. Each of the groups studied provides primary care, responsible for producing baseline assessments of the patients' needs and responding with the appropriate type of treatment or referring the patient to the necessary specialist. Each group also has a similar workload. Groups are staffed so that one doctor and two support staff are assigned to a group for each risk-adjusted panel of approximately 2,000–2,500 patients who are treated by that group.[4]

Second, each healthcare group has a common network composition, comprised of identical staff positions and IS. Each group consists of approximately four to six doctors and eight to 12 clinical and administrative support staff. Group members have similar training, educational backgrounds, experience, and organizational responsibilities. Each group also shares an identical set of six primary IS systems—scheduling, laboratory, radiology, population registry, medical abstract, and conferencing—which represent the core portfolio of IS essential for conducting the group's tasks (see Table 1).

Third, these groups are independent from one another. Geographic proximity, scheduling procedures, and colocation of paper-based records mean that doctors within a healthcare group often treat one another's patients but rarely treat patients from other groups. This enables us to clearly identify which employees and patients belong to which group, defining and analyzing each group as a distinct multimodal network. Different groups have virtually no interaction with one another in terms of patient care. Each group is defined and evaluated as a separate, independent unit by HealthProviders when assessing healthcare outcomes.

[4] Each team is controlled to have a roughly equal number of patients, adjusted for demographics and risks. For instance, a team with a high number of older high-risk patients would have a lower gross number of patients compared to a team with the same number of younger, relatively healthy patients. Each patient population would require roughly the same amount of attention to provide effective healthcare.

Fourth, these groups rely heavily on IS to share information. Because groups coordinate the immense resources of the organization to address the healthcare needs of a large panel of patients, the information systems play a critical role in providing that care. Recent research has noted that it is virtually impossible to deliver the type of care required by organizations such as HealthProviders without the extensive and effective use of IS (Ortiz and Clancy 2003). Furthermore, these groups rely on information management systems for information-sharing tasks, allowing us to isolate and examine the features of IS as electronic nodes in a network.

Despite the commonalities between these groups, anecdotal evidence suggested that group interacted with the IS very differently, resulting in different multimodal network structures. This setting provides us the ability to control for many network (group) factors and isolate the effects of the different multimodal network structures on organizational performance outcomes.

Data Collection

We administered a survey to 614 members of 40 healthcare groups in the regional division of HealthProviders in early 2005. The survey was both pretested and pilot tested with a small group of respondents prior to administration, ensuring that the survey and our administration procedures captured the network features in which we were interested. The survey was a standard sociometric instrument that provided respondents with a roster of group members and of the six systems that the organization had identified as being most critical for outcomes across all groups. Respondents were asked to rate the frequency and depth of their interaction with other members of the group and with the systems used by the group. The specific questions of the survey instrument and the anchors can be found in Appendix A. We enjoyed strong organizational support for our survey, achieving generally good response rates ($n = 557, 91\%$). Furthermore, no group had less than a 79% response rate, an important threshold for whole-network analysis (Sparrowe et al. 2001).

Independent Variables

We employed two independent variables of interest to test the hypotheses of our study. First, *user-system tie*

Table 1 Information Systems Used by the Healthcare Groups

System	Description	Influence on efficiency outcomes	Influence on quality outcomes
Lab	Doctors order lab tests through this system. The system traces the sample through the lab, and results are sent electronically to physician inbox.	The lab facilities are on-site and typically conducted during the patient visit. More timely entry and retrieval of information from the lab system moves patients through the visit more quickly.	HbA1c and other blood sugar tests are essential to the monitoring and control of diabetic patients. The lab system provides and organizes the results of the tests, strongly influencing the quality of care provided.
Scheduling	This system manages appointments, patient flow, and patient contact/ benefits information.	The scheduling system can be used to schedule patients and monitor real-time patient flows. Effective use allows teams to compensate for doctors who may be behind.	This system is essential for identifying patients who require follow-up and outreach by the doctor, an important factor in treating diabetes.
Radiology	This system is used only for scheduling radiology tests. Radiologist analyzes results and inputs diagnosis into system.	Similar to the lab system, the radiology facilities are on-site. The results from the radiology system are often necessary to proceed with treatment (e.g., broken bones).	The radiology system helps identify and diagnose complicating factors of diabetes, such as congestive heart failure and problems in the extremities (e.g., feet).
Medical abstract	This system synthesizes doctor diagnoses, treatment recommendation, and pharmacy information over past 10 patient interactions. This information is used to augment the full medical record or take its place if the record is unavailable.	The medical abstract system provides a snapshot of the patient's 10 most recent visits and serves as a valuable complement to the patient's medical record. Effective information summary permits doctors to interact with patients more efficiently.	The medical abstract system can be used to summarize diabetes care and can provide information on how often patients are refilling and using insulin, providing more reliable information than that self-reported by the patient.
Population registry	This system tracks patients with chronic diseases (e.g., diabetes, asthma), identifying and maintaining the recommended testing and treatment procedures for patients with chronic diseases.	The population registry system captures information on patient's vital information (e.g., blood pressure) and helps identify what tests a patient with chronic diseases might be due for. Prevents redundant testing.	The population registry system tracks and organizes the information regarding care for the diabetic patients. Helps remind doctors what treatments are recommended for patients, given their condition.
Conference system	This system is used by the organization to distribute results of recent medical research and the implications of these findings for healthcare practice.	The conferencing system provides doctors with information about current medical practices, helping the doctors access the information when needed during or in anticipation of a patient visit. Valuable quick reference.	The conferencing system helps doctors remain aware of the current best practices for diabetes care and tailor their treatments accordingly.

