IEEE TRANSACTIONS ON

ENGINEERING MANAGEMENT

A PUBLICATION OF THE IEEE ENGINEERING MANAGEMENT SOCIETY

FEBRUARY 2005 VOLUME 52 NUMBER 1 IEEMA4 (ISSN 0018-9391)

IEEE

Continuance in Expertise-Sharing Networks: A Social Perspective

Amrit Tiwana and Ashley A. Bush

Abstract—**As engineering firms, R&D groups, and technical organizations recognize the centrality of their engineers' expertise to their performance, they are widely investing in knowledge management (KM) initiatives. Contemporary KM initiatives increasingly include expertise-sharing networks that help answer questions about *who knows what*. These systems allow organizations to locate and leverage the specialized engineering and technical expertise that is held in the minds of dispersed individuals. However, stories of such expertise-sharing networks that languish from under-use and abandonment abound and the issue of continuance has received very little attention in prior research. In this paper, we explore this understudied issue. We develop a model of expertise-sharing network system continuance through a four-year observational study of 418 users of two such systems and then empirically test it using multiperiod data collected from 122 users of four such systems. The concept of irretrievable investments was used to guide theoretical development in the initial observational phase of the study.**

The study makes several unique theoretical contributions. First, it develops a model that illustrates how irretrievable postadoption investments (sunk costs) by individual users of expertise-network systems increase continuance. We empirically show that the model explains approximately half of the total variance in continuance intention. This model advances continuance beyond the traditional expectation-satisfaction model of initial adoption to more advanced postadoption stages of use and theoretically incorporates the network-specificity aspect of postadoption investments in explaining continuance. Specifically, we show that individual users': 1) reputation among peer users of a system increases continuance; 2) system-mediated relationships with other users of the system increase continuance; and 3) investments in personalization of a system initially diminish continuance. Another notable contribution is the development and validation of several new measures for expertise-sharing network constructs.

Index Terms—**Expertise networks, information systems continuance, knowledge management (KM), knowledge networks, peer-to-peer, personalization Siemens ShareNet, reputation, sunk cost.**

> *"Between 60 percent and 80 percent of value-added we generate is linked directly to knowledge—and the proportion is growing."*
>
> *Heinrich von Pierer, President and CEO, Siemens AG*

Manuscript received October 1, 2003; revised July 1, 2004. Review of this manuscript was arranged by Department Editor R. T. Keller.

A. Tiwana is with the Goizueta Business School, Emory University, Atlanta, GA 30322 USA (e-mail: atiwana@bus.emory.edu).

A. A. Bush is with the College of Business, Florida State University, Tallahassee, FL 32306-1110 USA (e-mail: abush@cob.fsu.edu).

Digital Object Identifier 10.1109/TEM.2004.839956

I. Introduction

RECOGNITION of knowledge as a critical asset [1], [18], [62] is encouraging many engineering firms, R&D groups, and technical organizations to pursue knowledge management (KM) initiatives [58].[1] Since much engineering and technical expertise is held tacitly in the minds of individuals, firms are increasingly developing expertise-sharing networks to complement library-like knowledge repositories.[2] An expertise-sharing network is defined as an information system that allows dispersed individuals to both locate and share individually held expertise.[3] The motivation behind such expertise-sharing networks is that individuals can exploit the distributed expertise and skills of their peers without them having to formally codify such knowledge in knowledge repositories. A fundamental advantage offered by a network over repository-oriented KM system is that it provides opportunities for finding and exploiting diverse and potentially novel information, advice, insights, pointers, and ideas among individuals who might not previously know each other [15], [80]. This simultaneously

[1]Knowledge is defined as actionable information [63] and the term "expertise" refers to the *largely* tacit facets of such knowledge. Although the precise distinctions between information and knowledge remain an unresolved debate among scholars, we follow Nonaka's [63] pragmatic definition of knowledge as actionable information. Information is inactionable when the recipient is unable to utilize it or act on it, such as due to its cognitive complexity for the recipient or the ambiguity associated with interpreting it. Others have used the term information to refer to knowledge that can be codified and readily expressed and knowledge to refer to actionable information that is largely tacit and, therefore, difficult to codify in written form or in artifacts [52]. Therefore, in the remainder of this paper, we use the term individual expertise to refer to individually held actionable information.

[2]Expertise-sharing network systems differ from library-like repositories that collect explicit knowledge in forms such as databases, reports, presentations, and documents. Expertise-sharing networks attempt to tap into the tacit knowledge, especially when it is globally dispersed across individuals in various locations, functions, and departments. Unlike repository-oriented systems that aggregate codified knowledge (i.e., documents, files, instructions, and other knowledge artifacts) in a central repository, expertise-sharing networks facilitate knowledge *application* through collaboration, interaction, and relationships among individual users [4], [44]. Unlike technical libraries and knowledge repositories, expertise-sharing networks allow person-to-person exchange of expertise. They connect individuals seeking knowledge to others who possess it and facilitate sharing of only partially codifiable knowledge primarily through pointers, conversations, hyperlinks, and multimedia. The objective of such systems is to facilitate the flow of individually held knowledge among peer users of the expertise-sharing network system. Moreover, in industries that are rapidly and radically evolving—telecommunications in the case of Siemens—*technical* knowledge in repository-like KM systems can rapidly become obsolete. Expertise-sharing networks are less prone to the problem of accidentally relying on obsolete knowledge stored in a knowledge repository. Expertise-sharing networks, therefore, complement other types of KM systems.

[3]Unlike communities of practice this conceptualization of expertise-sharing networks: 1) is entirely electronic and completely system-facilitated and 2) members are not necessarily within the same narrow professional domain. In this sense, expertise networks can be viewed as a subset of communities of practice.

solves two particularly difficult problems that KM initiatives face—the disinclination of individuals to make their expertise a "public good" (e.g., by posting it on a Web site or database) and the difficulty of representing complex expertise in database-like repositories [29]. Such a system addresses two aspects that make it difficult to leverage existing but dispersed expertise: First, it helps answer the question about "who knows what," i.e., locate the individual(s) who possess the needed expertise and second, it facilitates sharing that expertise.[4]

A prominent expertise-sharing network of this type is the ShareNet system used by Siemens (a leading global engineering organization) that allows Siemens' 19 000 technical specialists in 190 countries to help each other in solving technical problems both by providing technical advice and suggestions, as well as engaging in collective problem-solving. It facilitates exploitation of expertise and solutions across sales regions, projects, and markets in an environment where expertise sharing and contributing was voluntary, and the level of formality in use was low. Three instances of recent engineering contracts won by Siemens through effectively *locating* and dispersed expertise illustrate how an expertise-sharing network goes beyond traditional collaborative information systems and knowledge repositories.

- In one case, in Switzerland, Siemens won a $460 000 contract to build a telecommunications network for two hospitals even though its bid was 30% higher than a competitor's. The clincher: via ShareNet, colleagues in Holland provided technical data to help the Swiss team prove that their system would be more reliable.
- In another case, in Malaysia, ShareNet helped land a $3 million contract for a pilot broadband network. Using ShareNet, the Malaysian team discovered that a team in Denmark had completed a nearly identical project. Using the Danish group's experience, the Malaysian team won the job.
- In yet another case, one project manager in South America was trying to find out how dangerous it was to lay cables in the Amazon rain forest in order to determine the type of insurance his project needed. He posed the question on ShareNet and within hours a project manager in Senegal who had encountered a similar situation responded. Getting the right, *actionable* information before the cables went underground saved the company several million dollars in insurance costs.

These examples illustrate the value of being able to locate and exploit expertise that is ordinarily out of sight so that potential users are simply unaware of it. They also illustrate that expertise exchanges between particular individuals in expertise-sharing networks—while valuable—might be a onetime only interaction.

While such systems are valuable, they are costly to develop. Instances of organizations that have enthusiastically implemented such expertise-sharing systems but have been unable to sustain their use are widespread [e.g., [3], [14], and [73]. The results are what McDermott [59] describes as information junkyards: massive collections of context-less and inactionable *information*. Integral to the success of an expertise-sharing network is retaining existing users past their initial adoption of the system because their value rests largely on their widespread use. Continued use, however, remains an elusive design objective, especially as organizations continue to use *information* management tools and information management concepts to design KM systems [59]. Sustaining system use requires successfully building a thread of temporal persistence for each individual user across discrete—even onetime—interactions with multitudinous individuals so that benefits cumulatively accumulate to an individual user from expertise sharing in discrete exchanges over time.[5]

Initial adoption models such as technology acceptance model (TAM) barely shed light on how to sustain their use because continuance occurs at a more advanced postadoption stage. The factors that drive continued use *emerge from the use of the system but do not exist before its initial adoption*.[6] Moreover, understanding user continuance behavior requires viewing expertise-sharing networks as technology-facilitated *social* networks—which few prior studies have even attempted [5], [75]. The issue of what predicts continued use of expertise-sharing networks, therefore, remains woefully understudied. In this study, we address the following research question surrounding this gap in the literature:

What are the key factors that emerge *after* the initial adoption of an expertise-sharing network system that influence its continuance at the individual level?

Given the lack of in-depth prior research on continuance but recognizing the potential complementarities with some prior literature in the collaborative systems realm, we adopted a multimethod approach, sequentially combining the richness of in-depth observations over four years with the parsimony of quantitative survey data. We develop a theoretical model based on detailed observations in the field over an extended period of four years (1998–2002). We then empirically test this model using multiperiod data collected from 122 users of four expertise-sharing networks. Our results provide strong support for the proposed model, albeit with some surprising findings.

The key contribution of this study is the development of an expertise-sharing network continuance model (Fig. 2) that shows how factors that emerge through irretrievable investments by individual users *after* initial adoption influence continuance. The model advances continuance beyond the traditional expectation-satisfaction model of initial adoption to more advanced postadoption stages of use and explains approximately half of the variance in continuance intention. To preview the insights offered by our results—individual users' perceptions of: 1) their own reputation among peer users of a system increases continuance; 2) system-mediated relationships with other users of the

[4]Addressing the first aspect while ignoring the second is likely to mitigate expertise sharing, largely because of the limited incentives that might exist for a far-flung colleague to take the time and expend the effort of sharing his or her expertise with another individual.

[5]Ebay provides an example of such aggregation. Although an individual seller might interact with one buyer only once, the feedback from each such discrete transaction aggregates over all such onetime transactions. This aggregated feedback profile provides a thread of persistence across seemingly unconnected individual transactions.

[6]The factors that predict the continued use of previously adopted expertise-sharing networks will likely differ from those identified in the well-accepted TAM because they emerge only *after* their initial adoption [10].

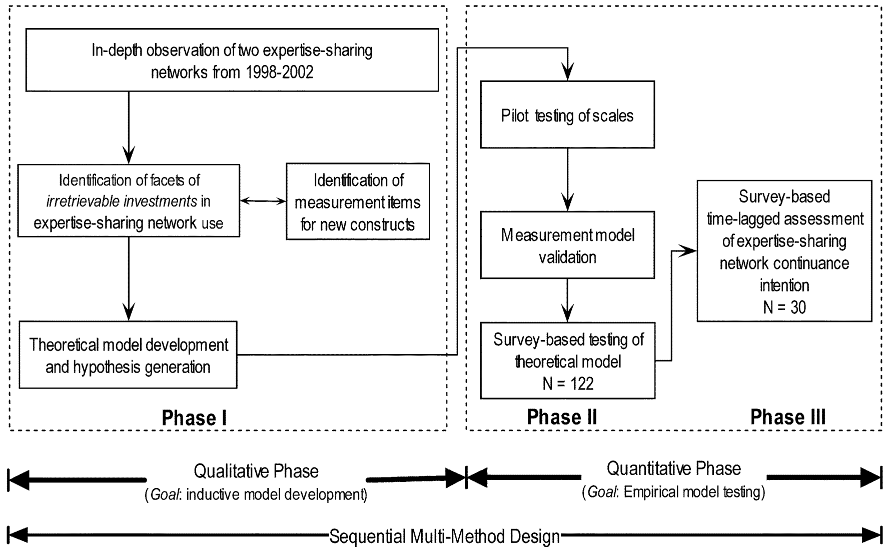

Fig. 1. Overview of the research approach.

system increase continuance; and 3) investments in personalization of a system counter intuitively initially diminish continuance but later increase it. Another notable contribution is the development and validation of several new measures for expertise-sharing network constructs.

