Why Do Group Members Provide Information to Digital Knowledge Repositories? A Multilevel Application of Transactive Memory Theory

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The proliferation of digital knowledge repositories (DKRs) used for distributed and collocated work raises important questions about how to manage these technologies. This study investigates why individuals contribute information to DKRs by applying and extending transactive memory theory. Data from knowledge workers ($N = 208$) nested in work groups ($J = 17$) located in Europe and the United States revealed, consistent with transactive memory theory, that perceptions of experts' retrieval of information were positively related to the likelihood of information provision to DKRs. The relationship between experts' perceptions of retrieval and information provision varied from group to group, and cross-level interactions indicated that trust in how the information would be used and the interdependence of tasks within groups could explain that variation. Furthermore, information provision to DKRs was related to communication networks in ways consistent with theorizing regarding the formation of transactive memory systems. Implications for theory and practice are discussed, emphasizing the utility of multilevel approaches for conceptualizing and modeling why individuals provide information to DKRs.

Faced with complex problem-solving challenges that require collaboration across multiple knowledge areas (Nonaka & Takeuchi, 1995), organizations increasingly rely on work groups made up of members who possess expertise in diverse work domains (Boh, Ren, Kiesler, & Bussjaeger, 2007). Within these groups, members are expected to identify, share, and integrate diverse information to be more productive and innovative (Vishwanath, 2006). Such groups when effective can help create shared mental models of tasks, identify organizational expertise, and reduce the information management burdens that groups face (Hollingshead & Brandon, 2003). However, research has indicated that work groups too often suffer from ineffective knowledge management (Wittenbaum, 2000) and inadequate expertise coordination (Wilkesmann, Wilkesmann, & Virgillito, 2009).

Propelled by such challenges, digital knowledge repositories (DKRs) have become prominent tools for supporting knowledge management and information sharing in the workplaces (Hollingshead, Fulk, & Monge, 2002; Kankanhalli, Tan, & Kwok-Kee, 2005). Digital knowledge repository is a broad term that refers to electronic systems that archive, store, and publish information to support the work of organizational members. Levitt (1996) reported that over two thirds of the Fortune 500 companies already had or were considering implementing DKRs such as corporate intranets within and across their organizations, and their pervasiveness has increased dramatically since then (Kankanhalli et al., 2005).

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The importance of DKRs in today's workplace is twofold. First, given the geographical and temporal constraints inherent in collaborative work, human expertise and interpersonal communication may not always be readily available or possible. People may be reluctant to engage in direct person-to-person information sharing due to busy schedules, inadequate communication channels, or high coordination costs of knowledge transfer. DKRs promise to support knowledge management in lieu of person-to-person knowledge sharing. Second, the abundance and complexity of information available today render orthodox knowledge repositories short of capacity and efficiency. DKRs promise to enrich existing group processes to help manage and derive value from this abundance and complexity. Therefore, it is imperative to understand why organizational members *actually* use DKRs by contributing work-related information to such systems. This study applies and extends transactive memory theory to model simultaneously knowledge-area-, individual-, and group-level factors to explain individuals' information provision to DKRs.

DKRs exist in various forms. A popular example is the intranet. General-purpose, intraorganizational intranets typically allow users to upload, edit, and download files, data, and tools in work-related domains (Lee & Kim, 2009). More advanced features include collaborative editing, real-time updating, and tracking the readership of published documents. DKRs designed for specific purposes can support information dissemination and provide customized expertise for problem solving. Examples of such systems are Answer Garden (Ackerman, 1994) and Answer Garden 2 (Ackerman & McDonald, 1996). Other digital knowledge repositories such as Referral Web (Kautz, Selman, & Shah, 1997) not only store work-related documents and data files but also point to external expertise holders, including both human and nonhuman knowledge sources. Some digital repositories such as Expertise Recommender (McDonald, 2001) and PeCo-Mediator-II (Ogata, Yano, Furugori, & Jin, 2001) implement a recommendation system that provides advice to information seekers about the best or fastest way to find quality information within the organization or community. The Cyber Infrastructure Knowledge Networks on the Web (CI-KNOW) recommender system (Contractor, 2009) taps into knowledge networks and provides recommendations to information seekers about people, documents, data, tools, and workflow streams in geographically dispersed groups and communities.

In recent years, increasing attention has been paid to the adoption and implementation of cloud-based knowledge repositories in organizational contexts in both the popular press (Whadcock, 2009) and academia (Leavitt, 2009; Vouk, 2008). The U.S. Department of Commerce's National Institute of Standards and Technology defined cloud computing as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" (Mell & Grance, 2011, p. 2). Accompanied by the escalating popularity of services such as Google Drive, Amazon Cloud Drive, Apple iCloud, MicroSoft SkyDrive, and Dropbox in the public sphere, organizations also are utilizing company-specific cloud-based knowledge repositories (Chowdhury, 2012). Examples of these cloud-based knowledge repositories include Best Buy's Blue Shirt Nation, McGraw-Hill's Buzz, SAS's Socialcast (internally known as the Hub), Southwest Airlines' SWALife, and Wells Fargo's iCEO system. These systems not only serve as a repository of employees' knowledge and expertise but also provide a networking platform for employees to locate, share, and transfer individually possessed knowledge and information resources. These newly emerged cloud-based knowledge repositories have started to advance or even replace many of the traditional knowledge-storage systems, and hold promise for building environmentally friendly and sustainable knowledge management systems (Chowdhury, 2012). However, regardless of whether organizations are using traditional or new DKRs, questions of why and under what conditions organizational members contribute to these knowledge repositories persist.

With the proliferation of organizational DKRs (Blackman, 2007; Olson, Zimmerman, & Bos, 2008), recent scholarship has called for "fine-grained analysis of how people cognitively process and interact with others' knowledge virtually" (Zammuto, Griffith, Majchrzak, Dougherty, & Faraj, 2007, p. 755). As groups turn to DKRs to seek and share individually possessed knowledge, scholars and practitioners have asked what motivates group members to contribute and share "what they know" to such knowledge management systems (DiMicco et al., 2008). Blair (2002) argued that having a DKR is only a necessary, but not a sufficient, condition for effective and successful knowledge management in organizational settings. Too many organizations implement such systems that are ill-used or unused altogether. Thus, the goal of this study is to unravel the factors that influence organizational members' utilization of DKRs based on transactive memory theory (Wegner, Erber, & Raymond, 1991; Wegner, Giuliano, & Hertel, 1985), a theory that explains how group members encode, store, and coordinate each other's knowledge that can be productively applied to DKRs (for a thorough review of this theory, see Hollingshead & Brandon, 2003; Palazzolo, 2010).

Transactive Memory Theory: A Focus on Information Provision to DKRs

Hollingshead and Brandon (2003) argued that the benefits provided by groups accrue because groups create transactive memory systems that allow for more efficient knowledge work. A transactive memory system (TMS) is a combination of domain-specific knowledge possessed by individual members and a shared understanding of "who knows what" in the group. In a TMS, individuals develop an internal memory of each other's expertise by encoding the subject of a knowledge area and identifying who possess adequate knowledge in that particular area (Nevo & Wand, 2005). In this way, group members are able to label each other's expertise without necessarily knowing the knowledge itself. In a well-developed TMS, group members have specialized expertise only in a few areas, but they have an accurate perception of what each other knows in knowledge areas outside their own specialties. The benefits of such a system include the reduction of overlapped expertise within the group and increased access to larger pools of expertise across more diverse knowledge areas (Hollingshead & Brandon, 2003; Littlepage, Hollingshead, Drake, & Littlepage, 2008).

TMS development depends on three key mechanisms: *expertise recognition*, *information retrieval*, and *information provision*. Expertise recognition is a crucial process wherein group members become aware of and validate others' expertise in the relevant knowledge areas. It is through the expertise recognition process that members are able to encode "who knows what" (Wegner, 1995). The second key mechanism in a TMS development is information retrieval. When group members have internally encoded each other's knowledge and receive work tasks that require knowledge outside their own areas of expertise, they can simply turn to the experts that they have identified for information rather than making an effort to learn the knowledge themselves (Hollingshead, 1998b). The third key mechanism, information provision (also known as *information allocation*), occurs when individual members come across information outside their specialized knowledge area. According to transactive memory theory, members would not take the responsibility for storing and handling such information. Instead, they would provide such information to whom they perceive to be the experts so that the information could be properly stored and retrieved for later use.

