Everybody Needs Somebody: The Influence of Team Network Structure on Information Technology Use

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ABSTRACT: Team network structure has been shown to be an important determinant of both team and individual performance outcomes, yet few studies have investigated the relationship between team network structure and technology usage behaviors. Drawing from social network and technology use literature, we examine how the structure

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of a team's advice-seeking network affects individual use of a newly implemented information technology. We develop cross-level hypotheses related to the effects of the structure of mutually interconnected ties within the team (i.e., internal closure) as well as the structure of nonredundant ties outside the team boundaries (i.e., external bridging). The hypotheses are tested in a field study of 265 employees working in 44 teams in a large financial services institution. Results show that internal closure has a U-shaped effect on individual use such that individual usage of the system is higher when the number of internal advice-seeking ties within the team is low or high, suggesting that medium levels of internal closure are the least desirable network configurations because in such instances teams neither realize the benefits of high closure information sharing nor are they able to avoid in-group biases associated with low closure conditions. Our results also reveal that in addition to having a direct positive effect on individual use, external bridging interacts with internal closure in a complex manner. The U-shaped effect of closure is dominant when bridging is high but assumes an inverted U-shaped pattern when bridging is low. Several implications for managers follow from these findings. First, in order to increase usage of technology, in teams characterized by low internal closure, managers should encourage the development of ties across team boundaries. Second, managers should maximize within-team interconnections in order to facilitate the circulation of external knowledge within team boundaries. Finally, managers should be aware that maximizing internal closure by facilitating interconnections among team members could be dangerous if not accompanied by mechanisms for external bridging.

Key words and phrases: advice-seeking network, external bridging, integration perspective, internal closure, social categorization theory, technology use.

It is widely accepted that individuals underutilize newly implemented technologies in work settings, limiting their interaction with the new system to a narrow set of features, often with low utilization [41]. Previous research has noted that users typically use only 20 percent of the features found in technologies 80 percent of the time [41]. Indeed, the term "shelfware" has become part of the business lexicon, in referring to systems that are acquired by organizations and not utilized to their fullest extent. When system use is limited in breadth across features and depth across work tasks, the organization's ability to appropriate value from its investments is constrained [55, 108].

Key reasons why individuals fail to exploit the capabilities of technological innovations include uncertainty about the value of the technology and uncertainty about how to extract value from using the technology [94]. Uncertainty is pervasive when new technologies are introduced: they may create disruptions in existing work patterns [31], they often require potential users to incur costs related to learning, and their value relative to the effort that must be expended for productive use may not be immediately obvious. Questions such as "How do I use this new system to complete work tasks?" "Where do I go to get help?" and "How will it change my work activities?" dominate the organizational discourse.

Previous research suggests that influence from others, which shapes individuals' beliefs and behaviors, plays a pivotal role in helping resolve the uncertainty created by new technology (e.g., [58, 62, 81, 83, 84, 107, 110]). The dominant view in the literature relies on the notion of subjective norm, where individual behavior toward technology is argued to be affected by the pressure exerted by social referents such as peers [110]. While the subjective norm perspective has accumulated significant empirical support, theoretically it provides an incomplete understanding because it fails to incorporate the concept of informational influence, which has been identified as another type of social stimulus affecting individual behavior [20, 44, 114, 117]. *Informational influence* is experienced as a result of the individual's purposive decision to seek relevant information [117]. It derives from the desire of the actor to resolve uncertainty and equivocality [20, 70] by activating his or her network to seek out information so that a high-quality decision can be made [13, 26, 43, 117].

While informational influence based on social network configuration has been shown to exhibit effects on a range of outcomes such as contract fulfillment [38], learning [75], and extra-role behaviors [93], limited work has adopted such a perspective for studying individual behaviors toward technology (exceptions include [83, 84, 86, 96]). To the extent that the configuration of social ties determines the ease with which individuals have access to others' information, it provides a useful lens for investigating social influence and the conditions under which the pattern of social ties are more likely to influence technology use behaviors and outcomes [10].

Although previous studies have highlighted the role of structural factors of network characteristics on individual adoption and use, several gaps remain. First, prior research has predominantly focused on relatively simple technologies. As information systems become increasingly more complex and configurable [96], users are likely to encounter escalating knowledge barriers, that is, "informational gaps" constraining their use. Second, when studying the effects of the structural configuration of networks on acceptance of technology, there is a need to extend beyond a dichotomous approach (i.e., adoption versus nonadoption), which fails to reflect the full continuum of use and its complexities. An approach that takes into account diverse instantiations of use could provide a more granular perspective of the way in which social structure affects individuals' interaction with technology.

Third, previous research that has used a network lens for studying users' behaviors [82] has largely focused on individual level or dyadic levels of analysis [96, 110]. A more comprehensive cross-level analysis of use, including team-level influences, has yet to be conducted. To the extent that teams are increasingly used as preferred work structures in organizational settings [25], it is plausible that influence emanating from the team is germane to individuals' behavior. In fact, others [25] have advocated a team-level perspective, arguing that while certain structural configurations might be effective for diffusion of information, they might not be effective for leveraging distributed expertise among team members, thus affecting their behavior in interacting with a technology.

Building on a network structure perspective [69, 84, 85, 92], we investigate how the configuration of advice-seeking ties (i.e., the individual requests concerning how to interact with the system) within and across a focal team affects individual technology use behaviors. Our core theoretical argument is that the team network configuration of advice-seeking ties allows individuals to leverage conduits and obtain access to information regarding how to better use the system for accomplishing tasks.

We test our cross-level hypotheses using hierarchical linear modeling (HLM) on data from 265 employees belonging to 44 teams, using a new customer relationship management system within a large financial services institution. We find that the structural characteristics of the team's social network play a significant role in explaining use of technology above and beyond that of subjective norms.

Theoretical Background and Hypotheses

Our conceptualization builds on theory and findings from two distinct bodies of research: social networks and technology acceptance and use. Prior work suggests that there is no single or all-encompassing social network theory [47]; however, social network scholars have long debated the relative explanatory power of two network patterns—team internal closure and team external bridging[1]—as determinants of individual and team outcomes [14]. The characteristics of internal closure and external bridging are a function of the ties that connect individuals in the network. These ties serve to facilitate or constrain the flow of information and norms.

Prior research has identified two different types of ties on the basis of their function [40]: expressive ties and advice ties. Expressive ties are more likely to convey social support, values, and friendship, and information that is more affect-laden [40, 54]. By contrast, advice ties are considered pathways for work-related help [40, 96], where the primary objective is the exchange of information that is instrumental for accomplishing a task, such as using a specific technology effectively. While expressive and advice ties are not mutually exclusive, and an overlap in the two types of connections can occur [10], previous research suggests that focusing on advice networks is preferred when investigating task-related phenomena (e.g., [78, 93]). Given our objective of exploring the effects of network patterns on individual technology use for task-related purposes, we focus on advice-seeking ties that are predicated on the provision of informational resources to resolve uncertainty and achieve a specific task-related goal [23, 67, 118]. Our study examines the influence of a focal team's network structure and that of the broader organizational network on an individual's use of a new technology. Figure 1 summarizes the cross-level theoretical framework that provides the foundation for the specific research hypotheses.

