How Knowledge Validation Processes Affect Knowledge Contribution

ALEXANDRA DURCIKOVA AND PETER GRAY

Alexandra Durcikova is an Assistant Professor at the Eller College of Management, University of Arizona. She earned her Ph.D. in Information Systems from University of Pittsburgh. Her research interests include knowledge management and knowledge management systems, the role of organizational climate in the use of knowledge management systems, and IS issues in developing countries. Dr. Durcikova's research appears in the *Journal of Management Information Systems, Communications of the ACM,* as well as in various national and international conference proceedings.

Peter Gray is an Assistant Professor of Information Systems at the McIntyre School of Commerce, University of Virginia. He has a background in electronic commerce and online information systems, having worked in various information technology and management consulting positions. Dr. Gray researches the intersection of cognition and technology, and focuses on the individual and organizational effects of social technologies, such as knowledge management systems, online communities, and other technologies that enable virtual interaction. His research has been published in *Management Science, Journal of Management Information Systems, MIS Quarterly, Journal of Strategic Information Systems, Information Technology & People, Information & Management, Decision Support Systems,* and *Communications of the AIS.*

Abstract: To ensure that knowledge repositories contain high-quality knowledge, knowledge management research recommends that contributions to a repository undergo stringent validation processes. To date, however, no research has studied the impact of such processes on contributors' repository-related perceptions or behaviors. To address this gap, we develop a model based on signaling theory and reinforcement theory to explain how individuals' perceptions of three primary validation process characteristics (duration, transparency, and restrictiveness) impact their perceptions of repository knowledge quality and their contribution behaviors. Our empirical results confirm the importance of implementing review processes that are transparent and developmentally oriented as a way of encouraging knowledge contribution. More broadly, this study underscores the need to develop integrated theoretical models that draw from a variety of reference theories when attempting to explain knowledge-related behaviors.

Key words and phrases: knowledge contribution processes, knowledge management, knowledge repositories, knowledge sharing, knowledge sourcing, reinforcement theory, signaling theory, validation processes.

Over the past decade, researchers and managers have investigated methods for improving organizational performance by providing employees with better ways of

Journal of Management Information Systems / Spring 2009, Vol. 25, No. 4, pp. 81–107.

0742–1222 / 2009 $9.50 + 0.00.
DOI 10.2753/MIS0742-1222250403

accessing one another's knowledge [3, 22]. Such knowledge management (KM) efforts often rely on information technologies (IT), including one important class of KM initiatives that employ IT-based repositories, to capture employees' knowledge and make it available to a broad range of potential recipients [11, 33]. Although knowledge repositories have generated significant benefits for some organizations [51, 52], research suggests that many repositories fail to enhance knowledge transfer [7, 20].

To succeed, a repository must contain knowledge that will prove useful for employees looking for answers to their questions and solutions to their problems [9, 10]. The task of ensuring the quality of knowledge in a repository often falls to subject matter experts who filter employees' contributions, rejecting those that are redundant, incorrect, ineffective, outdated, or otherwise unhelpful [19, 40]. Without such a validation process, a repository "soon overflows with knowledge assets of questionable value" [64, p. 122] and can, as a result, lose its credibility with employees [70].

Despite their importance in ensuring a high-quality knowledge base, knowledge validation processes may have unintended effects. Specifically, validation processes may lead to the failure of a repository if they are seen by employees as an obstacle to contributing. Anecdotal observations made in the literature on academic publishing processes suggest that individuals may grow discouraged if their contributions are often rejected, if they do not understand the processes that lead to rejection, and if decisions occur long after the initial submission [4, 32, 59]. Validation processes that minimize the effort required from expert reviewers and that lead to high rejection rates may therefore unintentionally choke off the flow of new knowledge to a repository. Without new contributions, a repository grows stale, and users soon abandon it [79].

Unfortunately, the information systems (IS) literature offers little guidance for managers who must grapple with the dilemma presented by the need to promote knowledge contribution behaviors while also ensuring that only high-quality content is published. Indeed, recommendations tend to focus on efficient validation processes, ignoring the impact of such processes on contributors' beliefs, perceptions, and behaviors [64, 89]. Managers who design and implement stringent validation processes may therefore unintentionally create new pitfalls and challenges for potential contributors.

To address this gap in the literature, we draw on signaling theory (e.g., [80, 81]) and reinforcement theory [39, 77] to explain how the perceptions individuals form as they interact with knowledge validation processes affect their beliefs about repository knowledge quality, as well as the rate at which they contribute new knowledge to the repository. Although they may not correspond exactly with actual process characteristics, individuals' perceptions provide a crucial link that can help bridge the theoretical gap between the design of validation processes and individuals' subsequent behaviors. We draw on signaling theory to predict that individuals' experience with a validation process will affect their expectations about the quality of the knowledge contained in a repository. We turn to reinforcement theory to predict that individuals' perceptions of the characteristics of a validation process act as reinforcers that may increase or decrease knowledge contribution behaviors. An analysis of our empirical results confirms that individuals' perceptions of validation processes matter, with useful implications for researchers seeking to develop more complete models of contribution behaviors. Our results also provide guidance for managers who wish to design effective knowledge validation processes that encourage, rather than discourage, knowledge contributions.

Knowledge Validation

Managers who seek to establish a knowledge repository must begin by making various choices regarding its purpose and governance—that is, decisions about its focus and scope, its strategic intent, and how it will be managed. One key governance decision concerns whether newly submitted knowledge will pass through a review process prior to publication, or whether a repository will simply accept every submission it receives. Our research concerns repositories of the former type, in which new contributions pass through a validation process that uses manual or automated workflow systems to route contributions for review by appropriate experts [31, 38, 54]. The KM literature holds that stringent validation processes will have a beneficial impact on the quality of knowledge contained in a repository, and will thus enhance the value of the repository to knowledge seekers [52, 64, 89]. This follows a "garbage in, garbage out" philosophy [37] that is also common in the data management literature [87].

A knowledge validation process begins when an employee submits a document containing a codification of some part of his or her knowledge, and ends when that contribution is either accepted for inclusion in a repository, or rejected. Validation cannot be performed automatically by the repository [54]; instead, assessing quality requires the insights of peer reviewers or subject matter experts [52, 79]. However, characterizing validation processes as simple sorting mechanisms fails to take into account the significant impact such processes may have on contributors who must interact with them [4, 32, 59]. To better understand these effects, we draw on two established bodies of theory: the literature on signaling theory helps explain how validation process characteristics can affect individuals' perceptions of repository quality, while the literature on reinforcement theory is useful in predicting how the same process characteristics affect actual contribution behaviors.

Prior to developing hypotheses based on these theories, we sought to understand which perceptions of knowledge validation processes might play important roles in influencing individuals' contribution behaviors. We began by reviewing the KM literature to determine the ways in which individuals' perceptions of these processes could vary [21, 52, 54, 64, 89]. We then discussed our preliminary findings with knowledge managers and knowledge contributors to identify the key characteristics that contributors are capable of observing and forming judgments about. This process converged on three such key characteristics:

1. the time lag between submission of a new contribution and a decision by a reviewer,
2. the extent to which contributors can observe the validation process in action, and
3. the restrictiveness (overall rejection rate) of the validation process.

Because each contributor will experience a unique set of interactions with a repository, his or her perceptions of the validation process along these three dimensions will vary. Perceptions are thus far more important in understanding contributors' behaviors than are any "actual" or "objective" measures of validation process characteristics. As with many things in life, people's perceptions are their reality; simply because of random distribution effects, some contributors are likely to experience a process as somewhat slow, opaque, and restrictive, while others may have had interactions that lead them to conclude that it is reasonably fast, transparent, and welcoming. While speed, transparency, and restrictiveness do not capture all of the possible characteristics of knowledge validation processes, they are prominent in the knowledge repository literature, consistent with the ways in which knowledge managers and contributors view repositories, and have clear connections to signaling theory and reinforcement theory, as discussed in the following two sections.

Signaling Theory

Signaling theory [80, 81] offers a robust explanation for how people make judgments about quality in a range of situations, particularly when quality is difficult or impossible to directly observe. For example, people looking for appropriate mates with whom to parent children, employers looking to hire employees, and customers looking to purchase services all face the same type of problem: the true quality of what it is they seek is impossible to assess a priori, and can only be understood fully after actually engaging in coparenting, observing someone working, or using the service, respectively (e.g., [10, 66]). Signaling theory argues that when facing such difficult decisions about quality, individuals attend to particular kinds of informational cues [12, 47, 90]: they look for indicators or correlates of quality that are difficult to fake. An aspiring parent would therefore be more impressed by a potential mate who has spent a summer volunteering to mentor underprivileged youth than with any verbal claims about liking children. A potential employer would be more impressed if an employee had earned high grades at a university that is known to have tough academic standards than with verbal assurances that the potential employee promises to perform well. And a potential consumer would be more impressed by a money-back guarantee than by a vendor's assurance that the service will leave them satisfied [10, 66]. In order to be seen as reliable, a signal must be more costly to produce for those individuals who lack an underlying quality-related characteristic than for individuals who possess it. Each instance described above identifies a signal that is "honest," in that it would be difficult and uneconomical for someone to fake if they did not possess a high level of quality in the area in question [55].