Moreland (1999) argued that members' expertise also may reside in nonhuman knowledge repositories such as digital databases or knowledge management systems. Such technology may thus make up the nonhuman components of a TMS. Group members can communicate to provide information directly through interpersonal channels with their colleagues or indirectly by uploading information to a shared resource. Such technologies can support the specialization, retrieval, and provision functions that may reduce the workload of individuals and redundant information within the group, which can support better group performance (Hollingshead & Brandon, 2003; Moreland & Myaskovsky, 2000).

The question of information provision to DKRs is especially important because the models that explain information seeking and retrieval may not apply to information provision (Wilkesmann et al., 2009). For example, organizational trust might exert greater influence on contribution than retrieval because it may be more difficult for contributors to know how their information would be used than for the retrievers to ascertain the credibility of the information. Information seeking and retrieval have received much attention in the group information-sharing literature (Hollingshead, 1998a; Palazzolo, 2005), and providing information is equally important (Moreland, 1999). Instead of aggregating communication activities associated with information exchange, such as providing and retrieving information (cf. Yuan, Fulk, Monge, & Contractor, 2010; Yuan et al., 2005), this study focused on information provision, per the literature on TMS (Moreland, 1999) and recent empirical findings on knowledge transfer (Wilkesmann et al., 2009).

Information provision to DKRs also is of particular importance not only because of the prevalence of the technologies but also because the motivational forces that explain information provision to colleagues may not directly apply to DKRs. Fulk, Schmitz, and Steinfield (1990) argued that "media use is known to be a function of a number of facilitating factors, such as media accessibility, availability of communication partners, experience with the medium, personal style in using media, time and cost advantages, and communication task requirements" (p. 118). Fulk, Monge, and Hollingshead (2005) and Hollingshead et al. (2002) applied transactive memory theory and public goods theory to the study of organizational intranets or shared digital repositories. Subsequent research has examined what motivates people to utilize shared group space and how group members complement each other's expertise by allocating information to and retrieving information from designated group experts (Brandon & Hollingshead, 2004; Palazzolo, 2005; Yuan et al., 2005).

Explaining information provision to DKRs can benefit from modeling multiple levels of analysis. Whereas the bulk of available research in this area tends to focus on individual factors or case studies of contextual factors, this study seeks to examine three levels of analysis and simultaneously model these three levels. Transactive memory systems are by definition group-specific. Hollingshead, Costa, and Beck (2007) argued that understanding information behavior in groups requires investigating (a) the motivations that influence information sharing, (b) the features of the group's social context that may influence information sharing, and (c) the ways those features of context interact.

Information provision also is multilevel in the sense that individuals are likely to provide information differently for different sorts of knowledge. That is, information behavior also varies depending on the characteristics of knowledge areas. For example, a group member may be more willing to share information about one knowledge area (e.g., human relations policy) than another (e.g., confidential work products). Aggregating observations across multiple knowledge areas is a useful research strategy (e.g., Yuan, Fulk et al., 2010; Yuan et al., 2005), but modeling the knowledge-specific nature of information-sharing behaviors can increase the power and precision of explanations of information provision.

A transactive memory theory-based rationale for this research follows, wherein we posit a multilevel model to explain group members' motivation for information provision to DKRs. Transactive memory theory emphasizes the influence of perceptions of expert behavior within the

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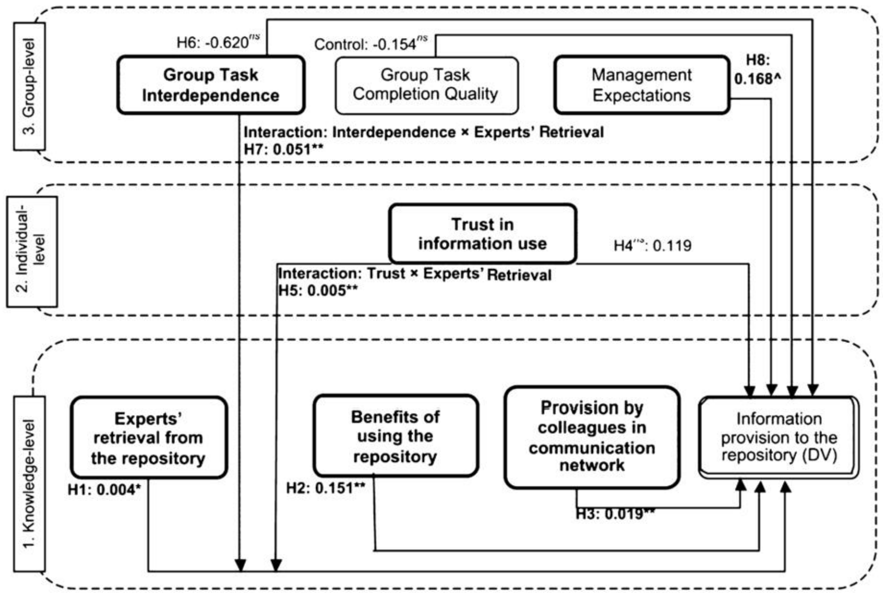

FIG. 1. Multilevel model of information provision to be shared, digital knowledge repositories. Significant results are boldfaced and flagged, $\dagger p < .10$. $*p < .05$. $**p < .01$. Gamma weights (see Table 4) cporresponding to each hypothesis also are provided.

system and perceptions of retrieval of information by experts and colleagues. We apply scholarship on information behavior to build on transactive memory theory explanations of information provision to DKRs across knowledge areas and groups (see Figure 1). An analysis of data from knowledge workers ($N = 208$) nested in work groups ($J = 17$) located in Europe and the United States provides evidence supportive of the model. We conclude with a discussion of the implications of the results for theory and practice.

Transactive Memory Theory Based Explanations of Information Provision

Wegner (1995) argued that group transactive memory systems work like computer networks linking information processors. Each group member has such a cognitive directory of "who knows what" in the group and updates this directory through communication with other group members. Group members coordinate information processing through communication activities, especially information retrieval from and information provision to group experts in specific knowledge areas.

Previous transactive memory research has developed an important distinction between *connective* and *communal* transactive memory systems in organizational contexts (Fulk, Flanagin, Kalman, Monge, & Ryan, 1996; Fulk et al., 2005; Yuan, Fulk, & Monge, 2007). In connective TMS, organizational members seek, share, and transfer information through direct person-to-person communication (Fulk et al., 1996). In contrast, in communal TMS, organizational members have equal and shared access to nonhuman knowledge repositories, and they can publish and retrieve information from these communal knowledge systems without necessarily knowing the contributors and consumers of the published information (Yuan et al., 2007). In this sense, the communal TMS is characterized by a generalized exchange of information through human-to-technology interaction as a replacement for direct interpersonal communication (Fulk, Heino, Flanagin, Monge, & Bar, 2004).

Compared to connective TMS, communal TMS provides organizational members a more flexible and convenient way to share and retrieve information due to decreased social costs and fewer geographical and temporal constraints (Fulk et al., 2004; Yuan et al., 2007). Organizational DKRs serve as alternative and important sources of information and expertise. Organizational members can publish and share information on them whenever and wherever they wish (Yuan et al., 2007). In addition, when experts within the organization are overwhelmed by direct and interpersonal information requests, they can publish and share "what they know" on DKRs from which individual information seekers can be directed to retrieve information. In this way, the time and effort involved in information seeking and sharing are reduced.

Perceptions of Expert Use of DKRs

Experts in a certain knowledge area accessible through interactive media can give others a strong incentive to use the technology (Markus, 1990). Experts may be more likely to contribute to the shared repository to manage the information needs of the entire group, and as more individuals contribute novel information to the repository, others may follow (Carley, 2002). The TMS in the group can be further developed when experts also retrieve and

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make use of information contributed to the shared repository by other members. When people come to know that many experts are retrieving new information from the shared-knowledge repository, they should be more likely to go to the shared repository to provide information as well. Thus, we hypothesize:

> **H1:** Group members' perceptions of experts' information retrieval from the DKR in a given knowledge area are positively related to their information provision to the DKR in that knowledge area.

Support for this hypothesis would provide evidence of the importance of expertise recognition for information provision per transactive memory theory.