strength is the average frequency and depth of interaction between people and information systems in the network. We added frequency and depth of interaction reported by all the group members with each of the systems at their disposal and then averaged the user-system tie strength across all people in the network. This method has emerged as the standard way to calculate tie strength in social network analysis (Mardsen and Campbell 1984, Hansen 1999). The frequency-of-interaction scale was shifted so that a response of "never" equaled 0, resulting in a scale of 1–12 for user-system tie strength.

Second, *IS centrality* was captured as the average eigenvector centrality of the systems within the group and was calculated using UCINET 6.97 (Borgatti et al. 2002). Network analysis has developed a number of different ways to define centrality within a network—betweenness, closeness, degree, and eigenvector. Although these centrality measures are typically very highly correlated, social network researchers have underscored the importance of selecting the most appropriate measure of centrality given the research setting and questions (Borgatti 2005). We chose eigenvector centrality as our measure of centrality.[5] Eigenvector centrality represents the centrality of a node as

[5] We also considered and rejected the viability of using the other centrality measures. Degree centrality was rejected because it

a function of the number and strength of direct ties a node has with other members of the network (direct user-system ties) and also how central those members to whom the node is connected are within the network as a whole. Thus, even if two different systems each only had a single user, they could have very different eigenvector centrality scores, depending on how well connected that sole user is in the social network. A well-connected user is better able to spread the information found in the system to other members of the network than a user who is isolated from the rest of the network.

Dependent Variables

Performance outcomes of healthcare groups can be evaluated in a number of ways. We examined two: efficiency of care and quality of care. Each of the systems used by the group is important for addressing different facets of these tasks, and their influence is detailed in Table 1 above. *Efficiency of care* captures how quickly the group is able to conduct their required healthcare tasks. Efficiency of care is operationalized at the doctor level in terms of patient wait time, the average time (in minutes) that a patient has to wait from when he or she arrives for the appointment to when the patient actually sees that particular doctor in the exam room.[6]

Quality of care captures the health of a patient based on the results of his or her lab tests. We operationalized this variable in terms of a patient's diabetes control, whether or not a patient's long-term blood-sugar level is within recommended guidelines.[7] HealthProviders had recently experienced a substantial increase in the cost of patient care, which further analysis demonstrated could be traced primarily to poorly managed diabetic patients. Other research has corroborated these findings in other settings, suggesting that the sharp increase in recent and projected U.S. healthcare costs could be traced to a small number of chronic diseases (Thorpe et al. 2004). Effective treatment of chronic disease will be a source of competitive advantage for healthcare companies in coming years (Porter and Teisberg 2004).

It should be noted that HealthProviders captured these data in different ways at different levels of analysis. Efficiency of care is a continuous variable, captured at the doctor level. Quality of care is a dichotomous variable, captured at the patient level. As a result, our models will differ slightly from one another in terms of the sample size analyzed or the data analysis approach as we appropriately account for these differences in dependent variables. Nevertheless, these dependent variables come from organizational records that are defined, collected, and audited according to industry standards.[8]

Control Variables

In addition to assessing key independent variables via survey, we also were able to obtain other metrics from existing organizational records for use in our analysis as control variables. First, we obtained individual-level data about the doctors and their roles in their group (Table 2). Although the group is generally responsible for the entire panel of patients, a patient only sees a single doctor during each visit. So, we must control for characteristics of the individual doctors to account more clearly for the group-level outcomes.

would only represent the direct user-system interactions. Betweenness centrality was also rejected because the premise of our multimodal network perspective posits that information system nodes play a more active role in a network than simply conveying information between people. Closeness centrality was rejected because it can only be calculated using dichotomized data, which would assume away many of the very complexities and nuances of user-system interactions we seek to understand.

[6] We obtained data for the same quarter as data collection. It consisted of a sample of 5,000 patient visits (an average of 125 patients per team). Daily patient load is centrally managed by a common call center, so all teams should theoretically have approximately the same patient load. Therefore, patient wait time should prove an effective metric of how efficiently a team shares knowledge to provide care.

[7] The "gold standard" for diabetes control is the HbA1C test, which captures the long-term average of blood-sugar levels. This variable is a dichotomous variable, assessing whether a particular patient's HbA1C level is above 9, the standard by which diabetes is deemed "under control" by common medical practice. We obtained data for all of the patients in the region diagnosed with diabetes.