The rest of the paper proceeds as follows. In Section II, we provide an overview of the sequential multimethod research approach that was used for theory construction (i.e., how the observational phase led to the model tested in the survey phase). In Section III, we describe the observational phase of the study (Phase 1). In Section IV, we describe survey phases of the study (Phases 2 and 3), followed by the analysis and results in Section V. Section VI explores the implications of these results for theory and practice. We summarize our conclusions in Section VII.

II. Overview of the Multimethod Research Approach

A two-pronged, sequential multimethod approach [60] was used for this study, where the observational phase (Phase 1) was used to inductively develop a testable theoretical model, which was empirically tested in Phase 2. Fig. 1 provides an overview of this research approach, which is described in detail in Appendix B. A multimethod approach is defined as "a combination of methods, embodying different paradigms, developed specifically for the task [60]." This approach was appropriate in this study for three reasons. First, prior research has not identified the factors that contribute to postadoption continuance in expertise-sharing networks. Based on observations of two expertise-sharing networks over a period of four years, we were able to identify the factors and patterns that led to the continued use of these systems. The concept of irretrievable investments theoretically guided the conceptual model development. Second, observation of the actions and interactions of participants of these expertise-sharing networks provided a richer understanding of postadoption continuance that was not possible with a single method approach. Third, our study builds up to a theoretical explanation of postadoption continuance using the variables that emerged from our observations to develop a testable model, which was subsequently tested in the study.

III. Theoretical Model Development (Phase 1)

In the following sections, we discuss the conceptual and theoretical foundations of systems use continuance, the integration of our systematic observational data with the guiding notion of irretrievable investments by individuals, and the inductive development of a research model for subsequent empirical testing. Throughout our theory development, we focus on the individual rather than the organization as the unit of analysis.

In Phase 1, we collected qualitative observational data on 418 users of two expertise-sharing networks from 1998 to 2002 to inductively identify patterns that drove their continued use (Table I). This allowed triangulation of insights by combining observations of multiple researchers (two in this case) and multiple data sources (two expertise-sharing networks in the observation phase, four in the subsequent empirical phase). Although the qualitative phase was theoretically informed by the notion of irretrievable investments, the theoretical explanation of the phenomenon of interest emerged from the observations in the field. In that respect, our approach was inductive, model-development oriented, but theoretically informed [60]. The observational phase helped us discover the beliefs and expectations of individuals within the expertise-sharing networks, as well as the relevant social practices and norms. Using the observational data, measures for the key new constructs were developed which were used to empirically test the model in the latter phases, as elaborated by Mingers [60]. The insights from the observational phase and their development into a testable model are described next.

A. Continuance Intention in Expertise-Sharing Networks

We define continuance intention as an individual user's intention to continue using an adopted expertise-sharing network system [10]. Technology adoption and continuance are temporally and conceptually distinct constructs because the psychological motivations that predict the latter emerge *after* the initial acceptance of a system. Continuance is, therefore, an *ex post* reconfirmation of the initial adoption decision. Is there really continuance in the use of expertise-sharing networks? In an expertise-sharing network—especially one that is larger in size—the knowledge exchanges between two individuals might be a discrete, one time event. Various case studies have observed that although organizations have enthusiastically implemented such networks, their early abandonment by individual users has led to their disuse before any observable benefits materialize from such investments [e.g., [3], [14], and [73]. Clearly, implementing even a well-conceived piece of technology does not necessarily lead to its continued use. Theoretical models such as the technology acceptance model (TAM [10] and TAM-2 [84]) that focus on the initial adoption of such systems do not sufficiently explain how their usage can be sustained in the more advanced postimplementation stages of adoption. It is here that the subtle differences between the antecedents of information sharing and expertise sharing surface. Unlike information sharing, expertise sharing has a competitive side to it because individuals tend to safeguard and protect their knowledge, especially when it cannot readily be observed or codified [23]. Since expertise-sharing network systems are costly to build, understanding their continued use by individual users is critical to deriving value from them. This requires an understanding of what motivates individual users to share their expertise using expertise-sharing networks.

B. Using Irretrievable Investments as a Theoretical Lens to Predict Continuance

The guiding conceptual lens that we used for our theoretical development emerged from sunk cost theory—the concept of irretrievable investments. The underlying premise of sunk cost theory is that individuals tend to persist in activities in which they have already invested considerable irrecoverable resources [6]. The purpose of using this as a theoretical lens is to parsimoniously organize and interrelate the patterns observed in the observational phase of the study. Irretrievable investments are defined as any irrecoverable prior investment of resources, time, effort, attention, or money through the use of an expertise-sharing network [6]. Such investments are irretrievable if they have high network specificity, i.e., the benefits derived from them cannot readily be transferred to another expertise-sharing network. We focus on the nonmonetary irretrievable investments made by individual users of an expertise-sharing network *after* its initial adoption.[7] We looked for patterns in which the value of postadoption investments by users was manifested *through the use of the system*, with high levels of network specificity. This core idea theoretically informed and helped parsimoniously interpret our observations. This approach for using the sunk cost theoretical lens to integrate interrelated concepts in the theoretical model is an appropriate use of the underlying theory (see [83] for a detailed discussion on how inductive theory construction can be theoretically informed). The underlying premise is that individuals tend to persist in activities in which they have already invested considerable resources, i.e., such irretrievable investments act as barriers to discontinuance of use of the system.[8] In this vein, Schultze and Liedner [75] have observed in their literature review that individuals exhibit a tendency to use KM systems in ways that increase their power in the network of other users; thus, they are likely to exhibit continuance intention after making value-enhancing irretrievable investments.

In our observational data, we found that users invest considerable time and individual effort in developing close interpersonal relationships with peer users of the expertise-sharing network system, building a reputation among them, and customizing the system to their personal preferences. As a result, they develop goodwill, trust, a sense of identity, and a reputation among their peer users which, in turn, enhances the value that they derive from using the system. It is only after an individual user has invested the necessary time and effort that expertise-sharing network-based interactions with other users become more coherent and valuable [17], [27].

A key consideration in our theoretical development is that these investments must have high network-specificity and must largely be irretrievable. Commitment to continue using the system emerges as individuals take into consideration such irretrievable investments in deciding whether to continue using the system. Although relationships and individual user reputation are valuable and durable in the networks in which they are developed [67], they are rarely transferable nor easily replicable in a different network. Individuals who have developed a reputation among their peers, built close working relationships, and extensively invested in customizing a system will be predisposed *against* walking away from the personal irretrievable investments of time and effort. Therefore, *perceptions of postadoption network-specific investments of time and effort by individual users act as discontinuance barriers* for individual users of an expertise-sharing network system even when viable alternatives exist.[9] They do so, because users accumulate network-specific benefits that they inherently value.

In order to separate the concepts that drive continuance in our model from those that are known in prior research, the latter

[7]Arkes and Blumer [5] have cautioned that research attention to monetary sunk costs should not obscure the fact that there are numerous nonmonetary sunk costs. Nonmonetary sunk costs implicitly under grid prominent theories of individual commitment to a variety of personal and social associations [49], [72]. For example, empirical studies on the "investment model" have shown that irretrievable investments of time and effort enter individuals' continuance decisions such that high investments increase individual continuance commitment [49], [72].

[8]This tendency—labeled the *sunk cost effect*—is manifested in a wide variety of personal and business decisions [6]. Although both classical economic theory and normative decision theories suggest that individuals' continuance decisions ought to be based solely on *incremental* gains or losses, prior research has consistently shown that prior investments enter individual continuation decisions [35], [36], [72]. This effect is further accentuated when individuals' investments are made publicly or are difficult to measure [45], [78]. Individuals then rationalize continuing on a chosen path of action if the costs of abandoning prior investments are *perceived* as being high [35], [50], [74].

[9]This perspective provides retrospective insights into discontinuance behaviors that have been observed in first-generation collaborative information systems. For example, Konstan *et al.* [55] found that many users abandoned the collaborative information filtering system GROUPLENS before ever receiving any benefits from it because they *perceived* their rating efforts were without rewards. However, users who invested time in using the system were likely to continue using it. Goldberg *et al.* [40] similarly found that users of the collaborative filtering system, TAPESTRY, viewed the system as being more useful when it allowed them to draw recommendations from peer users.

TABLE I
ELEMENTS OF IRRETRIEVABLE INVESTMENTS IDENTIFIED IN THE QUALITATIVE OBSERVATION PHASE AND THEIR ROLE IN THE THEORETICAL DEVELOPMENT OF THE RESEARCH MODEL

Examples of observations from the qualitative phase (Phase 1) *Column 1*	**Related constructs in the literature [source]** *Column 2*	**Underlying theoretical construct** *Column 3*	**Definition of construct** *Column 4*	**Derived from irretrievable investments?** *Column 5*	**Network-specificity** *Column 6*
▪ System assigned rankings based on number of posts ▪ "…I worked hard for the Elite Title" ▪ "your contributions are appreciated" ▪ "Your work is greatly appreciated!" ▪ "And many, many thanks for the very good, and the very entertaining, [contributions]. You are part of what makes [this network] what [it is]." ▪ "I've always enjoyed your posts. you are an asset to [this network]" ▪ "…I personally think that having a member who contributes so much to [this network] is a pretty hot deal..." ▪ "…his [contributions] are more useful than a lot of others…"	▪ Rating profiles [7] ▪ Status currency [66] ▪ Peer recognition [70, 79] ▪ Reputation in referral networks [51] ▪ Agent reputation [55, 69]	Reputation	An individual user's recognition as a valuable member by the peer group of users.	**Yes** Reputation is accumulated over time through interactions with other users and through contributions (ideas, information, and advice) that are considered useful, valuable, or helpful by other users.	High
▪ "a few years ago [I] got a lot of great deals from [this network]. So as a way of saying thanks I began posting here. I still appreciate everyone [here],and I hope that I can find more HD for you" ▪ "Not all his deals are hot but ppl just won't flame him. I guess that's why we have the "elite" status here [elite status indicates the highest level of contributions by the user]. They earned their respect." ▪ "My reasoning for starting the thread was to put out some constructive help in return for the help I've received from others on this [network]." ▪ "Alright, a lot of tax questions have been popping up the last couple of days, and since I have been helped numerous times by the denizens of [network members], I would like to extend my services to helping those with tax questions."	▪ Relational intimacy [19] ▪ Relational capital [49] ▪ Relational cohesion [56] ▪ Relational dimension of social capital [38] ▪ Relationship assets [33]	Relational Capital	The level of trust, reciprocity, and ties of the user with peer users of the system.	**Yes** Development of close collegial relationships in electronic environments takes more sustained participation and interaction.	High
▪ User icons ▪ Individualized signatures appended to each post ▪ Default number of topics displayed ▪ Select forum categories that are displayed ▪ "Buddy lists" ▪ "I agree, we should have a few more emotions and avatars."	▪ System personalization [61] ▪ User-driven tinkering [21]	Personalization	The time and effort invested in customizing the system to match idiosyncratic user preferences.	**Yes** Personalization of the system requires post-adoption investments of individual time and effort.	Moderate

must be taken into account. Satisfaction with a system is recognized as an important predictor of users' intention to continue using it [9]. Beyond satisfaction with a system, individuals' continuance is also influenced by the perceived costs of discontinuance [59]. Following the theoretically informed approach that we used in this study, we posit that *the perceived costs of leaving the network of peer users enter individuals' assessments about continuing to use the expertise-sharing network system*. For example, Siemens engineers considering discontinuing use of the ShareNet system are likely to consider the costs of severing ties to their network of peers with whom they exchange knowledge *through the system*. As individual users begin to consider their irretrievable investments following their adoption of a system, these costs come into play as predictors of continuance.