Team Network Structure and Individual IT Use

The *structure* of a team's social network is the configuration of team members' social relationships within the team as well as in the broader social structure of the organization [69]. The extent to which individuals are connected to one another will determine the volume of resources[2] that can move throughout the network, thus affecting both individual and team outcomes. Information and norms flow through internal and external relationships [15]. Internal closure emphasizes the *within*-team connections

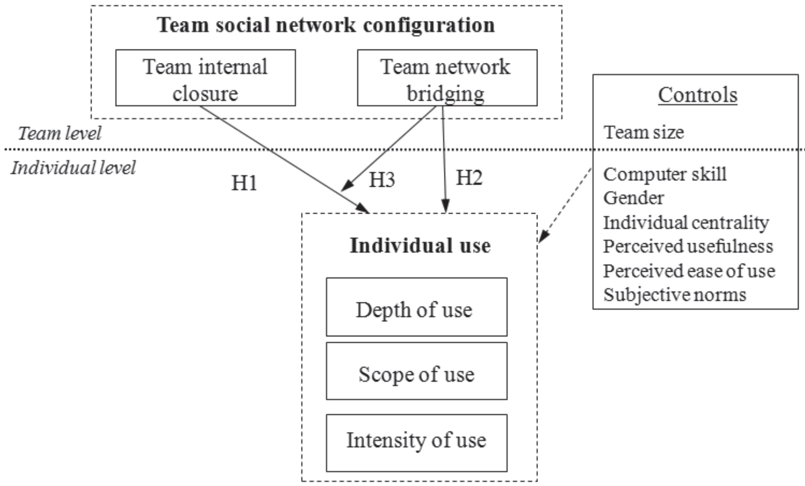

Figure 1. Research Model Depicting Relationship Between Network Configuration and Individual Use

among members [14] while the bridging mechanism emphasizes the importance of brokerage ties connecting different people *across* teams.

Early work from the 1970s and 1980s that focused on research and development (R&D) teams investigated the pattern of communication among members and highlighted the importance of boundary-spanning activities [46, 101, 103, 104]. However, this stream of research stops short of providing a complete picture of the social network because closure and bridging are not considered simultaneously. This limitation has been noted by others [75], and a more complex, multilevel model has been called for in an effort to fully understand how social network configuration affects individual outcomes.

In this study, we treat internal closure and external bridging simultaneously as team-level network characteristics [92]. In a setting where a new information technology has been implemented, individuals face the challenge of coping with new features and functionalities that often translate into work process changes. In such a scenario, individuals exchange information relative to how the system can be used and how it can enhance performance [73, 86, 96]. When seeking advice on how to solve a specific problem using the system, individuals are exposed to both explicit information they collect through asking for advice and to more implicit messages, for example, by observing the combination of features salient others prefer and use for accomplishing a task.[3] Thus, to the extent that the structure of the team's social network facilitates the exchange of informational resources, individual usage of this technology will vary accordingly. To illustrate, if a user has limited understanding of how to accomplish a specific work task using the system, and if he or she does not have a conduit to expertise that addresses his or her knowledge gap, then it is very likely that the user will fail to exploit the potential of the system. Prior research has demonstrated that the deployment of enterprise information systems is one context under which users will seek technical information from others in hopes of resolving confusion and uncertainty related to how to effectively use the system [28, 41, 72]. A recent study specifically notes that users will rely to a large extent on the knowledge of others within their social networks in an effort to "solve problems with the new technology and adapt it for their tasks" [86, p. 2], and furthermore that the introduction of a new system is characterized by "extensive interactions and exchange of information among employees as they learn to modify and adapt the system to the needs of their organizational tasks" [86, p. 3]. Our study specifically focuses on the configuration of these social structures and how they are appropriated by actors in order to discover new ways to use the system to accomplish tasks.

Team Internal Closure and Individual Use of Technology

Internal closure refers to a pattern of dense, mutually interconnected ties among the members of a network and is indicative of the level of material support received from others within the organizational unit [2]. Two complementary conceptual lenses—*social categorization theory* and an *integration perspective*—help clarify the relationship between team internal closure and individual use of technology. *Social categorization* theory argues that the number of interconnections within teams is related to in-group biases. For example, when team closure is very low, there are few mutual interconnections among team members, and therefore they will be subjected to less in-group bias due to the paucity of within-team connections and will be more open to input from beyond the team boundaries because of lower allegiance to internal ties [36, 68, 97]. As closure begins to increase to a moderate level, the negative effects of in-group bias begin to emerge. The natural result is that group norms begin to take hold, leading to a reduction in individual discovery-oriented behaviors because of the increased reliance on the in-group. Although moderately closed teams potentially have a richer array of information available—both from within the team and from external sources—empirical evidence indicates that in-group biases will overwhelm external sources of information [11]. Thus, team members are more likely to overvalue the information coming from the team and undervalue the information coming from nonmembers [11, 97]. As a consequence, individuals are more likely to interact with one another and restrict the inflow of new viewpoints. Even if members of the team are thought to be experts, over time their internal information will become out-of-date because commonly held beliefs within the team will be reinforced [68], while new information about the value of technology features and how they could be incorporated into their work will be rejected. This logic is consistent with insights from the *integration perspective.*

The *integration perspective* suggests that at moderate levels of internal closure, the interaction among team members is not extensive enough for members to develop strong ties. For knowledge to be integrated there must be trust, open communication, and knowledge awareness, but without it there is no shared interpretation of the environment. Such conditions exist when individuals wish to guard core capabilities or their capabilities may have devolved into core rigidities due to limited exposure to others [51]. As team closure increases beyond moderate levels, the integration perspective suggests that there will be a positive effect on individual use. Members will be less likely to adopt competitive orientations toward one another [67], opportunistic behavior is less likely to occur [32, 91], and in-group biases will be minimized because of increased levels of trust and shared mental models [6, 88]. High-closure teams are also more likely to have instituted information-sharing mechanisms in order to reap the benefits of pooled knowledge [115]. A high degree of closure in the team network allows members to foster collective interpretations through the development of common routines and shared language [75]. Members become aware of the localization of various knowledge within the team, that is, "who knows what" [22, 42], thus fostering the access to information, increasing communication efficiency, and reducing the probability for misunderstandings [100]. Consequently, this also means that individuals within the team will be more open to stimuli coming from the external environment since team members will not be judged by one another [6]. Thus, in high-closure teams, members are more prone to both share and receive information about the system, and the positive effects of network closure begin to be reasserted [92] because the communication processes between team members becomes more fluid [92, 93].

To summarize, moderate levels of closure allow the diffusion of responsibility but fail to develop trust and shared mental models, whereas a high level of internal closure facilitates information exchange and the integration of team members' knowledge [64]. Taken together, the social categorization perspective and the integration perspective posit that different triggers dominate at low and high levels of internal closure, suggesting a U-shaped relationship between closure and outcomes [82]. The use of complementary theories to support U-shaped relationships echoes the logic utilized in recent research [37, 98].

In practical terms, through interaction with close others, an individual with deep knowledge of a particular feature or function is likely to find teammates who have information about other features and functions and/or learn new ways to exploit their domain expertise for the good of the team. The greater the number of members involved in such an exchange of system-related information, the more pieces of system-related knowledge is shared. By advising one another, members learn about each member's system-related knowledge, which favors the development of a shared understanding and team cognition, and thus the accessibility to valuable knowledge [93, 118]. A dense advice-seeking network within the team can help members learn features unique to the system, gain the skills needed to deal with their tasks, and overcome uncertainty barriers in interacting with the system. To the extent that learning, skill acquisition, and uncertainty reduction facilitate technology use by eliminating impediments and by favoring the appropriation of system features, we predict:

Hypothesis 1: Team internal closure has a curvilinear (U-shaped) relationship with individual technology use such that the relationship is stronger at low and high levels of closure.

Team External Bridging and Individual Use of Technology

Structural hole theory offers an alternative to closure as an explanation for the benefits of network structure [14]. While closure recognizes the effect of internal information exchange and within-team norms, structural hole theory argues that benefits accrue through access to diverse information by spanning disparate clusters within the broader organizational structure [69]. As a result, teams who bridge otherwise disconnected people gain diverse information (e.g., [35]). It has been suggested that bridging may positively influence individual-level outcomes such as career success [76], member satisfaction [33], and job-seeking prospects [32]. At the team level of analysis, groups that interact with people outside the team boundaries are more likely to experience positive outcomes such as enhanced creativity [35], longevity [33], and improved performance [69] because they can more easily acquire ideas, information, and experience, which allows them to gain respect and support [5].