A similar signaling problem exists in the field of knowledge management: employees are urged to draw upon knowledge repositories, but may be reluctant to do so if they are uncertain about the quality of knowledge a repository contains. We define perceived knowledge quality as *the extent to which an individual believes that a repository provides precise and accurate content that meets his or her knowledge needs.* Unfortunately, the quality of a particular entry in a knowledge repository is impossible to assess a priori. Moreover, verbal exhortations by knowledge managers may act as weak and unpersuasive signals of quality. Although some halo effect is likely if employees assume that all knowledge in a repository is of similar quality to the specific entries he or she has read in the past, such inferences may be unwarranted. Much may also depend on the knowledge held by a particular employee; the same knowledge found in a repository may be trivial to some but profound to others. Managers who wish to encourage the adoption and use of knowledge repositories thus may benefit from an understanding of the potentially important and reliable signals of repository knowledge quality produced by the knowledge validation process.

All employees who contribute to a knowledge repository are exposed to the process by which their contributions are validated, and are left with certain perceptions of how that process works. The best predictor of product quality often is process quality [23], and in this case, the characteristics of the validation process are likely to have predictive value [18]: how individuals' new contributions are validated is likely to affect their perceptions of the quality of a knowledge repository. As we describe in detail below, each of the three characteristics of validation processes identified earlier (duration, transparency, and restrictiveness) are honest signals that are difficult to fake, reflecting the importance the organization places on obtaining high-quality knowledge.

First, the KM literature holds that high-quality knowledge repositories require validation processes that are of short duration [64, 76]. Reducing the duration of validation processes is a key managerial challenge [52], requiring significant resource allocation to ensure that knowledge "is not . . . published too late to be of any practical day-to-day use in the community" [78, p. 26]. This requires efficient processes to ensure that knowledge is rapidly refined and published [89].

For contributors, duration refers to *contributors' perceptions of the amount of time required to review a typical contribution to a knowledge repository and decide on its outcome.* When contributors experience validation processes that they believe have excessively long durations, they may grow to doubt the quality of the knowledge held in a repository. Lengthy delays may lead individuals to conclude that the knowledge in a repository is less current, more likely to be outdated, and thus of lower quality [40]. Conversely, prompt responses from KM personnel signal to contributors that reviewers are focused, attentive, professional, and dedicated to their work. Although it may not be a perfect signal of quality, it is one indicator of quality that is difficult to fake; reviewers who are distracted, inattentive, or uncaring will find it too effortful to behave as though they are responsive, and the duration of the validation process will lengthen. Unresponsive reviewers may simply not be interested in their task [85, p. 116], and some reviewers may be "tardy on purpose, to avoid current or future refereeing tasks" [6, p. 43]. Similarly, an organization that has underinvested in the validation process by assigning too few people to review submissions will not be able to rapidly assess contributions; long durations may therefore signal problems in the validation process. Duration is thus an honest signal of the amount of effort allocated to the validation process, and as signaling theory suggests, individuals would be likely to rely on it as a signal of the quality of the knowledge repository. Contributors are therefore likely to doubt the overall quality of knowledge held in the repository when they experience long delays after submitting knowledge for validation. Conversely, they are more likely to believe that the repository contains high-quality, current knowledge when they experience fast turnaround times on their own contributions.

Hypothesis 1: Perceived validation process duration is negatively associated with perceptions of repository knowledge quality.

A second important characteristic of the validation process is transparency. Knowledge validation processes may occur in a highly transparent manner, whereby contributors are informed of the status and progress of contributions as they are reviewed and judged. Alternatively, validation processes may lack transparency, and have little or no useful information about progress made available. Transparency is enhanced when there is a well-documented, detailed, and standardized set of review procedures that is published and accessible to contributors. Transparency is also enhanced when editors or reviewers notify contributors when key steps are taken regarding a contribution, and provide details about the results of those actions [48]. Transparent processes are perceived to be fair processes, because they establish clear expectations, invite individuals' involvement, and provide explanations for procedures and decisions [1, 46]. Designing and implementing fair processes is important when managing knowledge workers [45] and encouraging knowledge sharing [11]. Transparency lets contributors learn about the inner workings of the validation process, and would rank high in what Colquitt [17] termed "procedural justice."

For those making contributions to a repository, transparency refers to *contributors' perceptions of the degree to which they are kept informed about the status and progress of contributions as they travel through the validation process.* Contributors who believe that a validation process is transparent feel that they have the opportunity to observe how and why rules are applied by reviewers as they make decisions. Transparency is a reliable signal of quality; it would be difficult and time-consuming to attempt to make a process appear transparent when it is actually not. Unless reviewers understand and adhere to an underlying set of standards, procedures, and expectations designed to ensure clear and consistent interactions with contributors, their efforts will not be seen as transparent. Transparency is thus hard to fake. Contributors understand this, and are likely to see an association between fair validation processes and high-quality repositories. The education literature suggests that transparency is indeed often seen as a strong signal: perceptions of transparency and fairness in evaluation methods positively impact students' beliefs about their instructors and the educational process generally [15]. Conversely, a perceived lack of transparency undermines students' trust in the assessment process [72]. A process that lays out the steps, decisions, and rationales used in assessing contributions therefore signals to contributors that there is nothing to hide, and that it offers a consistent and effective approach for identifying high-quality knowledge contributions.

Hypothesis 2: Perceived validation process transparency is positively associated with perceptions of repository knowledge quality.

The KM literature also holds that repositories are less effective if they simply accept every contribution without filtering out those that are redundant, ineffective, or otherwise of questionable value (e.g., [30, 64, 65]). A validation process is thought to be vital for culling out those contributions that are unlikely to be of value for the target user base [9, 21] or are difficult to understand [50]. A key characteristic of such a process is its restrictiveness; that is, the proportion of contributions that are rejected [89]. Processes that are not very restrictive result in a wide range of content being accepted, while those that are highly restrictive produce a focused repository that is more likely to be valuable to its intended user base [26, 52].

There are two possible final outcomes of a validation process—acceptance or rejection. Based on their experiences with a validation process, contributors extrapolate to form general expectations about the likelihood that future contributions will be accepted or rejected [83]. These expectations can be expressed together as contributors' beliefs about validation process restrictiveness; that is, *contributors' perceptions of the proportion of all contributions to a repository that are accepted and subsequently published.* A restrictive validation process is a reliable signal of repository knowledge quality, as it indicates that the vast majority of contributions are not of sufficient quality to be accepted. Alternately, contributors who see that reviewers accept virtually every contribution are likely to believe that the knowledge in the resulting repository is of highly variable quality. Restrictiveness is difficult to fake; though it is possible that reviewers could just randomly accept only a small portion of submissions, this would be entirely inconsistent with their status as experts, and would ultimately undermine their own value to the firm. Qualitative research also supports the contention that restrictiveness provides an honest signal: individuals' perceptions of validation process restrictiveness may affect their perception of content credibility and legitimacy [65], as well as their beliefs about the quality of knowledge contained in a repository [31]. Because it is a strong signal of high standards, validation processes that are seen by contributors to be highly restrictive are also likely to be seen as indicating higher-quality knowledge.

Hypothesis 3: Perceived validation process restrictiveness is positively associated with perceptions of repository knowledge quality.

Reinforcement Theory

Reinforcement theory (see, e.g., [58, 77]) proposes that individuals' behaviors are shaped by the presence of pleasurable consequences (rewards) and the absence of aversive ones (punishments); such consequences affect the likelihood that an individual will repeat a given behavior. Reinforcement theory is fundamentally a theory of learning. When an individual is rewarded for having engaged in a behavior, he or she is more likely to do so again; similarly, individuals are less likely to engage in a behavior when they learn that punishments will follow. Reinforcement theory has been widely accepted by groups as varied as neuroscientists attempting to explain learning [86], educators interested in instructional design [75], and psychologists seeking to control a variety of disorders [53]. Reinforcement theory has also greatly influenced the practice of education, shaping a variety of teaching models [41, 71]. The IS literature has also used it for theoretical support, for instance, in research on technology adoption (e.g., [2, 69]).