[8] All dependent variables used in this study are carefully collected by HealthProviders according to standards established and audited by the National Council on Quality Assurance (NCQA). NCQA is a nonprofit organization charged with establishing, maintaining, and tracking standards for care for healthcare organizations.

Table 2 **Doctor-Level Control Variables**

Variable name	Variable type	Definition
Dr. Age	Continuous	Doctor age (in years).
Dr. Race	Dichotomous	The racial heritage of the doctor (1 = white, 0 = minority).
Dr. Gender	Dichotomous	Whether the doctor is male or female (1 = male, 0 = female).
Dr. Tenure	Continuous	How long the doctor has been employed at HealthProviders (in years).
Group leader	Dichotomous	Whether the doctor is a group leader (1 = yes, 0 = no).
Dr. PCM	Dichotomous	Whether the doctor is a population care manager (1 = yes, 0 = no).
Dr. Certification	Dichotomous	Whether the doctor is an MD (as opposed to a nurse practitioner or a doctor's assistant) (1 = yes, 0 = no).

Several of these variables are particular to the organizational structure of HealthProviders and merit further explanation. For instance, each group has a doctor who is designated as a group leader. This doctor receives a lower standard patient load in exchange for serving as the primary administrative officer for the group and the key liaison with the regional office. Similarly, each group has a population care manager (PCM), who also receives a lower standard patient load in exchange for tracking the chronic care needs of the patient in the group. It is possible that doctors in these roles may perform differently than others in the group, so we control for these factors.

In addition to the doctor-level control variables, we also were able to obtain control data for group-level characteristics (Table 3). These data accounts for various other possible explanations for outcomes that may be attributable to group composition. Social network research has found that the interpersonal network alone influences outcomes in knowledge-intensive settings (Borgatti and Foster 2003). To ensure that these interpersonal interactions do not influence our analysis, we control for this feature of the network.

Third, we had patient-specific data for quality outcomes, assessing the health outcomes of a particular patient. In this instance, it is also important to control for patient-level factors that represent elements of diabetes control that are outside of the scope of the primary care group (Table 4). The eye exam, cholesterol screening, and nephropathy screening are all part of effective diabetes care but are conducted by specialists outside of the primary care setting. These variables may also serve as a proxy for which the patient

Table 3 **Group-Level Control Variables**

Variable name	Variable type	Definition
Group size	Continuous	The number of total employees (doctors and nurses) in a healthcare group.
Group practice	Series of dummy variables	Whether the primary care group designated as an Internal Medicine, Pediatric, OB, or Family Practice Group (IM, Ped, OB, FP).
Average age	Continuous	The average age of the members of a group (in years).
Racial diversity	Percentage	The percentage of the group that is white (versus minority).
Average tenure	Continuous	On average, how long group members have been employed at HealthProviders (in years).
Gender diversity	Percentage	The percentage of males within a group's employees.
Pct. doctors	Percentage	The percentage of doctors (as opposed to support staff) within a group's employees.
Pct. MD/RN	Percentage	The percentage of the group's employees with certification as either MD or RN (as opposed to physician's or nurse's assistants).
User-user tie strength	Continuous	The interpersonal tie strength reported between users, in terms of frequency and depth of interaction.

Table 4 **Patient-Level Control Variables (Quality of Care Outcomes Only)**

Variable name	Variable type	Definition
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 care (i.e., heart disease) (1 = yes, 0 = no)?

manages his or her own diabetes control. Whether or not the patient seeks these outside treatments is likely indicative of the degree to which the patient is an active participant in his or her own care.

Data Analysis

Data were entered into Excel and audited by an independent third party to ensure accuracy. These data were then imported into the statistical package R for analysis. Multiple regression was chosen as the data analysis method. A key consideration in the data is that the doctors and patients are clustered within groups, violating the independence of errors assumptions of the ordinary least squares (OLS) regression. To correct for this multilevel clustering of data in the model, We employ the Huber-White robust variance/covariance matrix.[9] The Huber-White approach is based on the assumption that the error terms are correlated within clusters but uncorrelated across clusters. Because of differences in the data available for each of the dependent variables (continuous versus dichotomous), slightly different versions of the Huber-White method were necessary—one using multiple regression and the other using logistic regression. These corrections lead to the following regression equation:

$$Y_{ij} = \alpha + \beta X_{ij} + \boldsymbol{\gamma} Z_i + \varepsilon_{ij}$$

$i =$ cluster, $1 \ldots n$ (i.e., healthcare group)
$j =$ doctor within cluster i, $1 \ldots m_i$
$X =$ doctor-level variables (e.g., *doctor tenure*)
$Z =$ cluster/group-level variables (e.g., *average group tenure, network density*)
$Y =$ *efficiency of care* (average patient wait time) $\mathrm{Var}(Y_i) = \sigma^2 * V_i$.