Extant research also notes that cross-fertilization is enabled when teams are exposed to interactions with others outside the team boundaries, promoting learning and innovation [101, 103, 104, 106]. The presence of nonredundant ties outside the team boundaries may equip a team with a wider range of information to rely on when performing or coordinating a task, stimulating divergent thought processes that can lead to the development of diverse and more effective processes [5, 69]. To the extent that external information provides access to a wider set of information regarding system use by providing new knowledge [5, 69], it is likely to lead to more comprehensive and faster appropriation of the system features. This reasoning is consistent with previous research outlining that exposure to external contacts enhances the likelihood of innovation adoption [48]. However, other research warns of the difficulty of transferring knowledge across organizational boundaries, especially when knowledge is tacit and relationships are not well established [63]. Because our study focuses on advice-seeking ties, which stresses the motivation of individuals to use their network to actively seek information related to system use, we feel confident that the advice-seeking network provides a conduit through which new uses and features are searched across team boundaries, ultimately leading to increased appropriation of the system. It has been shown that even in teams that are not tasked with goals that are inherently innovative, information-seeking behavior still occurs [121]. Thus, teams with high levels of external bridging will have superior access to external knowledge and, as a result, their team members are likely to increase their use of the system due to a broader understanding of its functionalities. Therefore, we test:

> *Hypothesis 2: Team external bridging is positively associated with individual technology use within the focal team.*

The Interaction Between Team Internal Closure and Bridging

Although the theoretical arguments related to external bridging and closure have, for the most part, been treated separately, some studies (e.g., [92]) have ana-

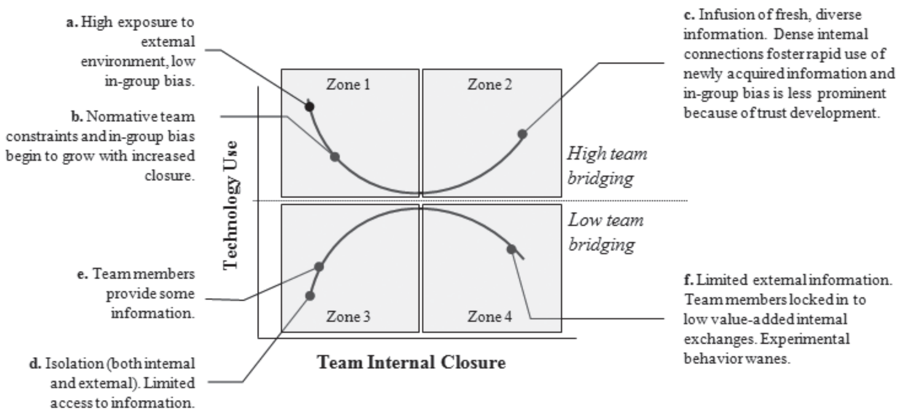

Figure 2. Interaction Between Team Internal Closure and Team Network Bridging

lyzed the two perspectives in a simultaneous fashion. Drawing on this logic, we expect that the U-shaped closure relationship proposed in Hypothesis 1 interacts with the linear bridging relationship asserted in H2. Specifically, we expect the interaction between closure and bridging to yield two opposing U-shaped curves as they relate to technology use (see Figure 2). This reasoning complements the theoretical underpinnings adopted in H1 by going above and beyond the simple consideration of closure with no variation in team external bridging connections. As with all main effect hypotheses, in formulating H1 we assume external bridging values to be at the mean. By considering internal closure and external bridging and their interaction in a simultaneous fashion, we theoretically unpack the effect of internal closure under different conditions of bridging, thus complementing the arguments leading to H1 and H2. In an effort to simplify the complex theoretical mechanisms under which a linear relationship is argued to interact with a quadratic relationship, we identify four distinct zones to formulate the logic for our third hypothesis (see Figure 2).

Zone 1: High Bridging and Low Internal Closure

In teams characterized by low closure, external bridging may be necessary in order to discover new features and uses for the technology. If the team maintains external relationships that span many structural holes (i.e., bridge nonredundant ties) over a wider external network across team boundaries, it is more likely to gain access to diverse sources of ideas and information [14]. Access to this diverse information helps the seekers discover new ways to use the system to support their needs and develop expertise in solving technology-related problems that hinder the completion of job tasks [86]. It also ensures users are better poised to interpret the complexity of the context in which they are embedded [59]. We argue that use is higher when closure is lower because team members are less likely to be subject to in-group bias, which makes them more receptive to external stimuli (see point a in Figure 2).

As closure begins to rise, a different dynamic can occur in which the individual tendency toward the discovery of new features and new ways of accomplishing tasks with the system declines (point b, Figure 2). While the literature has not directly discussed this condition, indirectly it has noted that team member satisfaction and performance can suffer under high bridging conditions, attributing the negative outcomes to the reduction in group cohesiveness and threats to shared team identity [4, 29, 102]. We suggest that, in much the same way as described above, with an increase in closure, the negative effects of social pressure that foster biases and stereotypes emerge, enhancing the likelihood of overlooking or rejecting the information coming from outside the group [90]. Therefore, even if the team is exposed to a wide array of external contacts, when in-group biases increase, team members tend to become more insular and less receptive to external ideas with limited desire to apply external information about system use to their context.

Zone 2: High Bridging and High Internal Closure

There is a point at which the positive effects of closure become salient and the benefits of both external bridging and close relationships among actors can be realized [76]. As the degree of closure increases beyond this point of inflection, the increasingly positive effects of enhanced efficiency, trust, shared mental models, and quality associated with high closure begin to manifest [92, 111], and these effects are complemented by the positive effects of bridging (point c, Figure 2). The trust between team members that arises from cohesive relations eliminates the need for engaging in time-consuming and costly efforts to control the reliability and authenticity of information coming from a particular team member's external contact [111]. In fact, the existence of external connections may act as a debiasing mechanism that mitigates the occurrence of in-group biases and fosters the positive effect of high levels of internal closure. We argue that the greater a focal team's bridging connections, the lower the risk of in-group biases since team members have more opportunities for exposure to diverse external views and information. This expectation is consistent with previous research emphasizing that positive outcomes can be reached by combining elements of cohesion within the team with the presence of bridges with the external environment [79, 80, 101]. It is also supported by recent research noting that the presence of a connection between two teams is a potential advantage for members, but only when coupled with close internal interactions and linkages [7, 120]. In the context of technology use, while high levels of bridging allow for the infusion of fresh and diverse information about the system from outside, dense internal connections that foster shared language and mental models support the exploitation of acquired information immediately.

Zone 3: Low Bridging and Low Internal Closure

When external bridging is low we expect a significant difference in the effect of closure on individual technology use. In particular, we suggest that the lack of bridging across teams represents a critical condition that alters the direction of the main relationship:

low bridging reverses the U-shape relationship between closure and use, transforming it to an inverted U-shape (concave shape). When closure is low and bridging is low, team members are isolated, thus there is little to no within-group links and few, if any, connections to the out-group (point d, Figure 2). In such a scenario, the individual has neither access to information that could be useful for understanding the features of the system nor information that may be instrumental in unraveling how the technology would fit with specific work tasks. Team members are likely to experience frustration in interacting with the system because they are attempting to find the best way to fit its functionalities with their job [16]. In addition to having limited avenues of acquiring domain expertise, individuals also have few means to capitalize on it. This further diminishes the triggering of the discovery process that usually occurs through social interaction [65]. Thus, the lack of information coming from teammates and other colleagues hampers individual stimulus for activating discovery-oriented behaviors in the attempt to assimilate and adapt the system to their particular work [3], thereby reducing individual use.

In contrast, as internal closure increases, despite the fact that the team is isolated from the external environment, members could benefit by accessing information internal to the team, without the risk of reprisal for bringing in external information and contaminating the team (point e, Figure 2). However, beyond a certain level of closure, the lack of access to diverse information outside the team boundaries will dramatically handicap the team and hinder individual use of the system.