Communication-Derived Perceptions of Information Retrieval

Hollingshead and Brandon (2003) stated that interpersonal communication is the central facilitator of transactive memory development. Scholars have long advocated for examining the influence of individuals' social networks on information exchange and knowledge sharing (Haythornthwaite & Wellman, 1998; Yuan, Carboni, & Ehrlich, 2010). Contractor and Eisenberg (1990) forwarded a relational model to study social contagion effects that posited that individuals are likely to influence and be influenced by others in their social network. The social influence and social contagion literatures offer a theoretical perspective to explain how individuals' attitudes, beliefs, and behaviors are influenced by others with whom they have frequent social interactions (Fulk, Schmitz, & Ryu, 1995; Schmitz & Fulk, 1991) and how TMSs develop through social networks (Su & Contractor, 2011). Communication among group members can increase the opportunities for exposure to work-related predilections and practices and therefore can increase the chance of mutual intellectual influence and assistance.

Indeed, transactive memory is "transactive" because it is through communicative processes that knowledge is encoded, stored, and retrieved within the group (Gupta & Hollingshead, 2010). Su and Contractor (2011) found that the driving factors for organizational members to seek and retrieve information from digital sources in work settings were the quantity of information provided by the digital system as well as whether their close colleagues (i.e., coworkers with whom they have frequent social interactions) also were using the digital knowledge sources. When people are exposed to others' preferences or behaviors about provision to the digital repository in a group communication network, they are likely to be influenced by what they are exposed to and consequently become more similar to others in the communication network in the ways they think and behave. Hence,

> **H2:** Group members' perceptions of information provision by colleagues in their communication network to the DKR in a given knowledge area are positively related to their information provision to the DKR in that knowledge area.

Support for this hypothesis would extend current research to include information provision to DKRs, providing support for the communicative processes inherent in TMS development.

Building on Transactive Memory Theory

Transactive memory theory explanations of why individuals provide information to DKRs can be enhanced by the literature on group information behavior. Such explanations may build on perceptions of the TMS itself to include perceptions of knowledge areas, individual preferences, and beliefs about the particular group within which information behavior is taking place.

Benefits of Using Repositories

The free-rider phenomenon commonly found in the use of a shared resource (i.e., using resources without contributing) has been documented in the public goods and collective action literatures (Bimber, Flanagin, & Stohl, 2005; Hollingshead et al., 2002; McLure Wasko & Faraj, 2005). A group's digital knowledge repository is not a public good in the traditional sense (compared to parks, libraries, or streets) but it is accessible and maintained by a group of people who all have some stake in it. The DKR is, in that sense, a public good shared by a particular group of people. The free-rider problem and the motivational mechanisms associated with contributing to public goods in general are likely to apply, and the creation of a DKR to which no one contributes is a principal concern (Hollingshead et al., 2002). However, these public goods mechanisms are likely complicated in the case of "information goods" because users' perceptions of the state of an information goods commons are incomplete and subjective (Fulk et al., 2004, p. 571).

According to public goods theory, the motivation to contribute to public goods is a function of the perceived costs and value of one's contribution (Fulk et al., 1996). Specifically, in the case of perceptions associated with contributing to digital repositories, perceived gain is likely determined by subjective perceptions of the information available in the digital repository (Yuan et al., 2007). Thus, we hypothesize:

> **H3:** Group members' perceptions of the benefits in using the DKR in a given knowledge area are positively related to their information provision to the DKR in that knowledge area.

Support for this hypothesis would confirm the work of Fulk et al. (2005) and Hollingshead et al. (2002) that integrated transactive memory and public goods explanations and the efficacy of modeling TMSs as public goods.

Individual- and Group-Level Factors in Information Provision

Thus far, we have focused on factors specific to knowledge areas. As we argued in the introduction, multilevel models of information provision may provide more robust

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explanations by exploring individual- and group-level factors that may influence the use of DKRs. These factors likely vary from knowledge area to knowledge area, and they likely interact with perceptions of how information is negotiated within groups. Thus, we ask:

> **RQ1:** Will the relationships between information provision and knowledge-area level factors (perceptions of experts' retrieval, information provision by colleagues in the communication network, and benefits of provision) vary from group to group?

Evidence addressing this research question will allow us to begin to explore and explain the multilevel nature of information provision and TMS development.

Individuals' Trust in Information Use

Previous research on knowledge management considers trust a critical factor for explaining information sharing (Kanawattanachai & Yoo, 2002) and building group knowledge sharing culture (Davenport & Prusak, 1998). In the context of transactive memory development, group members' trust in connective and communal knowledge sources should influence how they utilize and coordinate each other's expertise. Group members' trust in connective knowledge sources is related to interpersonal trust, which affects their decision on "with whom to share" and "what to share" within the work group. On the other hand, group members' trust in communal knowledge sources (the focus of this study) refers to their trust in collectively accessible knowledge repositories such as DKRs and how that information will be used once it has been provided.

Because this study focuses on group members' information provision to DKRs, it is important to understand how their provision behaviors would be influenced by their trust in the appropriate use of information that they contribute to the communal knowledge sources. For example, Sarvary and Chard's (1997) case study of the use of a company-wide knowledge management system at Ernst & Young revealed that consultants were hesitant to use and contribute to the knowledge repository because they were concerned about client confidentiality and the inappropriate use of their information shared through the knowledge management system. In TMS, the more people trust that their information will be used appropriately by others on the communal knowledge repository, the less time and effort they will spend on monitoring the use of their contributed information and the more likely they will provide information to DKRs. Thus, we hypothesize:

> **H4:** Group members' trust in the appropriate use of published information on the DKR across knowledge areas is positively related to their information provision to the DKR.

Trust in this sense should directly influence information provision and also moderate the influence of the perceptions of group members.

Trust is not a given in groups but it may be essential to information provision and TMS development. Kraekel (2005) argued that sharing knowledge in an organization may be exceptional to the degree that it occurs at all, especially contrasted with the benefits of withholding knowledge. Wittenbaum, Hollingshead, and Botero (2004) argued that much of the research on information sharing in cooperative groups has assumed cooperativeness and unbiasedness in group work. Group members may not be cooperative due to individual goals and motives during information sharing (Hollingshead et al., 2007). Thus, we hypothesize:

> **H5:** Group members' trust in the appropriate use of published information in the DKR across knowledge areas will moderate the relationship between their perceptions of experts' information retrieval and information provision to the DKR.

Support for this hypothesis might indicate that the variability of expertise recognition's influence on provision at the knowledge-area level can be explained in part by the moderating influence of trust in the later use of information provided.

Group-Level Task Interdependence

Task interdependence is a well-documented component of the group-task environment, which is an important source of preexisting structures of group context (Sharma & Yetton, 2003). Task interdependence is defined as the exchange of materials and information essential to perform organizational tasks. For instance, the use of word processing, spreadsheets, and other personal productivity applications is characterized by low levels of task interdependence whereas the use of information and communications technology innovations such as enterprise resource planning systems is characterized by high levels of task interdependence. Many recent studies have found that high task interdependence is positively related to desirable group processes and outcomes. For instance, high task interdependence has positive effects on virtual group performance (Bacharach, Bamberger, & Vashdi, 2005; Rico & Cohen, 2005), group effectiveness (Hertel, Konradt, & Orlikowski, 2004), job and group satisfaction (van der Vegt, Emans, & van de Vliert, 2001), helping behavior (Allen, Sargent, & Bradley, 2003), and group loyalty and prosocial behavior (Ramamoorthy & Flood, 2004). Hollingshead (2001) argued that the formation of TMSs depends to some degree on interdependence. Thus, we hypothesize:

> **H6:** Group-level task interdependence is positively related to group members' information provision to the DKR in a given knowledge area.

In a tightly knit group where task interdependence is high, information exchange among group members becomes even more critical, encouraging group members to understand, coordinate, and make use of each other's expertise. Members in such a group are more likely to actively develop and maintain their group TMS through information provision.

When such a group uses digital repositories to support its TMS, if experts in certain knowledge areas are actively getting information through the shared repositories, the group in general will be more likely to use this supplemental digital way to support such expertise specialization and development by providing more information to the repositories. Task interdependence should operate not just directly on information provision but also should mean that perceptions of experts' retrieval will have more influence as well (Hollingshead, 2001). Thus, we hypothesize:

H7: Group-level task interdependence will moderate the relationship between group members' perceptions of experts' information retrieval and their information provision to the DKR in a given knowledge area.

