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Knowledge Sharing on Online Platforms within Organizations:

An Interactionist Perspective on Generalized Exchange

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Ethics and Integrity

The study was conducted strictly in compliance with ethical standards in the treatment of all participants. Also (1) this manuscript represents results of original work that have not been published elsewhere, (2) it is not being considered concurrently for publication elsewhere, and (3) the research reported in the manuscript was conducted in accordance with the ethical guidelines of the authors' institutions. This study uses original data that the first author collected as part of his doctoral study, and we have published or plan to publish no other papers that use the same dataset.

Data Availability

We refrain from making the dataset publicly available, because we collected data upon the condition that we do not disclose the data to any third parties.

Conflict of Interests

We recognize no potential conflict of interests in this study.

ABSTRACT

Organizations are increasingly introducing online platforms to facilitate knowledge sharing among employees across organizational boundaries. Nonetheless, individuals do not always share knowledge on such platforms. This study aims to identify the factors that can motivate individuals to share knowledge on an online platform drawing on social exchange theory and the idea of generalized exchange, a form of social exchange identified on online knowledge-sharing platforms in previous studies. Specifically, we propose that individuals are more likely to share knowledge on online platforms when they have requests from an employee with whom they have worked in the same office in the past but don't currently work in the same office location (i.e., *past-collocation history*), have high levels of *generalized exchange orientation*, and need to use a wide variety of knowledge to complete their jobs (i.e., *knowledge variety*). Using a longitudinal dataset spanning six months among 100 users on an in-house online platform of a professional service firm, we find support for the three-way interaction hypothesis in a three-level analysis. We discuss implications on knowledge sharing on in-house online platforms.

Key words: knowledge sharing; online platforms; generalized social exchange; generalized exchange orientation

Knowledge Sharing on Online Platforms within Organizations:

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An estimated 1 billion location-independent workers will exist by 2035 (*The Economist*, 2019). The rise of digital nomads—people who can work from anywhere in the world—means more and more people will primarily interact and share knowledge online, and this trend is likely to accelerate in the post-COVID era of work. Organizations are also keen on mobilizing their knowledge across geographic and organizational boundaries to foster problem-solving, cost reduction, and customer satisfaction (McKinsey & Company, 2013). Against this background, organizations are increasingly using online knowledge-sharing platforms, which provide an online, text-based discussion space where a large number of participants can ask questions, respond to them, and browse ongoing and prior interactions by other participants (Hwang, Singh, & Argote, 2015). Such a virtual space can facilitate open, flexible, and speedy flows of knowledge sharing among employees from an organization's various units and locations (Leonardi & Neeley, 2017).

However, sharing knowledge on the online platforms can also be risky as the return is uncertain (Wasko & Faraj, 2005). As such, participants on the organizational online platforms are likely to share their knowledge by responding to questions from some, but not all participants, to reduce potential risk in sharing while maximizing chances to receive valuable knowledge in the future. Supporting this view, Hwang et al. (2016) found that participants on the organizational online platforms are likely to respond to questions from requestors currently working in the same location and belonging to the same hierarchy (i.e., categorical similarities) or requestors in the same job, such as sales, consultants, R&D, or administration (i.e., expertise similarities), because they could request useful information from peers working in a similar context or position. The lens of categorical or expertise similarities between participants and requestors, however, only helps us understand knowledge sharing between those working in in a similar context or position. Because the benefit of having the organizational online platforms is to facilitate knowledge exchange widely, identifying factors that can motivate participants to respond to a question on an online platform by sharing their knowledge beyond those with categorical or expertise similarities is thus important.

Drawing on the lens of generalized exchange (Yamagishi & Cook, 1997; Molm, 2003; 2010), which researchers have adopted to understand knowledge sharing on online platforms (Baker & Bulkley, 2014; Faraj & Johnson, 2011; Wasko, Teigland & Faraj, 2009; Wu & Korfiatis, 2013), we seek to identify factors that can facilitate participants' knowledge sharing beyond those with categorical or expertise similarities. Generalized exchange is a collective and indirect form of social exchange that takes place in a social group with three or more members (Flynn, 2005). In generalized exchange, participants do not receive benefits directly from the one to whom they provided resources, but rather from someone else in the social group (Yamagishi & Cook, 1993). As such, engaging in generalized exchange means one has to rely on multiple, unidentified individuals in the chain of indirect reciprocation, and thus involves high risks of not receiving returns (Molm, Collet, & Shaefer, 2007). In line with this fact, online knowledge-sharing initiatives tend to attract many "silent" participants who acquire knowledge from others but do not share their own knowledge (Nonnecke & Preece, 2000). Following this perspective, we argue that participants on the online platforms will consider with whom they should share in order to enhance their chances of having indirect reciprocation in return.

Specifically, beyond those with categorical or expertise similarities, we suggest three conditions that interactively affect participants' responses to requests on online platforms. The first condition is whether the participant has interpersonal ties with the requestors through past-collocation history, that is, whether the requestors have previously worked in the same location with the participants but now work in a different location (i.e., past-collocation history between participants and requestors). We focus on past-collocation history between a participant and a requestor for two reasons. First, past collocation brings familiarity to participants, attracting participants' attention to requests from someone they can link to. Participants may also see that sharing with someone with whom they previously collocated has lower risks than sharing with others with whom they have not collocated. Second, because those requestors are currently working in different locations, they may have new knowledge to share. More importantly, participants could expand their generalized exchange network by responding to past-collocated requestors, because the action of knowledge sharing on the platform may be observed by the people who know the requestors, thus enhancing the possibility of receiving indirect reciprocation from them. In brief, we propose that past-collocation history between participants and requestors will be positively associated with participants' online knowledge sharing.

Nevertheless, not all participants will be keen to respond to the request of past-collocated requestors, because not everyone would subscribe to the idea of generalized exchange or see the value of exchanging knowledge with someone who now works in a different location. As such, we seek to identify two conditions under which past-collocation history can be more influential to participants' responses. We examined two moderators: generalized exchange orientation (GEO), or one's dispositional beliefs in collective reciprocity (Yoshikawa, Wu, & Lee, 2020), and knowledge variety, or a wide range of knowledge required to do one's work (adapted from the concept of skill variety) (Morgeson & Humphrey, 2006). Whereas GEO reflects employees' readiness for generalized exchange, knowledge variety captures a situational cue that motivates employees to solicit knowledge from a range of different sources. As we elaborate ahead, we expect that knowledge variety provides situational demands that motivate the participants of high GEO to engage in knowledge sharing with past-collocated requestors. We therefore propose that higher GEO will strengthen the relationship between past-collocation history and participants' online knowledge sharing, and such a moderating effect will be more salient when participants' jobs are characterized by higher knowledge variety.