The resulting logistic regression equation is as follows:

$$P(Y_{ij} = 1) = \frac{\exp(\alpha + \beta X_{ij} + \boldsymbol{\gamma} Z_i)}{1 + \exp(\alpha + \beta X_{ij} + \boldsymbol{\gamma} Z_i)}$$

$i =$ cluster, $1 \ldots n$ (i.e., healthcare group,)
$j =$ patient within cluster i, $1 \ldots m_i$
$X =$ patient-level variables (e.g., *patient insurance plan*)
$Z =$ cluster/group-level variables (e.g., *average group tenure, network density*)
$Y =$ *quality of care* (diabetes control).

Because the level of analysis is at the whole-network level, the primary independent variables of interest are specified at the group/cluster level (Z_i).

Model Specification

Another challenge faced in data analysis was the amount of control variables needed to account for possible alternative explanations. Because the multimodal network perspective on user-system interactions is relatively novel, we needed to account for a wide variety of explanations that might affect either the user-system relationships or the interpersonal ones. Fortunately, we were able to gather data from the organization on a large number of these potentially relevant variables. Unfortunately, including all of these variables in a single-regression equation quickly reduces its power to well below acceptable levels.

Our solution to this problem was to use backward stepwise regression, in which the model is estimated and the control variables that contribute least are dropped one by one until all variables are significant at the 0.10 level at least. Backward stepwise model specification simultaneously avoids the dual problems of model overspecification and omitted variable bias. We employed a two-stage method to eliminate the inclusion of irrelevant control variables. We first entered all of the control variables into the regression equation, utilizing the stepwise procedure to eliminate the control variables that were not at all related to the dependent variables. Once all of the irrelevant control variables had been eliminated from our model, we entered our independent variables into the equation and analyzed the results. As a robustness check, we conducted a Chow test that compares lack-of-fit of the final, parsimonious model to the full, saturated models.[10] The Chow test was not

[9] Another method for dealing with multilevel clustering in a data set would be to employ hierarchical linear modeling (HLM). The Huber-White approach was chosen because it is a more appropriate means of analysis given the sample size (Hox 1998).

[10] The Chow test has an F-distribution and a test statistic of s and $(n-k)$ degrees of freedom and is specified

$$\frac{n-k}{s} \cdot \frac{\mathrm{SSE}_{\mathrm{restricted}} - \mathrm{SSE}_{\mathrm{unrestricted}}}{\mathrm{SSE}_{\mathrm{unrestricted}}},$$

found to be significant in any of the models. Therefore, there is no evidence that the backward stepwise procedure omitted any control data—individually or in combination—that would significantly contribute to the fit of the final, parsimonious models.

Model Assumptions

Before proceeding with data analysis and interpretation, we checked to ensure that our data conformed to the assumptions underlying the modeling approach. Two assumptions of OLS regression—constant variance and independence of the error terms—are accounted for and corrected by the Huber-White robust variance/covariance matrix and need not be tested. The other assumptions or common problems facing multiple regression—linearity, normality, and multicollinearity—are examined in context of the relevant models.

First, multiple regression is built on the assumption that, if there is a relationship between the independent variable and the dependent variable, then that relationship is linear. The assumption of linearity was met by examining scatter plots of the dependent variables versus each independent variable and by plotting fitted values against their residuals. None of these analyses demonstrated any evidence of nonlinear relationships in the data set.

Second, multiple regression assumes that the error terms are normally distributed. If this assumption is violated, it does not bias either the estimates or their standard errors, but it does render the hypotheses tests invalid. We used the Kolgomorov-Smirnov test to assess whether the residuals of our models were normally distributed. The errors related to the *efficiency of care* models were not normally distributed. We applied a cube-root transformation to the wait-time data, which resulted in the error terms of the resulting models conforming to the normality assumption.

Third, a problem common in regression models is multicollinearity. Multicollinearity results from two or more dependent variables being too highly related to one another, resulting in overly high standard errors and inflated R^2 statistics. As a rule of thumb (Neter et al. 1990), each variable should have a variance inflation factor (VIF) < 10. None of the VIFs were greater than 3, so we could eliminate multicollinearlity as a potential data analysis problem. Once our models conformed to all these assumptions of linear regression, we proceeded with data analysis.

where n is observations, k is the number of independent variables in the saturated model and s is the number of restrictions.

Results

Data were entered into Excel and audited by an independent third party to ensure accuracy. These data were then imported into the statistical package R for analysis. Descriptive statistics and a correlation matrix can be found at the end of the paper (Appendices B and C).