Next, we discuss three key variables that persistently emerged *through the use of the system* in our systematic observations during Phase 1 of the study that appear to influence continuance in expertise-sharing network systems. We describe each variable, how our observations in Phase 1 led to it, the irretrievable postadoption investments associated with its development, and why it influences continuance intention. We use the guiding lens of irretrievable investments to interpret these observations and formulate a theoretical model that we subsequently tested empirically.

A summary of the observational analysis appears in Table I. This table illustrates the progression from the observational insights in Phase 1 (column 1), related constructs in the literature (column 2), the underlying theoretical concept that encompasses the observations illustrated in column 1 (column 3), its definition (column 4), and whether it met the two criteria suggested by the theoretical lens that was used to coherently summarize the observational data in Phase 1: derivation through irretrievable investments (column 5) and network-specificity (column 6).

C. Reputation

Reputation refers to an individual user's recognition as a valuable member among the peer group of users of the expertise-sharing network [34]. This conceptualization captures three important elements of reputation: 1) it is a characteristic ascribed to an individual by others in the group [80]; 2) it is a measure of an individual's standing *relative* to others in the group [9]; and 3) it is socially constructed over time [76].

Many of the visible cues through which reputational information is conveyed in face-to-face interactions are nonexistent in electronic networks. Reputation in electronic networks is accumulated over time based on the interactions of an individual [8] through contributing ideas, information, and advice that are consistently recognized as being useful, valuable, and helpful by other users. In our observations, we found that an individual user can build a reputation by:

- **contributing** high quality ideas or knowledge artifacts (e.g., documents, directions, and reports) to the peer user network [28], [70];

- **revealing** the depth of their expertise in answering questions posed by others [57];
- **being personally identified** with a valuable or clever idea, solving a difficult problem, or being accepted as a thought leader [46], [79].

Why should individual users of an expertise-sharing network value their reputation?[10] An individual derives future benefits from developing a strong reputation within an expertise-sharing network by gaining easier access to other users' knowledge, increased credibility for oneself [16], [46], [77], and legitimacy among peer users [26]. Interactions among individuals with no history of collaboration occur in the shadow of their inability to assess others' past behavior [54]. Individual reputation then influences future exchanges and interactions by lending credibility to the user [22], [51], although developing a reputation might also be an end in itself for some users. For this reason, individuals prefer collaborating with individuals of known reputation [42]. In the networks we examined, individuals could remain completely anonymous; user names, profiles, and personalization did not necessarily reveal an individual user's location, actual name, or positional status in the real world. So, reputation was largely a result of interaction *through the system* and investments in developing a reputation have high network-specificity because reputation carries limited value outside the expertise network in which it is developed [15]. Therefore, the cost of foregoing future benefits from the irretrievable investments in establishing a reputation enters an individual's decision to discontinue use of a system.

Because building reputation takes both time and effort, and is valuable for individual users, they exhibit reputation-preserving behavior. Such a tendency to safeguard and preserve developed reputation has been observed among Ebay users [6], as well as members of e-mail groups [66]. A comment by a ShareNet user captures this idea: "Getting recognition for how much our daily job is appreciated is the most important thing. That's what counts and motivates us." Therefore, we expect that individuals who have developed stronger reputations among their network of peer users of the expertise-sharing system are less likely to discontinue its use. This leads to our first hypothesis.

Hypothesis 1: Individual users' reputation among peer users of an expertise-sharing network system is positively associated with their continuance intention.

D. Relational Capital

Relational capital refers to the level of trust, respect, and tie strengths that characterize the relationship of an individual with peer users of an expertise-sharing network system [50]. Relational capital resides in an individual's relationships with the rest of the peer user group, which are created through a history of irretrievable investments of personal time and effort.

These close working relationships with other users provide individuals access to new information, knowledge, and opportunities that are embedded in the network of peer users [28], [38], and in turn, enhance the value of the expertise-sharing network for an individual user. Trust, respect, and tie strengths that characterize relational capital facilitate privileged access to such resources. Specifically, trust promotes cooperation and provides access to information that would otherwise lay hidden from view [51], and as an attribute of the relationship (in contrast to trustworthiness which is an attribute of an individual) is not easily transferable out of the relationship network in which it is developed. Besides, the quality of the relationships of an individual with other peers influences their willingness to share valued information [53]. The costs of sharing knowledge among individuals who are connected by strong interpersonal ties are lower than for those who are connected by weak relationships [43]. By virtue of these attributes, relational capital affects the extent of knowledge sharing, disclosure, and screening of information contributed by the individual.

Relational capital, however, is a network-specific asset that cannot be transferred from one expertise-sharing network to another because is developed through a history of interaction and exchange with other users [13], [19]. It loses its meaning and, therefore, its usefulness outside of the social network in which it was developed. The network-specificity of the investments that led to its development increases the opportunity costs of discontinuing use of the system. Furthermore, frequent interaction by itself produces attachment wherein an individual user's association with the group becomes a valued object itself and there is a positive association between an individual's perception of his or her relationship with the peer group and the individual's intention to remain in the group [56]. Therefore, as higher levels of relational capital are cumulatively developed by an individual through ongoing irretrievable investments, it is likely to influence the decision to continue using an expertise-sharing network system. In summary, our expectation that relational capital will increase individual users' continuance intention leads to our second testable hypothesis.

Hypothesis 2: Individual users' relational capital among peer users of an expertise-sharing network system is positively associated with their continuance intention.

E. Personalization

Personalization refers to customizing an information system to an individual user's preferences. Users invest in personalizing an expertise-sharing network system when they have relatively high expectations of benefiting from doing so or when they have unique needs that cannot be met by the default configuration of the system [61], [64]. Morrison *et al.*'s [61] study of the OPAC library information system—perhaps the most detailed account of personalization in prior research—showed that users locally modified or customized their installations of the system to meet

[10]The centrality of individual reputation to the functioning of collaborative networks of various types is also apparent in the design of earlier generations of collaborative systems such as recommendation systems [55], collaborative filtering systems [40], reputation aggregators [69], reputation management systems in referral networks [51], and rating profiles in transactional electronic networks such as eBay [7]. Although reputation management mechanisms have been proposed in previous systems, their design has largely been guided by observational insights and has lacked empirical validation [see, for example, [27] and [79]. Moreover, reputation in these systems is largely implicit and conveyed by aggregated proxy information such as peer user opinions, ratings, or recommendations.

their idiosyncratic needs, largely motivated by the expectation that they would derive additional value in use by doing so.

In expertise-sharing networks, we found that individual users derive additional value through personalization by: 1) reducing the costs associated with projecting persistent social cues and 2) filtering peer contributions based on personal preferences. The former is valuable because many social cues that are the norm in face-to-face interactions are difficult to convey in electronic interaction environments [31]. The motivation underlying this is to persistently project socially salient cues that their peers can use in governing their interactions [27]. The latter is motivated by the desire to cope with information overload [8]. In the observational phase of our study, we found several patterns through which personalization was manifested in expertise-sharing networks. Examples of these include pictures (or avatars) attached to usernames, signatures that are automatically appended to contributions, use of memorable, personality-projecting personal usernames, creation of "buddy lists," and customization in the software preferences for what contributions the user sees, in what order, and when (e.g., preferential ordering of new contributions).

In summary, personalization of an expertise-sharing network system requires investments of individual time and effort. Individuals are unlikely to be able to directly transfer these investments to another system, thus rendering them expertise-sharing network-specific. Therefore, we expect that as individuals invest in increasing personalization of an expertise-sharing network system, they are less likely to discontinue using the system. This leads to our third hypothesis.

Hypothesis 3: Individual users' investments in personalization of an expertise-sharing network system are positively associated with their continuance intention.

F. Rival Explanations and Variables From the TAM

To separate our lens of irretrievable investments from competing theoretical explanations and build on prior research, we identify satisfaction with the system as an alternative explanation for continuance intention, and control for individual history of using the system and the extent to which the system is used as other variables that are known from prior research to influence continuance. Recall that we focus only on individual level variables since that is the unit of analysis of the proposed model; no organization-level controls are, therefore, used. Although it is conceptually plausible, prior empirical research found no significant effects from the key variables in the preadoption TAM model such as ease of use and perceived usefulness on continuance intention [10]. Instead, prior research found that their influence is mediated by satisfaction. Therefore, ease of use and perceived usefulness are not included in the model.

Satisfaction is defined as postacceptance affect given preadoption expectations about a system [10]. An individual is likely to be satisfied with a system if it confirms his or her preacceptance beliefs about its use. Based on Bhattacherjee's [10] recent empirical findings of a strong, positive association between satisfaction and continuance intention, we control for satisfaction as an alternative explanation for continuance. Nevertheless,

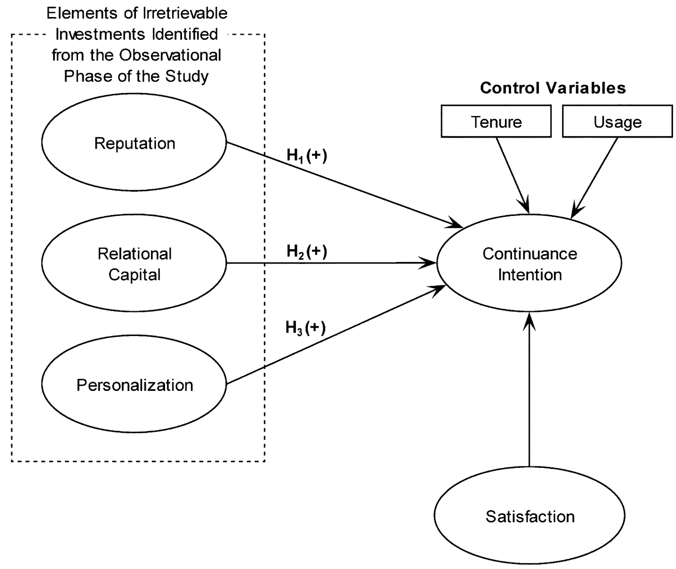

Fig. 2. Research model.

users who are dissatisfied with a system might still perceive a loss of their investments of time and effort in developing a reputation, building relational capital, and personalizing the expertise-sharing network system if they discontinue its use. Elsewhere, in the context of interpersonal relationships, studies have shown that if individuals *perceive* the costs of discontinuance as being high, they are likely to remain committed to a relationship even if they are dissatisfied with it [48]. This leads to our final hypothesis.

Hypothesis 4: Irretrievable investments associated with an individual user's reputation, relational capital, and personalization of the system induce continuance above and beyond satisfaction with an expertise-sharing network system.