In the context of our study, reinforcement theory implies that the consequences that result when an employee submits knowledge to a validation process may affect the likelihood that he or she will contribute in the future (depending on whether the reinforcement is a reward or a punishment, or neither). Contributors' perceptions of validation process duration, transparency, and restrictiveness thus may directly influence their contribution frequency; that is, the rate at which they submit new knowledge to the repository. Below, we elaborate on these three hypothesized effects.

First, we consider the possibility that contributors will be discouraged by validation processes that they believe to be excessively long in duration. It is clear from reinforcement theory that rewards and punishments that are temporally proximal to a behavior have the strongest effects (e.g., [68]). However, the lack of a response (when a process has a long duration) may produce what reinforcement theory terms "extinction"; that is, when a lack of reward leads individuals to cease engaging in a behavior. (As the weeks go by without a response, contributors may assume that their contribution has not been accepted, may grow discouraged, and may choose to invest their energies in more rewarding activities.) Support for this claim can be found in the knowledge repository literature, which holds that lengthy delays may lead contributors to conclude that the anticipated benefits of knowledge contribution may not be realizable, thus deterring them from making future knowledge contributions [52, p. 79]. More generally, individuals who expect a response but do not receive it are likely to experience higher levels of uncertainty and dissatisfaction with the process [84], as well as uneasiness and anxiety [56]. These emotions constitute negative reinforcements that, according to reinforcement theory, would lead individuals to decrease the frequency with which they contribute. It is thus not surprising that academic authors are more likely to submit manuscripts to journals that they perceive as having a rapid turnaround [29, 48], which they believe benefits them professionally [5]. Ceteris paribus, interactions characterized by timely responses are more likely to act as positive reinforcers of contribution behaviors, while validation processes that are perceived to be overly lengthy may extinguish contribution behaviors.

Hypothesis 4: Perceived validation process duration is negatively associated with repository contribution frequency.

Perceived validation process transparency may affect knowledge contribution frequency. Low-transparency validation processes offer few reinforcements; that is, it may be difficult for contributors to follow what is happening to their contribution at any given time, and contributors may not understand what must happen before a decision is reached on their contribution. At the extreme, employees may experience negative emotions when processes lack transparency and result in outcomes that they perceive as unfair. Employees who believe that these processes are transparent are thus more likely to share their knowledge [57, 60], partly because they understand what is required of them, but also because opaque processes produce negative reinforcements (or no reinforcements), which may extinguish contribution behaviors. Consistent with the justice literature (e.g., [17]), individuals who believe that validation processes are opaque will be less likely to contribute knowledge, while those who believe the validation process is transparent will be more likely to contribute.

> *Hypothesis 5: Perceived validation process transparency is positively associated with repository contribution frequency.*

Validation processes that are seen as very restrictive are likely to negatively impact contribution frequency. Rejection of a contribution is, in the language of reinforcement theory, a punishment that will reduce the likelihood that an individual will contribute knowledge to a knowledge management system (KMS) in the future. Given that the contribution of knowledge can involve considerable effort [52], the perception that this effort may well be wasted is likely to deter individuals from contributing [6], and this deterrent effect may increase as perceived restrictiveness increases [29]. Individuals who are repeatedly rejected may doubt whether their future behaviors will lead to the desired outcomes [56], and may question their skill at writing useful contributions [32, p. 146]. Alternately, individuals who are rewarded by having their contributions accepted are more likely to contribute in the future. Consistent with reinforcement theory, the outcome of making a contribution influences the probability of that behavior reoccurring. Validation processes that are perceived as being very restrictive therefore may achieve content quality at the expense of content quantity [27].

> *Hypothesis 6: Perceived validation process restrictiveness is negatively associated with repository contribution frequency.*

Finally, individuals' perceptions of repository knowledge quality may also affect their contribution frequency [91]. In particular, we hypothesize that individuals who believe a repository contains high-quality knowledge are less likely to contribute. Reinforcement theory deals with the anticipated rewards and punishments associated with an action, and the extent to which individuals believe a repository contains high-quality knowledge may reflect their expectations about the likely outcomes of contributing. Two theoretical paths are possible, both of which arrive at the same conclusion. The first concerns the difficulty of crafting a contribution: users who believe that a repository contains high-quality knowledge may feel deterred from contributing, as anything they write would have to meet this high standard of quality. Users may therefore feel intimidated and more doubtful that their contributions could add value to this high-quality repository, and contribute less. Contributing to a high-quality repository may also require more effort, again making it less likely that individuals will do so. Conversely, repositories that are believed by a contributor to contain lower-quality knowledge are easier targets, and users would be more likely to contribute because they anticipate, ceteris paribus, that their contributions would be more likely to be of an acceptable level of quality. The second theoretical path focuses on opportunities: the higher the quality, the more helpful the knowledge contained in the repository [52]—but when the repository is already very helpful, users may

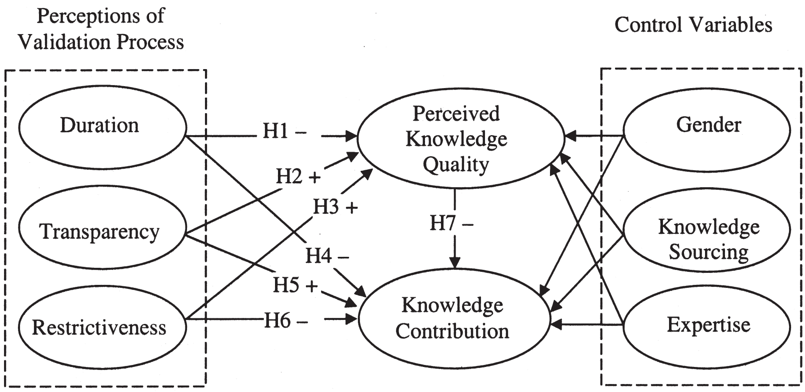

Figure 1. Research Model

believe that there are fewer opportunities to make new nonredundant contributions. In such situations, when individuals believe that there is little opportunity to make unique contributions, they are less likely to contribute [8], as redundant contributions will not result in any desirable outcomes [44]. In contrast, the relative lack of useful content in a low-quality repository provides individuals with many opportunities to improve on what is there and fill in gaps around existing content [49]. Both of these theoretical paths (effort required to craft a contribution, difficulty finding an opportunity to make a contribution) are consistent with the idea that positive perceptions of knowledge quality can extinguish contribution behaviors, while negative perceptions can reinforce them.[1]

Hypothesis 7: Perceived repository knowledge quality negatively influences repository contribution frequency.

We have also incorporated three control variables into our model—knowledge sourcing (e.g., [34, 35]), gender, and expertise. The frequency with which individuals source knowledge from a repository may affect their perceptions of the quality of that repository, and may also affect their contribution behavior. Research has also suggested that experts judge knowledge content differently than do novices [36, 82]; thus, expertise may play a role in predicting both perceived knowledge quality and contribution frequency. Figure 1 summarizes the research hypothesis.

Research Method

To test these hypotheses, we gathered data about the contribution behaviors of knowledge repository users, and surveyed them about their perceptions of their repository's validation processes. In this section, we first describe our research site, instrument, and data collection efforts. Next, we describe our analysis of the data using partial least squares (PLS Graph, version 3.00), including assessments of measurement and structural models that follow established procedures [16, 42].

Data Collection

For our sample, we approached senior managers at a large American firm (referred to hereafter as “HelpCo”) that provides outsourced technical help desk support services. At the time that we conducted our survey, HelpCo had more than 50,000 U.S. employees in various call centers, in addition to operations in 44 other countries. Each call center served employees at multiple client companies, offering both basic and advanced assistance with computer-related problems. In exchange for the promise of a report describing our findings, senior managers at HelpCo agreed to let us survey help desk analysts at one site located in the northeast United States, and promised to provide employee-level data for actual knowledge contribution frequency.

In the summer and autumn of 2004, HelpCo had redesigned the knowledge repository (“KBase”) that it used to support its help desk analysts, and the new system came online on January 1, 2005. To allow analysts sufficient time to learn the new system, we conducted the survey after KBase had been in place for six full months. We administered the survey at one HelpCo site in July 2005, and then in January 2006 we were provided with data about analysts’ actual contribution behaviors for 2005.

The knowledge contained in HelpCo’s KBase was intended to help analysts rapidly provide effective solutions to customer problems. Solutions contained in KBase ranged from process oriented (e.g., how to reset a lost password) to environment oriented (e.g., why a particular server was not responding and how to work around this problem) to technically oriented (e.g., how to troubleshoot a malfunctioning piece of hardware). The software provided both hierarchical drill-down features for finding solutions and key word search functionality.