Efficiency of Care

The results of the regression analysis in relation to efficiency of care are presented in Table 5. It is important to note that, in terms of efficiency of care, the signs will be opposite from hypothesized relationships (i.e., a positive sign indicates longer wait time, which is undesirable). We find that the *user-system tie strength* is not significantly related to patient wait time. Thus, the more frequently and more deeply the individuals in a group directly interact with the IS does not appear to influence the amount patients have to wait or how quickly they move through the group. Hypothesis 1 is not supported in terms of efficiency of care. *IS centrality*, capturing the position of the systems within the multimodal network as a whole, is supported and is negatively related to patient wait time ($t = -2.140$, $p < 0.05$). The more the healthcare

Table 5 Results for Efficiency of Care

	Coefficient	S.E.	t-value	p-value
Intercept	3.63	0.385	9.427	0.000
Family practice group	0.22	0.105	2.111	0.036
OB/GYN group	−0.30	0.047	−6.286	0.024
Group leader	−0.09	0.037	−2.376	0.018
Dr. Tenure	0.01	0.004	1.640	0.101
Dr. Gender	−0.08	0.035	−2.149	0.033
Racial diversity	−0.22	0.073	−3.016	0.001
Gender diversity	0.51	0.331	1.541	0.125
Pct. doctors	0.63	0.406	1.553	0.122
User-system tie strength	**−0.07**	**0.037**	**−1.791**	**0.075**
IS centrality	**−0.01**	**0.003**	**−2.140**	**0.033**

Notes. $N = 188$ doctors, cube-root transformation of dependent variable. Backward stepwise model specification. Adjusted $R^2 = 0.25$.

Table 6 Results for Quality of Care

	Coefficient	S.E.	Z	p-value
Intercept	−2.70	0.557	−4.85	0.000
Eye exam	1.14	0.102	11.18	0.000
Cholesterol screen	2.03	0.093	21.66	0.000
Nephrology screen	0.77	0.078	9.92	0.000
Insurance plan	0.73	0.077	9.54	0.000
High risk	0.44	0.139	3.17	0.002
Average tenure	−0.04	0.021	−1.66	0.097
Gender diversity	1.00	0.129	7.76	0.000
Pct. doctors	2.93	0.831	3.53	0.000
User-system tie strength	**−0.12**	**0.007**	**−1.74**	**0.082**
IS centrality	**0.02**	**0.008**	**2.50**	**0.012**

Notes. $N = 9{,}516$ patients, logistic regression. Backward stepwise model specification. Nagelkerke $R^2 = 0.19$. Hosmer and Lemeshow $p = 0.174$.

groups are structured to permit information to flow to and from the system to all group members, the less time patients have to wait and the more quickly they move through the group. Hypothesis 2 is supported in terms of efficiency of care.

Quality of Care

The results for quality of care are presented in Table 6. Results are similar for quality of care as for efficiency of care. *User-system tie strength* is not significant in terms of quality of care outcomes. The frequency and depth with which group members on average interact directly with the information systems is not significantly related to the quality of care a group is able to deliver. Again, Hypothesis 1 is not supported. *IS centrality* is significantly and positively related to outcomes ($z = 2.50$, $p < 0.05$). The centrality of the information systems within the multimodal network is positively associated with a patient's chances of keeping their diabetes under control. Similar to our results on efficiency of care, Hypothesis 2 is also supported in terms of quality outcomes.

Discussion

This paper explores two different mechanisms for accounting for the user-system interactions at the group level: *user-system tie strength* that aggregates the direct user-system relationships across the group and *IS centrality* that also accounts for indirect access to the information system by all members of the group. We found that *user-system tie strength* at the group level was not significantly related to group-level performance outcomes, but that *IS centrality* is significantly related to both efficiency and quality outcomes at the group level. These results suggest that the impact of IS on organizational performance outcomes depends on more than simply the dyadic interactions of individual users interacting with individual systems. Rather, the impact of IS on organizational outcomes depends on the interplay between digital and social networks.

IS centrality captures important dynamics that are overlooked in traditional dyadic views of IS use. It captures the nature of IS users as social actors, enmeshed in a wider web of interpersonal actors (Lamb and Kling 2003). Interpersonal interactions between users can support multiple types of indirect interactions with the information systems, in addition to or instead of the direct user-system interactions. Whether the group as a whole is effectively structured to permit information to flow readily between the system and the entire group, not just between the system and the direct users, is a critical factor influencing the impact of IS on organizational performance outcomes.

Theoretical and Methodological Implications

This work has implications for both the theory and methods used by IS researchers to examine the impact of IS on organizational performance outcomes. Most significantly, it suggests that IS use in a multiuser, multisystem group differs in important ways from IS use at the individual user level. Because organizations typically consist of multiple users and multiple systems, the results of this study imply that IS researchers should move away from an exclusive focus on dyadic user-system interactions that have been the dominant paradigm through which they have been understood in the past. The structural features of the wider multimodal network have important explanatory power for how IS impacts organizational performance outcomes.