This study contributes to the literature in four ways. First, our examination of past-collocation history suggests knowledge sharing on online platforms can go beyond requestors who share categorical or expertise similarities. Nevertheless, it also suggests knowledge sharing on online platforms are constrained by the organization's broader social structure, extending recent findings (e.g., Hwang et al., 2015) that challenge the notion that online platforms eliminate geographical and social distances (e.g., Friedman, 2006; Siegel et al., 1986). Second, by examining the effect of GEO, we provide a disposition-based explanation for why some individuals provide knowledge more frequently than others (Wasko, Teigland, & Faraj, 2009). However, we further note situational cues are also important to activate such dispositional tendency in engaging in online knowledge sharing, which leads to the third contribution of our work. Third, by identifying knowledge variety as a situational factor, our study highlights the importance of job design in promoting the use of knowledge sharing on online platforms. Whereas extant research on online knowledge-sharing behaviors has rarely discussed the role of job design, we argue the variety of knowledge required for one's job can shape the value of knowledge sharing on online platforms for individuals and thus their behaviors on online platforms. Altogether, to better understand an individual's knowledge-sharing behaviors on online platform, our study suggests the need to understand who the requestor is, what the individual believes in social exchange, and the job that she or he holds. Finally, our study also contributes to the literature of individual differences in generalized exchange. Extant studies in the literature largely take a structural perspective and rarely examined individual differences (Yoshikawa, Lee, & Wu, 2020). By showing the role of GEO, our study shows individual differences also matter for generalized exchange, expanding prior findings on individual differences in reciprocal exchange (Cropanzano & Mitchell, 2005).

Theory and Hypothesis

Online Knowledge-Sharing Platforms and Generalized Exchange

In recent years, organizations have increasingly adopted online knowledge-sharing platforms because such adoption has three major advantages in facilitating knowledge sharing within organizations: openness of access, boundaryless interaction, and asynchronous communication. First, online platforms are open to a wide range of employees in an organization, and participants can see ongoing and past interactions between other participants and can jump into those conversations. By contrast, in closed-communication media such as emails, participants are pre-selected, and new participants can join only if someone already in the interaction invites them. Second, online knowledge-sharing platforms are accessible through electronic networks within an organization (e.g., intranet); thus, firm-based online platforms allow employees from any unit or location to participate in the virtual space. Along with openness, this virtual connectivity allows participants to get to know and interact with other participants they might not have a chance to communicate with in real space. Third, participants can post their ideas whenever doing so is convenient for them, without needing to synchronize with other participants on the platforms. Therefore, unlike teleconferences, video conferences, and face-to-face conversations (Dennis, Fuller, & Valacich, 2008), online platforms do not need participants to coordinate their schedules with their counterparts.

Because of these features, participants on the platforms can send their requests to all other participants or respond to requests from people on the platform who are often not in their interpersonal networks, organizational unit, or office location. Such knowledge sharing is not confined to interactions in the form of reciprocal exchange, not only because all participants can see and answer each other’s requests, but also because a recipient who received answers from a participant in the past may not have the knowledge necessary to answer the participant’s request. Instead, as we noted earlier, evidence suggests knowledge-sharing behavior on online platforms follows generalized exchange among their members. For example, Wasko, Teigland, and Faraj (2009) analyzed survey responses and interaction patterns of participants of an online platform of a US professional legal association and found the knowledge flows on the platform were largely unilateral, with only less than a fifth of individuals who provided advice receiving direct reciprocation from the recipient of the advice. Faraj and Johnson (2011) studied five internet-based online platforms and found that individuals who received a response from other participants tended to give responses to others on the platform. Wu and Korfiatis (2013) showed participants on internet-based Q&A platforms tend to answer those who frequently answer others' requests. Consistently, Baker and Bulkley (2014) also found MBA students demonstrate such behaviors that responses form a chain of unilateral giving among multiple members. These findings indicate generalized exchange is a key mechanism behind the flow of knowledge on online platforms, unlike reciprocal exchange based on dyads of interpersonal connections (e.g., Bouty, 2000; Cross & Cummings 2004; Levin, Walter, & Murnighan, 2011; Reinholt, Pedersen, & Foss, 2011). Following this view, we identify three factors that jointly determine employees' online knowledge-sharing behaviors.

Past-Collocation History and Online Knowledge Sharing

Because knowledge sharing on an online platform is supported by generalized exchange based on indirect reciprocation under the idea of collective reciprocity, individuals will likely share their knowledge with selected targets who protect collective reciprocity on the platform. For example, prior studies found individuals tend to engage in generalized exchange when they interact with individuals with shared identity (Flynn, 2005; Westphal et al., 2012; Willer, Flynn, & Zak, 2012); such perceptions promote positive assessment of the counterpart's likeliness to protect collective reciprocity. Drawing on these findings, we argue that past-collocation history helps individuals assess the quality of requestors. We suggest individuals are more likely to share their knowledge with requestors whom they know due to a shared collocation history than with requestors with whom they have no previous link, for two reasons.

First, when one interacts with an unknown requestor (with whom one does not have past-collocation history), lack of social information keeps the counterpart a rather anonymous, faceless entity with little psychological connection. By contrast, when an individual finds a question posted by another participant with a past-collocation history, this encounter is likely to generate some sense of shared identity with the requestor. Even if one does not know the counterpart very well, collocation history—and resulting experience of knowing the counterpart in person—would trigger the memory of the social environment of the office (e.g., organizational culture and routines, other colleagues, clients, and business partners of the office), which can function as a source for constructing a shared identity (Ashforth, 2001; Bardon, Josserand, & Villèseche, 2015). Shared identity then brings social information, which is otherwise sparse on online platforms, where characteristics of other participants are displayed on users' screens (see Lea & Spears, 1991). This information would thus lead an individual to assess the requestor with a past-collocation history as a trustworthy counterpart (Brewer, 1996; Kramer, 2017) who will support the platform's collective reciprocity.

Second, a past-collocation history means the counterpart (requestor) is working in a different location than the responder and thus is likely to have access to non-redundant knowledge (Granovetter, 1973), which is potentially beneficial for the requestor in the future. More importantly, such a requestor is connected with other members of the organization, with whom the responder may not be directly connected. Hence, by responding to a requestor with past-collocation history, one can increase the potential to receive indirect reciprocation, because such act of sharing may be observed by others who are connected to the requestor. Because "third parties are disciplinarians, rewarding reputations for helpfulness and punishing reputations for unhelpfulness" (Baker & Bulkley, 2014, p. 1504), one is likely to share knowledge with past colleagues because the sharing will help build a positive reputation among the people around the past colleagues and will help them receive rewards. Moreover, sharing knowledge with past colleagues will increase the chance of future returns, because this knowledge sharing helps maintain past ties on the platform. As indicated by Baker and Bulkley (2014, p. 1504), "what looks like prosocial citizenship behavior (helping others at a cost to self) may be motivated by the anticipation of future self-benefit."

By contrast, employees are less likely to respond to requests from colleagues who currently share the same office location, because employees can use other channels to exchange knowledge directly, such as face-to-face interaction, without making efforts to form a response on the platform. In sum, we suggest sharing knowledge with those who have a past-collocation history can protect collective reciprocity on the platform and increase the chances of returns in future.

Hypothesis 1: Past-collocation history between the responder and the requestor is positively associated with the likeliness of knowledge-sharing behaviors by the responder to the requestor.