Analysts were asked by their managers to make at least three knowledge contributions each quarter. With the rollout of the new KBase software, users were provided with a special interface that asked them to describe their knowledge contribution. After users provided this information, it was automatically routed to the appropriate subject matter expert or process expert for review. Reviewers were notified electronically about the presence of a new contribution, and were asked to vet the contribution for accuracy, completeness, and nonredundancy. Reviewers’ evaluations were then routed automatically along with the original contribution to a manager for final approval. If approved, the contribution was routed to the knowledge management team for final revisions and formatting prior to being published in the knowledge repository.

We developed our survey instrument following Dillman’s [24] approach. Items measuring perceived quality of knowledge were adapted from Doll and Torkzadeh [25], and were refined based on inputs from HelpCo managers, who identified certain items as key in their context, and others as irrelevant. Items measuring frequency of contribution were adapted from Kankanhalli et al. [43]. Knowledge sourcing items were adapted from Gray and Durcikova [34]. The remaining three constructs (perceived duration, transparency, and restrictiveness of the validation process) were newly developed. Following established practices in measuring knowledge sourcing [35], we asked analysts to think of knowledge as “expertise, opinions, insights, and experience.” All items were measured on a seven-point Likert scale anchored on 1 (strongly disagree) and 7 (strongly agree). We refined the instrument by pretesting it with five management information systems (MIS) Ph.D. students and five MIS faculty. To ensure that the items were meaningful to individuals in our subject pool, we met individually with five analysts and had them complete draft surveys. During these meetings, we encouraged analysts to verbalize their thoughts as they progressed with the survey. This enabled us to fine-tune our instrumentation to fit the language used at HelpCo. The final items used in this study are shown in Table 1.

Participation was solicited via e-mail. First, a senior manager at HelpCo informed analysts that they would be invited to participate in a survey to evaluate their KBase, and that the results of the survey could benefit both HelpCo and the analysts. Analysts then received an e-mail from the researchers in which they were invited to participate in an online survey. Two reminders to participate were subsequently sent, and the survey closed 30 days after the initial invitation was e-mailed. We received a total of 118 usable responses within 30 days of our request, with no significant differences between early and late responders. Of the 300 analysts working at the site, this represented a 39 percent response rate. Respondents ranged in age from 21 to 67 years, with an average age of 37 and a mean job tenure of 7 years. Forty-nine percent were female and 51 percent were male. Following Podsakoff and Dalton [67], we tested for common method bias by using a factor analysis procedure to search for a common method influence on all factors, and found none. Further, our use of a nonsubjective measure of knowledge contribution behavior also reduces the likelihood that these results are an artifact of our research method. These responses were subsequently analyzed using PLS, a structural equation modeling technique that employs principal components analysis, path analysis, and regression to simultaneously evaluate data and theory [62].

Measurement Model

We assessed the adequacy of the measurement model using three common tests of convergent validity [42] that employ statistics produced by our PLS analysis. After removing three items that correlated poorly with their construct, all remaining items were more strongly correlated with their respective construct than with other constructs (Table 2), at levels greater than 0.707, indicating that there was more shared variance between a construct and measure than there was error variance [14]. Furthermore, Table 3 contains the factor structure for all self-reported items, generated without any a priori expectations of which item should load on which construct. All item loadings were greater than 0.707, with the exception of one item for the knowledge sourcing control variable (loading of 0.68). However, given that we did in fact have a priori expectations about the structure of these data, the item construct correlation matrix (Table 2) is a superior assessment of discriminant and convergent validity. Second, we assessed the internal consistency of each scale using composite reliability [88], and found that the lowest was 0.85, well in excess of Nunnally's [63] 0.7 guideline. Third, average variance extracted (AVE) [28], which measures the average amount of variance that a construct captures from its indicators relative to the amount due to measurement

Table 1. Survey Items

Item code	Item wording
Duration	
DUR1	The review process for [contributions[1]] to the KBase occurs in a timely manner. (R)
DUR2	The review process for [contributions] to the KBase takes far too long.
DUR3	I am satisfied with the amount of time it typically takes for [contributions] to be reviewed and processed. (R)
Transparency	
TRA1	I am kept informed about the status of my [contributions] to the KBase.
TRA2	It is easy for me to see the status of my [contributions] to the KBase.
TRA3	I can check at any point in time the status of my [contributions] to the KBase.
TRA4[2]	Overall, the [contribution] review process is clear.
Restrictiveness	
RES1	It is difficult to get [contributions] approved.
RES2[2]	Getting [contributions] approved and accepted is easy. (R)
RES3	In your experience, what proportion of [contributions] that you submit to the KBase end up being rejected? (Response options: 10%, 20%, ... 90%, 100%)
RES4	Based on the experiences your colleagues have shared with you, what proportion of all [contributions] that are submitted to the KBase end up being rejected? (Response options: 10%, 20%, ..., 90%, 100%)
Knowledge quality	
QUA1	The knowledge in the KBase is precise.
QUA2	The content of KBase meets my needs.
QUA3	The knowledge in the KBase is accurate.
QUA4	Overall, the quality of knowledge in the KBase is high.
Knowledge sourcing	
SOU1	I rarely use the KBase as a way of acquiring knowledge. (R)
SOU2	I frequently check in the KBase when I need to improve my knowledge on a topic or issue.
SOU3	When I am working on a problem, I often look in the KBase to find solutions to similar problems.
SOU4[2]	I often obtain knowledge through the KBase.
Expertise	
EXP1	I am very good at solving our customer's technical problems.
EXP2	I am an expert technical troubleshooter.
EXP3	My colleagues would consider me to be an expert in my areas of technical knowledge.

Notes: R = reverse coded. [1] HelpCo's idiosyncratic term used in place of the word "contributions" has been omitted. [2] Item dropped from the final analysis.

Table 2. Item Construct Correlations

	Transparency	Duration	Restrictiveness	Knowledge quality	Knowledge sourcing	Expertise
TRA1	**0.85**	0.38	–0.36	0.40	0.18	0.12
TRA2	**0.92**	0.29	–0.42	0.32	0.15	0.22
TRA3	**0.94**	0.27	–0.44	0.37	0.12	0.17
DUR1	0.36	**0.93**	–0.47	0.45	0.34	–0.01
DUR2	0.22	**0.89**	–0.52	0.31	0.21	–0.01
DUR3	0.36	**0.95**	–0.50	0.45	0.28	–0.04
RES1	–0.32	–0.48	**0.80**	–0.15	–0.16	–0.01
RES2	–0.24	–0.26	**0.88**	–0.16	–0.23	0.10
RES3	–0.45	–0.52	**0.89**	–0.15	–0.16	0.07
QUA1	0.28	0.33	–0.13	**0.94**	0.55	–0.07
QUA2	0.42	0.47	–0.19	**0.94**	0.54	–0.04
QUA3	0.34	0.34	–0.18	**0.94**	0.47	–0.06
QUA4	0.39	0.42	–0.27	**0.87**	0.57	0.00
SOU1	0.13	0.24	–0.10	0.29	**0.76**	0.13
SOU2	0.13	0.22	–0.18	0.56	**0.86**	–0.08
SOU3	0.15	0.20	–0.21	0.45	**0.79**	0.01
EXP1	0.06	–0.05	0.15	–0.09	0.06	**0.84**
EXP2	0.17	0.04	0.03	–0.04	–0.03	**0.96**
EXP3	0.16	–0.03	0.04	–0.06	0.01	**0.96**

Note: Correlations in boldface represent intraconstruct coefficients; those not in boldface are interconstruct coefficients.