Support for this hypothesis also might indicate that group-level task interdependence explains in part the variability in the relationship between knowledge-area factors and provision to DKRs.

Management Expectations

Knowledge creation is context-dependent and requires specific leadership. If DKRs are to support transactive memory systems, group members must use them. Although leadership support for technology is not sufficient for adoption and use, it still may have some influence on information provision. Leaders act as prominent communicators in the diffusion and use of media in the workplace (Contractor & Eisenberg, 1990). Project group leaders likely influence other group members' adoption and use of a communication technology because they tend to be hierarchically powerful and structurally central communicators. When group members perceive strong management support for using a communication technology, they should be more likely to adopt as well.

Brandon and Hollingshead (2004) argued that a well-developed transactive memory should have high levels of accuracy (i.e., the degree to which group members have accurate perceptions about others' knowledge), sharedness (i.e., the degree to which members have a shared representation of the transactive memory system), and validation (i.e., the degree to which group members participate in the transactive memory system). For validation to occur, members need to accept the responsibility of contributing knowledge and expertise desired by others and making them accessible to other members, either interpersonally or electronically. Information provision to the DKR contributes to the validation process by making group members' expertise accessible and available to other group members beyond temporal and geographical constraints. As Brandon and Hollingshead argued, "When there is correspondence between expectations and actions, there is validation" (2004, p. 640). Thus, when organizational management expects its employees to utilize the DKR for contributing and sharing knowledge, individual members are likely to take such actions. Such correspondence helps develop and validate an effective transactive memory system. Thus, we hypothesize:

H8: Management expectations for using the DKR are positively related to group members' information provision to the DKR in a given knowledge area.

We now turn to the methods used to test the model suggested by these hypotheses.

Methods

Data were collected from 208 individuals working in 17 work groups (5–20 members in each group) across the United States and Western Europe. All participants worked in intact groups (i.e., preexisting work groups formed to complete real-life work tasks in real-world organizations). Unlike ad hoc groups assembled to perform simulated tasks in lab settings (which is a popular approach taken in experimental research), members of these 17 work groups had been working together for at least 6 months at the time of this study ($M = 4.23$ years, $SD = 4.75$ years). These groups came from a wide array of fields, including legal, research, aerospace, manufacturing, military, public relations, and consulting industries. The use of data from intact groups is a principal strength of this study in that it addresses calls for testing experimentally established constructs in real-world settings. Table 1 summarizes the demographics of these participating groups.

In each group, members had equal access to a DKR that was established and maintained by the organization. Some of these DKRs took the form of an organizational intranet, and others existed in the form of digital databases or web folders on shared network drives. Membership in the groups and access to a DKR did not overlap. Each group had its own DKR. On average, group members reported infrequent usage of the DKR during a typical work week ($M = 1.993$ and $SD = 0.993$) on a scale of 0 (*Never*) to 4 (*Very Often*).

When participants did report using the DKR, they indicated that they used them to obtain information needed for their work that was not available elsewhere; to locate someone who could get them needed information for their work; to find out who was knowledgeable about a particular problem, issue, or topic; to identify experts in a particular area; and to provide information to the DKR. Although the specific names and formats of these DKRs varied from group to group, they all served as a digital storage of organizational knowledge and provided multiple gateways to organizational resources such as data, files, documents, tools, solutions, deliverables, and other work-related information. These technologies exemplify the variety of DKRs that currently prevail in organizational knowledge management.

Data were collected through a web-based Knowledge Asset Mapping Exercise (KAME). KAME is based on a network data-collection tool called *IKNOW* (Contractor, Zink, & Chan, 1991). Prior to conducting the KAME in each work group, group leader(s) or senior group member(s) completed a pre-interview protocol and identified key group tasks, knowledge areas utilized in the group's daily tasks, and the basic functions and structures of shared DKRs. A

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TABLE 1. Demographics of participating groups.

Group	Group size (n)	Knowledge areas	Location	Gender F/M	Age *M*	Age *SD*	Years in group *M*	Years in group *SD*
1	11	5	USA	9/2	40.73	14.66	4.98	6.97
2	13	5	USA	1/11(1[a])	42.85	10.48	6.11	6.31
3	13	5	USA	1/12	44.00	9.83	4.31	2.11
4	16	6	Europe	6/10	33.44	7.54	0.90	0.55
5	9	6	Europe	6/3	33.33	3.28	2.42	1.07
6	17	6	USA	4/13	43.44	5.93	0.61	0.34
7	10	6	USA	4/6	54.30	6.36	3.18	2.42
8	5	5	USA	2/2 (1[a])	41.50	9.04	1.46	0.42
9	12	7	Europe	1/6 (6[a])	30.67	2.94	1.58	0.63
10	12	5	Europe	5/7	29.08	2.31	2.42	1.17
11	8	8	Europe	3/5	30.00	2.20	2.38	1.14
12	11	7	Europe	5/6	30.10	4.40	1.73	1.18
13	13	5	Europe	2/11	47.10	7.61	9.22	4.41
14	20	6	Europe	2/18	33.25	7.62	2.75	4.65
15	12	6	Europe	2/10	34.91	7.69	5.36	5.12
16	13	7	Europe	5/8	33.46	4.03	3.70	3.19
17	13	4	Europe	2/11	29.85	1.41	2.51	1.35

Note. Of all 11 European work groups, only one group was composed of members of heterogeneous national origins. All other groups were composed of members of homogeneous national origins. Because the data collection was group-based, only groups that had all members complete the survey were used. Therefore, the response rate in each group was 100%, although a very small percentage of group members chose not to answer a few of the questions.
[a]Some participants did not answer the question about gender.

TABLE 2. Descriptive statistics and zero-order correlations for knowledge-area-, individual-, and group-level variables.

	n	*M*	*SD*	1	2	3	4	5	6	7
1. Information provision (deviance)	1,207	0.93	1.22							
2. Experts' retrieval	1,207	23.22	29.6	0.443**						
3. Benefits of provision	1,207	1.74	1.65	0.304**	0.383**					
4. Provision by colleagues in communication network	1,207	21.99	43.01	0.633**	0.562**	0.320**				
5. Trust in information use	208	3.14	0.68	0.087**	0.123**	0.091**	0.000			
6. Group task completion quality	17	1.86	0.9	0.150**	0.097**	0.095**	0.101**	0.003		
7. Management expectations	17	5.29	1.43	0.333**	0.420**	0.313**	0.392**	0.042	0.591**	
8. Group task interdependence	17	0.59	0.12	−0.059*	0.036	−0.005	−0.091**	0.296**	0.175**	0.239**

Note. These results do not account for the fact that knowledge-level and individual-level data might be affected by nesting. They provide a rough sense of the data, but should be interpreted with caution.
$*p < .05$. $**p < .01$.

KAME was customized for each group, and a unique invitation was sent to each group member.

Network data collection is labor-intensive, but the results are valuable (Contractor, Wasserman, & Faust, 2006; Wasserman & Faust, 1994). Network data collection in this case meant asking each member of the group to answer questions about his or her relationships with other members of the group and nonhuman nodes such as DKRs as well as completing orthodox questionnaire items.

However, the intensive nature of the collection of network data often necessitates the use of single-item measures. Although the use of single-item measures is not ideal and requires caution in interpretation, it is not always inappropriate. Having more items does not guarantee reliability (Embreston, 1996). Single-item measures can perform as well as do multiple-item measures (Gardner, Cummings, Dunham, & Pierce, 1998; Wanous & Reichers, 1996). A brief description of each measure follows. The level of analysis is given in parentheses.

Measures

Information provision (knowledge-area level). Participants used a 5-point Likert scale (*never*, *seldom*, *sometimes*, *often*, *very often*) to identify how often they provided information to the DKR in each of the group-specific knowledge areas.

Experts' information retrieval (knowledge-area level). This variable referred to group members' perceptions of expert colleagues' retrieval from the intranet in each knowledge area. It was calculated using network data as the multiplication of member i's perception of member j's knowledge level (including none, beginner, intermediary, and expert) in knowledge area k and how much information

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j retrieves from the intranet in knowledge area *k* on a scale of 0 (*none*) to 4 (*very often*). The "product" function for matrix operation in UCINET 6 (Borgatti, Everett, & Freeman, 2002) was applied to each pair of corresponding knowledge level and information retrieval matrices. Each multiplication result indicated each member's perception of information retrieval from the DKR by experts in his or her network in each knowledge area.