Generalized Exchange Orientation

Although past-collocation history signals the protection of collective reciprocity, not every individual may react the same way to such a signal. Extant research suggests individuals have different beliefs regarding social exchange relationships, which can stem from a history of interactions with others at work (Eisenberger et al. 2004), and such dispositional differences may lead individuals to behave differently in exchange situations (Cropanzano & Mitchell, 2005). Indeed, a recent study found individuals have different levels of GEO, or a belief in following the rule of collective reciprocity in interactions with others at work (Yoshikawa et al., 2020), and we expect GEO to shape how individuals respond to a request posted by other members with past-collocation history.

Because individuals high in GEO believe benefitting others will eventually benefit themselves through indirect reciprocation, they are more likely than those low in GEO to expect returns from knowledge-sharing behaviors. Therefore, when they encounter a request by a requestor with a past-collocation history, individuals high in GEO will be more likely than those low in GEO to respond to a request. High levels of GEO also mean they believe one's positive reputation will increase the chance of receiving indirect rewards (i.e., rewarding reputation, Baker & Bulkley, 2014); therefore, individuals with high GEO are more likely to see a request from past colleagues as an opportunity to build their reputation. Furthermore, the belief in the rule of collective reciprocity means individuals with high GEO are less likely to be discouraged to respond even if the probability of direct reciprocation from the past-collocation requestor is low. By contrast, individuals who are low in GEO are skeptical about indirect reciprocation, because those individuals barely believe that unilaterally providing resources to other individuals will eventually lead to indirect return to them (Yoshikawa et al., 2020). Thus, they are less likely to respond to the requests even when they are posted by the colleagues with past-collocation history. Hence, we argue responders' GEO moderates the impact of past-collocation history.

Hypothesis 2: GEO moderates the relationship between past-collocation history and the likeliness of knowledge-sharing behavior, such that the relationship is stronger when the responder has higher levels of GEO.

Knowledge Variety

We further propose that employees who need to apply a wide range of knowledge to do their work (or knowledge variety) are more likely to see the benefits of participating in generalized exchange on the online platform. The reason is that the online platform is a channel where individuals can acquire knowledge with fewer barriers than other communication channels. We regard knowledge variety as a job-design factor, defined as the scope of knowledge for individuals to complete a job. Unlike skill variety (Morgeson & Humphrey, 2006), which involves applying a wide range of skills to complete one's job, knowledge variety involves the scope of knowledge; thus, the construct helps capture the need to use knowledge-sharing online platforms at work.

The key characteristics of online platform are its openness and boundaryless. The questions posted on online platforms are visible to all employees, and thus, employees do not need to know in advance who might have relevant knowledge to answer their question. By contrast, sharing knowledge via other means such as phone calls, emails, or face-to-face conversations requires individuals to first identify whom they should ask questions. In other words, online platforms allow individuals to access nonredundant knowledge (Granovetter, 1973) from diverse others, beyond their usual contacts, through broad search (Levine & Prietula, 2014). Such an ability is particularly valuable for the type of job for which knowledge variety is high; thus, the needed knowledge may not always be available within immediate, in-person work contexts. On the other hand, if individuals need only a narrow or limited range of knowledge for the job (i.e., low knowledge variety), such needs can be fulfilled within the known contacts of expertise, and thus, the prospective benefits of engaging in online platforms is relatively small.

Trait-activation theory (Tett & Guteman, 2000; Tett & Burnett, 2003) suggests that a dispositional trait is "activated" to govern one's trait-related behaviors only when individuals are presented with a situational cue that is relevant to the trait. Accordingly, we posit that knowledge variety is an activator of GEO when one engages with an online knowledge-sharing platform. The reason is that people engage in exchange when they can see the benefit of doing so (Blau, 1964; Emerson, 1976; Homans, 1961), and thus, jobs with higher knowledge variety will increase the attractiveness of potential return from generalized exchange on an online platform. By contrast, the potential return of engaging in an online platform is not very meaningful if one's job only requires a narrow range of knowledge. In other words, when an individual with strong GEO encounters a request from someone with past-collocation history, high levels of knowledge variety would activate GEO by increasing the attractiveness of future benefits from generalized exchange. On the other hand, low levels of knowledge variety are likely to decrease the attractiveness of potential return, and thus would not activate GEO. Based on this chain of logic, we hypothesize a three-way interaction between past-collocation history, GEO, and knowledge variety. Figure 1 illustrates our research model with the three-way interaction.

Hypothesis 3: Past-collocation history, GEO, and knowledge variety have a three-way interaction such that the relationship between past-collocation history and the likeliness of knowledge sharing is stronger when the responder has higher levels of GEO and works in a job that requires higher levels of knowledge variety.

Insert Figure 1 about here

METHOD

Participants and Procedure

We collected data from a professional service organization in Japan. This firm provides consulting and training services across various industries and has offices in major cities across the country. Being a leading professional firm with multiple offices scattered around the country, it introduced an online knowledge-sharing platform through which the consultants can exchange their knowledge on its products and services, client problems, and solution ideas. Employees voluntarily ask and respond to questions. Participants typically seek industry insights, previous project cases, or solution ideas from people beyond their immediate colleagues, in relation to specific clients and their problems. The platform had been used for three years at the start of data collection, and the executives of the company are pleased with the success of the platform based on the positive feedback from their employees noting the benefits received from the platform. In addition, they consider it a success because the platform has been continuously used since its introduction, without active organizational interventions for promoting it, such as tangible incentives of rewards or recognition for the users.

We obtained data from three different sources: the user survey, the platform's log data, and the users' personnel records. First, we sent out an online survey that included GEO, knowledge variety, and several control variables to 193 employees who belong the employee segment who are supposed to be the target users of the platform and received 111 responses (response rate = 65.7%). We excluded 11 respondents from the analysis because they accessed the platform less than once a month over the three-month period before the start of survey. Our focus in this study is on examining the determinants of knowledge-sharing responses to a request, and thus, those who hardly access the platform (and thus do not know the requests) are not relevant to our study. We use the remaining 100 responses to analyze their behaviors as respondents on the platform. Second, we obtained the platform's log data for six months before and six months after the survey. They include detailed information such as the questions posted, by whom, and on which date, as well as the responses given, to which question, by whom, and on which date. We used the log data of the six months after the survey as the observation period and the data from the six months before the survey to operationalize some control variables. During the observation period, 108 questions were posted on the platform, and each question created a response opportunity for the users other than the requestor. Hence, in theory, 108 questions result in 108 x (total number of users – 1) times the number of response opportunities. For our analysis, we use the 10,745 response opportunities that involve the 100 active users, from whom we have survey responses, as respondents.[i] Among these response opportunities, the 100 users provided 267 responses by sharing their knowledge. Finally, we obtained personnel records, including the users' current and past office locations, job type, and hierarchical position.

Dependent Variable

Knowledge-Sharing Behaviors

As we noted earlier, our dataset includes 10,745 response opportunities, and for each response opportunity, a respondent either responds to the request by sharing knowledge or not. Because our interest is in analyzing the determinants of choices, we coded each participant's reaction using a binary variable (1 = response, 0 = nonresponse).