Table 3. Exploratory Factor Analysis

	1	2	3	4	5	6
RES1	–0.114	0.028	**0.770**	–0.227	–0.451	0.068
RES3	–0.139	0.128	**0.891**	–0.369	–0.360	–0.143
RES4	–0.170	0.154	**0.872**	–0.376	–0.485	–0.021
DUR1	0.389	–0.091	–0.375	0.296	**0.894**	0.254
DUR2	0.287	–0.033	–0.518	0.187	**0.886**	0.138
DUR3	0.382	–0.101	–0.412	0.294	**0.944**	0.160
TRA1	0.329	0.089	–0.225	**0.871**	0.301	0.101
TRA2	0.297	0.200	–0.347	**0.913**	0.255	0.022
TRA3	0.332	0.119	–0.366	**0.928**	0.223	–0.034
QUA1	**0.933**	–0.060	–0.120	0.273	0.319	0.299
QUA2	**0.909**	–0.061	–0.162	0.364	0.365	0.329
QUA3	**0.932**	–0.073	–0.138	0.324	0.293	0.225
QUA4	**0.910**	–0.006	–0.221	0.372	0.374	0.353
SOU1	0.269	0.150	–0.050	0.057	0.208	**0.897**
SOU2	0.690	–0.080	–0.154	0.115	0.320	**0.699**
SOU3	0.592	0.058	–0.304	–0.035	0.072	**0.679**
EXP1	–0.085	**0.878**	0.174	0.048	–0.097	0.166
EXP2	–0.029	**0.955**	0.055	0.146	–0.018	–0.003
EXP3	–0.032	**0.940**	0.041	0.192	–0.112	0.096

Note: Items in boldface indicate loadings of items on their intended construct; all nonboldface items are cross-loadings.

error, was calculated for each scale; all scales exceeded Chin's [16] guideline of 0.5, meaning that at least 50 percent of variance in indicators was accounted for by their respective construct. Further, the square root of AVE for each construct exceeded all respective interconstruct correlations, providing further evidence of discriminant validity. Table 4 provides the results of these measurement model analyses.[2]

Data Analysis and Results

We tested our hypotheses by examining the size and significance[3] of structural paths in the PLS analysis and the percentage of variance explained. Results are reported in Figure 2.

First, the model explained 48.0 percent of the variance in perceived knowledge quality. Perceived validation process duration (H1, $\beta = -0.31$, $p < 0.01$), transparency (H2, $\beta = 0.33$, $p < 0.01$), and restrictiveness (H3, $\beta = 0.21$, $p < 0.05$) all influenced knowledge quality as hypothesized. Of the control variables, knowledge sourcing ($\beta = 0.47$, $p < 0.01$) and expertise ($\beta = -0.13$, $p = 0.10$) significantly influenced knowledge quality, but gender did not ($p > 0.1$).

Second, the model explained 18.5 percent of the variance in knowledge contribution. Of the hypothesized antecedents, perceived validation process transparency (H5, $\beta = 0.23$, $p < 0.01$), restrictiveness (H6, $\beta = -0.21$, $p < 0.05$), and knowledge quality (H7, $\beta = -0.26$, $p < 0.05$) all affected knowledge contribution frequency as

Table 4. Convergent and Discriminant Validity

	Construct	Number of items	Response mean	Standard deviation	Cronbach's alpha	Internal consistency	Average variance extracted (percent)
1	Perceived transparency of validation process	3	5.8	1.41	0.89	0.93	81
2	Perceived duration of validation process	3	4.8	1.70	0.91	0.94	85
3	Perceived restrictiveness of validation process	3	3	2.02	0.81	0.91	71
4	Perceived quality of KBase	4	5.2	1.37	0.95	0.96	88
5	Knowledge sourcing	3	5.7	1.28	0.73	0.85	65
6	Gender	1	n.a.	n.a.	n.a.	n.a.	n.a.
7	Expertise	3	5.6	1.48	0.92	0.94	84
8	Log of system-reported contributions	1	1.2	0.67	n.a.	n.a.	n.a.

	Construct	1	2	3	4	5	6	7	8
1	Perceived transparency of validation process	0.90							
2	Perceived duration of validation process	–0.34	0.92						
3	Perceived restrictiveness of validation process	–0.45	0.54	0.84					
4	Perceived quality of KBase	0.40	–0.44	0.18	0.94				
5	Knowledge sourcing	0.16	–0.31	–0.21	0.56	0.81			
6	Gender	0.06	0.21	0.13	–0.15	–0.22	n.a.		
7	Expertise	0.19	0.02	0.06	–0.06	0.01	0.26	0.92	
8	Log of system-reported contributions	0.28	–0.19	–0.32	0.03	0.21	0.01	0.10	n.a.

Notes: Diagonal elements are the square root of average variance extracted. All correlations less than –0.18 or greater than 0.18 are significant at the $p < 0.05$ level. Total annual contributions prior to the log procedures featured a mean of 54.1 and a standard deviation of 9.3, with a range of 1 to 567. n.a. = not applicable.

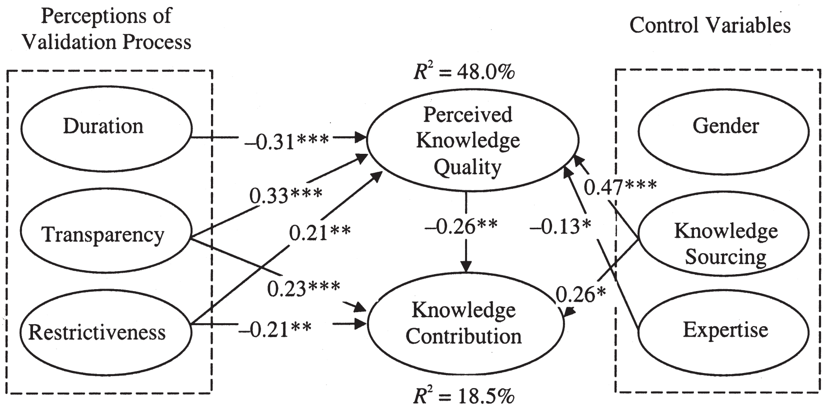

Figure 2. Significant Paths in PLS Analysis
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

hypothesized. However, perceived validation process duration (H4, $\beta = -0.05$, n.s. [not significant]) did not. Of the control variables, knowledge sourcing ($\beta = 0.26$, $p < 0.05$) had a positive effect on knowledge contribution, while neither gender nor expertise had a significant effect ($p > 0.1$ for both).

Discussion and Implications

The results of this study substantiate two broad theoretical paths that help to explain how individuals' perceptions of validation processes affect their repository-related beliefs and behaviors. Validation processes that are designed purely for the purpose of efficiently filtering out low-quality contributions (e.g., [70]) may have unintended effects on contributors' contribution behaviors. Given the considerable investment that organizations are making in repository-based KM efforts [52], an understanding of these effects on individuals' behaviors is key to maximizing their chances of success. Our findings provide insights for managers who must grapple with this dilemma in order to succeed at the ongoing challenge of encouraging employees to contribute their knowledge. The findings should likewise prove useful to researchers who wish to develop a more holistic understanding of the theoretical paths by which validation processes affect knowledge repository success.

In the remainder of this section, we first consider the implications of our findings for managers, and then for researchers. Although these findings concern individuals' perceptions of knowledge validation process characteristics, there are clear implications for the design and management of these processes. If managers can implement process changes that positively affect individuals' perceptions, then these changes are likely to be associated with desirable behavioral outcomes. Our recommendations for managers therefore address the kinds of changes that are likely to influence contribution behaviors via the theoretical processes supported by our findings.

Implications for Management

First, our findings regarding transparency and duration have implications for the prioritization of efforts intended to improve contribution frequency. Managers who face a choice between allocating resources to the design of more transparent validation processes versus assigning more reviewers to speed up the validation process should prioritize the former over the latter. Our results show that transparency positively influenced knowledge contribution while duration had no effect on it. Managers should therefore investigate new ways of improving validation process transparency—for example, by educating contributors about the procedures used in knowledge validation, through improved interfaces that communicate details of the status of an employee's contributions, or through enhanced dialogue between reviewers and contributors over the life cycle of a contribution. Although we cannot vouch for the effects of such process-enhancing changes on individuals' perceptions, our findings suggest that any change that causes contributors to perceive processes as more transparent is likely to improve contribution rates and enhance perceptions of knowledge quality.

The above discussion should not be taken as a rejection of the need to reduce validation process duration, as duration clearly influences perceptions of knowledge quality. Although managers could reduce duration by engaging more subject matter experts in the validation process, a more prudent approach may instead be to change contributors' *expectations* about duration. Contributors' satisfaction with validation process duration is influenced in part by the expectations they hold about how long it *should* take to validate a contribution. If managers can change contributors' normative expectations about how long it should take to validate contributions, then contributors' satisfaction with the duration of their wait might be easily improved without any changes to actual duration. For example, this could be accomplished by explaining to contributors why it is important to give reviewers enough time to do a good job, why a multistage review process is necessary, and why efficient management of the contribution queue necessitates some delays. Educating contributors in this manner would also align well with the previously noted approaches for enhancing transparency through education and communication.