This research should not be interpreted to mean that the dyadic user-system relationships in an organization are *un*important. A robust cumulative research tradition has demonstrated the value in examining user-system interactions at the individual level (e.g., Davis 1989). This research tradition should neither be ignored nor discarded as a result of our findings, because our findings address the features of group-level multimodal interactions on group-level performance outcomes. The primary implication for our results is that the impact of information systems on organizational outcomes at the group level is not a function of *only* the dyadic user-system relationships. We have demonstrated that certain structural features of the wider multimodal network are important, and future research may examine whether other features of the multimodal network (structural, relational, cognitive) may also be important for understanding the impact of IS on organizational outcomes (see Adler and Kwon 2002, Nahapiet and Ghoshal 1998 for examples).

We hope that researchers will use this work critically to consider broader understandings and examinations of user-system interactions—not as an excuse to abandon methods, perspectives, and research questions that have proven valuable in the past. A number of reasons may explain why direct user-system relationships are not significant in our model. One reason may be simply that direct use is incorporated into our measures of IS centrality. Without effective direct user-system interactions, users would be unable to transfer information to others in the group. The impact of direct user-system interactions may also be moderated in part by other relational factors that are not addressed in our study, such as how willing the users are to depend on the information found in the system. Because the first-order correlation between direct use and performance outcomes is effectively zero, we find some evidence for this interpretation that direct use may be significant only in the presence of other variables. Further research should explore these and other possible explanations for our findings.

One methodological implication of this paper is that the multimodal network perspective represents a viable approach to analyzing complex relational structures of multiuser, multisystem groups that typify many organizations. Social network measures and their associated theories embody a valuable avenue for exploring and explaining the complex interactions between multiple people and multiple information systems. It should be noted, that this paper has used network measures at only one level of analysis (the whole-network level), but corresponding measures and methods may also apply at other network levels, such as the ego-network level. However applicable, social network measures should not be applied uncritically to multimodal networks. Incorporating IS as equivalent nodes within a social network can have important implications for the social network theories and methods on which this approach is based. IS nodes are not subject to the same assumptions or limitations that characterize human nodes. For instance, it is possible for a single information system to be present in multiple networks simultaneously without diminishing the potential impact of those nodes in the network. This enables different types of analyses than has traditionally been possible in purely social networks (e.g., *IS centrality*). Future research into multimodal networks should remain cognizant of the assumptions on which these network methods are based and where a multimodal network perspective might depart somewhat from more traditional applications of social network methods.

Managerial Implications

This research also has implications for managerial practice. The idea that the impact of information systems is a function of the indirect user-system interactions suggests that managers should pay special attention to the role of both user-system and interpersonal interactions when seeking to improve performance outcomes through information systems. Managers might improve organizational performance by supporting the user-system interactions through initiatives such as increased training for "key" users. This study offers novel insight into which these key users may be. They may not only be defined by their personal characteristics (e.g., their ability to use information systems), but they may be defined, at least in part, by their position in the social network.

Another implication for managers is that, in an underperforming group, neither the interpersonal nor the user-system relationships may require intervention themselves. Rather, managers might focus on improving the interplay between interplay digital and social networks to improve organizational performance outcomes. It is possible that both the user-system and interpersonal relationships are functioning well independently but that they are not functioning well as an integrated multimodal network. If the network is not structured to allow effective information flow between the digital and social networks, the network as a whole might underperform. Managers might consider ways to increase the interplay between these networks, such as recruiting or identifying employees that can serve as a liaison between direct users and other group members or create opportunities for interaction and exchange between members of the respective subnetworks. How the multimodal network functions as a coherent whole may be more than a sum of the individual user-user and user-system relationships that comprise it.

Limitations and Future Research

This study has limitations, which should be carefully considered when assessing its impact. First, our setting was chosen to test hypotheses related to multimodal networks because the similarities of the groups provided an opportunity to isolate multimodal network structures for analysis. Further research would be needed to assess the generalizablity of the multimodal network perspective in settings where network composition and task may differ between networks. Second, we examine a static snapshot of a network at a single moment in time. The network structures will likely evolve over time as employees or information systems are added or removed from the network or as the networks respond to different environmental conditions. Our research does not address these issues, nor does it address how particular network features might emerge within particular groups.

Third, this study represents only an initial test of the viability of the multimodal network perspective. Further research is necessary to more fully understand the implications and nuances of how multimodal network structure influences organizational outcomes. For instance, we treat all users and systems as identical nodes in a network, but it may be that the role of a given user or the characteristics of a particular information system may be important moderating variables to address in future research. We also aggregate the network characteristics of the system within each group. It may be that the effect of multimodal network structures in relation to individual systems may depend somewhat on the characteristics of the system itself or of the tasks it supports. The goal of this research was only to test the need of IS researchers to examine user-system interactions beyond the dyadic level, and further research might help identify how outcomes related to the structure of multimodal networks might be task or system dependent.