Benefits of use (knowledge-area level). Participants responded to "How much do you believe the [name of DKR] is beneficial to you in each knowledge area?" on a scale of 0 (*none*) to 4 (*a lot*).

Information provision by colleagues (knowledge-area level). This variable measured the level of information provision to the DKR in each knowledge area by someone with whom the participant communicated. It was calculated using network data as the product of each member *i*'s perception of member *j*'s information provision to the DKR in each knowledge area and how often member *i* communicates with member *j* on a scale of 0 (*never*) to 5 (*once per day*) in UCINET 6. Each multiplication result indicated each member's perception of information provision to the DKR by other members in his or her network.

Trust in information use (individual level). Participants were asked to report their expectations about how information would be used by others with access to the DKR based on their experience and knowledge to date. They responded to three items regarding trust of colleagues, information use, privacy, and system safety on a scale of 1 (*strongly disagree*) to 5 (*strongly agree*). The items were "I trust my colleagues to use information appropriately when it is made available to them on the [name of DKR]," "I am worried about how the information will be used after I upload it onto the [name of DKR]," "The [name of DKR] is a threat to my privacy," and "Competitors will not receive information provided on the [name of DKR]." The average of the scores from the items for each person was used as individual-level trust ($\alpha = 0.67$).

Management expectations (group level). Participants were asked to report to what extent all the information that they provided to the DKR was due to requirements by management, and the provided information was specifically required by management. The question used a 10-point scale ranging from 1 (*none*) to 10 (*totally*).

Task interdependence (group level). Participants were asked to report whether their key group tasks were interrelated by checking the box for each pair of interrelated tasks. The value for each entry was either 0 (*no interrelation*) or 1 (*interrelation*).

Quality of group task completion (group-level control variable). We included group task completion quality to control for group performance. The relationship between performance and information behavior is likely to be recursive to some degree. High-performing groups may share information because they are high performers, and become high performers because they share information (e.g., see the recursive relationship between job performance and job satisfaction: Judge, Thoresen, Bono, & Patton, 2001). As the interest of this study focused on information provision rather than on performance, we have included it as a control variable. Participants were asked to rate the quality with which the group accomplished tasks irrespective of the time that they spent on them. The 5-point scale ranged from 0 (*very poor*) to 4 (*excellent*).

The descriptive statistics of all variables, as well as their zero-order correlations, were summarized in Table 2.

Analysis

The model proposed to explain information provision to the DKR (see Figure 1) ties together relationships at the knowledge-area, individual, and group levels of analysis. Group members' perceptions of a particular knowledge area were in part influenced by their perceptions of their other knowledge areas and their presence in a particular group. In other words, members' perceptions of each knowledge area were in part driven by something distinctive to that knowledge area (Level 1), but also distinctive to each individual (Level 2) and each work group (Level 3). Including knowledge area as a level of analysis allowed us to control for the nonindependence in participants' perceptions of each knowledge area without losing information by aggregating their perceptions across knowledge areas. We were able to investigate how relationships between information provision and knowledge-area specific variables varied from group to group. Whereas individual-level data described the characteristics of individuals (e.g., how much trust a person has in a DKR) and group-level data pertained to qualities of the group as a whole (e.g., how strong managements' expectations are for DKR use in this group), data at the knowledge-area level referred to measures specific to each group-specific knowledge area.

Prior to responding to the KAME, each group had identified several key knowledge areas essential for task completion. Each KAME was customized based on the name and number of knowledge areas solicited from the groups. There were a total of 99 knowledge areas across these 17 groups, ranging from four to eight knowledge areas in each group. The KAME measured variables specific to each knowledge area. We also asked questions about individuals' perceptions of their DKRs, and there were a total of 208 individuals across these 17 groups. Based on the nested nature of the data, we tested the model proposed using HLM 6.05 (Raudenbush, Bryk, & Congdon, 2007).

Testing for the existence of a multilevel structure. Per Raudenbush and Bryk's (2002) recommendations, we first investigated the hierarchical structuring of the dependent variable by constructing an intercept-only model of

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TABLE 3. Multilevel model building to predict information provision.

Model	Variables added	Deviance	Parameters	δDeviance
1	Intercept-only model	3342.806	4	–
2a	Experts' retrieval (Level 1)	3269.567	5	73.239 (1)**
2b	Benefits of provision (Level 1)	3233.947	6	35.620 (1)**
2c	Provision by colleagues in communication network (Level 1)	2946.770	7	287.177 (1) **
3	Trust in information use (Level 2)	2941.954	8	4.816 (1)*
4	Task interdependence, task quality, management expectation (Level 3)	2940.228	11	1.726 (3)
5a	Experts' retrieval random slope	2922.746	13	17.482 (2)**
5b	Benefits random slope	2896.354	16	26.392 (3)**
6	Interaction (Trust × Experts' Retrieval)	2888.631	17	7.723 (1)**
7	Interaction (Task Interdependence × Experts' Retrieval)	2881.747	18	6.884 (1)**

Note. The change in deviance (δdeviance) is distributed as a χ^2 with *df*s equal to the difference in the parameters between models (indicated in parentheses).
$^*p < .05$. $^{**}p < .01$.

information provision (a model of the dependent variable without predictors). The results showed that the variance of information provision could be decomposed into three levels (see Table 4). To provide an indicator of the strength of associations at each level, intraclass correlations (ICCs) were calculated. An ICC may be interpreted as the expected correlation between the responses of two randomly chosen units at each level. The ICC for the group level is calculated by dividing the variance at the group level by the total variance, and the ICC for the individual level is calculated by dividing the group and individual-level variance by the total variance. At the individual level, the expected correlation would be influenced not only by individual differences but also by group differences (Hox, 2010, p. 32). The ICC at the individual level (Level 2) was .50, indicating a high degree of association within each individual's information provision across various knowledge areas. The ICC at the group level (Level 3) was .22, again indicating a high degree of association on information provision between individuals within each group. Per Hayes' (2006) recommendation for multilevel modeling, when ICCs exceed 0.05, the results confirm it as an appropriate and necessary strategy.

Model building for hypothesis testing. To explore the relationships described in the hypotheses, this study developed an overall model based on the theoretical predictions using the procedure outlined by Hox (2010), which tests the incremental improvement offered by each theoretically important addition to the model. Each immediately preceding model was used as the point of comparison, beginning with the intercept-only model (see Table 3). In the construction of these models, all explanatory variables were grand-mean centered. Comparisons between the models were made by examining the change in deviance. Test of significance for comparisons between models and at Levels 1 and 2 used a standard alpha level ($\alpha = .05$), but given the exploratory nature of the study and the limited power at Level 3, we used a slightly less conservative standard at that level ($\alpha = .10$). The final model integrates all the variables and is reported in Table 4.

Results

Incremental Model Building: Variable Blocks

As shown in Table 3, the incremental model building improved on the intercept-only model. Although the straightforward use of variance explained is somewhat complicated in multilevel analysis, estimates of variance accounted for provide an indicator of the explanatory power of a model (Hox, 2010). Together, the indicators explained a substantial amount of the variance in information provision. The final model (Table 4) explained 29, 54, and 13% of the variance at the knowledge-area (Level 1), individual (Level 2), and group (Level 3) levels, respectively.

To investigate the relationship between information provision and perceptions of experts' retrieval (H1), individual benefits (H2), and information provision by colleagues (H3), each explanatory variable was added at Level 1 (Models 2a–2c, Table 3). Each addition built significantly on the previous model, per the changes in model deviance, $\delta\text{Deviance}_{2a,2b,2c} = 73.239, 35.620, 281.177$, $p < .05$. Hypothesis 4 suggested that trust in how information would be used would help explain the propensity to provide information. Trust, the only individual-level explanatory variable, was added in Model 3. It added significantly, $\delta\text{Deviance}_3 = 4.816$, $p < .05$, to the model containing all the Level 1 variables. Next, the contributions of the group-level (Level 3) variables were included. Although none of these variables added significantly to the previous model, these group-level variables were retained, Model 4, $\delta\text{Deviance} = 1.726$, $p > .05$, because cross-level interactions might help explain the variance at each level, and in the final model, the contribution of these variables might be made clear (Cohen, Cohen, West, & Aiken, 2003).