Zone 4: Low Bridging and High Internal Closure

Without access to external information a high-closure team can fall into the trap of circulating suboptimal internal information. Thus, as the degree of closure increases with low degrees of external connection, we expect individual use to decrease (point f, Figure 2). While a high degree of network density is, on average, positive because it triggers trust, shared mental models, and fluid communication patterns, teams that lack connections to diverse knowledge from the external environment have a potential disadvantage in that the information exchange may be comfortable but not necessarily productive or valuable for them [61]. It may lock team members into endless mutual exchanges, even if such exchanges do not provide any added value for gaining insights into better use of the system. In such a contingency, teams have access to a single set of resources, skills, and perspectives that constrain members from being inquisitive or discovering how different features of the system may fit with their tasks [15]. Our logic for interplay between closure and bridging is consistent with recent studies that suggest that while a dense network plays a pivotal role in stimulating initiative, this occurs only when it does not compromise access to novel information [50]. Based on all of the arguments proposed above, we hypothesize:

> *Hypothesis 3: Team bridging moderates the relationship between team internal closure and individual technology use. The relationship is U-shaped when team bridging is high, but inverted U-shaped when team bridging is low.*

Methods

Study Context and Sample

We tested our research hypotheses in the context of a field study conducted in a large financial services advisory company (Alpha). Alpha, headquartered in the northeastern United States with distributed locations in several states, is in the banking business and has divisions that focus on advising clients about their investment portfolios and providing commercial lending services. The setting for data collection was the introduction of a new customer relationship management (CRM) system for use by its "client" and "commercial lending" businesses. Advising and lending activities at Alpha are performed in "relationship management teams" that consist of relationship managers, sales assistants, tax and credit experts, and other workers responsible for collectively servicing a client portfolio. The CRM system was introduced into the company expressly for the purposes of providing a shared knowledge management platform [8] for the activities of all relationship management teams, a common customer database, and a centralized repository within which to store all customer interactions. In simple terms, employees were expected to use the CRM to acquire client-specific information from the system (e.g., name, address, family members, investments), conduct queries (e.g., present all client accounts with a net worth exceeding $5 million, list all verbal communications with Mr. or Mrs. XYZ during the prior quarter), sort and categorize client information based on specific criteria (e.g., clients who graduated from universities in the northeast, clients with a tax burden in excess of 34 percent), perform mail merges in which only select clients were invited to events, and so forth. Some of these uses were considered intuitive while others were quite complex. In addition, as is common with complex information systems, new uses were discovered (e.g., integration with the corporate e-mail system) as familiarity with the system increased [71].

Alpha had used a variety of client management systems in the past but the new system was the first to offer full interoperability with other systems (tax, marketing, personal banking, brokerage, commercial lending, etc.) and accessibility to other client records outside of those managed by one's relationship management team. While client inquiries were directed first to the relationship management team handling the account, theoretically anyone with appropriate credentials in the firm could access the client's records and respond to the inquiry. The CRM tracked each inquiry and date/time stamped it, noting the employee accessing the record. Not only was each inquiry noted in the user's log but the amount of time spent using the system was also captured. Because this particular CRM also included an add-in that interfaced with the e-mail system, each e-mail either sent or received that matched a client e-mail address populated a record within the CRM system.[4]

Data for this study were collected primarily through a paper-based questionnaire and archival data but were also supplemented by qualitative and observational work. Prior to administering the survey, we conducted unstructured, formal and informal, impromptu interviews with key informants in order to get a better understanding of the research context and the personnel involved in the implementation of the CRM. During this stage of research we were invited to observe the CRM task force meetings in which implementation challenges, training, and compliance with use were discussed. From this qualitative process we were able to fine-tune our survey and, more importantly, ascertain the importance of some key issues that faced top management and the task force. For example, we learned that Alpha had been unsuccessful in recent attempts to implement "customer service related" information technologies for which use was mandated. They attributed this to the preference by some users for legacy systems that were more familiar to them. The task force also noted that some high-performing wealth managers were reluctant to change what had brought them success in the past. This led our research team to question whether the "mandate" was real or a veiled threat. The task force noted that although the use of the CRM was strongly encouraged, there was no policy in place for noncompliance. In addition, even though senior management were being issued monthly individual usage reports, no punitive actions against low users were taken, suggesting that system use was actually voluntary.

The questionnaire was administered approximately six months after the CRM system was rolled out. The process for data collection, sample construction, and response rate determination is described below.

- Step 1: We were provided with a list that included every employee at Alpha who had access to the CRM system. This list included 437 names.
- Step 2: Paper surveys were sent to all 437 people via Alpha's interoffice mail.
- Step 3: Of the 437 surveys sent, we received 265 usable responses.
- Step 4: Working with an organizational chart and also with human resources personnel at Alpha, we identified that out of the 172 nonrespondents, 110 of them did not work in teams. Because our research question specifically focuses on team dynamics, we eliminated 110 nonrespondents from the sample, leaving us with 62 nonrespondents (i.e., response rate of 81 percent, 265/327) who were part of teams.

The 265 survey respondents belonged to 44 teams. Our within-team response rate is above the 70 percent criterion typically adopted by social network researchers [113]. In the final sample, 55 percent of the respondents were female, the largest age group was 41–50 (35.7 percent), and the most common job titles were tax expert and sales assistant (29.4 percent and 17.3 percent, respectively). Tests for nonresponse bias between the first and second waves (after one reminder) of respondents indicated no significant differences in the values of the major variables. Moreover, we did not find significant differences between respondents and nonrespondents in the demographic characteristics or the objective system use (actual individual CRM use, discussed below), which we obtained from archival data.

Operationalization of Variables

Responses to the survey were not anonymous, therefore, from the organization charts we were able to determine the team to which each individual belonged. To identify the sources of informational influence, we followed the standard name generation approach, which has the advantage of reliably eliciting the most salient relations of the respondent [57, 78]. Specifically, the advice network was assessed by soliciting a person's advice network contacts [76] by asking each respondent to list the name of others he or she "would consult when trying to learn what features of the system to use for accomplishing a specific task (excluding the helpdesk)." We excluded the possibility of naming individuals who were part of the helpdesk for the following reasons. First, although firms provide formal support and assistance through a helpdesk, this support often overlooks the on-the-job, situated learning process of incorporating and sharing information in the context of actual work-specific tasks [86]. Second, during the introduction of a complex system (e.g., ERP [enterprise resource planning] or CRM) users interact with each other and are likely to rely on other users for assistance and for gaining a better understanding of how they can better appropriate the system functionalities and discover new ways to accomplish their tasks through the system [28, 41, 72]. Respondents were allowed to list as many individuals as they thought appropriate so as to reduce measurement error [116]. On average, the number of "nominees" (an individual whose names were elicited by the above question) indicated by each participant was 5.64 (standard deviation = 3.27). Therefore, the name generation approach allowed us to develop a roster of contacts on the basis of the names elicited by individuals [55]. Relying on the lists provided by participants and a company-supplied organization chart, we were able to verify if each nominee was located within or outside the team of the respondent.

If an individual i selected individual j as the person whom he or she goes to for advice, the cell entry X_{ij} equaled 1 in the advice network. Conversely, if individual j did not select individual i as the person whom he or she goes to for advice, the cell entry X_{ji} equaled 0 in the advice network. As other studies have suggested, advice networks are not necessarily symmetrical matrices because people may not reciprocate advice seeking from others [57]. Figure 3 illustrates the relational contexts in which team closure and bridging were computed.

Team Internal Closure

Team closure was measured as a group's density in the network of advice-seeking relationships [15] by considering the sum of the existing ties in the team divided by the total possible sum of ties among all members within the team [89].