Independent Variables

GEO

We used a 12-item measure of GEO from Yoshikawa et al. (2020), incorporating a 7-point Likert scale. The measure includes three lower-order facets, which correspond to UG, PIF, and RR. Each lower-order facet is measured by four items, and sample items include "I think kindness to others in the workplace will eventually come back to me in some way" (UG), "When someone in the workplace makes extra efforts for me, I often start thinking what I can do for others" (PIF), and "When a colleague who often gives support to others is in trouble, I should do something for him/her (RR)." Cronbach's alpha is .77, based on the scores of UG, PIF, and RR.

Knowledge Variety

We adopted a three-item measure of skill variety from the Work Design Questionnaire (Morgeson & Humphrey, 2006) and modified the items by replacing the word "skills" with "knowledge." Participants responded to the following items, using a 7-point Likert scale: "The job requires a variety of knowledge," "The job requires me to utilize a variety of different knowledge in order to complete the work," and "The job requires the use of a wide range of knowledge." Cronbach's alpha is .95.

Past-Collocation History

Based on the personnel records of the company, we created a binary variable and assigned it a value of 1 when the person asking a question (requestor) and the one responding to it (responder) had worked in the same office location before the observation period but were located in different offices from each other during the observation period, and 0 otherwise. Although the indictor of past-collocation history does not directly reflect the two know each other, our knowledge of the organizational context informed by human resources managers in the organization suggests collocated colleagues knew each other. Specifically, the organization's offices typically have 10-20 employees, and the organization regularly organizes formal and informal gatherings for office members.

Control Variables

We included several control variables. First, we controlled for individuals' prosocial values because prosocial individuals are interested in promoting others' welfare, and thus tend to engage in behaviors that benefit others (Grant, 2008), regardless of potential personal gain from such behaviors. We adopted five items from Rioux and Penner (2000). Cronbach's alpha is .89.

Second, we also controlled for individual orientation toward other forms of social exchange, namely, *negotiated exchange orientation* (NEO) and *reciprocal exchange orientation* (REO), because they might negatively affect individuals' engagement in online knowledge-sharing behaviors. Online platforms connect individuals beyond organizational boundaries; therefore, participants of online platforms often lack established interpersonal ties with one another (cf. Wasko et al., 2009). As a result, individuals have difficulty assessing the likelihood of direct reciprocation from the recipient (Bouty, 2000), and thus, individuals with strong orientation toward reciprocal exchange are likely to avoid sharing knowledge on online platforms (cf. Wasko and Faraj, 2005). Furthermore, online platforms do not allow participants to explicitly negotiate the terms of exchange in advance. Hence, individuals with strong orientation toward negotiated exchange are also less likely to share their knowledge on online platforms. We adopted scales from Yoshikawa et al. (2020). The scales include four items each, and sample items include "At work, it generally pays to clarify rewards before making extra efforts for others" (NEO) and "When I receive support from a colleague, I should remember to give something back to him/her" (REO). All items are measured on a 7-point Likert scale. Cronbach's alphas for NEO and REO are .82 and .77, respectively.

Third, we controlled for *interaction history* on the online platform, because in analyzing similar data, Baker and Bulkley (2014) found these factors have a significant effect on online knowledge-sharing behaviors. The variable *received responses* represents the number of responses that each respondent received in the past 1–7, 8–14, 15–21, and 22–28 days. The variable *provided responses* represents the number of responses that the requestor provided in the same periods. We also controlled for *indebtedness*, which represents whether the responder owed a response to the requestor; this factor is a binary variable equal to 1 when user i owed a requestor j (i.e., when the total number of responses from j to i was greater than from i to j in the last 28 days) to control for direct reciprocation on the platform. Among the cases of knowledge sharing (i.e., *response* = 1), the mean scores of received responses (.28-.53) and provided responses (.09-.54) were much bigger than the score of indebtedness (.004), consistent with prior findings that indirect reciprocation plays a major role on online platforms.

Fourth, we included *categorical similarities* (whether the respondent and the requestor currently worked in the same location and belonged to the same hierarchy) and *expertise similarities* (whether they were in the same job type—sales, consultants, R&D, or administration) to control for the potential impact of homophily (McPherson, Smith-Lovin, & Cook. 2001) on online interactions. Hwang et al. (2016) found categorical and expertise similarities facilitate knowledge-sharing behaviors in an online community.

Finally, we included the respondent's *gender* (0 = male, 1 = female), *age* (in years), and position (0 = front-line employees, 1 = managers). Baker and Bulkley (2014) found female participants are significantly more likely than male participants to respond on an online platform. Older employees or those in managerial positions, as they have more work experience than others, could be more knowledgeable to answer questions on the platform. Table 1 summarizes descriptive statistics and the correlation matrix. VIF scores are all below 2.50, suggesting multicollinearity is not a serious concern in this analysis.

Insert Table 1 about here

Analytical Approach

The dataset has a complex nested structure because (1) each of the 100 respondents had a response opportunity every time a question was posted on the platform, and (2) some employees asked questions multiple times on the platform during the observation period. As a result, the 10,745 response opportunities include multiple response opportunities between the same requestor-responder dyads as well as for each responder. To deal with the nested structure of the dataset, we adopted a three-level multilevel analysis with *response opportunity* as the first level (n = 10,745), *responder-requestor dyad* as the second level (n = 4,968), and *responder* as the third level (n = 100). Our dependent variable (knowledge sharing) is positioned at the first level. In terms of independent variables, past-collocation history resides in the second level, and GEO and knowledge variety (KV) at the third level. Mathematically, the model is formulated (control variables are omitted for simplicity) as follows:

$$Response_{ijk} = \gamma_{000} + \gamma_{001}\, GEO_k + \gamma_{002}\, KV_k + \gamma_{003}\, GEO_k\, KV_k + \gamma_{010}\, PastCol_{jk} + \gamma_{011}\, PastCol_{jk}\, GEO_k + \gamma_{012}\, PastCol_{jk}\, KV_k + \gamma_{013}\, PastCol_{jk}\, GEO_k\, KV_k + \mu_{01k}\, PostCol_{jk} + \mu_{00k} + \gamma_{0jk} + e_{ijk},$$

where $Response_{ijk}$ is the predicted probit-transformed response probability of responder k for requestor j's question i, $PastCol_{jk}$ is the collocation history for the dyad of responder k and requestor j, and GEO_k and KV_k are GEO and knowledge variety for responder k, respectively. γ_{000} is the intercept. γ_{001} and γ_{002} are coefficients for responder-level variables (i.e., GEO and KV), and γ_{003} denotes the coefficient for their interaction. γ_{010} is the coefficient for the responder-requestor dyad-level variable (past-collocation history), and $\gamma_{011} - \gamma_{013}$ are coefficients for cross-level interactions. μ_{01k} captures how the impact of collocation history varies by responder, and μ_{00k} captures how the response probability varies between individuals. r_{0jk} is the residual at the second level (responder-requestor), and e_{ijk} is the residual at the first level (response opportunity).