Incremental Model Building: Random Slopes and Cross-Level Interactions

To address RQ1, random slopes for the Level 1 indicators were added at Level 3 to see if the relationship between the Level 1 predictors varied from group to group. We tested

TABLE 4. Multilevel analysis of information provision: intercept-only and final models.

Predictor	Intercept-only model	Final model	
Fixed components	Coefficient	Coefficient	*SE*
Intercept, γ_{000}	0.885**	1.034**	0.133
Experts' retrieval (H1), γ_{100}		0.004*	0.001
Provision by colleagues (H2), γ_{200}		0.019**	0.001
Benefits of provision (H3), γ_{300}		0.151**	0.042
Trust in information use (H4), γ_{010}		0.119	0.063
Trust × Experts' Retrieval (H5), γ_{110}		0.005**	0.002
Task interdependence (H6), γ_{003}		–0.620	0.760
Task Interdependence × Experts' Retrieval (H7), γ_{103}		0.051**	0.016
Management expectations (H8), γ_{002}		0.168†	0.080
Group task completion quality (control), γ_{001}		–0.154	0.127
Variance of Random Components			
Experts' retrieval (random slope), u_{10}		0.000001**	
Benefits (random slope), u_{20}		0.0211**	
Knowledge-level variance component, e	0.708	0.504	
Individual-level variance component, r_0	0.394**	0.182**	
Group-level variance component, u_{00}	0.317**	0.275**	

Note. Explanatory variables were grand mean centered. The formula for the final model may be written as: Predicted Information Provision = γ_{000} + γ_{001}TASKQUAL + γ_{002}MGT + γ_{003}TASKITDP + γ_{010}TRUST + γ_{100}ER + γ_{110}TRUST*ER + γ_{103}TASKITDP*ER + γ_{200}Benefits+ γ_{300}COP + u_{10}ER + u_{20}Benefits + u_{00} + r_0 + e.
†$p < .10$. *$p < .05$. **$p < .01$.

each knowledge-area level variable separately. We then added those that on their own had added significantly to the model. The data only supported two random slopes: experts' retrieval, Model 5a, δDeviance = 17.842, $p < .05$, and individual benefits, Model 5b, δDeviance = 26.392, $p < .05$.

Cross-level interactions (H5 and H7) were tested to explain this group-to-group variance. We tested interactions between each of the knowledge-area variables and each of the individual- and group-level variables. Benefits of use and information provision by colleagues did not significantly interact with any of the individual- or group-level variables. Management expectations did not significantly interact with any of the knowledge-area-level variables. For brevity, our discussion of potential interactions will focus on those confirmed in the data; interactions between trust and perceptions of experts' retrieval, Model 6, δDeviance = 7.723, $p < .05$, and task interdependence and experts' retrieval, Model 7, δDeviance = 6.884, $p < .05$, were confirmed.

Hypothesis Testing

At the knowledge-area level (Level 1), consistent with H1, the perception that experts retrieve information from the DKR in a certain knowledge area was positively related to information provision to the DKR in that knowledge area, $\gamma_{100} = 0.004$, $SE = 0.001$, $p < .05$, but that relationship may be best understood in the context of cross-level interactions (discussed later). To put that in context, a 1 *SD* increase in perceptions of experts' retrieval would result in a 0.12 (or a 10% of 1 *SD*) increase in information provision. A significant positive relationship was found between information provision by colleagues in one's communication network and the dependent variable, $\gamma_{200} = 0.019$, $SE = 0.001$, $p < .01$, which provided support for H2. A 1 *SD* increase in information provision by colleagues would result in a 0.82 (or a 67% of 1 *SD*) increase in information provision. Consistent with H3, perceptions of the benefits of using the digital repository in a certain knowledge area were positively related to information provision to the DKR in this area, $\gamma_{300} = 0.151$, $SE = 0.042$, $p < .01$. A 1 *SD* increase in benefits would result in a 0.25 (or a 20% of 1 *SD*) increase in information provision.

At the individual level (Level 2), consistent with H4, one' trust on the appropriate use of information published on the DKR was related to one's information provision to the DKR in an interaction between trust and experts' retrieval. At the group level (Level 3), consistent with H8, management expectations for the use of the DKR was positively related to information provision, $\gamma_{002} = 0.168$, $SE = 0.080$, $p < .10$. However, this variable met only an exploratory standard for significance. A 1 *SD* increase in management expectations would result in a 0.24 (or a 20% of 1 *SD*) increase in information provision. There was no significant direct effect of either group task interdependence (H6) or group task completion quality (control); however, providing support for H6, task interdependence and experts' retrieval did interact to predict information provision to the DKR.

Interaction Effects

We report interactions (see Figure 2) following Cohen et al.'s (2003) recommendations. In support of H5, the data confirmed an interaction between trust and experts' retrieval. For individuals with relatively lower trust (i.e., 1

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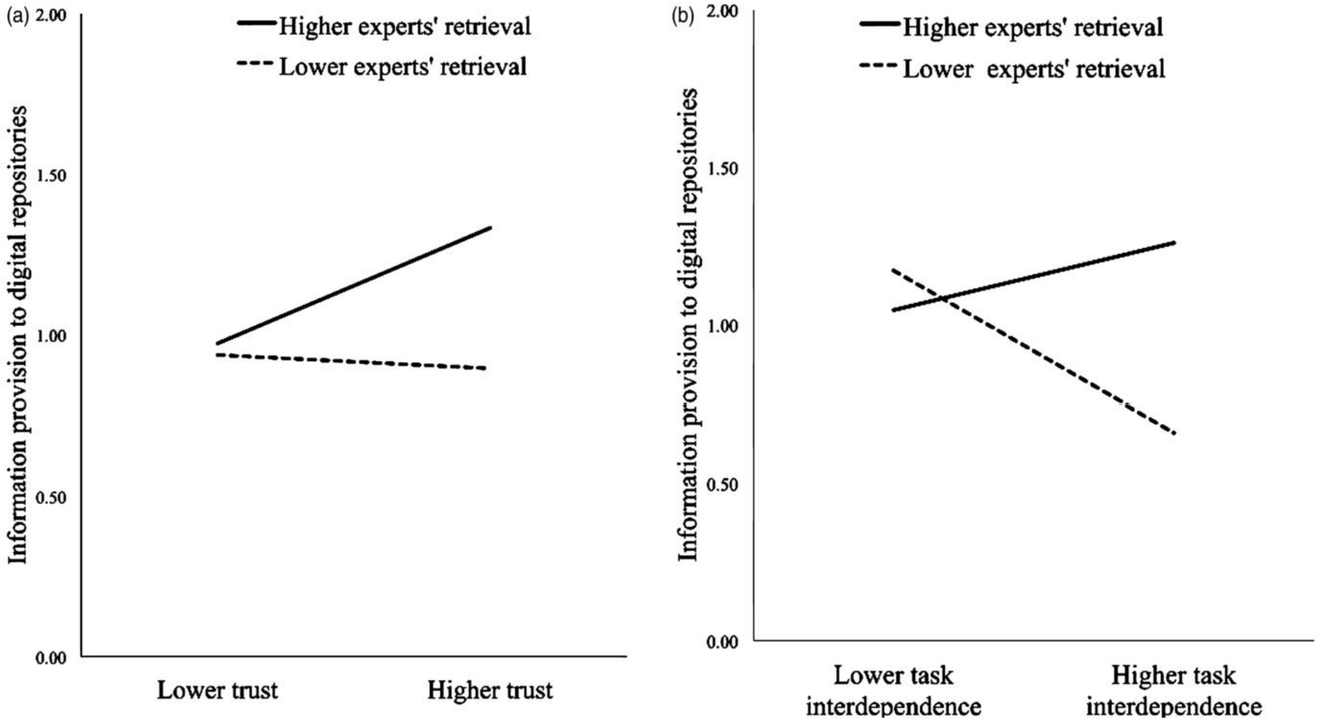

FIG. 2. Interaction between trust and experts' retrieval on information provision to be shared, digital knowledge repositories. Lower and higher values were defined as −1 and +1 *SD* from the mean of the variable (a). Interaction between task interdependence and experts' retrieval on information provision to be shared, digital knowledge repositories. Lower and higher values were defined as −1 and +1 *SD* from the mean of the variable (b).