Team External Bridging

We calculated team bridging following the procedure recommended by Burt [15] for identifying structural holes. Specifically, the number of structural holes brokered by an individual i was captured using the network constraint measure excluding the ties among members within the team [14]. Extant research suggests that network constraint effectively measures an actor's *lack* of access to structural holes [14, 119]. Put another

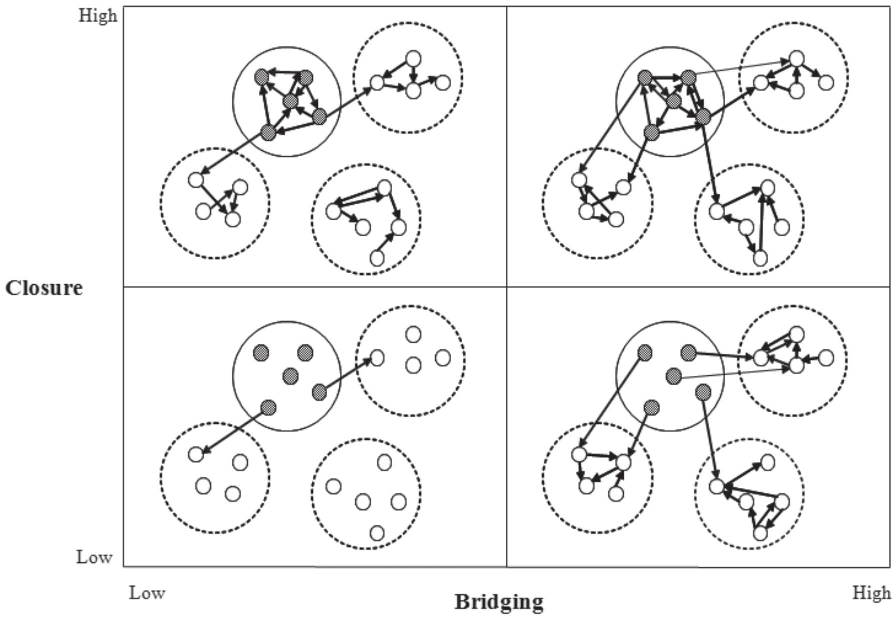

Figure 3. Team internal closure and network bridging

Note: Members of the focal group are shaded.

way, constraint is an index that measures the extent to which a person's contacts are redundant. Conceptually, the more that i's network is directly or indirectly concentrated in a single contact, the more constrained i's network is, and hence the fewer structural holes brokered by i. Operationally, the constraint posed by a contact (j) to i is computed as follows: $c_{ij} = (p_{ij} + \sum_q p_{iq} p_{qj})^2$ for $q \neq i,j$, where p_{ij} is the proportion of i's relations that are directly invested in j [14]. The sum of the squared proportion $\sum_j c_{ij}$ is the network constraint index C. We then averaged each member's individual score C at the level of the team network to obtain the constraint score at the team level. Following the work of others [92], we multiplied the value of the team-level constraint by –1 in order to capture structural holes (the "opposite" of constraint). Aggregating at the team level by averaging individual scores reflects previous research that considers team structural holes as a team configurational property that originates and should be measured at the individual level but is accumulated at the team level of analysis, thus allowing us to consider structural holes as a team-level characteristic [49].

Individual Use

In order to employ a rich conceptualization of individual system use [41], we adopted multiple perspectives for capturing the way through which individuals interact with the system. Following recommendations in recent work that exhort researchers to use objective measures as well as appropriate subjective measures in predicting system

Table 1. Descriptive Statistics

Description	Mean	Standard deviation
Depth of use (count of interactions)	39.33	57.13
Scope of use		
Percent of client interactions	33.61	35.18
Percent of features used regularly	2.10	1.23
Intensity of use		
Duration of use per day	2.49	1.29
Frequency of use	3.85	1.56
Computer skills	3.59	0.73
Perceived usefulness	4.14	1.42
Ease of use	4.50	1.30
Subjective norms	4.72	0.79
Team size	7.65	4.54
Team bridging	0.47	0.11
Team closure	0.05	0.07

Notes: Percent of client interactions was measured on a scale of 0–100. Percent of features used regularly was measured on a scale of 1–6 (1 = < 10, 2 = 10–24, 3 = 25–49, 4 = 50–74, 5 = 75–94, 6 = 95+). Duration of use per day (1 = 0 minutes, 2 = 1–20 minutes, 3 = 21–60 minutes, 4 = 61–120 minutes, 5 = 121–180 minutes, 6 = 180+ minutes). Frequency of use (1 = never, 2 = a few times a year, 3 = monthly, 4 = weekly, 5 = daily, 6 = nearly all the time). All the other constructs were measured on a scale of 1 = strongly disagree to 7 = strongly agree.

use [109], we assessed individual use through depth, intensity, and scope of use using objective and subjective data. Depth of use was measured through objective data collected at the individual level and reflected the actual number of interactions with the CRM system as assessed by transactions entered, modifications made to entries, and deletions. Alpha collected usage data on a real-time basis and provided us with monthly reports. In an effort to smooth peaks and valleys resulting from disruptions, such as vacations and tax season, we averaged the data over a three-month period.

Scope and intensity of use were operationalized using subjective, self-report measures. Following previous research [45], scope was measured with two items tapping the percent of system features used regularly by the respondent, and the percent of client interactions managed through the system (Cronbach's $\alpha = 0.74$). Intensity was measured through a two-item scale developed by Karahanna et al. [45] tapping the frequency of use and amount of time spent on the system per day (Cronbach's $\alpha = 0.82$) (see Tables 1 and 2).

Control Variables

We included a robust set of control variables at both individual and team levels that are not of primary interest in this study but may nonetheless capture variance in use behavior. First, we include perceived usefulness and perceived ease of use as two

Table 2. Factor Analysis

	EOU	PU	SN	INT	SCO
EOU1: Learning to operate the [system] is easy for me	**0.894**	0.433	0.269	0.319	0.464
EOU2: My interaction with the [system] is clear and understandable	**0.889**	0.565	0.382	0.308	0.480
EOU3: It will be easy for me to become skillful at using the [system]	**0.878**	0.465	0.401	0.331	0.479
EOU4: I find the [system] easy to use	**0.894**	0.556	0.306	0.213	0.420
PU1: Using the [system] in my job will increase my productivity	0.574	**0.989**	0.528	0.386	0.508
PU2: Using the [system] will enhance my effectiveness on the job	0.506	**0.952**	0.478	0.373	0.507
PU3: Using the [system] will make it easier to do my job	0.560	**0.951**	0.523	0.381	0.455
PU4: Using the [system] in my job will enable me to accomplish tasks more quickly	0.537	**0.954**	0.483	0.361	0.468
SN1: My relationship management team thinks that I should use the system	0.371	0.523	**0.902**	0.367	0.359
SN2: My coworkers think I should use the system	0.330	0.431	**0.915**	0.402	0.376
INT1: How frequently do you access the [system]?	0.310	0.340	0.363	**0.916**	0.624
INT2: During a typical day, how many minutes would you spend using the [system]?	0.308	0.380	0.418	**0.933**	0.581
SCO1: Of all the features and functions available in the [system], what percentage would you estimate that you use on a regular basis?	0.460	0.465	0.387	0.574	**0.886**
SCO2: Approximately what percentage of all your client interactions are managed using the [system]?	0.453	0.417	0.319	0.565	**0.865**

Note: EOU = ease of use; PU = perceived usefulness; SN = subjective norms; INT = usage intensity; SCO = usage scope. Boldface values indicate the factor on which an item has the highest loading.

significant drivers of use as evidenced in a significant body of prior work [27, 108, 110], some of which was conducted with subjects who were professionals [21]. The four-item perceived usefulness scale and the four-item ease of use scale were derived from the work of Davis [27] and Lewis et al. [52]. Both scales present high levels of reliability (perceived usefulness: Cronbach's $\alpha = 0.95$; ease of use: Cronbach's $\alpha = 0.91$). Second, our primary focus in this study is on informational influence as derived from teams' social network configuration. Because previous studies have established that what others think about the use of a technology may affect individual behavior toward it [99, 108], we include a measure of normative social influence at the individual level. Subjective norms emanating from key referents was operationalized in the standard fashion through two items (Cronbach's $\alpha = 0.79$) (see Table 2).

