Factors Affecting Information Seeking and Evaluation in a Distributed Learning Environment

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ABSTRACT

The purpose of this study was to identify and analyze the processes of seeking information online and evaluating this information. We hypothesized that individuals’ social network, in-out group categorization, and cultural proclivity would influence their online information-seeking behavior. Also, we tested whether individuals differentiated information values based on the information source. A total of 78 students from two universities in different geographical regions of Singapore participated in a collaborative information-seeking exercise using a computer-mediated collaborative system. The information-seeking data were analyzed with multivariate p* network analysis. The findings of this study showed that interpersonal social networks, in-out group distinctions, and individuals’ cultural proclivity significantly affected the information exchange process between different groups. However, it was found that individuals did not differentiate the values of information according to whether the source of the information was within their social network or school.

Keywords

Social network, CMC, Information sharing, Cultural proclivity, Social categorization, Information evaluation

Introduction

Computer-supported collaborative learning (CSCL) involves interpersonal processes by which students work together to complete a learning task designed to promote learning and intellectual discovery (Alavi, Wheeler, & Valacich, 1995). The distinguishing feature of CSCL is interaction among distributed learners. Peer-to-peer sharing of information, ideas, and knowledge is important for learners in increasing exposure to diverse problem-solving approaches, conflicting viewpoints, and different sets of knowledge. Each of these points enhances an individual’s ability to recognize opportunities, to adapt, and to learn (Cohen & Levinthal, 1990). From this perspective, learning is an active, social process involving knowledge construction by community members rather than a cognitive process involving the acquisition of knowledge or skills by individuals.

Because of the fast development of communication technologies in recent decades, computer-mediated communication (CMC) has become an essential element in mediated learning environments such as distance learning (Lee, Cho, Gay, Davidson, & Ingraffea, 2003; Yeh, 2010). One of the underlying assumptions of using CMC tools in education is that learners with diverse pieces of information and multiple perspectives will interact with each other more efficiently with the help of CMC. That is, CMC participants are believed to be less bound by geographical and time barriers or other social contextual elements, and this greater freedom creates conditions for rapid information exchange among learners with diverse information and multiple perspectives.

In practice, however, previous research has consistently reported that using CMC tools in distributed learning does not always produce the expected results (Cho & Lee, 2008). For instance, distributed learning environments such as CSCL often fail to provide students with learning environments that have shared social contexts, which foster a seamless engagement in social interactions and learning (Cho, Lee, Stefanone, & Gay, 2005). This is largely because of the nature of the distributed learning environment, which prevents distributed learners from establishing a shared learning context (Huang, Jeng, & Huang, 2009).

Often, multiple-level social, psychical, and cultural boundaries divide distributed learners into discrete subgroups. These boundaries create substantial challenges for distributed learners who need to bridge the “discontinuities” (Watson-Manheim, Chudoba, & Crowston, 2002). With more of these boundaries, the “virtuality” of the team increases, creating “fault lines.” “Fault lines” are hypothetical dividing lines that split a group into subgroups according to one or more social or cultural attributes such as demographic attributes, organizational affiliations, or nationalities (Lau & Murnighan, 1998).
A salient fault line causes people to categorize members of their own subgroup as an in-group and view other subgroups as out-groups. This can cause group members to communicate and share information within rather than across their subgroups (Katz & Allen, 1982). Such segregated communication and information sharing can degrade a group’s ability to learn, performance, and satisfaction. As social network studies have demonstrated, strong social ties within groups can create a social circle/barrier that prevents group members from acquiring innovative and creative ideas from out-group members (Granovetter, 1973). When team members’ interactions are confined to subgroups, they tend to exchange overlapping, redundant, or local information. Consequently, the existence of fault lines can significantly limit the effective exchange of information and reduce the opportunity for collaborative learning and knowledge construction.

In addition, individuals’ characteristics play a significant role in the explanation and prediction of learning behavior (Jensen, 2003). Different learners have different instructional preferences, information processing styles, and personality types, which have significant impacts on the ways in which learners engage in various learning activities (Jones, Reichard, & Mokhtari, 2003). For instance, personality types and cognitive styles affect participation in a networked learning environment, collaboration method, and instructional media preferences (Sadler-Smith & Riding, 1999).

Hence, in order to develop an effective CSCL environment, one must consider both the individual characteristics of distributed learners and multiple-level social barriers that divide these people into subgroups. However, research examining the influences of multiple-level social boundaries (e.g., group and relational boundaries) together with individual traits on the learning practice in a distributed learning environment is difficult to find. That is, scholars have seldom attempted to investigate the interactions among pre-existing group- and individual-level social boundaries and individual characteristics or the simultaneous influence they have on students’ learning practices in CSCL. Given the increasing proliferation of CSCL, this line of research will not only contribute to the related literature but will also provide practitioners with useful guidelines for successful CSCL.

We undertook this research to empirically examine how students separated by physical distance share and transfer information using a CMC system. We tried to identify social and individual factors affecting the information-seeking processes within and across two different locations. Students from two universities in different geographic regions of Singapore participated in a collaborative learning exercise using a computer-mediated collaborative system. We tested how social contexts such as interpersonal social networks, social categorization, and individuals’ cultural proclivity facilitated or constrained the flow of information across CMC groups. In addition, we tested whether social and individual factors affect the information-evaluation process.