Other implications flow from our finding that individuals who felt the validation process was restrictive also believed that the repository contained knowledge that was higher in quality, but were less likely to contribute knowledge. Managers who anticipate only the beneficial effects of a restrictive validation process on knowledge quality thus may fail to recognize a powerful demotivator to contribute. However, this does not suggest that validation processes should be weakened in order to maximize contributions; the positive link between knowledge quality and knowledge sourcing established in previous research [91] makes it apparent that doing so would be very damaging. Instead, one possible strategy for lessening the negative effects of restrictive validation processes without weakening knowledge quality would be to implement the kind of developmentally oriented validation processes that are found in academia. Developmental validation processes encourage reviewers to look for any potentially valuable ideas contained within a contribution, and rather than rejecting the contribution outright, encourage contributors to refocus their work on these ideas. We approached managers at HelpCo to explore this idea, and confirmed that because of resource constraints, the firm did not have a developmental review process in place. In academic settings, developmental reviewers encourage authors to engage more fully and work to improve the quality of their contributions [73, 74]. This results in a larger number of iterations between academic reviewers and authors, but over time produces higher-quality contributions, fewer rejections, and more acceptances [73, 74]. Knowledge managers who adopt this strategy for enhancing contribution quality would expect to see a reduction in the perception of restrictiveness among contributors, which in turn would encourage contributions without lowering quality standards. There may be additional benefits to adopting such a strategy, including improving employees' contribution skills and thereby lowering the number of low-quality contributions over time [73, 74]. While this synthesis of our findings and the literature on academic reviewing seems logical, future research is needed to test whether these connections are in fact valid in nonacademic settings.

Implications for Research

Our research is the first to systematically study the effects of validation process characteristics on perceptions and behaviors. While our theory development section includes a range of references to various literatures (principally education and academic publishing) that provide anecdotes and observations that are consistent with our hypotheses, ours was not a simple replication of other studies. Indeed, we were unable to find any articles in these source literatures that offered explanatory theories for the phenomena they describe or conducted any rigorous quantitative analyses. One contribution of our work, then, is a set of explanatory theories, situated in a knowledge contribution setting, which we have offered and tested. To our knowledge, no similar research has ever been performed, even in these source literatures. Education scholars and researchers who study academic publishing therefore may find our study very helpful in theorizing and bringing a level of methodological rigor to related research in their own fields.

Despite a range of qualitative observations made in the knowledge repository literature about the possible effects of validation processes, the knowledge repository literature has not theorized the ways in which individuals' beliefs and behaviors are shaped by their perceptions of validation processes. This study opens up a new theoretical perspective on validation processes that helps explain why employees vary considerably in their rates of contribution to knowledge repositories. A core contribution of this paper is thus to expand our understanding of validation processes beyond simple filtering mechanisms by theorizing and confirming that what individuals learn about validation processes matters: consistent with signaling theory, these perceptions are strong indicators of repository knowledge quality, and consistent with reinforcement theory, they have significant effects on knowledge contributions. However, there is clearly room for improvement. While perceived duration, transparency, and restrictiveness are important, they are unlikely to be the only characteristics that influence contributor behaviors. Future research that expands on this set of antecedents is likely to provide additional insight into the ways that validation processes affect important behavioral outcomes.

The finding that perceived validation process transparency has a significant effect on knowledge contribution frequency is consistent with signaling theory, and confirms that contributors who can observe how and why rules are applied in the process of knowledge validation take this as a reliable signal of the quality of the repository. This suggests that research to investigate how improved transparency can be achieved—without generating undesirable externalities—would be valuable for those managing and researching knowledge repositories. Future research could also help to distinguish between different kinds of perceived transparency, as there may be different signals of quality; for example, differentiating between the transparency created by the validation workflow process and the transparency created by making public the rules or heuristics used when judging quality. Theorizing the various antecedents of multiple kinds of perceived transparency and their respective effects on downstream variables might also provide the basis for a more generalizable theory of process transparency that could apply beyond the knowledge validation setting.

While there are similarities between the academic publishing context and the industry-focused knowledge repository setting, there are also differences; for instance, while academic journals have a restricted number of pages, knowledge repositories typically are not limited in what they can include. Do these and other theoretical differences between these contexts moderate the expression of signaling theory and reinforcement theory? We found that when acting as a control variable, perceptions of knowledge quality were negatively related to knowledge contribution behaviors. This suggests some tantalizing differences between academic and industry contexts: in an academic context, perceptions of quality would be expected to attract, and not repel, contributions. Clearly, the kind of incremental rewards associated with contribution behaviors (which vary from large in the academic setting to very small in the HelpCo context) may have important influences. This is an area for future research that is both relevant and timely for academic fields that are grappling with issues that are similar, but not identical, to those of knowledge managers. In particular, research to establish whether individuals' perceptions of knowledge validation process characteristics have similar effects when different kinds of reward mechanisms are offered seems timely and valuable.

A broader implication of our findings is that more extensive applications of signaling theory may be useful in IS research. For instance, data quality researchers may benefit from our approach by conducting studies that establish the degree to which different aspects of a system's design and architecture are more likely to signal to users that the data it contains are high quality. Our results suggest that not all characteristics are equally persuasive in influencing perceptions of quality, suggesting the possibility of a hierarchy of signals, from relatively strong to weak. Future research that sought to develop models that could integrate findings from both the knowledge-related perspective we have taken here and the broader information-related perspective of the field could be particularly valuable. Understanding what aspects of a system's interface, contents, and functionality are typically seen as more reliable signals of quality across a range of technologies offers an exciting new direction for IS adoption research.

Although widely accepted as an explanation for human behavior, reinforcement theory has seen only limited use in the IS literature (e.g., [2, 69]). Our study thus adds weight to the body of evidence that suggests that this mature theory base can be profitably employed to explain issues of IS adoption and ongoing use. For instance, it may provide theoretical support for efforts to design IS that do not require manuals or help files, on the basis that interfaces that explicitly channel users' behaviors in ways that are productive (reinforcing use) and away from unproductive wanderings (negative reinforcements) might produce self-reinforcing positive spirals of use and reinforcement. Beyond interfaces, other potentially interesting applications of reinforcement theory include the design of systems to enhance mindfulness (e.g., [13]). For example, users who regularly receive IS-generated reports that include only data that are consistent with their perception of reality may experience this lack of new information as negative reinforcement, or at the very least as an absence of positive reinforcement. This, in turn, may lead users toward less mindful behavior as they disregard or ignore the reports over time. Regardless of the specific domains studied, our results are encouraging for researchers who seek to enhance the field through the use of motivational theories such as reinforcement theory.

We also see productive avenues by which to extend this research. For example, compared to the relatively fine-grained approaches that have been used to understand data quality (e.g., [61]), our study offers a very general and high-level conceptualization of knowledge quality. While clearly effective enough for our research, this unidimensional approach to knowledge quality could be profitably expanded. Future work that unpacked the dimensions of knowledge quality—particularly in contrast to the dimensions of data quality—would advance KM research by showing how (and whether) users apply different standards when evaluating the quality of transactional data versus the quality of knowledge contributions. A second possibility pertains to the significant ($p < 0.10$) finding that our expertise control variable negatively predicted perceived knowledge quality. One explanation for this finding is that as individuals' levels of expertise increase, their standards for what constitutes high-quality knowledge also increase. Although we offered no specific theory to test expertise as a control variable, this effect is interesting and suggests the need for future research to discover whether expertise plays a more important role in influencing other repository-related perceptions.

Limitations

In general, our findings must be interpreted in light of the limitations of single-firm cross-sectional research. Other limitations include the possibility that unmeasured variables, general in nature or particular to this organization, produced the observed pattern of results. It is also possible that knowledge repositories used in technical support environments are entirely unlike repositories used in other contexts. All these are possible threats to the validity and generalizability of our research, which only future replication in alternate contexts can conclusively dispel.

Because our data are not longitudinal, we are unable to conclusively confirm the direction of causality. While we feel that the balance of logic in our study supports the idea that perceptions influence behaviors, longitudinal research would help researchers to better understand the temporal relationships between our constructs, and would especially help tease out whether there are multiple bidirectional sources of causality between perceived knowledge quality and knowledge contribution behaviors. Future longitudinal research that seeks to establish whether there are indeed reinforcing bidirectional forces that play out over time would further serve to advance knowledge in this area.

We also note that our definition of knowledge quality was narrower than other definitions of data quality, which have included dimensions such as consistency, validity, and completeness. Research that employs a different operationalization of knowledge quality may therefore obtain different results. While this remains a limitation of our work, we note that the particular aspects of quality that we measured were consistent with what managers at HelpCo felt was most important in assessing repository quality. Future research that seeks to develop a robust knowledge quality construct may be particularly helpful in building a cumulative body of evidence in this area. Similarly, our operationalization of validation process duration did not specify a referent time frame: it is possible that, when they were responding, users were not thinking about the expected duration of the validation process stipulated by knowledge managers at HelpCo. Future research that can test the validity of this measure by correlating subjective measures of duration with actual system-generated metrics for the extent to which an individual's contributions were responded to faster or slower than the published target time frame would be helpful in this regard.