SD below the *M*, 2.46), the perception of how much experts retrieved information from the DKR did not matter as much. However, for individuals with relatively higher trust (i.e., 1 *SD* over the *M*, 3.82) the perception that experts were more likely to retrieve information from the DKR was associated with participants' increased information provision to the DKR (Figure 2a). Second, the data confirmed an interaction between experts' retrieval and task interdependence, which supported H7. In groups with relatively lower task interdependence (i.e., 1 *SD* below the *M*, 0.47), the perception of how much experts retrieved information from the DKR did not matter much. However, in groups with relatively higher task interdependence (i.e., 1 *SD* over the *M*, 0.71) the perception that experts were more likely to retrieve was associated with participants' increased information provision to the DKR (Figure 2b).

Discussion

Results of this study offer support for the proposed multilevel model of information provision to shared-knowledge digital repositories based on transactive memory theory and related scholarship. In work groups, transactive memory systems (as manifested in the influence of experts' retrieval and colleagues' provision) influenced individuals' contributions to DKRs. Whereas much of the transactive memory theory research to date has been conducted in laboratory settings, these results provide confirmation of transactive memory systems in real organizational work groups. Members in real-life work groups drew on what they knew about "who knew what" to make choices about information seeking and provision. Consistent with concerns about the actual use of DKRs, participants reported providing information to DKRs relatively infrequently; however, these results indicate reasons why information provision occurs when it does.

Implications for Theory

Transactive memory mechanisms varied at multiple levels of analysis. Multilevel modeling proved an appropriate and elegant analytical strategy for investigating information provision as driven by knowledge-area, individual-, and group-specific factors. As an approach, it answered calls for frameworks that associate work context and work behaviors (Monge & Contractor, 2003). The strong intraclass correlations meant that the information behaviors studied were specific in part to the levels of analysis under study. The multilevel approach helped disentangle the explanatory power of multiple theoretical explanations (Monge & Contractor, 2003). The results confirm the efficacy of transactive memory theory for explaining information behavior at multiple levels of analysis and provide further warrant for the simultaneous examination of multiple levels of analysis in the study of group information behavior (Hollingshead et al., 2007).

Transactive memory mechanisms varied from group to group. Transactive memory mechanisms may have more or less influence on information provision depending on group context. An important contribution to the study of group information behavior was the observed variability in the relationships between (a) experts' retrieval and information provision and (b) perceived benefits and information provision. Cross-level moderators helped explain the variability in the relationship between experts' retrieval and information provision (discussed later); however, we were unable to discover interactions that explained the variability in perceptions of benefits and information provision from group to group. In some cases, seeing provision as beneficial mattered, and in some cases it did not.

Influence of benefits of use. Scholars, designers, and implementers of DKRs often take as a given the rational belief that individuals will use DKRs when they feel it is in their own interest to do so. In these data, the intensity of the relationship between benefits varied extensively. Calculating a 95% confidence interval for the multilevel estimator from group to group (Hox, 2010, pp. 18–19) suggests that the average value of 0.151, $\gamma_{300} = 0.151$, $SE = 0.042$, $p < .01$, could range from as low as –0.133 in some groups to as high as 0.436 in others.

Explaining the features of groups that shape this fundamental aspect of motivation to provide information should be an essential concern of future research. Although we explored cross-level interactions between individual- and group-level variables and benefits, these data offered no concrete explanation of why the relationship between benefits and provision varied. However, given the relatively low power at the group level, the potential value of the variables in this study should not be abandoned. Transactive memory theory suggests that perceptions of benefits in knowledge systems are still grounded in expertise recognition and specialization. In groups with highly developed TMSs that integrate DKRs, perceptions of benefits may be more positively related to information provision because the DKR is viewed as part of a communal TMS. In such a group, the view may be that everyone benefits when everyone contributes. A negative relationship between the benefits of use and information provision may occur in those groups where DKRs are not viewed as an information good or where providing information is seen as a hassle, inverse to the benefits of the system.

Task interdependence, experts' retrieval, and information provision. Two cross-level interactions were confirmed that could explain the variability in the relationship between experts' retrieval and information provision. Consistent with transactive memory theory (Hollingshead, 2001), interdependence of tasks within a group shaped how much perceptions of experts' retrieval mattered for information provision. In groups without task interdependence, perceptions of experts' retrieval had less impact. This cross-level interaction is supportive of the view of TMS development as contingent on the tasks at hand. Without interdependence, group members may not be motivated to provide information regardless of their sense of experts' use of the information published on the DKR. Expertise recognition and its effects on information provision—essential TMS mechanisms—depend on the necessity of expertise recognition in the first place.

Trust, experts' retrieval, and information provision. Perceptions of experts' retrieval had a stronger influence on information provision when the individuals reported trusting in the reliability of information provided to DKRs. Information withholding is likely linked to factors other than trust, but the importance of the sort of trust under investigation may be of particular importance to the study of information provision to nonhuman entities in TMSs. Trust ranged in these data from 1.67 to 4.33, suggesting that trust in how information would be used was not uniform, confirming the argument that taking a prosaic views of groups is not an appropriate assumption (Kraekel, 2005). Putting information in a DKR involves relinquishing control of that information in a way that is different than sharing information with a colleague. The task of making information explicit (formalizing, writing, etc.) for provision to a DKR raises concerns about the life of information once it is shared. Trust in how the information would be used once posted to the DKR moderated the influence of TMS mechanisms. Taking these two cross-level interactions into account reduced the variability in experts' retrieval from group to group. With these interactions in the model, a 95% confidence interval for the estimator of perceptions of experts' retrieval from group to group, 0.004, $\gamma_{100} = 0.004$, $SE = 0.001$, $p < .05$, indicated a range from 0.002 to 0.005.

Extending transactive memory theory to include nonhuman elements. An important contribution of this study was the adaptation of theories previously applied only to human-to-human interaction to TMSs that include nonhuman nodes, DKRs. The great promise of knowledge management technologies depends on the social as well as material construction of the technologies. Ramirez and Zhang (2007) argued that the entry of ICTs into work groups can have profound effects on relationships in groups. These groups' use of a shared DKR depended on the perceptions of those relationships—the network of other group members using the DKRs.

Communication drives TMSs. The transactive nature of group information processing tied together much of these results. The communication networks in the groups influenced information provision. Perceptions of individuals' colleagues' use of the DKR was directly positively related to information provision. Group members' provision mimicked the provision of those with whom they communicated more.

Communication also may explain the importance of task interdependence as a moderator of the influence of

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perceptions of experts' retrieval. In groups with higher task interdependence, group members may be more likely to have frequent interactions with each other; thereby, they may be likely to have more interest, stake, and more chance of knowing how colleagues are using the DKR. When group task interdependence is higher, one's perception that many experts actively retrieve from the DKR is even more likely to motivate one to provide information to the DKR. However, in groups with high task interdependence, if experts' retrieval from the DKR is low, one's information contribution to the DKR is likely to be low as well. This might be due to higher usage by experts of alternative communication channels other than the DKR. The moderating role of task interdependence may mean that the influence of experts' retrieval depends on the nature of the task *and* the communicative efforts required to accomplish it.

It is likely that task interdependence and intragroup information sharing are recursively related. Whereas these data show that high task interdependence may necessitate and trigger an enhanced level of information sharing among group members, note that frequent and sustained information-sharing relationships may in turn strengthen task interdependence within the group. Failures in information sharing may encourage groups to operate in ways that maintain the independence of tasks.

Transactive memory mechanisms may be knowledge-specific. The strong intraclass correlation at the individual level indicated that much of how these participants dealt with information was individual-specific and applied across knowledge areas. However, there was still significant knowledge-area-level variation. Information behavior was not just specific to individuals but also specific to the sort of information with which they were working. The demonstrable efficacy of modeling information behavior specific to *particular* knowledge areas also is an important insight for future research and practice. Work-related knowledge has become so specialized that each knowledge area entails intrinsic characteristics and properties. The differentiation of these knowledge areas requires different ways to store, archive, retrieve, and transfer such knowledge. Individuals' information-provision behaviors cannot be assumed uniform across different knowledge areas, yet our interest is often in explaining what is true of information behavior across knowledge areas.