The analysis is conducted using Mplus version 8.3 (Mithén & Muthén, 1998–2017) with the Bayesian estimator.[ii] As we noted above, our outcome variable is binary, and thus, we use a probit regression (logit link is not available for our model on Mplus). The Bayesian estimator is computationally efficient for estimating random-effects models with categorical outcome variables (Asparouhov & Muthèn, 2010). Bayesian estimation provides null-hypothesis significance testing (Zyphur & Oswald, 2015) and has been increasingly used in a wide range of natural and social science disciplines (Mckee & Miller, 2015). A simulation study shows Bayesian estimation generates very close results to maximum likelihood estimation when the sample size is large and diffuse priors are used (Browne & Draper, 2006), and our study satisfies these conditions. Following conventional approaches in applied research (Zyphur & Oswald, 2015) and default settings on Mplus (Muthen, 2010; Aparouhov & Muthen, 2012), we used two Markov chain Monte Carlo (MCMC) chains with a Gibbs sampler and diffuse priors to conduct the analysis.[iii] We chose this approach because we aim to use Bayesian analysis for computing purposes and thus do not have specific reasons to choose alternative approaches. To examine convergence, we used the proportional scale reduction (PSR) factor to analyze convergence and for each analysis, we conducted 20,000 iterations and confirmed the PSR factor converges close to 1, following recommendations by Zyphur and Oswald (2015). We also report posterior predictive *p* values (PPP), which are commonly used indices to review estimation quality and compare models, although they are not available for models with cross-level effects.

RESULTS

We first conducted a series of CFA with the MLM estimator on Mplus to examine our measured variables (n = 100). First, we examined a model with GEO's three first-order latent factors, UG, PIF, and RR, and the factors of NEO, REO, knowledge variety, and prosocial values. The model shows an acceptable fit (χ^2 = 395.51, *df* = 278, *p* = .00, *CFI* = .91, *TLI* = .90, *RMSEA* = .06, *SRMR* = .06). Twenty-one alternative models, collapsing two of the seven factors, show a significantly worse fit ($\Delta\chi^2$ = 39.05 – 274.84, Δdf = 6, $p < .01$). Second, we analyzed a model with GEO, NEO, REO, knowledge variety, and prosocial values, parceling three first-order latent factors of GEO with an internal-consistency approach (Kishton & Widaman, 1994). This model also results in satisfactory fit (χ^2 =163.70, *df* = 109, *p* = .00, *CFI* = .94, *TLI* = .92, *RMSEA* = .07, *SRMR* = .06). Four alternative models, collapsing GEO with one of the other latent variables, show significantly worse fit ($\Delta\chi^2$ = 19.36 – 170.23, Δdf = 4, $p < .01$).

Table 2 summarizes the results of Bayesian three-level probit regression analyses. Model 1 includes all variables except interactions, Model 2 introduces the first-order interaction between past-collocation history and GEO, and Model 3 includes other two-way interactions as well as the three-way interaction between past-collocation history, GEO, and knowledge variety. Following the recommendation by Zyphur and Oswald (2015), we report priors, point estimates (median, or μ^{β}, and standard deviation, or S.D.), and the posterior credible interval (CI) for each variable. CI is similar to confidence intervals in the frequentist approach; if it does not include a null value, we reject the null hypothesis as improbable (Berger, 2003). PPP for model 1 is .53, very close to .50, implying a fairly good model fit (Zyphur & Oswald, 2015). In Model 1, whereas past-collocation history has a positive coefficient (μ^{β}= .20), its 95% CI ([-.01, .38]) includes zero, implying Hypothesis 1 (main effect of PCH) is rejected. However, in Model 2, we found the first-order cross-level interaction between past-collocation history and GEO has a positive and significant effect (μ^{β}= .26, CI = [.02, .50]). This finding provides support to Hypothesis 2, in which we proposed the effect of past-collocation history is stronger when the responder has high levels of GEO. In Model 3, we also found a positive and significant effect for the three-way interaction between past-collocation history, GEO, and knowledge variety (μ^{β}= .36, CI = [.09, .66]). This finding provides support to Hypothesis 3. To further examine the nature of this three-way interaction, we estimated the probability of response with different levels of GEO and knowledge variety (= ± 1 *S.D.*), as well as with and without a shared past-collocation history. Figure 2 indicates the results. When the responder has a past-collocation history with the requestor, high levels of GEO, and knowledge variety, the probability of response is above 1.00%. On the other hand, in conditions without a shared collocation history, or when the responder has low levels of GEO or knowledge variety, the probabilities stay at much lower levels, at around .20%. Table 3 shows the tests of conditional effects of shared past-collocation history with high and low levels of GEO and knowledge variety (± 1 SD). The analysis shows past-collocation history has a significant positive effect (μ^{β} = .51, credibility interval = [.17 – .85]) when GEO and knowledge variety are high, but not in other conditions. This result is consistent with our three-way-interaction hypothesis that the combination of GEO and knowledge variety foster the impact of past-collocation history on knowledge sharing on online platforms.

Insert Table 2, Table 3 and Figure 2 about here

Supplemental Analysis

We conducted supplementary analyses to examine whether past-collocation history and GEO have effects distinct from similar constructs. First, we also conducted analyses with categorical and expertise similarities as alternative main effects for past-collocation history. Hwang et al. (2016) found working in the same location or hierarchy (categorical similarities) or in the same job type (expertise similarities) facilitates online knowledge-sharing behaviors, by promoting a sense of common identity, and GEO and knowledge variety may promote the effects. However, we did not find a significant effect of categorical and expertise similarities and their interactions with GEO and knowledge variation on online knowledge-sharing behaviors in our sample.

Second, we also tested alternative models with NEO or REO as substitutes for GEO. The model with NEO shows no significant effect for the three-way interaction between NEO, knowledge variety, and past-collocation history, whereas it shows a significant and positive interaction between knowledge variety and past-collocation history (μ^{β} = .26, credibility interval = [.01 - .54]). The model with REO shows a positive significant two-way interaction between past-collocation history and knowledge variety (μ^{β} = .35, credibility interval = [.02

- .71]) and a three-way interaction between REO, past-collocation history, and knowledge variety (μ^{β} = .32, credibility interval = [.02 - .67]). A test of conditional effects for REO indicate it has a negative significant effect (μ^{β} = -.68, credibility interval = [-1.28 - -.16]) when the requestor and responder share a past-collocation history and knowledge variety is low. The negative conditional effect for REO is consistent with prior findings by Wasko and Faraj (2005) that individuals' preference for direct reciprocation has a negative effect on online knowledge sharing. We speculate that when an individual with strong REO knows the requestor, the individual might prefer to contact the requestor directly via closed media (e.g., email, phone call) rather than the online platform, thus avoiding sharing knowledge with others who may not reciprocate. Low knowledge variation might further exacerbate the individual's reluctance to use the online platform, because it decreases the value of the potential return from generalized exchange.