We included a user's computer skill because it has been shown to influence individual behavior toward a new technology. This was operationalized with the question: "How would you rate your computer skills?" with anchor values of "none" to "very extensive." This represents an unambiguous item and therefore is acceptable as a single-item indicator [112]. Furthermore, we controlled for individual centrality because it has been demonstrated that centrality shapes individual behaviors and outcomes [74]. Centrality was calculated for each individual and operationalized using the in-degree centrality index, which measures the number of ties received by an individual [105]. In-degree centrality is a form of degree centrality that counts only those connections to a focal individual reported by others, and it thus does not suffer from the limitations of self-reports [9]. Specifically, we calculated the normalized degree centrality in order to account for different sized teams [93].

At the team level of analysis, we controlled for team size because we reasoned that the larger the size of a team, the more opportunities for finding answers within the team. Finally, because some of the dimensions of use, such as transaction activity, may be a function of the type of job that an individual possesses or the branch in which he or she works, we tested for differences across job categories and locations. Using analysis of variance (ANOVA) and planned post hoc comparisons, we found no significant differences between use relative to job role or the location of the branch; therefore we collapsed across all the job categories and all the branches.

Analysis and Results

Data Analysis

Table 1 shows the descriptive statistics of all the variables used in the analysis. The psychometric properties of the scales are assessed in terms of item loadings, discriminant validity, and internal consistency. All the constructs exhibit good internal consistency, presenting composite reliability scores above the suggested threshold of 0.70 (see [30]). Results of the factor analysis established the discriminant and convergent validity of the scales. As Table 2 indicates, all the items loaded on the expected factors and have low cross-loadings on other factors. Furthermore, examination of the interconstruct correlations and square root of average variance extracted (AVE, on the diagonal) in Table 3 reveals that all the constructs share considerably more variance with their indicators than with the other constructs.

Hierarchical Linear Models

Given the hierarchically nested structure of the data and the research model, it was necessary to use a random coefficient modeling technique since it has been noted that traditional statistical techniques such as multiple regression are inadequate to assess cross-level predictions [77]. Random coefficient modeling enables researchers to examine relationships that span levels of analysis through meaningfully partitioning the variance components in outcome variables [39], thus we adopted HLM to test the proposed hypotheses (e.g., [53, 60]). The indicators of use and several control variables were measured at the individual level (level 1) and the key independent variables of interest were operationalized at the team level (level 2: team size, team internal closure, and team external bridging).

For each construct of use we first estimate a null model for which there are no individual- or team-level predictors included. This enables us to test a necessary precondition related to the existence of significant variation in individual use [12]. If there is significant variation in use, we can add individual-level variables. In the second model we add team-level predictors, and in the final model we include the interaction terms. The formal specification of the model for each of the measures of use is as follows:

Null model:

$$Use_{ij} = \beta_{0j} + r_{ij}$$

Individual-level model:

$$\begin{aligned} Use_{ij} = {} & \beta_{0j} + \beta_{1j} * \mathit{Computer\ skills}_{ij} + \beta_{2j} * \mathit{Gender} + \beta_{3j} * \mathit{Individual\ centrality} \\ & + \beta_{4j} * \mathit{Perceived\ usefulness} + \beta_{5j} * \mathit{Ease\ of\ use} + \beta_{6j} * \mathit{Subjective\ Norms} + r_{ij} \end{aligned}$$

Team-level model:

$$\begin{aligned} \beta_{0j} = {} & \gamma_{00} + \gamma_{01} * \mathit{Team\ size}_j + \gamma_{02} * \mathit{Closure}_j + \gamma_{03} * \mathit{Closure\ sq}_j + \gamma_{04} * \mathit{Bridging}_j \\ & + \gamma_{05} * \mathit{Bridging} * \mathit{Closure}_j + \gamma_{06} * \mathit{Bridging} * \mathit{Closure\ sq}_j + u_{0j}. \end{aligned}$$

For each HLM estimated (described below), all the predictors at level 1 were grand-mean centered [39]. We calculated the proportion of variance explained at each level, that is, level 1 within-group variance ($R^2_{\text{within-group}}$) and level 2 between-group variance ($R^2_{\text{between-group}}$) [53].

Null Models

As noted, the null model represents a precondition for testing the multilevel model. In order to proceed with the tests of these hypotheses, there has to be significant

Table 3. Composite Reliability, Average Variance Extracted, and Correlations

	Variable	Composite reliability	1	2	3	4	5	6	7	8	9	10
1	Depth of use	NA	**NA**									
2	Scope of use	0.86	0.52**	**0.87**								
3	Intensity of use	0.92	0.61**	0.64**	**0.92**							
4	Individual centrality	NA	–0.05	–0.01	–0.04	**NA**						
5	Computer skills	NA	0.00	0.15*	0.14*	–0.03	**NA**					
6	Perceived usefulness	0.96	0.21	0.47**	0.38**	–0.02	0.05	**0.93**				
7	Ease of use	0.93	0.24	0.49**	0.33**	0.00	0.26**	0.57**	**0.88**			
8	Team size	NA	0.18**	0.26**	0.32**	–0.03	0.09	0.10*	0.17**	**NA**		
9	Subjective norms	0.90	0.21	0.36**	0.39**	0.00	–0.02	0.23**	0.23**	0.33	**0.90**	
10	Team bridging	NA	0.07	0.07	0.05	–0.05	0.03	0.01	–0.01	–0.16**	0.09	**NA**
11	Team closure	NA	0.10	0.02	0.11	0.05	–0.07	–0.10	–0.07	–0.23**	0.06	0.05

Notes: To compute the correlations, we assigned team-level variables to each individual in that team as in Cullen et al. [24]. Average variance extracted is shown in boldface. NA = not applicable. * $p < 0.05$; ** $p < 0.01$.

between-team variance in each construct related to use. Using HLM, we estimated a series of null models in which no predictors were specified for either level 1 or level 2 functions and also tested if the level 2 residual variance of the intercept was significant. The test results indicate significant residual variance in the three conceptualizations of use: scope ($\chi^2 = 117.8$, df [degrees of freedom] = 43, $p < 0.01$), intensity ($\chi^2 = 200.6$, df = 43, $p < 0.01$), depth ($\chi^2 = 66.5$, df = 43, $p < 0.01$). Because our hypotheses refer to the effect of team-level predictors on individual outcomes, we assessed the ICC1 (interclass correlation index) for each dependent variable, which is the proportion of variance in each outcome variable that resides between teams. These analyses yielded the following results: scope (ICC1 = 0.23), intensity (ICC1 = 0.31), depth (ICC1 = 0.10). These results are consistent with the recommended ICC values reported in the literature [53].

Adding Individual-Level Predictors

In the second model we added the individual-level predictors. Recall that we do not propose hypotheses related to individual-level effects but instead include them as controls in the model because they represent commonly used predictors for individual use of technologies. Our controls included computer skill, gender, individual centrality, perceptions of usefulness and ease of use, and subjective norms. As with most prior technology acceptance research at the individual level, perceived usefulness, ease of use, and subjective norms were all significant predictors of all three measures of individual use (see Table 4).[5] The significant result of subjective norms can be explained by the fact that, in voluntary settings characterized by an absence of rewards for use or sanctions for nonuse, subjective norms affect individual intentions and behaviors through a process of internalization, rather than compliance. We did not find significant effects for computer skills, gender, or individual centrality. The proportion of variance explained by level 1 predictors ($R^2_{\text{within-group}}$) is 0.18, 0.31, and 0.23 for depth, scope, and intensity of use, respectively. These results are in line with previous studies that focused on hypothesizing cross-level phenomena [56].