Implications for Practice

Organizations may be quick to embrace new knowledge management technologies such as DKRs, but getting organizational members to use the technologies is a persistent challenge. Technically functional, but unused or underused, information systems carry a high cost. According to a large-scale analysis of 400 companies and their use of knowledge management systems, Koenig (2001) found that 85% of the firms where knowledge management systems were in place reported that such systems failed to meet their expectations. It is not clear that the mere use of digital knowledge management tools will translate into performance improvements, per se. We included the quality of task completion as a variable to consider information behavior controlling for performance. In the final model, information allocation was not significantly related to quality of task completion, $\gamma_{200} = -.154$, $SE = 0.127$, $p = .24$. Use is, however, a prerequisite to the sorts of benefits promised by such technologies.

Technology giants such as Microsoft, IBM, BEA, and Google have started marketing new software to address the problems of traditional DKRs with new strategies such as improving search functions, deleting old or duplicated content, and using social networking tools (Blackman, 2007). It is not yet clear if these new features will encourage more use. In these data, the DKRs were likewise not used too frequently; however, the results provide insights that might be used to encourage information provision to DKRs.

Traditional incentives may not work for DKRs. The variability in the relationship between the benefits of a DKR and provision to a DKR means that the balance of self-interest versus cost does not always apply. Creating straightforward incentives for providing information to DKRs may not work in all groups. A transactive memory theory based explanation confirmed in these data highlights instead the importance of the patterns of day-to-day group information management.

Communal DKRs depend on communication. It may be tempting to conceive DKRs in communal transactive memory systems as replacing direct interpersonal communication, and although that likely happens to some degree, the use of communal DKRs still depends on interpersonal communication. The DKRs investigated here were communal in the sense that they were electronic repositories for information for later use by group members. The role of communication in connective transactive memory systems is inherent. The point of a connective transactive memory system is to enable communication between "who knows what." However, communication with colleagues who provided information still had a direct positive relationship with information provision to *communal* DKRs. We use communication to come to know *who knows what*, and communication creates relationships through which we establish *why we want to know who knows what* and why we might provide information to a DKR.

Limited effects of management expectations. Our results confirmed what is well-understood in the implementation of new technology (Leonardi, 2009): Management expectations may be necessary, but they are not sufficient to engender the use of knowledge management technologies. Recent studies have suggested, for example, that managers should encourage and facilitate channels for contributors to receive feedback about how and in what context others use published information on the intranet (Bock, Rajiv, & Qian, 2008) to encourage use. Yet, compared to other factors,

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management expectations only weakly predicted information provision. Instead, the mechanisms of TMS development and social networks offer more robust factors that organizations should consider in designing and implementing DKRs. Managers may have a stronger influence on how users interact with each other and with DKRs (Aakhus, 2007; Aakhus & Jackson, 2005). Making choices about how to influence such interaction may be enhanced by understanding DKRs in relation to existing communication networks and transactive memory systems.

Assessment should tailor DKRs to existing TMSs and social networks. Knowledge mapping tools such as C-IKNOW (Contractor, 2009; Contractor, O'Keefe, & Jones, 1997) may be used to assess existing TMSs and social networks to influence the design and implementation of DKRs. For example, a team building a DKR might want to elect features that support existing transactive memory systems. A team that depends on sharing information from person to person may want features that support the formation of connective transactive memory systems. Designers and implementers should at the very least consider if they want to support existing patterns of use or encourage new ones. Any new technology may play a role in the development of new patterns of use (even one intended only to encourage existing patterns), but the question is important for those who might hope to improve group information management through technology. The change management efforts that accompanied implementation would be different.

This study confirms that such assessment should take into account features of the group context (Bock et al., 2008; Hollingshead et al., 2007) such as task interdependence. Assessment also should account for the fact that information behavior and, in particular, the factors that influence information provision vary from knowledge area to knowledge area. Assessment that begins by enumerating the multiple knowledge areas relevant to a group's work may more effectively provide insights for design and implementation. By not glossing the difference between knowledge areas, potential functionality useful in one knowledge area but not in others will not be lost. Tools that allow for multilevel, network data collection about the existing communication networks of groups are particularly valuable.

Application to social media tools for user-driven content production. It is tempting to extend these findings to contexts where knowledge management systems are designed not just to support group work but to generate revenue through user-created content. For example, customers and users have been recognized as an untapped source for innovation and business growth (Gurgul, Enkel, Rumyantseva, & Ulrich, 2007), as represented in the Web 2.0 literature (O'Reilly, 2005). The adoption of the features of the popular social media sites to organizational knowledge management makes it all the more tempting to try to explain information provision using the same frameworks. However, the importance of trust in these data (not to mention the pervading concerns about the control users have of their information in social media communities) suggests caution. Information provision is context-, user-, and knowledge-area-specific. Posting a status or personal photo to update friends and family likely evokes completely different considerations than does sharing work products. However, these results do confirm the efficacy of transactive memory theory as an approach with which scholars and practitioners may begin to disentangle the implications of social media for organizational knowledge management.

Limitations and Future Research

Even though the model received strong support in these data, the coefficients indicated small to medium effects, and the overall explained variance at each level of analysis was moderate. One possible reason is due to the use of single-item measures, which may have increased measurement error. Using single-item measures makes the results more vulnerable to variation in the different interpretations of items by participants. The value of the KAME data collection tool lay in the richness of the multilevel, network data, but completing it requires substantial time and necessitates using single-item measures to balance the burden on participants. The use of single-item measures should not obviate the value of the insights in these data (Gardner et al., 1998), but it suggests caution in the interpretation of results.

This study confirmed the variability of information provision behaviors across knowledge areas, individuals, and groups; however, we did not examine the effects of the intrinsic characteristics of knowledge areas on intragroup information sharing and knowledge management. That the factors measured here were allowed to vary from knowledge area to knowledge area was an important contribution, but research has advocated for efforts to uncover how specific knowledge characteristics such as knowledge explicitness and tacitness could influence organizational knowledge sharing and transfer (Nonaka & von Krogh, 2009; Su & Contractor, 2011; Szulanski, 2000; Zander & Kogut, 1995). These results provide further support for the need for research that looks at the characteristics of specific knowledge areas.

For example, when knowledge is deeply embedded in the context and personal experiences through which it is gained, it is more difficult to be transferred in codified forms, which makes the knowledge more tacit and less explicit. Dixon (2000) asserted that organizational knowledge falls on a continuum from very explicit to very tacit, and should not be strictly categorized as either explicit or tacit knowledge. Previous research has suggested that as knowledge becomes more tacit and less explicit, people tend to rely on direct person-to-person communication to seek and transfer such knowledge (Byström, 2002; Hansen, 1999). When knowledge becomes more explicit and less tacit, people are more likely to share and transfer information through DKRs because the digital systems provide a reliable and efficient platform in transferring and retrieving codified information

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(Hertzum & Pejtersen, 2000). Therefore, where organizational knowledge falls on the continuum could influence the likelihood and effectiveness of sharing such information on the DKRs. These data not only confirm that more research is needed to investigate the nature and characteristics of organizational knowledge domains in which information sharing and transfer take place but also indicate that the effects of those knowledge domains will play out in ways influenced by the trust individuals have in DKRs and groups' TMSs and communication networks.

Due to privacy concerns and security measures taken by the organizations under study, we were not able to gain access to and actually experience the features of DKRs utilized by our participants. The material differences among these DKRs (e.g., the physical design, functionalities, and security) surely had an impact on users' perceptions and usage of these technologies. Moreover, organizational members are increasingly utilizing external knowledge repositories such as the World Wide Web for work-related information (Hirsh & Dinkelacker, 2004). The data do, however, indicate factors for future research (e.g., trust, expertise recognition, benefits of use) that may be influenced by the affordances of particular DKRs. It is likely that the specific features of DKRs have effects to the extent that they influence perceptions of such factors.

Finally, given the focus of this study on examining information provision in work groups, the analysis measured variables at the knowledge-area, individual-, and group levels, but excluded the influence of variables at a national or cultural level. One of the 17 work groups was composed of members of heterogeneous national origins. This study did not have adequate data to investigate the effects of nationality or cross-cultural differences on intragroup knowledge provision and sharing. Diversity, including cultural heterogeneity, may have particularly important consequences for perceptions of expertise. This limitation reflects a larger need to be cautious in generalizing findings from this small sample of groups.

Despite its limitations, this study demonstrates the feasibility and utility of extending a transactive memory theory-based multilevel framework to information provision to DKRs. Based on the conceptualization of the multilevel model and results from work groups in organizations located in the United States and Western Europe, this research confirmed a set of knowledge-, individual-, and group-level contextual factors predicting information provision to organizational DKRs.

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