Robustness Check

To check the robustness of the results, we conducted two additional analyses. First, we conducted analyses dropping all control variables from the proposed model. Second, we adopted an alternative approach, a cross-classified model, to account for the nested structure of the data, by clustering the data by responders and requestors.[iv] We obtained consistent results in both models. Overall, these results indicate individuals are more likely to respond to a request by someone with past-collocation history, when the individuals have high levels of GEO and knowledge variety.

DISCUSSION

In this study, we drew on a lens of generalized social exchange to understanding knowledge-sharing behaviors on online platforms. Specifically, we proposed that past-collocation history promotes knowledge-sharing behaviors on online platforms, and two conditions, GEO and knowledge variety, jointly moderate the relationship. Our analysis supported our three-way interaction model, suggesting participants of an online platform are more likely to share knowledge when they have past-collocation history with the requestor while being strongly disposed to believe in generalized exchange, and are required to use a variety of knowledge to do their jobs.

Theoretical Implications

This study advances an inquiry into what promotes knowledge-sharing behaviors on an online platform, by identifying three factors that can jointly explain one's knowledge-sharing behavior on the platform: past-collocation history, generalized exchange orientation, and knowledge variety.

First, our findings regarding past-collocation history suggests online knowledge-sharing behaviors go beyond requestors with categorical or expertise similarities (Hwang et al., 2016), suggesting online platforms help extend knowledge sharing within organizations. Unlike Hwang et al. (2016), we did not find significant effects of similarities in hierarchy, location, or expertise on knowledge-sharing behaviors. We have one potential explanation based on our study's empirical setting. The participants in our sample are less geographically dispersed and less diverse in terms of their areas of technical expertise than Hwang et al.'s (2016) sample. Specifically, our participants work in the company's offices in the same country and are specialists in general domain knowledge, namely, training and consulting, whereas Hwang et al.'s (2016) participants work in their clients' offices spread around the world and are specialists in specific IT knowledge domains such as Java and .Net. In other words, the lower levels of geographical dispersion and expertise diversity of our sample, compared with those of Hwang et al. (2016), might explain the non-significant relationships between the location and expertise similarities and knowledge-sharing behaviors. However, whereas prior studies suggest online platforms help remove geographical and social distances in knowledge exchange (e.g., Friedman, 2006; Siegel et al., 1986), our findings highlight the importance of social ties in online knowledge sharing. Specifically, our finding regarding the impact of past-collocation history suggests the social structure of the real space still has a considerable impact on the interactions in the online virtual space. For example, our results echo some of the earlier findings that highlight the importance of shared identity and social characteristics, which can be developed based on collocation, as a condition for generalized exchange behavior (Willer et al., 2014; Westphal et al., 2012). Indeed, our findings are consistent with recent work that emphasizes the importance of physically visiting each other's distant locations, when possible, even in virtual teams (e.g., Hinds & Cramton, 2014; Hinds & Mortensen, 2005), as well as the widespread use of practices such as the rotation of staff across locations, with the aim of encouraging knowledge-sharing behaviors among employees (e.g., Levine & Prietula, 2012).

Second, our study provides insights into the role of individual differences in knowledge-sharing behaviors on online platforms. Studies on knowledge-sharing behaviors on online platforms have thus far primarily taken a structural perspective by analyzing the structural pattern of interactions and the characteristics of social structure (e.g., Baker & Bulkley, 2014; Hwang et al., 2016; Wasko & Faraj, 2005; Wasko, Tiegland, & Faraj, 2009). Although studies have found some individuals provide knowledge more frequently than others (Wasko, Teigland, & Faraj, 2009), investigations into individual differences have remained scarce in the literature (Baker & Bulkley, 2014). Our study addresses this gap by examining the role of one's social exchange orientations in shaping online knowledge-sharing behavior. In brief, we did not observe main effects of GEO and REO in predicting online knowledge-sharing behavior, but we found GEO can facilitate and REO can inhibit one's online knowledge-sharing behavior in responding to requests from the colleagues of collocation history (albeit at a specific level of knowledge variety). Although our finding suggests social exchange orientation is an important individual-difference factor to understanding why some people are more likely to share knowledge in an online platform than others, it also reveals that individual social exchange orientations alone cannot explain online knowledge-sharing behavior, denoting the need to consider the specific contexts (e.g., requestors and job characteristics).

Third, our findings on knowledge variety highlight the role of job characteristics in online knowledge-sharing behaviors, offering a fresh angle for investigating online knowledge-sharing behaviors. Prior research has identified the motivational function of job design (Morgeson & Humphrey, 2006; Campion & McClelland, 1993) on knowledge sharing in the workplace in traditional channels (Foss, Minbaeva, Pedersen, & Reinholt, 2009; Foss, Pedersen, Reinholt Fosgaard, & Stea, 2015). For knowledge sharing on an online platform, Pee and Lee (2015) suggested that job characteristics (i.e., job autonomy, task feedback, and task significance) promote individuals' intrinsic motivation to share knowledge online. However, whether job-design factors can also shape one's knowledge-sharing behaviors on online platforms is still unknown. Our study fills the gap by showing job characteristics, in particular, knowledge variety, can play a role in shaping one's online knowledge-sharing behaviors. Such understanding is important because it suggests that to motivate employees to engage in online knowledge sharing, they should be able to see the value of using an online knowledge-sharing platform to do their jobs. As such, researchers should pay close attention to understanding how job design might shape one's motivation to use an online knowledge-sharing platform. Our study offers a first step to include job design in the equation by examining the effect of knowledge variety on online knowledge-sharing behavior.

Finally, our study also provides implications for research on individual differences in social exchange and generalized social exchange more specifically. Although the impact of individual differences on social exchange is widely recognized (see Cropanzano & Mitchell, 2005 for a review), prior studies in this field have predominantly focused on reciprocal social exchange between employees and their organizations (e.g., Coyle-Shapiro & Newmann, 2004; Eisenberger et al. 2001; Lynch, Eisenberger, & Armeli,1999; Shore et al., 2009), and little evidence exists for the impact of exchange orientation on peer-to-peer exchange relationships, except for a few experimental studies (e.g., Cotterell et al., 1992; Eisenberger et al., 2004; Gallucci & Perugini, 2003). Furthermore, individual differences in generalized exchange remain unexplored, because generalized exchange literature has largely adopted a structural perspective (Yoshikawa, Lee, & Wu, 2021). Hence, our study advances the field by showing the role of GEO in predicting knowledge-sharing behaviors on online platforms. Whereas our study focused on online interactions, the implications of GEO from our findings may also apply to real-space interactions, particularly ones in which individuals have frequent interactions with a large number of colleagues in their workplace (Flynn, 2005).

Practical Implications

Our study has a number of practical implications for organizations that wish to utilize online platforms to facilitate knowledge sharing among employees. First, we suggest that organizations pay attention to their employees' job design, because not all jobs can equally motivate employees to engage in knowledge sharing on online platforms. Our finding shows employees' needs for a diverse set of knowledge (i.e., knowledge variety) can facilitate online knowledge-sharing behaviors (although two other conditions should be also met: employees should have high levels of GEO and share a past-collocation history with the requestor). Organizations should examine if they have such a job-design feature to motivate employees to use an online knowledge-sharing platform. If employees' jobs do not require a variety of knowledge, introducing online platforms may not be an effective investment for organizations.