Conclusion

In this paper we argue that IS researchers have typically examined the user-system relationship as an isolated dyad between a single user and a single information system. We argue that this conceptualization does not adequately represent most organizations in which multiple users interact with multiple information systems within a group. We explore two different ways to account for the impact of information systems on organizational performance outcomes in this setting—aggregating the user-system interactions and assessing the centrality of the information systems in the social network. We find that the centrality of the information systems within the network is significantly associated with both efficiency and quality outcomes, but that the average strength of the user-system interactions is not. Implications are that managers and researchers should examine the wider multimodal network of multiple users and multiple systems to assess the role of IS in organizations more fully.

Appendix A. Survey Questions to Assess Multimodal Network

How frequently do you interact with this person? (*interpersonal frequency of interaction*)

1—Never, 2—Rarely, 3—A few times per month, 4—Weekly, 5—Daily, 6—A few times a day, 7—Hourly or more.

How close is your working relationship with this person? (*Interpersonal depth of interaction*)

1—Very distant, 2—Distant, 3—Somewhat distant, 4—Somewhat close, 5—Close, 6—Very close.

How frequently do you interact with this system (i.e., personally use with keyboard and/or mouse)? (*User-system frequency of interaction*)

1—Never, 2—Rarely, 3—A few times per month, 4—Weekly, 5—Daily, 6—A few times a day, 7—Hourly or more.

I use all of the functionality available in this system. (*User-system depth of interaction*)

1—Strongly Disagree, 2—Disagree, 3—Somewhat disagree, 4—Somewhat Agree, 5—Agree, 6—Strongly Agree.

Appendix B. Descriptive Statistics

		N	Minimum	Maximum	Mean	Std. dev.
Dependent variables	Efficiency of care	190	2.4461	3.7995	2.972	0.2741
	Quality of care	9,516	0	1	0.66	0.474
Patient-level control variables (quality of care only)	Eye exam	9,516	0	1	0.18	0.388
	Cholesterol screen	9,516	0	1	0.94	0.234
	Nephrology screen	9,516	0	1	0.67	0.469
	Insurance	9,516	0	1	0.1935	0.39503
	High risk	9,516	0	1	0.0211	0.14380
Doctor-level control variables	Dr. Certification	190	0	1	0.69	0.462
	Group leader	189	0	1	0.14	0.351
	Dr. PCM	189	0	1	0.13	0.340
	Dr. Tenure	190	0.69	24.04	8.3631	5.07931
	Dr. Race	169	0	1	0.57	0.497
	Dr. Gender	188	0	1	0.44	0.498
	Dr. Age	190	30.0	67.7	47.410	7.3177
Group-level control variables	Pediatrics group	40	0	1	0.19	0.397
	OB-GYN group	40	0	1	0.32	0.468
	Family practice group	40	0	1	0.04	0.201
	Number in group	40	7	29	17.11	5.713
	Avg. age	40	37.37	53.54	45.1835	2.87985
	Avg. tenure	40	3.41	11.82	7.3592	2.02483
	Racial diversity	40	0.00	0.89	0.4130	0.27456
	Gender diversity	40	0.09	0.29	0.1654	0.05241
	Pct. doctors	40	0.22	0.54	0.3648	0.0610
	Pct. MD/RN	40	0.294	0.600	0.4402	0.0702
	User-user tie strength	40	7.0667	11.0329	9.4307	0.84951
Independent variables	Hypothesis 1: User-system tie strength	40	7.1415	9.6994	8.5905	0.61478
	Hypothesis 2: IS centrality	40	22.8530	53.5877	31.5492	5.3695