Support for this hypothesis would suggest that our proposed model of continuance theoretically extends our ability to predict continuance above and beyond previously existing models.

Control Variables: All else being equal, the length of time that an individual has used a system (**tenure**) and the extent to which the individual uses a system (**usage**) are likely to be positively associated with continuance intention. Our expectation that tenure is positively associated with continuance is grounded in Rothaermel's [71] expectation that individuals' transactions with their peers are positively influenced by how long they have belonged to that network. Likewise, individuals who exhibit higher levels of participation in an expertise-sharing network are more likely to be committed to continue [24]. Therefore, tenure and usage are modeled as control variables. Fig. 2 summarizes the resulting research model, which was derived inductively as described in the preceding sections.

IV. Survey Methodology (Phases 2 and 3)

The study followed a sequential multimethod approach, as summarized previously in Fig. 1. A testable theoretical model emerged from the observational phase of the study (Phase 1 is described in Section II). This model was then empirically tested in two subsequent phases, as described in the following sections.

TABLE II
SUMMARY OF THE FOUR EXPERTISE-SHARING NETWORKS IN THE SAMPLE

Expertise-sharing network	*Size (users)*	*# Threads*	*#Total expertise contributions*
Alpha	Not available	13237	81730
Beta	10,135	15989	50666
Gamma	3,100	3840	19359
Delta	30,737	5462	41345

A. Description of the Research Setting

The observational phase of the study involved systematic in-depth observation of two expertise-sharing networks from 1998–2002, as described in Section II. This was followed by a survey with cross-sectional data collected in four expertise-sharing networks at two different points in time. Four expertise-sharing networks that allow users to electronically access, share, and contribute information, insights, suggestions, and ideas about pricing information on various products and services were chosen for the study. The back-end, server-side software of each of these networks is a database-driven, pull-based system that tracks each individual's contributions and usage behavior. The front-end, user-side interface is Web-based requiring only a Web browser to access the expertise-sharing network's functionality. Knowledge exchanges occur in the form of ongoing "threads" of conversations, each initiated by an individual who has a potentially interesting nugget of knowledge to share or seeks other users' expertise in answering a specialized question. (Specific details of the individual expertise-sharing networks cannot be revealed for confidentiality reasons.) Three attributes of this portfolio of expertise-sharing networks made them particularly suitable to this study: 1) they used the same underlying software system (FuseTalk Virtual Meeting); 2) the content and scope of each was of a directly comparable nature; and 3) use of these systems by individuals was completely voluntary. The key characteristics of the four expertise-sharing networks in our study are summarized in Table II.

B. Data Collection for the Empirical Test of the Model

1) Phase 2—Survey Data Collection and Empirical Analysis: In Phase 2, we administered a survey to a random sample of users of four different expertise-sharing network systems via a secure Web-based questionnaire which prevented the same respondent from answering the survey more than once. We were able to track the total number of times the request for participation was viewed in each expertise-sharing network, so we used a novel approach to compute the response rate. We equated the number of views with the number of mailings in traditional mail surveys, assuming that each "hit" or view was generated by an independent user reading our request for participation. Then, we computed the response rate as the ratio of the number of actual responses we received to the number of times our message had been viewed (no reminders were allowed). We received 122 responses, of which two were unusable because of missing data. The overall response rate was 20.6% (122 responses/593 views). (See Table III for a breakdown.)

TABLE III
SUMMARY OF RESPONSE RATES ACROSS ALL FOUR GROUPS OF RESPONDENTS

Source	*Views*	*Responses*	*Response rate*
Alpha	83	16	19.3%
Beta	231	49	21.2%
Gamma	11	3	27.3%
Delta	268	54	20.1%
Total	**593**	**122**	**20.6%**

2) Phase 3—Survey-Based Temporally Lagged Continuance Intention Assessment: In the third phase of data collection conducted three weeks after completion of Phase 2, we collected time-lagged data on continuation intention. The purpose of this step was to mitigate the threat of mono-methods bias (see [30] for an elaboration on this approach). We contacted all respondents from the Phase 2 who had voluntarily provided their e-mail addresses and received 30 responses from the 42 e-mail requests (71.4% response rate).

C. Construct Operationalization

Five main constructs were measured for the empirical test of the model developed in Phase 1: expertise-sharing network continuance intention, satisfaction, reputation, relational capital, and personalization. The unit of analysis is the individual; therefore, all constructs are operationalized at the individual level. Reflective measures for these constructs were adopted from existing studies where possible, while some were developed beginning with similar constructs in preexisting literature but operationally refined using the observational data collected in Phase 1 of the study. All new and adapted scales were pilot tested with 18 users before the survey data were collected in Phase 2. Based on the results of the pilot test, scale items were refined for clarity and the number of items in the initial pool for the new scales was reduced to five or six items each. The full text of these scale items is reproduced in Appendix A. (See Table IV for a summary.)

Continuance intention was measured using Bhattacherjee's [10] three-item Likert information systems continuance intention scale.[11] **Satisfaction** was assessed using Bhattacherjee's [10] four-item semantic differential scale with bipolar anchors.[12] **Reputation** was measured using five items that were derived from the observational phase of the study. We specifically captured individuals' perceptions of their reputation and operationalized the measure based on patterns of reputation

[11]The first two items in this scale assessed the respondents' intention to continue using the expertise-sharing network or using an alternative one. The third was a reverse-scored item that assessed overall discontinuance intention.

[12]This scale, unlike other satisfaction measures used in previous information systems research (e.g., [25] and [47]) had the advantage that it measured satisfaction as an affect toward the system rather than through beliefs about the quality, timeliness, and reliability of the information provided by it. This is advantageous because we were interested in users' assessments of the system itself rather than the quality of the content and information provided by the system.

TABLE IV
OPERATIONALIZATION OF KEY CONSTRUCTS

Construct	Operational definition	# Items	Type of scale	Source of scale
Continuance intention	User's intention to continue using the system.	3	Likert	[10]
Satisfaction	User's affect with prior system use.	4	Semantic differential	
Reputation	User's recognition as a valuable member by the peer group of users.	5	Likert	Scales items previously used by Pierce et al. [67] and Constant et al. [21] were adapted to the reflect the ways in which reputation was manifested in expertise-sharing networks, based on patterns identified in the observational data from Phase 1 of the study.
Relational capital	The level of trust, reciprocity, and proximity of ties of the user with peer users of the system.	5	Likert	Scale items from Kale et al. [50] were adapted to the reflect the ways in which relational capital was manifested in expertise-sharing networks, based on patterns identified in the observational data from Phase 1 of the study.
Personalization	The time and effort invested by a user in customizing the system to match his or her idiosyncratic preferences.	6	Likert	Items used by Morrison et al. [62], and Finholt and Sproull[30] were adapted to tap into patterns through which personalization was done by users examined in the observational data from Phase 1 of the study.
Tenure	The total number of months a respondent has used the system	1	Single-item	Self-reported
Usage	Hours per week that a respondent uses the system	1	Single-item	Self-reported

development that we observed in the two networks examined in the initial observational phase of the study: the extent to which they perceived that their peer expertise-network system users considered their expertise contributions as being valuable, helpful, useful, and important.[13] Since reputations are subjectively constructed by the individuals who rely on them [12], the construct is best assessed using a subjective measure. The scale for **relational capital** was adapted from Kale *et al.*'s [49] five-item measure for individual perception of relational capital among *individuals* in organizational collaborations.[14] The anchors of this scale were adapted to reflect the ways in which relational capital is manifested in expertise networks, based on our observations in Phase 1 of the study. Scale items to measure **personalization** were based on patterns identified in the observational data collected in Phase 1 of the study, as summarized in Table I. The final scale consisted of five items that tapped into the amount of time and effort that a respondent had invested in choosing a user name, creating a detailed personal profile, creating a personalized footer, choosing a user icon, customizing preferences for the system, and an overall item that assessed their investment in customizing their system settings. The two **control variables** were self-reports on the total number of hours per week that the respondent used the system (**usage**) and the total number of months that the respondent had used the system (**tenure**). All demographic variables including educational level, profession, age bracket, and the total number of contributions were self-reported.

[13]We used Pierce *et al.*'s [68] organization-based self-esteem scale as the starting point for developing a measure for reputation but adapted the items to reflect the specific context of this study, i.e., ways in which reputation is manifested.

[14]Although Kale *et al.*'s study was in the context of interfirm-alliances, their measure was strictly at the individual level. We adapted the overall anchor statement for the scale to fit this study's context, and based on feedback received during the pilot study. The adapted scale items assessed the extent to which the respondent's overall relationship with the peer user group was personally friendly, mutually trusting, respectful, reciprocal, and close.

V. STATISTICAL ANALYSES AND RESULTS

We used the partial least squares (PLS) structural equation modeling approach to validate the construct measures (the measurement model) and to test the hypothesized relationships (the structural model) in the proposed theoretical model. PLS-Graph 3.0 was used for the analysis. Our choice of PLS was motivated by two considerations. First, two constructs in this study used newly developed scales. PLS allowed us to assess the measurement model in the context of its theoretical model. Second, unlike covariance-based approaches to structural equation modeling such as LISREL, PLS makes no apriori assumptions about the normality of the data [20].

A. Measurement Model Assessment

The first step in assessing a PLS model is to assess the measurement model. This step tests whether the construct scales exhibit sufficient discriminant and convergent validity. Convergent validity is assessed in two ways: 1) the internal consistency reliability (ICR) estimate for each construct must exceed 0.7 [32] and 2) measurement items must exhibit statistically significant loadings on their respective constructs with path coefficients of 0.7 or larger. As Table V shows, all items loaded significantly on their constructs at the 1% level, and with the exception of one item for reputation, all items met the recommended threshold of 0.7. The ICR values for all constructs also exceeded the 0.7 threshold. To assess discriminant validity, we first performed exploratory factor analysis using the data on all items for the various construct scales. As shown in Appendix A, the analysis revealed five underlying factors corresponding to the five main constructs in our study. The overall factor solution has an acceptable loading pattern and explained 74.9% of the total variance. The eigenvalues for each of the factors exceeds unity. In the PLS measurement model, two other conditions must be met to ascertain discriminant validity: 1) the indicators should

TABLE V
COVARIANCE MATRIX AND PSYCHOMETRIC PROPERTIES OF KEY CONSTRUCTS

Construct	Mean	S.D.	ICR	ρ_{vc}	1	2	3	4	5	6	7
1. Reputation	4.92	1.06	.98	.76	.87						
2. Relational capital	5.07	1.09	.88	.70	.50	.84					
3. Personalization	2.57	1.22	.95	.73	.09	.06	.85				
4. Satisfaction	5.56	1.28	.79	.82	.33	.55	-.11	.91			
5. Continuance intention	5.76	1.10	.71	.62	.43	.49	-.25	.54	.79		
6. Tenure (months)	11.9	9.24	—	—	.03	.20	-.07	.28	.27	—	
7. Usage (hours/week)	7.51	8.43	—	—	.13	.12	.05	.33	.26	.17	—

Notes: Shaded diagonal elements are the square root of the shared variance between the constructs and their measures
Off-diagonal elements are the correlations between the different constructs
ICR = Fornell and Larcker's (1981) Internal Consistency Reliability

load higher on their own constructs than on other constructs and 2) the square root of the average variance extracted (ρ_{vc}) should exceed the correlations between constructs. The first condition is met if the ratio of the variance in the indicators for a construct relative to the total amount of variance exceeds 0.5 [32]. As shown in Table V, ρ_{vc} for each construct exceeds 0.62, well above the recommended threshold of 0.5. The second condition is met if the diagonal elements representing the square root of ρ_{vc} exceed the off-diagonal elements in the construct correlation matrix. An examination of the shaded diagonal elements in the correlation matrix in Table V reveals that each of these exceeds the corresponding off-diagonal elements. Overall, these results suggest that our measurement model exhibited sufficient convergent and discriminant validity to proceed to the assessment of the structural model.