Second, our findings suggest individuals with high levels of GEO are likely to engage in knowledge-sharing behaviors on online platforms, expecting indirect reciprocation. Given that receiving responses from other participants tends to promote recipients' tendency to respond to other requests (i.e., PIF) for a prolonged period of time, such as weeks (Baker & Bulkley, 2014), high-GEO individuals are likely to prompt other participants to become active on the platform. Hence, organizations will benefit from attracting and selecting individuals with strong GEO, because they contribute to online knowledge sharing by encouraging other participants to engage in online knowledge-sharing platforms, as well as by actively providing responses.

Finally, if possible, organizations may promote mobility of individuals across different locations. For example, organizations may consider the practices of routinely relocating employees across different office locations, providing employees opportunities to visit and work in different office locations, or promoting global gatherings of employees from different locations (Levine & Prietula, 2012). Job rotation helps employees develop skills and a broader understanding of the organization and has a positive impact on employees' career progress (Campion, Cheraskin, & Stevens, 1994), even though such practice may incur costs for an organization (Levine & Prietula, 2012) and may temporarily disrupt employees' work routines (Campion et al., 1994). Our study indicates that in addition to the development- and career-related outcomes, job rotation could also help promote knowledge sharing in a virtual environment, especially for organizations in multiple locations, because people tend to share knowledge with those with whom they share a past-collocation history. Hence, organizations that wish to promote knowledge sharing among a wide range of employees on online platforms may reassess the potential costs and benefits of employee rotation and other employee mobility programs.

Limitations and Future Research

We suggest a number of future research directions that would address some limitations of this study. First, we encourage future research to adopt alternative research designs such as experiments to further corroborate the causal link between past-collocation history and knowledge-sharing behaviors. Whereas this study adopted a lagged design by measuring independent variables before capturing the dependent variable and included a series of control variables such as prior interaction history and participants' demographic characteristics in the analysis, future research may benefit from alternative designs to further investigate the causal factors of online knowledge-sharing behaviors.

Second, the data were collected in an organization in a single country; thus, this study provides limited evidence for the generalizability of our findings. Future studies may examine the robustness of the relationships by replicating the study in other organizational and societal settings. In addition, examining what other organizational and/or societal-level factors may shape knowledge-sharing behaviors is interesting in its own right.

Third, our study focused on behaviors of individuals who are already using online platforms. Because knowledge sharing can occur in an organization in many ways, future studies could also investigate what shapes individuals' choice of channel for knowledge sharing.

Conclusion

We draw on the lens of the generalized social exchange perspective to examine knowledge-sharing behaviors on online platforms. By considering factors in three aspects (i.e., requestors, responders, and responders' job characteristics), our study highlights the complexity in explaining knowledge-sharing behaviors on online platforms. We encourage future studies to adopt a research design to examine the interplay of these aspects to better understand online knowledge-sharing behaviors.

[i] As we noted in the manuscript, we distributed the survey to 193 users of the platform, and we obtained 100 usable responses. We found no significant difference in job type and group affiliation between the 100 participants and the remaining 93 users (*ps* > .05 in chi-square tests; we do not have other demographic data, such as gender and age, for those who did not respond to the survey). Because we construct the dataset by matching the survey data of the 100 participants with the log data of the platform, we only used the response opportunities that involved the 100 participants as respondents. Among the 108 questions, 55 were posted by one of the 100 participants, and 53 were posted by other users in our sample. This approach resulted in 55 x (100-1) + 53 x 100 = 10,745 response opportunities in our dataset.

[ii] The Bayesian estimator was the only available option for our model on Mplus, because estimation of random-effects models with categorical outcome variables by maximum likelihood requires a substantial number of numerical integrations and thus huge computational power (Asparouhov & Muthèn, 2010).

[iii] Bayesian analysis estimates the probability distributions of parameters (e.g., regression coefficients) given the observed data, combining initial hypotheses about the probability distributions of parameters based on knowledge prior to the current study with the probability of observed data based on the parameters (Howson & Urbach, 1993). The initial hypotheses for the probability distributions of parameters are called priors, and the resulting probability distributions and point estimates (e.g., medians), derived from the estimated probability distributions, are called posteriors. We used non-informative, diffuse priors, which are recommended when little prior knowledge is available and/or researchers decide to eliminate the influence of priors during estimation. Mplus uses N (0, infinity) for parameters of continuous variables and N (0, 5) for parameters of categorical variables, which are numerically equivalent to a distribution with constant density of 1 on an interval of [-infinite, infinite].

[iv] Due to limitations in model specification in Mplus (it can deal with either a three-level hierarchical structure or a two-level cross-classified structure), we modelled response opportunities as the first-level category, and requestors and responders as the second-level categories.

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Table 1

Descriptive Statistics and Correlation Matrix

		Mean	*S.D.*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Response	.02	.16																				
	Requestor provided responses																						
2	(Past 1-7 days)	.54	1.76	.00																			
3	(Past 8-14 days)	.15	.82	-.01	-.05																		
4	(Past 15-21 days)	.30	1.06	-.01	.01	-.02																	
5	(Past 22-28 days)	.38	1.24	-.02	-.09	-.01	.24																
	Responder received responses	.12	.46	.14	.02	.00	-.02	-.01															
6	(Past 1-7 days)																						
7	(Past 8-14 days)	.10	.40	.08	.05	.01	.00	.00	.29														
8	(Past 15-21 days)	.10	.40	.08	.01	.02	.07	.02	.14	.23													
9	(Past 22-28 days)	.11	.42	.07	-.02	.00	.02	.06	.15	.10	.28												
10	Indebtedness	.00	.06	.00	.03	-.01	.00	-.02	.05	.03	-.01	-.01											
	Categorical similarity																						
11	(Same location)	.43	.50	-.01	-.11	-.09	-.10	.06	-.03	-.05	-.02	-.02	-.03										
12	(Same hierarchy)	.79	.40	.00	.02	.01	.02	.02	.00	.01	.01	-.01	.03	-.01									
	Expertise similarity																						
13	(Same job)	.56	.50	.02	.03	.02	-.02	.03	.02	.02	.03	.01	.04	-.12	.58								
14	Age	37.02	9.28	.02	.00	.00	.00	.00	.04	.04	.05	.04	-.04	-.02	-.19	-.19							
15	Gender	.34	.47	.00	.00	.00	.00	.00	.00	.00	-.01	.00	.03	-.05	.20	.18	-.26						
16	NEO	2.48	.95	-.01	.00	.00	.00	.00	-.02	-.03	-.04	-.03	.00	.05	-.01	-.04	-.16	.01					
17	REO	5.11	.85	-.01	.00	.00	.00	.00	-.02	-.01	-.03	-.01	.00	-.10	.08	.09	.07	.12	.07				
18	Prosocial values	5.86	.81	.05	.00	.00	.00	.00	.08	.08	.07	.07	.02	-.02	.07	.22	.06	.00	-.11	.36			
19	GEO	5.64	.70	.03	.00	.00	.00	.00	.03	.04	.03	.04	.02	.01	.07	.07	-.07	.03	-.01	.51	.64		
20	Knowledge variation	6.17	.91	.03	.00	.00	.00	.00	.05	.04	.04	.04	.01	.06	.13	.01	-.05	.10	-.24	.23	.32	.45	
21	Past-collocation history	.27	.45	.03	.14	.02	.15	.00	.04	.07	.04	.04	.03	-.54	.07	.05	-.04	.05	.01	.03	.02	.06	.06

Notes: n = 10745. Correlation above .02 is significant at .05 level.