Conclusions

Although validation processes are key to ensuring the quality of knowledge in a repository, they must be implemented with care so that they do not inadvertently discourage knowledge contributions. Individuals' perceptions of these processes shed new light on this challenge, and provide valuable points of theoretical connection between the design of knowledge validation processes and desirable outcomes for individuals. We hope that the ideas and challenges laid out above spur more IS researchers to theorize the perceptions that arise as individuals interact with knowledge repositories, and, by doing so, bring knowledge repository research squarely into the domain in which it properly belongs—that of IS research.

Notes

1. While our hypothesis is consistent in directionality with Zimmer et al. [91] and is supported by their findings, it is also possible that an individual's contribution behaviors would enhance his or her perceptions of knowledge quality. Here, the argument would be

that individuals who contribute frequently are more likely to believe that it is because of their contributions that the repository is high quality, and that individuals who do not contribute frequently believe that because of their low contributions, the repository is low quality. While this is possible, it seems less plausible than the argument advanced above. Perhaps a truly brilliant individual who has tremendous faith in his or her own skills might attribute the quality of an entire repository to his or her own efforts, but this seems far less likely to occur across hundreds of call center employees. Given the weight of the relative theoretical arguments, we side with the more common (and previously supported) model of perceptions influencing behaviors, rather than the opposite.

2. Submission frequency data were highly skewed. In order to meet the normality criterion required for our subsequent analysis, we used the log of total number of submissions to the KBase over this period as our measure of system-reported knowledge contributions.

3. PLS produces standardized regression coefficients for structural paths. Bootstrapping techniques, a nonparametric approach for estimating the precision of paths, were used to test for significance.

References

1. Abrams, L.C.; Cross, R.; Lesser, E.; and Levin, D.Z. Nurturing interpersonal trust in knowledge-sharing networks. *Academy of Management Executive, 17,* 4 (2003), 64–77.

2. Agarwal, R., and Prasad, J. Are individual differences germane to the acceptance of new information technologies? *Decision Sciences, 30,* 2 (1999), 361–391.

3. Alavi, M., and Leidner, D. Knowledge management and knowledge management systems: Conceptual foundations and research issues. *MIS Quarterly, 25,* 1 (2001), 107–136.

4. Ashford, S.J. The publishing process: The struggle for meaning. In P.J. Frost and M.S. Taylor (ed.), *Rhythms of Academic Life: Personal Accounts of Careers in Academia.* Thousand Oaks, CA: Sage, 1996, pp. 119–127.

5. Azar, O.H. The review process in economics: Is it too fast? *Southern Economic Journal, 72,* 2 (2005), 482–491.

6. Azar, O.H. The academic review process: How can we make it more efficient? *American Economist, 50,* 1 (2006), 37–51.

7. Bansler, J.P., and Havn, E.C. Building community knowledge systems: An empirical study of IT-support for sharing best practices among managers. *Knowledge and Process Management, 10,* 3 (2003), 156–163.

8. Beenen, G.; Ling, K.; Wang, X.; Chang, K.; Frankowski, D.; Resnick, P.; and Kraut, R.E. Using social psychology to motivate contributions to online communities. In J. Herbsleb and G. Olson (eds.), Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work. New York: ACM Press, 2004, pp. 252–261.

9. Birkinshaw, J., and Sheehan, T. Managing the knowledge life cycle. *Sloan Management Review, 44,* 1 (2002), 75–83.

10. Bloom, P.N., and Reve, T. Transmitting signals to consumers for competitive advantage. *Business Horizons, 33,* 4 (1990), 58–66.

11. Bock, G.-W.; Zmud, R.W.; and Kim, Y.G. Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate. *MIS Quarterly, 29,* 1 (2005), 87–111.

12. Boulding, W., and Kirmani, A. A consumer-side experimental examination of signaling theory: Do consumers perceive warranties as signals of quality? *Journal of Consumer Research, 20,* 1 (1993), 111–123.

13. Butler, B.S., and Gray, P.H. Reliability, mindfulness, and information systems. *MIS Quarterly, 30,* 2 (2006), 211–224.

14. Carmines, E.G., and Zeller, R.A. *Reliability and Validity Assessment.* Beverly Hills, CA: Sage, 1979.

15. Carroll, J. Fair assessment, fair policing and fair punishment: Building on reliability and validity. In N. Sharp (ed.), *Reflections on Assessment,* vol. II. Mansfield, TX: Linney Direct, 2005, pp. 60–67.

16. Chin, W.W. The partial least squares approach for structural equation modeling. In G.A. Marcoulides (ed.), *Modern Methods for Business Research.* Mahwah, NJ: Lawrence Erlbaum, 1998, pp. 295–336.

17. Colquitt, J.A. On the dimensionality of organizational justice: A construct validation of a measure. *Journal of Applied Psychology, 86,* 3 (2001), 386–400.

18. Cox, D.F. *Risk Taking and Information Handling in Consumer Behavior.* Boston: Harvard Business School Press, 1967.

19. Crowley, A. Memory bank: Companies try to record the knowledge of their information workers. *PC Week, 14* (1997), 101–102.

20. Damodaran, L., and Olphert, W. Barriers and facilitators to the use of knowledge management systems. *Behaviour & Information Technology, 19,* 6 (2000), 405–413.

21. Davenport, T.H., and Klahr, P. Managing customer support knowledge. *California Management Review, 40,* 3 (1998), 195–208.

22. Davenport, T.H., and Prusak, L. *Working Knowledge: How Organizations Manage What They Know.* Boston: Harvard Business School Press, 1998.

23. Deming, W.E. *Some Theory of Sampling.* New York: John Wiley & Sons, 1950.

24. Dillman, D.A. *Mail and Telephone Surveys.* New York: John Wiley & Sons, 1978.

25. Doll, W.J., and Torkzadeh, G. Developing a multidimensional measure of system-use in an organizational context. *Information & Management, 33,* 4 (1998), 171–185.

26. Dunford, R. Key challenges in the search for the effective management of knowledge in management consulting firms. *Journal of Knowledge Management, 4,* 4 (2000), 295–302.

27. Edwards, J.S.; Shaw, D.; and Collier, P.M. Knowledge management systems: Finding a way with technology. *Journal of Knowledge Management, 9,* 1 (2005), 113–125.

28. Fornell, C., and Larcker, D. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18,* 1 (1981), 39–50.

29. Frank, E. Authors' criteria for selecting journals: Perspectives on peer review. *Journal of the American Medical Association, 272,* 2 (1994), 163–164.

30. Garvin, D.A., and March, A. Note on knowledge management. Harvard Business School Case Study 9-398-031, Boston, November 26, 1997.

31. Goodman, P.S., and Darr, E.D. Computer-aided systems and communities: Mechanisms for organizational learning in distributed environments. *MIS Quarterly, 22,* 4 (1998), 417–440.

32. Graham, J.W., and Stablein, R.E. A funny thing happened on the way to publication: Newcomer's perspectives on publishing in the organizational sciences. In L.L. Cummings and P.J. Frost (eds.), *Publishing in the Organizational Sciences.* Homewood, IL: Irwin, 1985, pp. 138–154.

33. Gray, P.H. The impact of knowledge repositories on power and control in the workplace. *Information Technology & People, 14,* 4 (2001), 368–384.

34. Gray, P.H., and Durcikova, A. The role of knowledge repositories in technical support environments: Speed versus learning in user performance. *Journal of Management Information Systems, 22,* 3 (Winter 2005–6), 161–193.

35. Gray, P.H., and Meister, D.B. Knowledge sourcing effectiveness. *Management Science, 50,* 6 (2004), 821–834.

36. Gregor, S., and Benbasat, I. Explanations from intelligent systems: Theoretical foundations and implications for practice. *MIS Quarterly, 23,* 4 (1999), 497–530.

37. Gupta, A., and Govindarajan, V. Knowledge management's social dimensions: Lessons from Nucor Steel. *Sloan Management Review, 42,* 1 (2000), 71–80.

38. Hansen, M.T., and Haas, M.R. Competing for attention in knowledge markets: Electronic document dissemination in a management consulting company. *Administrative Science Quarterly, 46,* 1 (2001), 1–28.

39. Hill, W. Learning: A survey of psychological interpretations, 4th ed. New York: Harper and Row, 1985.

40. Huang, K.; Lee, Y.W.; and Wang, R.Y. *Quality Information and Knowledge.* Upper Saddle River, NJ: Prentice Hall, 1999.