Descriptive Statistics and Sample Characteristics: The median age of our respondents was 26–35 years. The typical respondent had completed four-year college, although our sample included a diversity of educational levels that ranged from less than high school through doctorates. Our respondents had a variety of professional backgrounds including engineers, programmers, lawyers, functional specialists (marketing, MIS, human resources), chemists, and sales staff. On average, the respondents had actively used their respective systems for over 11.9 months (s.d. 9.2 months, minimum 1 month, maximum 38 months). The level of user contributions to the expertise-sharing networks was high, with a mean value of 542 contributions by each respondent (s.d. 1710). On average, each respondent reported spending 7-1/2 h/week using that expertise-sharing network (s.d. 8.43 h). To test for nonresponse bias, we compared early respondents and late respondents. We found no significant differences in the age ($\mathrm{T-value} = -0.673, \mathrm{p} > 0.25$) or in the educational levels ($\mathrm{T-value} = 0.202, \mathrm{p} > 0.42$) in our T-tests comparing the first 15 and last 15 respondents.

B. Structural Model Assessment

A PLS structural model represents the relationships among the hypothesized model's constructs. Path coefficients in this model are interpreted as standardized regression weights and the loadings on each construct as loadings in principal component analysis. We used a bootstrapping procedure with replacement using 1000 subsamples to estimate the statistical significance of the parameter estimates. The results of the PLS structural model assessment are summarized in Fig. 3.

Reputation had a significant, positive effect on continuance intention ($\beta = 0.224, \mathrm{T-value} = 2.98, \mathrm{p} < 0.01$), supporting Hypothesis 1. Relational capital also had a significant, positive effect on continuance intention ($\beta = 0.227, \mathrm{T-value} = 1.71, \mathrm{p} < 0.05$), supporting Hypothesis 2. Personalization had a significant but negative effect on continuance intention ($\beta = -0.273, \mathrm{T-value} = -3.39, \mathrm{p} < 0.001$). Although the relationship predicted in Hypothesis 3 was significant, its direction was opposite to that hypothesized. To test Hypothesis 4, we first assessed the relationship between satisfaction and continuance intention. Satisfaction had a significant, positive relationship with continuance intention ($\beta = 0.269, \mathrm{T-value} = 2.06, \mathrm{p} < 0.05$). Of the total variance explained by our model, 29.6% was explained by satisfaction. An *additional* 15.1% was explained by reputation, relational capital, and personalization, lending support to our fourth hypothesis. For the control variables, tenure had a positive and significant relationship with continuance intention ($\beta = 0.099, \mathrm{T-value} = 1.95, \mathrm{p} < 0.05$). The relationship between usage and continuance intention was in the expected direction but was marginally nonsignificant ($\beta = 0.102, \mathrm{T-value} = 1.64$ ns). We took several additional steps to mitigate the threat of common-methods bias that commonly plague survey-based field studies.[15] Table VI summarizes the results of the hypothesis tests.

The explained variance ($\mathrm{R}^2 = 47.2\%$) and predictive relevance score ($\mathrm{Q}^2 = 0.278$) for the model suggest that it predicts

[15]We computed the stability of these results by comparing the continuance intention data from the second phase of the study (T_2) with continuance intention measures collected from 30 respondents three weeks after the first round of data collection (T_3). This time-lagged remeasurement approach has previously been used by Fichman and Kemerer [30] to mitigate the threat of bias in cross-sectional designs by measuring the dependent variable at two different times, and then assessing whether it is reasonably stable for every respondent across T_2 and T_3. We ran a separate model to test the correlation between the continuance intention item scores at T_2 and T_3 for the 30 respondents who participated in both phases. In estimating the correlations between the two time-lagged measures, we found that continuance intention at T_2 was significantly and positively correlated with that at T_3 ($\beta = 0.196, \mathrm{T-value} = 1.974, \mathrm{p} < 0.05$). Although the sample size at T_2 was too small to reestimate the complete model, this relationship suggests that our data reliably captured continuance intention and that common-methods bias is not a serious threat to our findings.

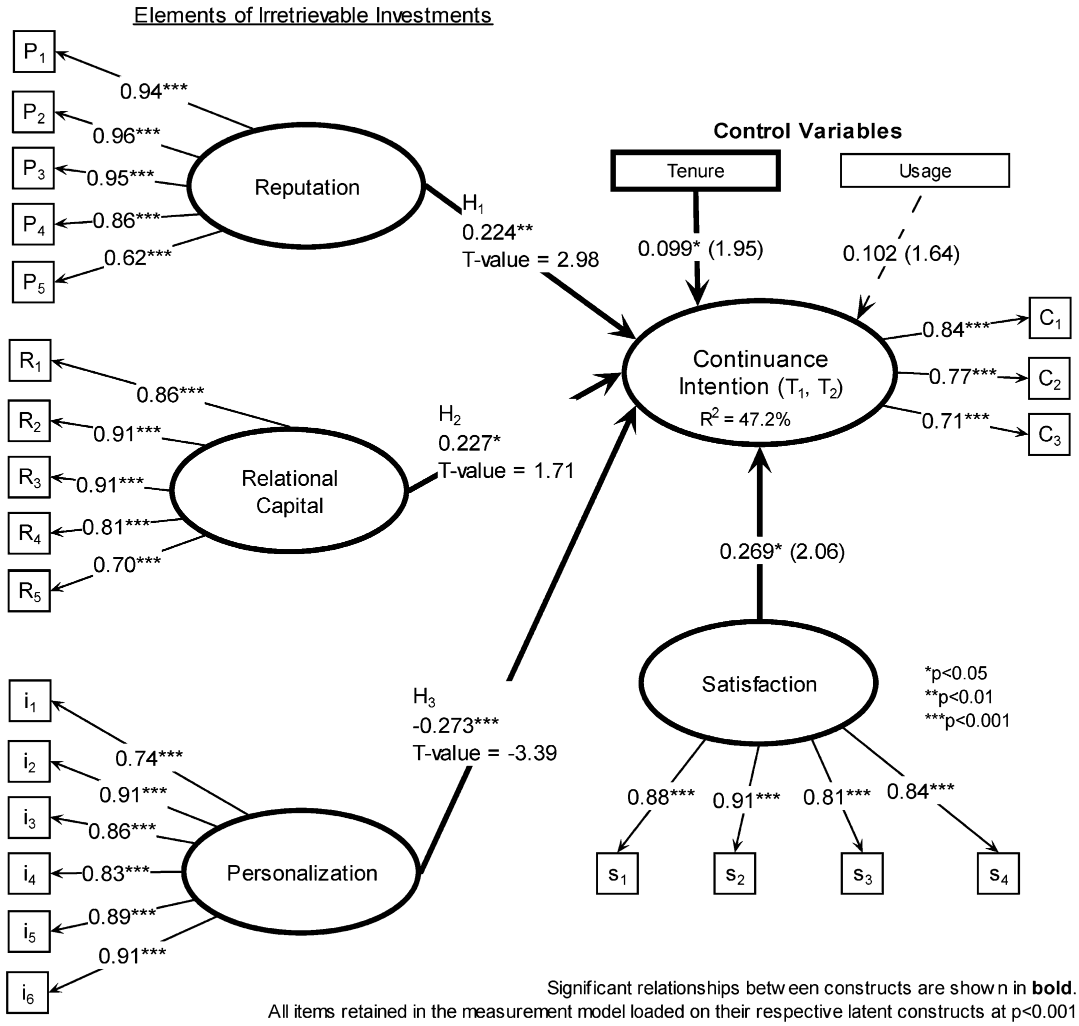

Fig. 3. PLS estimates for the structural model.

continuance intention reasonably well, and above and beyond prior explanatory models of continuance.[16]

VI. Discussion and Implications

The motivation of this study was to better understand the understudied problem of individual usage continuance in electronic expertise-sharing networks. Given the scant research in the area of continuance, we followed a multimethod approach in which an in-depth, four-year observational study of 418 users of two such networks was followed by two surveys in which the model developed in the observational phase was empirically tested using data collected from 122 and 30 users, respectively. The key idea was that reputation, relationships, and personalization that are developed through irretrievable investments in the use of expertise-sharing networks influence a user's intention to continue using the system. The subsequent tests showed that the proposed model predicted over half of the variance in continuance intention. The following section discusses these results of the tests of the hypothesized relationships and their implications for both theory and practice.

A. Implications for Research

We identified three elements through which postadoption irretrievable investments of time and effort by individual users of expertise-sharing network systems manifest themselves through the use of the system: reputation, relational capital, and personalization. The implications of the tests of the relationships between each of these predictors and continuance intention are discussed next.

[16]The predictive quality of our model can be assessed in two ways: (1) percentage of the total variance in continuance intention explained by it (R^2) and (2) its redundancy-based predictive relevance score (Q^2). Our model explained 47.2% of the total variance in continuance intention (no competing models were hypothesized). Of this, 29.6% was accounted for by satisfaction. An *additional* 15.1% of the variance was explained by reputation, relational capital, and personalization. (The change in R-square was assessed by estimating the model without satisfaction and then reestimating the model after adding satisfaction.) The two control variables accounted for the remaining 2.5% of the variance. This suggests that the model predicts continuance intention reasonably well. The second test involves computing the predictive relevance score Q^2. This computation involves a blindfolding procedure that omits part of the data for a given block of indicators and then attempts to estimate the omitted part based on existing parameter estimates [37]. We reestimated the model using omission distances of 11, 23, and 31 (all prime numbers). The Q^2 estimates obtained were 0.310, 0.269, and 0.254. The average Q^2 value across all three runs was 0.278, which suggests high predictive relevance. Together, the R^2 and Q^2 values suggest that the model predicts continuance intention reasonably well.

TABLE VI
SUMMARY OF HYPOTHESIS TESTS

Hypothesis	Hypothesized Effect	Observed Effect	Statistically Significant
H₁: Reputation→Continuance intention	+	+	Yes
H₂: Relational capital→Continuance intention	+	+	Yes
H₃: Personalization→Continuance intention	+	Curvilinear	Yes
H₄: Reputation, relational capital, and personalization predict continuance intention above and beyond satisfaction	ΔR^2	Significant change	Yes

Reputation: We hypothesized that an individual user's reputation among peer users of an expertise-sharing network system will increase continuance intention. A strong, positive relationship between individual users' reputation and continuance intention suggests that individual users who develop a reputation among peer users of a system are less likely to discontinue its use. Building a reputation requires investments of time and effort in the form of active participation in an expertise-sharing network, and such reputation provides future benefits to an individual user. If an individual with a developed reputation discontinues use of a system, these associated benefits no longer remain available. The theoretical implication of this finding is that individuals value their *perceived* reputation among peer users of an expertise-sharing network system.

Relational Capital: Our finding of a strong, positive relationship between relational capital and continuance suggests that an individual user's relational capital in an expertise-sharing network will increase continuance. Like reputation, individuals develop close and trusting relationships with other users of the system through considerable investments of time and effort. Such relationships provide privileged access to new information, knowledge, and opportunities that are embedded in the network of peer users. Individual users' continuance intention is influenced by their irretrievable investments in developing such relationships. An important theoretical insight that can be drawn from this finding is that individual users value the relationships that they foster through the use of a system. Once developed, these portfolios of system-mediated relationships are powerful inducers of continuance.