Appendix C. Correlation Matrix for Efficiency of Care Data

	1	2	3	4	5	6	7	8	9	10
1. Ped group	1	−0.338**	−0.103	0.009	0.142	−0.193**	0.335**	0.104	−0.036	0.227**
2. OB group	−0.338**	1	−0.144*	−0.254**	−0.055	−0.270**	−0.037	0.268**	−0.113	0.004
3. FP group	−0.103	−0.144*	1	0.139	−0.011	0.073	−0.029	−0.100	−0.005	−0.093
4. Dr. Certification	0.009	−0.254**	0.139	1	0.235**	0.120	0.062	−0.290**	0.447**	−0.098
5. Dr. Leader	0.142	−0.055	−0.011	0.235**	1	0.198**	0.234**	0.027	0.109	0.046
6. Dr. PCM	-0.193**	−0.270**	0.073	0.120	0.198**	1	−0.075	0.053	0.045	−0.045
7. Dr. Tenure	0.335**	−0.037	−0.029	0.062	0.234**	−0.075	1	0.130	0.131	0.313**
8. Dr. Race	0.104	0.268**	−0.100	−0.290**	0.027	0.053	0.130	1	0.023	0.247**
9. Dr. Gender	−0.036	−0.113	−0.005	0.447**	0.109	0.045	0.131	0.023	1	0.206**
10. Dr. Age	0.227**	0.004	−0.093	−0.098	0.046	−0.045	0.313**	0.247**	0.206**	1
11. *n* group	−0.256**	0.221**	−0.202**	−0.120	−0.097	−0.069	−0.146*	0.061	0.034	−0.046
12. Avg. age	0.430**	−0.135	−0.229**	−0.041	0.115	−0.145*	0.227**	0.082	0.055	0.325**
13. Avg. tenure	0.602**	0.039	−0.069	−0.035	0.097	−0.193**	0.320**	0.203**	−0.048	0.228**
14. Racial diversity	0.335**	0.167*	−0.029	−0.144*	0.042	−0.146*	0.189**	0.579**	−0.021	0.056
15. Gender diversity	−0.015	−0.176*	−0.054	0.126	0.049	0.128	−0.004	0.032	0.320**	0.052
16. Pct. Physician	−0.230**	0.532**	−0.038	−0.216**	−0.092	−0.196**	−0.103	0.297**	−0.117	−0.053
17. Pct. MD/RN	0.165*	−0.165*	0.111	0.243**	0.072	−0.016	0.095	−0.174*	−0.013	0.017
18. IS centrality	0.242**	−0.329**	0.104	0.125	0.094	0.112	0.160*	−0.139	−0.030	0.140
19. User-system tie strength	0.275**	−0.496**	−0.140	0.054	0.037	0.183*	0.082	−0.141	0.055	0.040
20. User-user tie strength	0.098	−0.086	0.060	0.048	0.060	0.038	0.015	0.008	0.029	−0.055
21. Efficiency of care	0.035	−0.372**	0.235**	0.011	−0.108	0.049	0.010	−0.212**	-0.060	0.034

Appendix C. (Cont'd.)

	11	12	13	14	15	16	17	18	19	20	21
1. Ped group	−0.256**	0.430**	0.602**	0.335**	−0.015	−0.230**	0.165*	0.242**	0.275**	0.098	0.035
2. OB group	0.221**	−0.135	0.039	0.167*	−0.176*	0.532**	−0.165*	−0.329**	−0.496**	−0.086	−0.372**
3. FP group	−0.202**	−0.229**	−0.069	−0.029	−0.054	−0.038	0.111	0.104	−0.140	0.060	0.235**
4. Dr. Certification	−0.120	−0.041	−0.035	−0.144*	0.126	−0.216**	0.243**	0.125	0.054	0.048	0.011
5. Dr. Leader	−0.097	0.115	0.097	0.042	0.049	−0.092	0.072	0.094	0.037	0.060	−0.108
6. Dr. PCM	−0.069	−0.145*	−0.193**	−0.146*	0.128	−0.196**	−0.016	0.112	0.183*	0.038	0.049
7. Dr. Tenure	−0.146*	0.227**	0.320**	0.189**	−0.004	−0.103	0.095	0.160*	0.082	0.015	0.010
8. Dr. Race	0.061	0.082	0.203**	0.579**	0.032	0.297**	−0.174*	−0.139	−0.141	0.008	−0.212**
9. Dr. Gender	0.034	0.055	−0.048	−0.021	0.320**	−0.117	−0.013	−0.030	0.055	0.029	−0.060
10. Dr. Age	−0.046	0.325**	0.228**	0.056	0.052	−0.053	0.017	0.140	0.040	−0.055	0.034
11. *n* group	1	0.090	0.024	0.084	−0.012	0.297**	−0.367**	−0.629**	−0.033	−0.422**	0.041
12. Avg. age	0.090	1	0.651**	0.364**	0.106	−0.200**	0.114	0.038	0.127	−0.012	−0.024
13. Avg. tenure	0.024	0.651**	1	0.505**	−0.028	−0.120	0.175*	−0.047	0.243**	0.125	−0.091
14. Racial diversity	0.084	0.364**	0.505**	1	−0.012	0.258**	−0.029	−0.159*	−0.136	−0.050	−0.210**
15. Gender diversity	−0.012	0.106	−0.028	−0.012	1	−0.244**	0.220**	0.018	−0.009	−0.018	0.096
16. Pct. Physician	0.297**	−0.200**	−0.120	0.258**	−0.244**	1	−0.257**	−0.302**	−0.519**	−0.383**	−0.083
17. Pct. MD/RN	−0.367**	0.114	0.175*	−0.029	0.220**	−0.257**	1	0.409**	−0.035	−0.017	0.035
18. IS centrality	−0.629**	0.038	−0.047	−0.159*	0.018	−0.302**	0.409**	1	0.243**	−0.228**	0.015
19. User-system tie strength	−0.033	0.127	0.243**	−0.136	−0.009	−0.519**	−0.035	0.243**	1	0.191**	−0.001
20. User-user tie strength	−0.422**	−0.012	0.125	−0.050	−0.018	−0.383**	−0.017	−0.228**	0.191**	1	−0.099
21. Efficiency of care	0.041	−0.024	−0.091	−0.210**	0.096	−0.083	0.035	0.015	−0.001	−0.099	1

$^{*}p < 0.05$, $^{**}p < 0.01$

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