Table 2

Variables	Priors	Model 1				Model 2				Model 3			
		Posterior Estimates		95% Credible Interval		Posterior Estimate		95% Credible Interval		Posterior Estimate		95% Credible Interval	
		μ^{β}	S.D.	Lower 2.5%	Upper 2.5%	μ^{β}	S.D.	Lower 2.5%	Upper 2.5%	μ^{β}	S.D.	Lower 2.5%	Upper 2.5%
1st level - response opportunities													
Requestor provided responses													
Past 1-7 days	N(.00, 5.00)	-.01	.02	-.05	.03	-.01	.02	-.05	.03	-.01	.02	-.05	.03
Past 8-14 days	N(.00, 5.00)	-.08	.06	-.19	.03	-.07	.05	-.20	.02	-.07	.05	-.17	.03
Past 15-21 days	N(.00, 5.00)	.00	.03	-.07	.07	.00	.04	-.08	.07	.00	.03	-.07	.06
Past 22-28 days	N(.00, 5.00)	-.07	.03	-.14	-.01*	-.07	.03	-.14	-.01*	-.08	.03	-.14	-.02*
Responder received responses													
Past 1-7 days	N(.00, 5.00)	.11	.05	.01	.21*	.11	.06	.01	.22*	.11	.05	.01	.21*
Past 8-14 days	N(.00, 5.00)	-.10	.07	-.24	.02	-.10	.07	-.22	.03	-.09	.06	-.21	.03
Past 15-21 days	N(.00, 5.00)	-.03	.07	-.16	.10	-.03	.07	-.16	.10	-.02	.06	-.15	.10
Past 22-28 days	N(.00, 5.00)	-.10	.06	-.21	.01	-.10	.06	-.23	.02	-.11	.06	-.22	.02
Indebtedness	N(.00, 5.00)	-.18	.56	-1.46	.73	-.12	.58	-1.48	.83	-.08	.59	-1.45	.88
2nd level - responder/requestor dyads													
Same location	N(.00, 5.00)	.16	.10	-.06	.34	.17	.12	-.06	.41	.18	.10	-.01	.38
Same hierarchy	N(.00, 5.00)	.13	.14	-.13	.41	.08	.13	-.15	.35	.17	.15	-.09	.50
Same job	N(.00, 5.00)	-.02	.15	-.39	.25	.05	.20	-.34	.42	-.08	.24	-.43	.44
Past-collocation history (PCH)	N(.00, 5.00)	.20	.10	-.01	.38	.11	.14	-.15	.40	-.01	.13	-.24	.25
3rd level - responder													
Age	N(.00, 5.00)	.01	.01	-.02	.03	.01	.01	-.02	.03	.01	.01	-.02	.03
Gender	N(.00, 5.00)	.06	.20	-.33	.46	.10	.20	-.28	.50	.07	.21	-.32	.49
Hierarchy	N(.00, 5.00)	.16	.27	-.38	.67	.16	.29	-.40	.72	.17	.32	-.43	.82
NEO	N(.00, 5.00)	-.14	.09	-.33	.04	-.12	.10	-.32	.08	-.15	.11	-.36	.05
REO	N(.00, 5.00)	-.12	.12	-.37	.12	-.13	.13	-.38	.12	-.10	.13	-.36	.15
Prosocial values	N(.00, 5.00)	.16	.14	-.12	.43	.16	.15	-.14	.48	.12	.15	-.16	.43
GEO	N(.00, 5.00)	.08	.19	-.29	.46	.06	.19	-.32	.43	.06	.20	-.35	.45
Knowledge variation (KV)	N(.00, 5.00)	.04	.12	-.20	.26	.02	.11	-.20	.26	.01	.14	-.24	.28
GEO x KV	N(.00, 5.00)									.02	.15	-.28	.30

Cross-level interaction													
PCH x GEO	N(.00, ∞)					.26	.12	.02	.50*	.16	.16	-.13	.49
PCH x KV	N(.00, ∞)									.21	.14	-.04	.48
PCH x GEO x KV	N(.00, ∞)									.36	.14	.09	.66*
Thresholds	N(.00, 5.00)	2.80	.13	2.55	3.05*	2.79	.12	2.59	3.04*	2.82	.13	2.56	3.07*
Posterior predictive p-value		.53											

Table 3

Analysis of Conditional Effects of Past-collocation history

	Posterior estimates		*95% Credible interval*		
Conditions	μ^{β}	*S.D.*	*Lower 2.5%*	*Upper 2.5%*	*Sig.*
Low GEO x Low knowledge variety	-.11	.21	-.53	.32	
Low GEO x high knowledge variety	-.36	.34	-1.07	.26	
High GEO x Low knowledge variety	-.11	.29	-.71	.40	
High GEO x High knowledge variety	.51	.17	.17	.85	*

Notes: n = 10,745 * significant at .05 level.

Figure 1

Research model

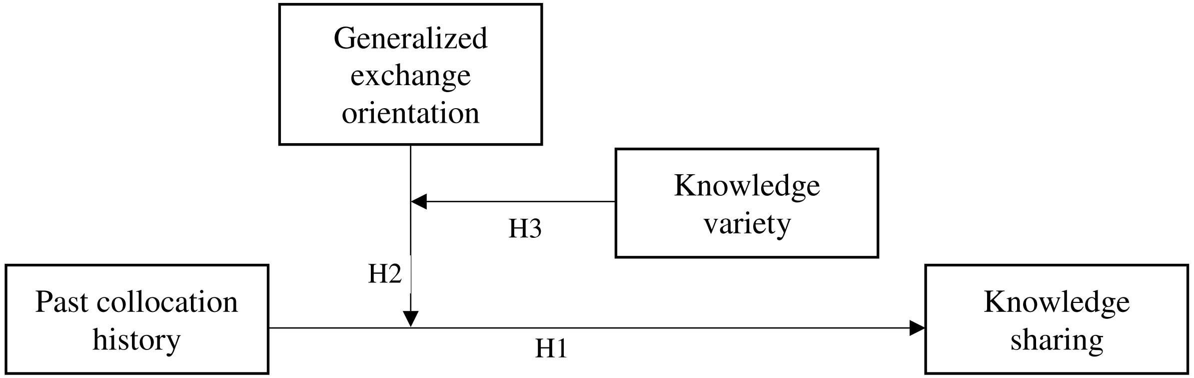

Figure 2

Predicted Probability of a Response to a Request.