Personalization: Our third hypothesis predicted that an individual user's investment in personalizing an expertise-sharing network system will increase continuance intention. The relationship between personalization and continuance intention was significant but in a direction opposite of that hypothesized. One interpretation for this finding is that investments in personalization, unlike reputation and relational capital, are readily transferable from one system to another. In other words, investments in personalizing a system might not be entirely irretrievable. Once a user has identified the optimal ways to customize her implementation of the system, the identified preference set can plausibly be replicated in a similar system elsewhere. Further, since individual investments related to personalization are not made as publicly, they might not invoke sunk cost rationalization to the same degree as the other variables in our model. Caution is necessary in interpreting this point because, unlike other variables in the model, personalization was measured in terms of the effort expended in personalizing the system (which in itself might negatively influence continuance intention). Prior research has presupposed that features of expertise-sharing networks that reduce the costs of contributing knowledge to the system will reinforce adoption of a system [41]. However, this finding cautions that notwithstanding the adoption stage benefits of such, it may trigger postadoption discontinuance of the system. We further explored this curious result by testing whether the relationship continuously remains negative. As Fig. 4 illustrates (and a curve-fitting model verified), the relationship between personalization and continuance intention appears to be U-shaped. This suggests that although personalization initially reduces continuance, beyond a threshold, its effect reverses direction. Drawing on the TAM literature, one interpretation for this reversal in direction is that once sufficient personalization has been done on the system by an individual user, the system's ease of use might increase. Hence, the result is an increase in the intent to continue using the system. Another interpretation is that there exists an upfront minimal investment in initial personalization until which no benefits are perceived (corresponding to the negative slope of the curve). After this point, benefits of personalization begin to materialize, hence, the positive relationship with continuance intention. This puzzling pattern of results requires more careful examination in future research.

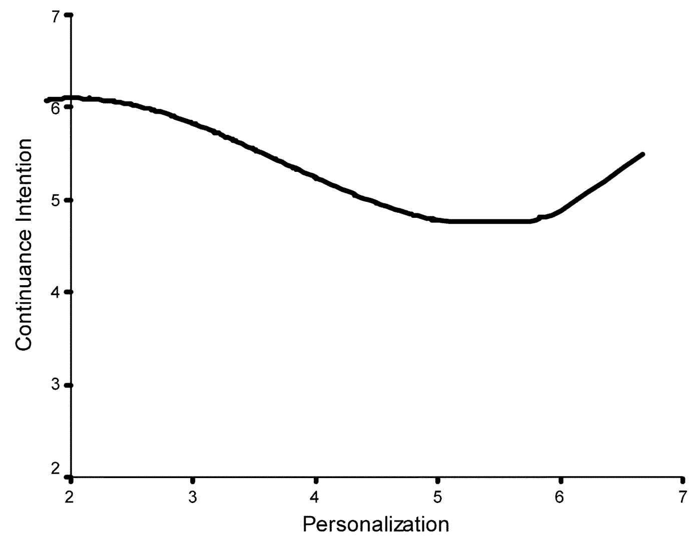

Fig. 4. Sensitivity analysis reveals a U-shaped relationship between personalization and continuance.

Relative Importance of Predictors: The relative importance of the predictor variables (indicated by their path coefficients) in our model provides another set of important theoretical insights. Personalization had the largest path coefficient of all the predictor variables in our model. Postadoption satisfaction was the next key predictor with a path coefficient of 0.269, which is strikingly consistent with Bhattacherjee's [10] earlier study of IS continuance. The third largest path coefficient was relational capital followed closely by reputation. While this pattern of findings reinforces the importance of postadoption satisfaction with a system, the results demonstrate the three variables with which irretrievable postadoption investments are associated further explain continuance. These findings directly address questions raised in previous research about how to design effective virtual networks for knowledge sharing [11], and about mechanisms that can help sustain their use [11], [17], [34]. Our model explains almost half of the total variance in continuance intention.

B. Implications for Practice

Our results offer several tactical implications for designers of expertise-sharing systems. The key insight for practice offered by our findings is that user *perceptions* influence continuance intention. Developers of such systems must: 1) make careful design choices about which cues to reveal or suppress and 2) implement features that maintain visibility and persistence across discrete exchanges that an individual has with other users. Revealing and emphasizing cues about reputation and relational capital that an individual user has developed and suppressing cues about personalization are likely to enhance continued use of such systems.

First, incorporating reputation tracking mechanisms into the design of systems is one way to reinforce continued use of the system. These mechanisms should be persistent and visible system-enabled indicators that track an individual user's reputation over time. System designers should consider incorporating publicly visible cues such as: number of user posts, length of membership, and membership status. This also requires providing users comparative feedback on their participation, usage, and contributions; or by comparing them to their peer users. In the case of Siemens, individual reputation for contributing knowledge to peer users seemed to have prompted active continued use of the ShareNet expertise-sharing network system. Here, details of individual ShareNet users including all their contributions and their perceived level of usefulness can be viewed by everyone using the system. Amazon.com's successful feedback system utilizes a similar approach wherein the top 100 reviewers are publicly recognized and each review can be rated by peer readers. The aggregated feedback profile is then publicly displayed, plausibly with the intention to motivate thoughtful reviews.

Second, a system should enhance the emerging and developed relationships of participants by increasing user awareness of the relational portfolios that develop through the use of the system. For example, system features such as "buddy lists" and personal person-to-person messaging/chat allow users to develop closer ties with each other. Yet another system feature that conveys relational capital is the ability for users to both rate and view the value of others' contributions. In turn, features such as these reduce the likelihood that users will transfer to other similar systems because they are more aware of their relationships with other users of the current system.

Third, system designers must exercise caution in providing extensive personalization capabilities to users. Systems should give users the ability to select unique user names, identify themselves with individualized user icons, include personalized footers with posts, and filter system content. However, these features should not overwhelm users to the point that they inhibit their ability to use the system immediately following their adoption. Personalization appears to be a more complex construct than we initially envisioned and clearly requires further, finer-grained research.

C. Limitations and Suggestions for Future Research

Limitations: This study has six limitations that must be considered before generalizing its findings. First, caution must be observed in generalizing these findings because the sample might not be sufficiently representative of other types of expertise-sharing networks. Second, our model measured continuance intention rather than actual continuation. Third, our model did not include ease of use, thereby limiting direct comparability to earlier studies based on the TAM model. However, we believe that this does not pose a persuasive threat to our findings because: 1) another recent study in a similar context (electronic commerce sites) found no significant relationship between ease of use and users' intent to return (which is conceptually close to continuance intention) [57] and 2) our respondents had sufficient experience using Web browsers (the primary access interface to all four expertise-sharing networks) as suggested by their average usage history of almost one year. Nevertheless, our model is not exhaustive and other factors such as the absence of an alternative system, cost of learning to use the system, and subjective norms might explain additional variance in future research. The mediating role of an *explicitly* measured irretrievable investments construct should also be empirically tested in future work. This approach was not taken in this exploratory study since the irretrievable investments perspective was used as a theoretical lens and the constructs themselves were measured reflectively (i.e., their observed level was a result of higher levels of irretrievable investments). Fourth, sunk cost theory was used as a theoretical lens in the observational phase of the study, but not in operationalizing the measurement scales in the survey phase (e.g., personalization was not measured as the whole cost of personalizing the system). Finally, alternative systems can compete for the scarce attention of individual users. A limitation of the current study is that it did not assess how strongly these predictors of continuance hold when viable alternative systems exist. Finally, our model does not explore the distinction between the two aspects of usage—providing advice and receiving expertise, which will likely have differing antecedents. Explicitly distinguishing such directionality of expertise flows is a limitation of the study and remains an important issue for future research. Although the threat of this limitation cannot be ruled out in this study, the voluntary use nature of the studied systems suggests that individuals were using them by choice rather than by mandate. In this regard, we expect that systems that make the contributions of a user *appear* indispensable will likely encourage knowledge contribution and those that engender credibility of expertise to other users will encourage usage.

Suggestions for Future Research: Our findings point to two promising areas for future research: 1) how do the technical features of an expertise-sharing network system influence individual continuance behavior and 2) how do the theories of individual behavior in group settings inform the design of expertise-sharing network systems? Our results indicate that individual *perceptions* of irretrievable investments associated with the use of a system are important predictors of continuance. This is especially important because perceptions are amenable to manipulation through system design interventions [2]. A promising avenue for future research is to explore how systems can be designed to manipulate (accentuate or deemphasize) user *perceptions* and awareness of their irretrievable investments. This area is also ripe for laboratory experiments in which the effectiveness of different types of perception manipulations in a system can be compared with a control group.

The second avenue for future research is to draw on the vast body of research on individual behavior in group settings and on technology cooperation to better understand how such expertise-sharing networks can be designed to be more "effective." Three research questions in this area beg attention. First, the level of interdependence among users of the system should be incorporated into the model. Second, complementary theoretical lenses on individual continuance commitment such as social exchange theory and relational cohesion theory can be used to identify additional variables that are associated with expertise-sharing network continuance. Interdependence and institutional theories can likewise be useful conceptual lenses for extending this work to the organizational level of analysis.

VII. Conclusion

As engineering and technology firms begin to implement networks for expertise-sharing among individual employees, their sustenance hinges on the continued use of such systems. Unfortunately, the observed trends present a bleak picture: Firms enthusiastically implement costly KM systems that languish from underuse by individual users. The motivation of this study was to understand how individual-level usage continuance in expertise-sharing networks can be improved. Given the limited research in this area, we developed a model using a sequential multimethod approach in which an in-depth, four-year-long observational phase was followed by two time-lagged surveys. The theoretical concept of irretrievable investments guided the observational phase of the study. We looked for conceptual explanations that were manifested through patterns of postadoption investments by users that simultaneously had high network specificity, were valuable, and were developed *through the use* of the system. Based on this observational phase, we developed a testable theoretical model. Subsequently, we empirically tested the model through two time-lagged surveys in four such networks. The resulting model explained over half the variance in continuance intention, suggesting a significant contribution to our understanding of the construct.

This study directly answers calls for research for developing effective technology-facilitated *social* network systems that help users locate and communicate with knowledgeable people in their area of interest, instead of trying to explicitly capture tacit knowledge [59], [75]. The key contribution of this study is the development of an expertise-sharing network continuance model that shows how factors that emerge through irretrievable investments *after* initial adoption influence continuance. A model was derived from a four year observational study of 418 users and empirically tested through two surveys of 122 and 30 users. The model advances continuance beyond the traditional expectation-satisfaction model of initial adoption to more advanced postadoption stages of use. Specifically, we showed that individual users' perceptions of: 1) reputation among peer users of a system increases continuance; 2) system-mediated relationships with other users of the system increase continuance; and 3) investments in personalization of a system initially diminish continuance. Together with the satisfaction construct identified in prior research, our model explains over half the variance in continuance intention. Another contribution is the development and validation of several new measures for expertise-sharing network constructs.

While this study provides a necessary first-step in examining this phenomenon of contemporary interest, the model is by no means complete. The use of irretrievable investments as a theoretical lens for the observational phase but its limited use in the survey phase should be considered in interpreting our findings. Further development of a model of the antecedents of continuance from a socio-technical perspective can provide insights into how organizations can design and implement expertise-sharing network systems that contribute sustainable value to organizations in the long run.

Appendix A

Please see Table VII.