Adding Team-Level Predictors

To test the cross-level hypotheses, we estimated an HLM in which we added the team-level predictors. In H1, we posited a U-shaped effect of team internal closure on use. To test this, we examined the sign and the significance of both the linear and the squared terms of the pair of coefficients that comprised the U-shaped effects. The significant negative coefficient for the linear term coupled with the significant positive coefficient for the squared term supports the U-shaped curvilinear prediction, therefore H1 is supported (see Table 4). The analysis to test H2 is much more straightforward and the posited relationship between team bridging and use is supported as evident by the positive significant coefficients for all three use variables. The between-group variance ($R^2_{\text{between-group}}$) explained by level 2 predictors was 0.81, 0.54, and 0.67 for depth, scope, and intensity of use, respectively. These findings are consistent with

Table 4. HLM Results for Predicting Individual Use

	Usage depth			Usage scope			Usage intensity		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Individual-level predictors	Team-level predictors	Team-level interactions	Individual-level predictors	Team-level predictors	Team-level interactions	Individual-level predictors	Team-level predictors	Team-level interactions
Level 1 (individual)									
Computer skills	–0.10	–0.12†	–0.11†	0.03	0.01	0.00	0.02	0.01	0.01
Gender	0.03	–0.00	0.13	–0.06	–0.08	0.13	–0.06	–0.08	–0.08
Individual centrality	–0.36	–0.14	0.30	0.14	0.26	0.10	–0.15	0.01	0.01
Perceived usefulness	0.08†	0.12	0.12	0.23**	0.24**	0.17*	0.23**	0.25**	0.24**
Ease of use	0.19**	0.18**	0.19**	0.26**	0.27**	0.31**	0.13**	0.13**	0.13**
Subjective norms	0.10*	0.03	0.03	0.13*	0.10†	0.01	0.17**	15**	0.16**
Level 2 main effects (team)									
Team size		0.02**	0.02*		0.15**	0.01		0.16**	0.04**
Internal closure		–0.42**	–0.36**		–0.42*	–0.17		–0.52*	–0.12
Internal closure^2		0.36*	0.27*		0.34*	0.16		0.48*	0.18*
External bridging		0.20**	0.20**		0.21**	0.31**		0.27**	0.27**

Level 2 interactions (team)									
External bridging × Internal closure			–0.24[†]			–0.60**			–0.49*
External bridging × Internal closure^2			0.30*			0.42*			0.47*
Model comparisons		Compared to model 1	Compared to model 2		Compared to model 1	Compared to model 2		Compared to model 1	Compared to model 2
Degrees of freedom		4	2		4	2		4	2
χ^2		29.05**	28.38**		51.19**	34.32**		77.25**	76.38**
$R^2_{\text{within-group}}$	0.18			0.31			0.23		
$R^2_{\text{between-group}}$		0.81	0.83		0.54	0.74		0.67	0.70

Notes: Individuals = 265, teams = 44. † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$.

previous studies noting that team-level variables account for a high percentage of between-team variance (e.g., [53]).

Adding Team-Level Interaction Terms

H3 predicts that team bridging moderates the relationship between team closure and use. In order to test a quadratic-by-linear interaction, such that the curvilinear relationship of internal closure with individual use varies as a function of team external bridging, we added the interaction terms as shown in Table 4, model 3, for depth, scope, and intensity. Specifically, we included the External bridging × Internal closure linear-by-linear interaction term (shown under the heading "Level 2 interactions (team)") as well as the External bridging × Internal closure^2 quadratic-by-linear term [1, p. 85]. In order to verify the existence of a curvilinear-by-linear interaction, the quadratic-by-linear coefficient (i.e., External bridging × Internal closure^2) must be statistically significant [1, p. 85].

As shown in the results for model 3 in Table 4, for each of the dependent variables, the interaction between the squared closure term and the linear bridging term is positive and statistically significant (depth: 0.30, $p < 0.05$; scope: 0.42, $p < 0.05$; intensity: 0.47, $p < 0.05$). Hence, the results corroborate H3. The inclusion of level 2 interaction terms increased the explained variance at level 2 ($R^2_{\text{between-group}}$) to 0.83, 0.74, and 0.70 of the available between-group variance in depth, scope, and intensity of use, respectively. To better interpret the interaction terms, we graphed the quadratic-by-linear effect using established procedures [1, p. 85].

As predicted, Figures 4, 5, and 6 show that the relationship between team closure and use follows a U-shaped pattern in teams with a high level of bridging and an inverted U-shape pattern in teams with a low level of team bridging. In particular, the results show that under the condition of high bridging the effects of closure on usage are more prominent at low- and high-level closure, rather than at moderate levels of closure (U-shaped effect). Moreover, the plots corroborate our expectations under the condition of low bridging by indicating that when the team is experiencing a lack of external connections, the effect of closure on usage is lower at low and high level of closure than at moderate levels of closure (inverted U-shape). The only exception is related to depth of use, which presents a slightly inverted U-shape under the condition of low bridging. While the shape is modestly curvilinear, both the results and the graphs (Figures 4, 5, and 6) illustrate that bridging significantly moderates the curvilinear effect of closure. Overall, in light of the statistical results, the increase in R^2, and the pattern of the plots, we find support for H3.

Discussion

Theoretical Implications and Future Research Directions

The present study offers several theoretical contributions as well as directions for future research. First, moving beyond the individual level of analysis that has dominated

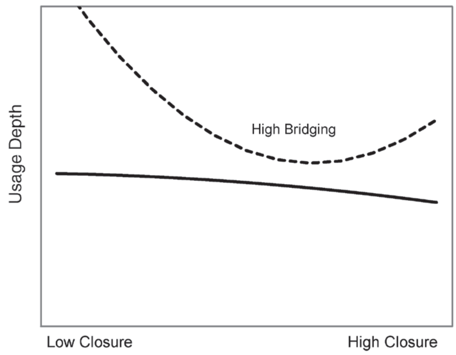

Figure 4. Quadratic-by-Linear Interaction Between Team Closure and Team Bridging on Usage Depth

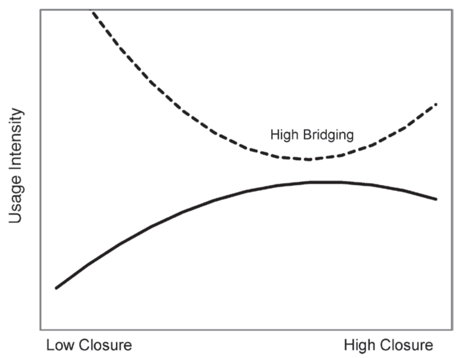

Figure 5. Quadratic-by-Linear Interaction Between Team Closure and Team Bridging on Usage Scope

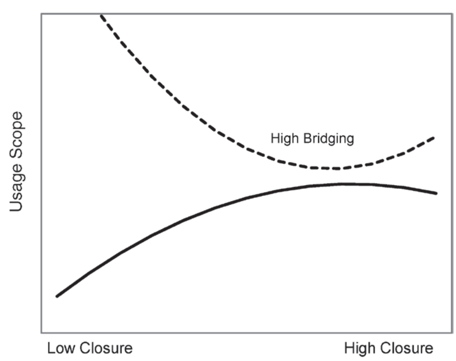

Figure 6. Quadratic-by-Linear Interaction Between Team Closure and Team Bridging on Usage Intensity

prior work, this study is one of a handful to bridge the gap between meso- and micro-approaches in investigating technology use behaviors. The use of cross-level analysis techniques is responsive to recent calls for studies that span organizational levels in order to provide a better understanding of the relationship between team-level factors and individual behaviors (e.g., [34]). It is also consistent with others who have noted that organizational phenomena are likely to cross levels of analysis [39], and it complements the results of studies that embrace a bottom-up perspective by looking at how individual attributes give rise to collective-level IT use patterns [17, 66].