41. Huitt, W., and Hummel, J. *An introduction to operant (instrumental) conditioning.* Valdosta State University, Valdosta, GA, 1997 (available at http://chiron.valdosta.edu/whuitt/col/behsys/operant.html).

42. Hulland, J. Use of partial least squares (PLS) in strategic management research: A review of four studies. *Strategic Management Journal, 20,* 2 (1999), 195–204.
43. Kankanhalli, A.; Tan, B.C.Y.; and Wei, K.K. Contributing knowledge to electronic knowledge repositories: An empirical investigation. *MIS Quarterly, 29,* 1 (2005), 113–143.
44. Karau, S., and Williams, K. Social loafing: A meta-analytic review and theoretical integration. *Journal of Personality & Social Psychology, 65,* 4 (1993), 681–706.
45. Kim, W.C., and Mauborgne, R. Fair process: Managing in the knowledge economy. *Harvard Business Review, 75,* 4 (1997), 65–75.
46. Kim, W.C., and Mauborgne, R. Strategy, value innovation, and the knowledge economy. *Sloan Management Review, 40,* 3 (1999), 41–54.
47. Kirmani, A., and Rao, A.R. No pain, no gain: A critical review of the literature on signaling unobservable product quality. *Journal of Marketing, 64,* 2 (2000), 66–79.
48. Koh, C.E. IS journal review process: A survey on IS research practices and journal review issues. *Information & Management, 40,* 8 (2003), 743–756.
49. Kollock, P., and Smith, M. Managing the virtual commons: Cooperation and conflict in computer communities. In S.C. Herring (ed.), *Computer-Mediated Communication: Linguistic, Social, and Cross-Cultural Perspectives.* Amsterdam: John Benjamin, 1996, pp. 109–128.
50. MacCormack, A. Siemens ShareNet: Building a knowledge network. Harvard Business School Case Study 9-603-036, Boston, November 5, 2002.
51. Malhotra, A.; Majchrzak, A.; Carman, R.; and Lott, V. Radical innovation without collocation: A case study at Boeing-Rocketdyne. *MIS Quarterly, 25,* 2 (2001), 229–249.
52. Markus, M.L. Toward a theory of knowledge reuse: Types of knowledge reuse situations and factors in reuse success. *Journal of Management Information Systems, 18,* 1 (Summer 2001), 57–94.
53. Martin, G. *Behavior Modification: What It Is and How To Do It.* Englewood Cliffs, NJ: Prentice Hall, 1988.
54. Marwick, A.D. Knowledge management technology. *IBM Systems Journal, 40,* 4 (2001), 814–830.
55. Maynard Smith, J., and Harper, D. *Animal Signals.* Oxford: Oxford University Press, 2003.
56. Meuter, M.L.; Ostrom, A.L.; Roundtree, R.I.; and Bitner, M.J. Self-service technologies: Understanding customer satisfaction with technology-based service encounters. *Journal of Marketing, 64,* 3 (2000), 50–64.
57. Michailova, S., and Husted, K. Knowledge-sharing hostility in Russian firms. *California Management Review, 45,* 3 (2003), 59–77.
58. Michener, H.S., and DeLameter, J.D. *Theoretical Perspectives in Social Psychology.* Fort Worth, TX: Harcourt Brace College Publishers, 1999.
59. Miner, J.B. Commentary on Arthur Bedeian's "The Manuscript Review Process: The Proper Roles of Authors, Referees, and Editors." *Journal of Management Inquiry, 12,* 4 (2003), 339–343.
60. Nambisan, S. Designing virtual customer environments for new product development: Toward a theory. *Academy of Management Review, 27,* 3 (2002), 392–413.
61. Nelson, R.; Todd, P.; and Wixom, B.H. Antecedents of information and system quality: An empirical examination within the context of data warehousing. *Journal of Management Information Systems, 21,* 4 (Spring 2005), 199–236.
62. Noonan, R., and Wold, H. Partial least squares path analysis. In J.P. Keeves (ed.), *Educational Research, Methodology and Measurement.* Oxford: Pergamon, 1988, pp. 710–716.
63. Nunnally, J.C. *Psychometric Theory,* 2d ed. New York: McGraw-Hill, 1978.
64. Offsey, S. Knowledge management: Linking people to knowledge for bottom line results. *Journal of Knowledge Management, 1,* 2 (1997), 113–122.
65. Olivera, F. Memory systems in organizations: An empirical investigation of mechanisms for knowledge collection, storage and access. *Journal of Management Studies, 37,* 6 (2000), 811–832.
66. Ostrom, A.L., and Iacobucci, D. The effect of guarantees on consumers' evaluation of services. *Journal of Services Marketing, 12,* 5 (1998), 362–375.
67. Podsakoff, P.M., and Dalton, D.R. Research methodology in organizational studies. *Journal of Management, 13,* 2 (1987), 419–441.

68. Porter, L.W.; Bigley, G.; and Steers, R.M. *Motivation and Work Behavior,* 7th ed. New York: McGraw-Hill/Irwin, 2002.

69. Prahalad, C.K., and Bettis, R.A. The dominant logic: A new linkage between diversity and performance. *Strategic Management Journal, 7,* 6 (1986), 485–501.

70. Probst, G.; Raub, S.; and Romhardt, K. *Managing Knowledge.* London: Wiley, 2000.

71. Reynolds, R.E., and Sinatra, G.M. Views of knowledge acquisition and representation: A continuum from experience centered to mind. *Educational Psychologist, 31,* 2 (1996), 93–104.

72. Sambell, K., and McDowell, L. The construction of the hidden curriculum: Messages and meanings in the assessment of student learning. *Assessment and Evaluation in Higher Education, 23,* 4 (1998), 391–402.

73. Saunders, C. From the trenches: Thoughts on developmental reviewing. *MIS Quarterly, 29,* 2 (2005), iii–xii.

74. Saunders, C. Looking for diamond cutters. *MIS Quarterly, 29,* 1 (2005), iii–viii.

75. Seattler, P. *The Evolution of American Educational Technology.* Englewood, CO: Libraries Unlimited, 1990.

76. Shin, M. A framework for evaluating economics of knowledge management systems. *Information & Management, 42,* 1 (2004), 179–196.

77. Skinner, B.F. *Science and Human Behavior.* New York: Macmillan, 1953.

78. Smith, R.G., and Farquhar, A. The road ahead for knowledge management: An AI perspective. *AI Magazine, 21,* 4 (Winter 2000), 17–40.

79. Soo, C.; Devinney, T.; Midgley, D.; and Deering, A. Knowledge management: Philosophy, processes, and pitfalls. *California Management Review, 44,* 4 (2002), 129–150.

80. Spence, A.M. Job marketing signaling. *Quarterly Journal of Economics, 87,* 3 (1973), 355–374.

81. Spence, A.M. *Market Signaling: Informational Transfer in Hiring and Related Screening Processes.* Cambridge: Harvard University Press, 1974.

82. Sussman, S., and Siegal, W. Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research, 14,* 1 (2003), 47–65.

83. Szenberg, M. Disseminating scholarly output: The case for eliminating the exclusivity of journal submissions. *American Journal of Economics and Sociology, 53,* 3 (1994), 303–315.

84. Taylor, S. Waiting for service: The relationship between delays and evaluations of service. *Journal of Marketing, 58,* 2 (1994), 56–69.

85. Thomson, W. *A Guide for the Young Economist: Writing and Speaking Effectively About Economics.* Cambridge, MA: MIT Press, 2001.

86. Timberlake, W.; Schaal, D.W.; and Steinmets, J.E. Relating behavior and neuroscience. *Journal of Experimental Analysis of Behavior, 84,* 3 (2005), 305–311.

87. Wang, R.Y.; Lee, Y.W.; Pipino, L.L.; and Strong, D.M. Manage your information as a product. *Sloan Management Review, 39,* 4 (1998), 95–105.

88. Werts, C.E.; Linn, R.L.; and Jöreskog, K.G. Intraclass reliability estimates: Testing structural assumptions. *Educational and Psychological Measurement, 34,* 1 (1974), 25–33.

89. Zack, M.H. Managing codified knowledge. *Sloan Management Review, 40,* 4 (1999), 45–58.

90. Zahavi, A. Mate selection—A selection for a handicap. *Journal of Theoretical Biology, 53,* 1 (1975), 205–214.

91. Zimmer, J.C.; Henry, R.M.; and Butler, B.S. Determinants of the use of relational and nonrelational information sources. *Journal of Management Information Systems, 24,* 3 (Winter 2007–8), 297–331.