Appendix B
An Overview of the Multimethod Research Approach

In this paper, we used a sequential multimethod design [60] (summarized in Fig. 1). A multimethod design refers to an approach where two different research methods are used in a sequence with results from one feeding into the later one. Such an approach is advocated over a more common mono-method approach by Mingers [60], who suggests that a multimethod approach helps both prior theories and the research situation as experienced by researchers build on each other rather than play a mutually exclusive role. This sequential progression of qualitative to quantitative methods across different phases of a study allows for a much richer and grounded understanding of the research phenomenon. In this study, we began with an in-depth qualitative observational phase (Phase 1) followed by

TABLE VII
SURVEY INSTRUMENT AND FACTOR ANALYSIS

INSTRUCTIONS: Please indicate the extent to which the following statements describe your personal experience in using <this knowledge network>.

		P	R	C	I	S
	Reputational Capital[a] Overall,					
P_1	…other members consider my posts valuable	**0.88**	0.27	0.12	0.09	0.13
P_2	…other members consider my posts useful	**0.90**	0.26	0.13	0.08	0.12
P_3	…other members consider my posts helpful	**0.90**	0.23	0.07	0.13	0.13
P_4	…other members consider my posts important	**0.78**	0.30	0.03	0.10	0.22
P_5	I enjoy a reputation for posting great deals	**0.67**	-0.14	0.30	-0.18	-0.18
	Relational Capital[a] Overall, how would you describe your relationship with other <knowledge network> members?					
R_1	Personally friendly	0.18	**0.75**	0.42	0.08	0.06
R_2	Mutually trusting	0.23	**0.80**	0.31	0.08	0.09
R_3	Mutually respectful	0.35	**0.75**	0.28	-0.03	0.12
R_4	Highly give-and-take	0.09	**0.81**	0.08	0.04	0.15
R_5	Close, personal interactions	0.19	**0.72**	-0.17	0.02	0.33
	Continuance Intention[a]					
C_1	I intend to continue using <this knowledge network> rather than discontinue its use	0.29	0.29	**0.63**	-0.14	0.16
C_2	My intentions are to continue using <this knowledge network> than use any alternative network	0.16	0.22	**0.56**	0.07	0.32
C_3	If I could, I would like to discontinue my use of <this knowledge network> (*reverse scored*)	0.17	0.03	**0.53**	-0.43	0.19
	Personalization[b] How much time and effort have you invested in the following activities on <this knowledge network>?					
I_1	Picking the perfect username	0.00	0.17	0.03	**0.79**	0.00
I_2	Creating a detailed personal profile	0.04	-0.05	0.00	**0.92**	0.08
I_3	Creating a nifty personalized footer	-0.01	-0.02	-0.01	**0.86**	-0.02
I_4	Choosing a user icon	0.10	0.06	-0.18	**0.79**	0.00
I_5	Customizing your preferences	0.02	-0.04	-0.05	**0.87**	-0.06
I_6	Overall, in personalizing <this knowledge network>	0.08	0.10	-0.09	**0.89**	-0.01
	Satisfaction[c] How do you feel about your overall experience using <this knowledge network>?					
S_1	Very dissatisfied—Very satisfied	0.09	0.43	0.44	-0.14	**0.54**
S_2	Very displeased—Very pleased	0.12	0.41	0.43	-0.16	**0.58**
S_3	Very frustrated—Very contented	0.10	0.14	0.18	0.06	**0.86**
S_4	Absolutely terrible—Absolutely delighted	0.10	0.16	0.12	-0.06	**0.90**
	Eigenvalue	3.92	3.62	2.61	4.73	2.36
	% variance explained	17.0%	15.7%	11.3%	20.6%	10.3%

[a]Anchors for these scales were: 1= Strongly Disagree; 2= Disagree; 3= Slightly Disagree; 4= Neither Agree nor Disagree; 5= Slightly Agree; 6 = Agree; 7= Strongly Agree
[b]Anchors for this scale were: 1= None; 2= Very little; 3= Little; 4= Some; 5=Much; 6=Very much; 7=A huge amount
[c] 7-point Semantic differential scale with the stated bipolar anchors.
Principal Components Analysis was used for factor extraction.

two quantitative phases (Phases 2 and 3) where the theoretical model developed in the observational phase was empirically tested using multiperiod survey data. The goal of the qualitative observational phase was hypothesis-generation leading to empirical testing in the subsequent phases [81].

The strength of this multimethod approach comes from its ability to draw on existing theoretical perspectives, while remaining open to new ideas that emerge from a grounded approach to theoretical development. In Phase 1, we collected qualitative observational data on 418 users of two expertise-sharing networks from 1998 to 2002 to inductively identify patterns that drove their continued use. This allowed triangulation of insights by combining observations of multiple researchers (two in this case) and multiple data sources (two expertise-sharing networks in the observation phase, four in the subsequent empirical phase). Although the qualitative phase was theoretically informed by the notion of irretrievable investments, the theoretical explanation of the phenomenon of interest emerged from the observations in the field. In that respect, our approach was inductive, model-development oriented, but theoretically informed [60].

This overlapping observation-analysis-theorizing approach to theory-building follows the logic recommended by Miles and Huberman [82]: Begin with an initial set of inductively derived hypothesized ideas that become increasingly explicit and grounded as they are evaluated against further observations. (This progression from observations to a testable model is summarized in Table I.) Using this approach, we began formulating a tentative model for continuance by identifying similarities and differences across individual user's histories and scrutinizing emerging hypotheses against newer observations. This iterative cycle was repeated until theoretical saturation was reached—the point at which additional observations generate no additional persistent patterns or constructs within the guiding perspective of irretrievable investments that conceptually circumscribe our theory development endeavor [39]. As recommended by Glaser and Straus [39], we combined the inductive concepts generated from the observational phase of the study with existing formal theory to develop a testable theoretical model, an approach adopted in earlier studies that combines inductive concepts generated from field observations with insights from existing formal theory (see [65]). The observational phase helped us discover the beliefs and expectations of individuals within the expertise-sharing networks, as well as the relevant social practices and norms. Using the observational data, measures for the key new constructs were developed which were used to empirically test the model in the latter phases, as elaborated by Mingers [60].

ACKNOWLEDGMENT

The authors gratefully acknowledge the insightful suggestions of A. Rai, Department Editor R. Keller, Sharky, and three anonymous reviewers in the development of this paper.

REFERENCES

[1] P. S. Adler, "When knowledge is the critical resource, knowledge management is the critical task," *IEEE Trans. Eng. Manage.*, vol. 36, no. 2, pp. 87–94, 1989.

[2] R. Agarwal and E. Karahanna, "Time flies when you're having fun: Cognitive absorption and beliefs about information technology usage," *MIS Quart.*, vol. 24, no. 4, pp. 665–694, 2000.

[3] M. Alavi, *KPMG Peat Marwick U.S.: One Giant Brain*. Boston, MA: Harvard Bus. Sch., 1997. Case 9-397-108.

[4] M. Alavi and D. Leidner, "Knowledge management and knowledge management systems: Conceptual foundations and research issues," *MIS Quart.*, vol. 25, no. 1, pp. 107–136, 2001.

[5] M. Alavi and A. Tiwana, "Knowledge integration in virtual teams: The potential role of knowledge management systems," *J. Amer. Soc. Inf. Sci. Technol.*, vol. 53, no. 12, pp. 1029–1037, 2002.

[6] H. R. Arkes and C. Blumer, "The psychology of sunk cost," *Org. Behav. Human Decision Process.*, vol. 35, pp. 124–140, 1985.

[7] S. Ba and P. Pavlou, "Evidence of the effect of trust building technology in electronic markets: Price premium and buyer behavior," *MIS Quart.*, vol. 26, no. 3, pp. 1–26, 2002.

[8] D. Banks and K. Daus, *Customer. Community*. San Francisco, CA: Jossey-Bass, 2002.

[9] J. Berger, B. Cohen, and M. Zelditch, "Status characteristics and social interaction," *Amer. Sociol. Rev.*, vol. 37, pp. 241–255, 1972.

[10] A. Bhattacherjee, "Understanding information systems continuance: An expectation-confirmation model," *MIS Quart.*, vol. 25, no. 3, pp. 351–370, 2001.

[11] M. Bieber, D. Engelbart, R. Furuta, S. Roxanne-Hiltz, J. Noll, J. Preece, E. Stohr, M. Turoff, and B. Van De Walle, "Toward virtual community knowledge evolution," *J. Manage. Inf. Sys.*, vol. 18, no. 4, pp. 11–36, 2002.

[12] S. Boon and J. Holmes, "The dynamics of interpersonal trust: Resolving uncertainty in the face of risk," in *Cooperation and Prosocial Behavior*, R. Hinde and J. Groebel, Eds. New York: Cambridge Univ. Press, 1991, pp. 190–211.

[13] P. Bourdieu, *Handbook of Theory and Research for the Sociology of Education*, J. Richardson, Ed. New York, NY: Greenwood, 1986, pp. 241–258. The Forms of Capital.

[14] J. Brazelton and G. Gorry, "Creating a knowledge-sharing community: If you build it, will they come?," in *Commun. ACM*, vol. 46, 2003, pp. 23–25.

[15] J. Brown and P. Dugid, "Organizational learning and communities of practice: Toward a unified view of working, learning, and innovation," *Org. Sci.*, vol. 2, pp. 40–57, 1991.

[16] R. Burt, "The contingent value of social capital," *Adm. Sci. Quart.*, vol. 42, pp. 339–365, 1997.

[17] B. Butler, "Membership size, communication activity, and sustainability: A resourse-based model of online social structures," *Inf. Syst. Res.*, vol. 12, no. 4, pp. 346–362, 2001.

[18] A. K. Chakrabarti, I. Dror, and N. Eakabuse, "Interorganizational transfer of knowledge: An analysis of patent citations of a defense firm," *IEEE Trans. Eng. Manage.*, vol. 40, no. 1, pp. 91–94, 1993.

[19] L. Chidambaram, "Relational development in computer supported groups," *MIS Quart.*, vol. 20, no. 2, pp. 143–165, 1996.

[20] W. Chin, "The partial least squares approach to structural equation modeling," in *Mod. Meth. Bus. Res.*, G. Marcoulides, Ed. Mahwah, NJ: Lawrence Erlbaum Assoc., 1998, pp. 295–336.

[21] C. Ciborra, "Notes on improvization and time in organizations," *Account., Manage., Inf. Technol.*, vol. 9, pp. 77–94, 1999.

[22] D. Constant, L. Sproull, and S. Kiesler, "The kindness of strangers: The usefulness of electronic weak ties for technical advice," *Org. Sci.*, vol. 7, no. 2, pp. 119–135, 1996.

[23] T. Davenport and L. Prusak, *Working Knowledge*. Boston, MA: Harvard Bus. Sch. Press, 1998.

[24] G. DeSanctis and R. B. Gallupe, "Foundations for the study of group decision support systems," *Manage. Sci.*, vol. 33, no. 5, pp. 589–609, 1987.

[25] W. J. Doll, T. S. Raghunathan, J. S. Lim, and Y. P. Gupta, "A confirmatory factor-analysis of the user information satisfaction instrument," *Inf. Syst. Res.*, vol. 6, no. 2, pp. 177–188, 1995.

[26] D. Dougherty and T. Heller, "The illegitimacy of successful product innovation in established firms," *Org. Sci.*, vol. 5, no. 2, pp. 200–218, 1994.

[27] T. Erickson, C. Halverson, W. Kellog, M. Laff, and T. Wolf, "Social translucence: Designing social infrastructures that make collective activity visible," in *Commun. ACM*, vol. 45, 2002, pp. 40–44.