The results of this study support the theoretical arguments concerning the existence of cross-level effects in explaining use, and HLM provided us with the tools to investigate the impact of team-level conduits on individual-level behaviors while maintaining the appropriate level of analysis for these predictors [39]. Thus, we advance the extant literature by theorizing and empirically demonstrating that models spanning levels are appropriate for providing richer explanations of an individual's behavior toward technology. The cross-level research presented here complements previous research on individual-level social influence by explicitly treating individuals as embedded in the social structure of teams, enabling greater granularity in understanding how the configuration of social interactions among individuals may influence their behaviors.

Our results show that team influence on each conceptualization of use is influenced by team social network configuration, which may facilitate or constrain the flow of information both within the team and beyond the team boundaries. Our results are particularly important because both forms of conduits have received extensive attention in the literature, yet efforts to examine their multiplicative effect were absent. Support for the U-shaped relationship that exists between team internal closure and use is interesting, but the multiplicative effect of bridging on this U-shaped relationship offers more useful insights. Although most of our results are consistent with current literature on social networks [92], at first glance our findings on team bridging appear to contradict early work on boundary spanning [46, 101]. We note that this body of work, while acknowledging the importance of external relationships that span team boundaries, also points out that the presence of an extensive boundary-spanning situation may be inefficient and detrimental for team outcomes (e.g., [101]). For example, if boundary spanning across team boundaries results in redundant ties, inefficiencies will be present [103, 104]. From our perspective, the benefits of bridging across different teams reside in the creation of external relationships that are nonredundant. For instance, as the seminal research on R&D teams notes, the team leader should not be the only member involved in bridging activities in order to avoid the occurrence of redundant contacts [46, 101].

Finally, understanding the three conceptualizations of system use is a step in the direction advocated by others [41] who called for richer conceptualizations of system use (see also [18]). Whereas previous research investigating the role of social networks on individual behaviors toward technology has accounted for individual adoption and use (for a review, see [82]), our conceptualization of use included three distinct aspects capturing depth, intensity, and scope, thereby addressing gaps in the extant work (see [18, 109]). Furthermore, our work goes beyond treating system use as a *measure* of the relevant behavior to treating it as a theoretical construct. In other words, we not only identified predictors of various conceptualizations of system use but also described the mechanisms by which such effects occur.

Numerous opportunities for future research remain with respect to individual behaviors toward technology. First, it stands to reason that individual differences such as personality traits would not only affect network structure but could also differentially influence the ways in which people seek information. For example, the extent to which dominant team members seek information (or hoard it) may moderate both closure and bridging relationships.

Second, in our theorizing and subsequent empirical work, we examined a limited set of relevant referents: peers within and outside the team. Others have argued that supervisors also play a role in providing social information that helps shape beliefs and actions (e.g., [83, 87, 114]). Although the empirical findings related to supervisory influence have been equivocal, a useful extension to this study would be to theorize about the relative effects of such compliance-based influence in addition to the informational influence examined here.

Third, the emphasis of this study was on the role of advice-seeking ties as determinants of behaviors. We did not examine the relationship between the source of social influence and performance outcomes. It could be argued that those with access to better resources in the form of "experts" in their informational influence network will achieve better performance. As indicated in previous literature, brokers can engage in calculated or involuntary filtering, distortion, and hoarding [14]. Following this reasoning, future research could investigate the role of brokers within each focal team and take into account possible contingencies, such as the presence of team learning and sharing climate, both of which could decrease the likelihood of withholding information from the wider network for self-serving reasons.

Finally, advice networks have inherent instrumental value for resolving uncertainty by exploiting the expertise of others [95]. Future studies should also address the effects of expressive ties, which are not necessarily activated for finding a solution to a problem but instead are used to affirm ideas, confirm judgments, or validate beliefs about a certain argument [105]. In the context of the introduction of a technology, the existence of such ties could plausibly propagate positive or negative sentiment through the network, inhibiting individual technology use and fostering resistance to change, or creating conditions for the technology to flourish. Furthermore, there could be interplay between expressive ties and advice-seeking ties [19], which presents an important area for further theoretical and empirical work.

Managerial Implications

The present study yields several implications for practice. The rapid pace of technological change is compelling organizations to adopt team-based work practices that enable greater flexibility [33]. In the context of such teams that need to use new technologies to execute their work, our findings underscore the importance of locating designated "experts" strategically. Managers responsible for the success of new technologies would find it fruitful to provide additional training to one or more individuals within work teams so that they are widely recognized as possessing the skill and competencies to assist others. To the degree that these experts have positive beliefs about the new technology and use it extensively, they not only can serve as important agents for successful implementation but also should act as liaisons that develop contacts with other expert users outside the team. This would have the intended effect of encouraging the circulation of useful information across the organization.

There are other actions managers could take if they know the social network configuration of their teams. First, if closure in a team is too low, bridging should be encouraged by facilitating interactions between key team members and experts on other teams or through strategic assignment of experts to teams. Second, in circumstances where bridging is low, moving personnel from their existing team to a new team would decrease closure, thus increasing usage. Third, because high bridging with low closure results in wasted human capital, it is imperative to identify the innovators and influentials in a firm and capitalize on their expertise by facilitating connections within the teams.

Finally, it is incumbent on managers to recognize that trade-offs may emerge between the desire for high levels of bridging and member commitment to the team. While high levels of bridging could be beneficial for individual team members, frequent requests for information outside the team boundaries may erode the cohesiveness of the team. We encourage scholars to provide a better understanding of the existence and dynamics of this trade-off.

Strengths and Limitations

Our research study has several strengths that should be noted. First, the study design involved data collection from multiple sources within participating teams, thereby avoiding the risk of single-source bias. This is particularly noteworthy given the difficulty of obtaining such data in a field setting. Second, the study departs from the individual level of analysis that dominates prior literature studying individual usage behaviors. Adopting a cross-level perspective enabled us to obtain a more nuanced grasp of the social factors that influence individuals' behavior toward technology. Specifically, we were able to strengthen our research design by focusing on the relationship among individuals in a field setting as they operated in their natural environment. Third, this study considers both objective and subjective data related to individual use, providing a richer perspective on individual behavior toward technology. Finally, the field study involved 265 participants in 44 different teams. Compared to previous field studies that adopted a cross-level approach, this is a robust sample size.

The findings of the study need to be interpreted in light of a few limitations. First, while the data were collected from multiple divisions and several different geographic locations, we were limited to a single firm in a specialized service industry. Second, our data do not allow us to examine the contents of the inquiry and response between the information seeker and the source; therefore, we do not know for certain how complex the request was or whether the response was appropriate. Related to that issue, we do not know if the quality of the response is better if the source was external to the team or within the team. Finally, although we incorporated several critical variables that have been shown to be significant covariates of individual technology use, there may be other controls for which we have not accounted.

Conclusion

The primary contribution of this work is the development and empirical validation of the logic underlying the effects of team level network configuration on individual technology use. From a theoretical perspective, the unique application of social network configuration acting in a cross-level manner provides new opportunities for extending research on technology use across levels. The fact that our data allow us to examine the effect of network effects on individual outcomes, thus spanning levels of analysis, is a strength of this study. An understanding of the effects of team-level network configuration would be of significant importance to practitioners who are attempting to implement new information technologies. We also believe that these results are generalizable in a variety of team-based contexts, and as discussed earlier, there are ways in which team composition can be altered to positively influence outcomes.

Notes

1. Prior research suggests that internal closure is a pattern of dense, mutually interconnected ties within the team and external bridging is the existence of nonredundant ties outside the team boundaries. We employ these definitions in our study when we refer to the terms "closure" and "bridging."

2. "Resources" in this instance refer to knowledge exchange specifically about features and functions of the information system.

3. We thank an anonymous reviewer for suggesting this interpretation.

4. As noted in the prior paragraph, this is one example of a new use that was discovered by users and subsequently diffused across the organization.

5. The one exception to this statement is in Model 1, where perceived usefulness is marginally significant ($p < 0.10$) in its relationship to depth of use. All the other variables are significant at $p < 0.05$ and lower.

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