[28] T. Erickson, W. Kellog, and W. Knowledge, "Communities: Online environments for supporting knowledge management and its social context," in *Sharing Expertise: Beyond Knowledge Management*, M. Ackerman, V. Pipek, and V. Wulf, Eds. Cambridge, MA: MIT Press, 2002, pp. 299–325.

[29] L. Fahey and L. Prusak, "The eleven deadliest sins of knowledge management," *Calif. Manage. Rev.*, vol. 40, no. 3, pp. 265–279, 1998.

[30] R. G. Fichman and C. Kemerer, "The assimilation of software process innovations: An organizational learning perspective," *Manage. Sci.*, vol. 43, no. 10, pp. 1345–1363, 1997.

[31] T. Finholt and L. Sproull, "Electronic groups at work," *Org. Sci.*, vol. 1, no. 1, pp. 41–64, 1990.

[32] C. Fornell and D. Larcker, "Structural equation models with unobservable variables and measurement errors," *J. Market. Res.*, vol. 18, no. 2, pp. 39–50, 1981.

[33] N. Fox and C. Roberts, "General practioners in cyberspace: The sociology of a virtual community," *Sociol. Rev.*, vol. 1999, pp. 643–671, 1999.

[34] N. Franke and S. Shah, "How communities support innovative activities: An exploration of assistance and sharing among end-users," *Res. Policy*, vol. 32, no. 1, pp. 157–178, 2003.

[35] H. Garland, "Throwing good money after bad: The effect of sunk costs on the decision to escalate commitment to an ongoing project," *J. Appl. Psychol.*, vol. 75, no. 6, pp. 728–731, 1990.

[36] H. Garland and S. Newport, "Effects of absolute and relative sunk costs on the decision to persist with a course of action," *Org. Behav. Human Decision Process.*, vol. 48, pp. 55–69, 1991.

[37] S. Geisser, "The predictive sample reuse method with applications," *J. Amer. Statis. Assoc.*, vol. 70, pp. 320–328, 1975.

[38] M. Ginsburg and S. Weisband, "Social capital and volunteerism in virtual communities: The case of the internet chess club," in *Proc. 35th Hawaii Int. Conf. Syst. Sci.*, 2002, pp. 1–10.

[39] B. Glaser and A. Strauss, *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Chicago, IL: Aldine, 1967.

[40] D. Goldberg, B. Oki, D. Nichols, and D. Terry, "Using collaborative filtering to weave an information tapestry," in *Commun. ACM*, vol. 35, 1992, pp. 61–70.

[41] P. Goodman and E. Darr, "Computer-aided systems and communities: Mechanisms for organizational learning in distributed environments," *MIS Quart.*, vol. 22, no. 4, pp. 417–440, 1998.

[42] M. Granovetter, "Economic action and social structure: The problem of embeddedness," *Amer. J. Sociol.*, vol. 91, pp. 481–510, 1985.
[43] M. Hansen, "The search-transfer problem: The role of weak ties in sharing knowledge across organizational subunits," *Adm. Sci. Quart.*, vol. 44, pp. 83–111, 1999.
[44] M. Hansen, N. Nohria, and T. Tierney, "What's your strategy for managing knowledge?," *Harvard Bus. Rev.*, pp. 106–116, Mar.–Apr. 1999.
[45] C. Heath, "Escalation and deescalation of commitment in response to sunk costs: The role of budgeting in mental accounting," *Org. Behav. Human Decision Process.*, vol. 62, no. 1, pp. 38–54, 1995.
[46] G. Huber, "Transfer of knowledge in knowledge management systems: Unexplored issues and suggested studies," *Eur. J. Inf. Syst.*, vol. 10, pp. 72–79, 2001.
[47] B. Ives, M. H. Olson, and J. J. Baroudi, "The measurement of user information satisfaction," in *Commun. ACM*, vol. 26, 1986, pp. 785–793.
[48] M. Johnson, "Commitment to personal relationships," in *Adv. Pers. Relation.*, W. Jones and D. Perlman, Eds, London: Jessica Kingsley, 1991, vol. 3, pp. 117–143.
[49] P. Kale, H. Singh, and H. Perlmutter, "Learning and protection of proprietary assets in strategic alliances: Building relational capital," *Strategic Manage. J.*, vol. 21, pp. 217–237, 2000.
[50] C. Kanodia, R. Bushman, and J. Dickhaut, "Escalation errors and the sunk cost effect: An explanation based on reputation and information asymmetries," *J. Account. Res.*, vol. 27, no. 1, pp. 59–77, 1989.
[51] H. Kautz, B. Selman, and M. Shah, "Referral web: Combining social networks and collaborative filtering," in *Commun. ACM*, vol. 40, 1997, pp. 63–65.
[52] B. Kogut and U. Zander, "Knowledge of the firm, combinative capabilities, and the replication of technology," *Org. Sci.*, vol. 3, pp. 383–397, 1992.
[53] P. Kollock, "An eye for an eye leaves everyone blind: Cooperation and accounting systems," *Amer. Sociol. Rev.*, vol. 58, no. 6, pp. 768–786, 1993.
[54] ——, "Social dilemmas: The anatomy of cooperation," *Annu. Rev. Sociol.*, vol. 24, pp. 183–214, 1998.
[55] J. Konstan, B. Miller, D. Maltz, J. Herlocker, L. Gordon, and J. Riedl, "Recommen-sys: Applying collaborative filtering to usenet news," in *Commun. ACM*, vol. 40, 1997, pp. 77–87.
[56] E. Lawler and J. Yoon, "Commitment in exchange relations: Tests of a theory of relational cohesion," *Amer. Sociol. Rev.*, vol. 61, pp. 89–108, 1996.
[57] E. Lesser and J. Storck, "Communities of practice and organizational performance," *IBM Syst. J.*, vol. 40, no. 4, pp. 831–841, 2001.
[58] G. Lynn, R. Reilly, and A. Akgun, "Knowledge management in new product teams: Practices and outcomes," *IEEE Trans. Eng. Manage.*, vol. 47, no. 2, pp. 221–231, 2000.
[59] R. McDermott, "Why information technology inspired but cannot deliver knowledge management," *Calif. Manage. Rev.*, vol. 41, no. 4, pp. 103–117, 1999.
[60] J. Mingers, "Combining IS research methods: Toward a pluralist methodology," *Inf. Syst. Res.*, vol. 12, no. 3, pp. 240–259, 2001.
[61] P. Morrison, J. Roberts, and E. von Hippel, "Determinants of user innovation and innovation sharing in a local market," *Manage. Sci.*, vol. 46, no. 12, pp. 1513–1527, 2000.
[62] D. Nembhard and M. Uzumeri, "An individual-based model of learning within an organization," *IEEE Trans. Eng. Manage.*, vol. 47, no. 3, pp. 370–378, 2000.
[63] I. Nonaka, "A dynamic theory of organizational knowledge creation," *Org. Sci.*, vol. 5, pp. 14–37, 1994.
[64] W. J. Orlikowski, "The duality of technology—Rethinking the concept of technology in organizations," *Org. Sci.*, vol. 3, no. 3, pp. 398–427, 1992.
[65] ——, "CASE tools as organizational change: Investigating incremental and radical changes in systems development," *MIS Quart.*, vol. 17, pp. 309–340, 1993.
[66] D. Owens, M. Neale, and R. Sutton, "Technologies of status management," *Res. Managing Groups Teams*, vol. 3, pp. 205–230, 2000.
[67] J. M. Pickering and J. L. King, "Hardwiring weak ties—Interorganizational computer-mediated communication, occupational communities, and organizational- change," *Org. Sci.*, vol. 6, no. 4, pp. 479–486, 1995.
[68] J. Pierce, D. Gardner, L. L. Cummings, and R. Dunham, "Organization-based self-esteem: Construct definition, measurement, and validation," *Acad. Manage. J.*, vol. 32, no. 3, pp. 622–645, 1989.
[69] P. Resnick, R. Zeckhauser, E. Friedman, and K. Kuwabara, "Reputation systems," in *Commun. ACM*, vol. 43, 2000, pp. 45–48.
[70] H. Rheingold, *Smart Mobs: The Next Social Revolution*. New York: Perseus Books, 2002.
[71] F. Rothaermel and S. Sugiyama, "Virtual internet communities and commercial success: Individual and community-level theory grounded in the atypical case of TimeZone.com," *J. Manage.*, vol. 27, pp. 297–312, 2001.
[72] C. Rusbult and D. A. Farrell, "Longitudinal test of the investment model: The impact on job satisfaction, job commitment, and turnover of variations in rewards, costs, alternatives, and investments," *J. Appl. Psychol.*, vol. 68, no. 3, pp. 429–438, 1983.
[73] M. Santosus, *A Penny for Your Thoughts*: CIO Magazine, 2002.
[74] J. Schaubroeck and E. Davis, "Prospect theory predictions when escalation is not the only chance to recover sunk costs," *Org. Behav. Human Decision Process.*, vol. 57, pp. 59–82, 1994.
[75] U. Schultze and D. Leidner, "Studying knowledge management in information systems research: Discourses and theoretical assumptions," *MIS Quart.*, vol. 26, no. 3, pp. 213–242, 2002.
[76] C. Smith, *Auctions: The Social Construction of Value*. New York: Free Press, 1989.
[77] L. Sproull and S. Kiesler, *Connections: New Ways of Working in the Networked Organization*. Cambridge, MA: MIT Press, 1991.
[78] B. Staw and H. Hoang, "Sunk costs in the NBA: Why draft order affects playing time and survival in professional basketball," *Adm. Sci. Quart.*, vol. 40, no. 3, pp. 474–494, 1995.
[79] A. Tiwana and A. Bush, "Peer-to-peer valuation as a mechanism for reinforcing active learning in virtual communities: An application of social exchange theory," in *Proc. HICSS-33*, Maui, HI, 2000.
[80] R. Wilson, "Reputations in games and markets," in *Game-Theoretic Models of Bargaining*, A. Roth, Ed. New York: Cambridge Univ. Press, 1985, pp. 27–62.
[81] R. Yin, *Case Study Research: Design and Methods*, 2nd ed. Newbury Park, CA: Sage, 1994.
[82] M. B. Miles and M. A. Huberman, *Qualitative Data Analysis: An Expanded Sourcebook*. Newbury Park, CA: Sage, 1994.
[83] G. Zaltman, K. Lemasters, and M. Heffring, *Theory Construction in Marketing: Some Thoughts on Thinking*. New York: Wiley, 1982.
[84] V. Venkatesh, "Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model," *Inf. Syst. Res.*, vol. 11, no. 4, pp. 342–365.

Amrit Tiwana received the Ph.D. degree in management information systems from Robinson College of Business, Georgia State University, Atlanta.

He is an Assistant Professor in the Goizueta Business School, Emory University, Atlanta, GA. He is currently in transition to Iowa State University. His work has appeared or is forthcoming in *California Management Review*, *Journal of Management Information Systems*, the *IEEE Software*, *IEEE Internet Computing*, *Communications of the ACM*, *Decision Support Systems*, *Information Systems Journal*, the *Journal of Knowledge Management*, *ICIS*, and others. His research focuses on knowledge management.

Ashley A. Bush received the Ph.D. degree in management information systems from Robinson College of Business, Georgia State University, Atlanta.

She is an Assistant Professor at the College of Business, Florida State University, Tallahassee. Her research has appeared or is forthcoming in *Communications of the ACM*, *Information and Organization*, *Information Systems Journal*, and the *Journal of Knowledge Management*. Her research focuses on E-business strategy, IS strategy, and knowledge management.