**Background**

**The social nature of information sharing using CMC**

Theories of collaborative learning such as the developmental theories of Vygotsky and Piaget, cognitive-elaboration theory (Brandon & Hollingshead, 1999; Webb & Palincsar, 1996), and situated learning theory (Lave & Wenger, 1991) state that peer interaction is a key mechanism whereby learners construct knowledge. For instance, situated learning theory holds that learning, both outside and inside school, proceeds through collaborative social interaction and the social construction of knowledge. From this perspective, the success of CSCL is more than just a matter of delivering information from one source to another (e.g., an instructor to students). The emphasis for teachers should be on how to provide a learning environment in which distributed learners can seamlessly engage in social interactions and community-based learning practices (Ajayi, 2009).

A number of researchers and practitioners have envisioned the possibility of creating effective online learning environments in which distributed learners co-construct knowledge through CSCL. CMC tools such as online discussion boards, instant messaging, video-audio conferencing, and email listservs are regarded as appropriate tools with which to support such collaborative knowledge sharing and learning practices (Lee et al., 2003). The high interactivity and connectivity afforded by CMC systems can also facilitate community-based learning by enabling active peer interaction, evaluation, and cooperation (Hiltz & Wellman, 1997). Moreover, a local transfer of knowledge (Joshi, Sarker, & Sarker, 2007) is less important, because CMC systems connect people across time and geographic barriers.
It has been suggested that the perceived quality of information and source expertise should be the main criteria guiding individuals' information-seeking behaviors. For instance, CMC participants will select information from sources perceived to offer the highest quality information in terms of relevancy, accuracy, reliability, and timeliness (El-Shinnawy & Vinze, 1998). However, it was argued that CMC environments which lack social cues reinforce the salience of inter-group differences and group identity compared with face-to-face settings, thereby strengthening the impacts of various social boundaries on the communication process (Lea & Spears, 1991).

Theoretically, studies on source credibility have suggested that the choice of information should be determined by its origin rather than by its face value, especially when individuals have difficulties determining which messages are valuable (Griffin, 1967). Similarly, the transactive memory (TM) theory explains that close interpersonal relationships often function as a form of transactive memory; that is, they constitute a repository containing information about "who knows what" (Wegner, 1986). Hence, when individuals approach information-seeking tasks, they may turn to the information from their social circle because they believe that these sources have expertise (Yuan, Fulk, & Monge, 2007). Previous research has reported that, especially in the context of a small group, such meta-memory influences the information exchange process (Palazzolo, 2005).

In summary, it is expected that the in-out group membership of an information source might act as a strong heuristic cue, especially when individuals face difficulty evaluating the quality of information and the expertise of sources in an online information space. In this case, interpersonal closeness and group membership may have more significant impacts on how individuals choose information than does the face value of the information. On the basis of these discussions, we suggest the following hypotheses.

Hypothesis 1: The possibility of information exchange between individual \(i\) and \(j\) will increase if \(i\) and \(j\) belong to the same group.

Hypothesis 2: The possibility of information exchange between individual \(i\) and \(j\) will increase if \(i\) has interpersonal social relationship with \(j\).

Cultural proclivity and information exchange

Individuals' cultural proclivity is reportedly an important contingent factor that reinforces or mitigates the influence of interpersonal and group effects on information exchange (Pook & Fustos, 1999). Culture is the “collective programming of the mind that distinguishes the members of one group or category of people from another,” and manifests usually in one’s values, behaviors, and actions (Hofstede, 2001, p. 9). Of the many dimensions of cultural beliefs identified in previous studies, individualism/collectivism (I/C) is commonly regarded as a fundamental element that distinguishes members of different cultural orientations (Hofstede, 1991). Individualistic people base their self-understanding on their own actions, which are usually understood independently of what others think (Earley, 1993). For this category of people, individual goals and self-actualization take precedence over group goals. In contrast, collectivistic people are easily integrated into strong cohesive groups such that they base their self-understanding on the reactions of others (Bond & Hwang, 1986). One attribute of collectivism is a “we” consciousness and an orientation to the collectivity (Triandis, 1995). For collectivistic individuals, belonging takes precedence over egoistic needs, and they have a supreme need for actualizing their in-group interactions to maintain group harmony.

The I/C construct has been identified in cross-cultural studies to explain similarities and differences in information sharing (Pook & Fustors, 1999) and information technology usage (Calhoun, Teng, & Cheon, 2002). With regard to information exchange, Cho and Lee (2008) recently reported that individuals from an individualistic culture show a greater tendency toward accepting information from out-group members than do those from collectivistic culture. Their finding suggests that individuals from different national cultures display some discernable behavioral patterns in terms of information seeking and sharing.

Although Hofstede’s (1991) I/C culture model has been adopted by many scholars, it has been criticized because it treats all individuals in a nation as homogeneous, sharing the same cultural values. Schwartz (1994) argued that individuals within a given society may deviate substantially from other members of the society in their personal values and may not hold similar values to those endorsed by their culture. As such, the main difference between individualistic and collectivistic cultures is that the probability of the individualistic attitudes, norms, values, and
behaviors being espoused or used is higher in the former type of person than in the latter (Triandis, 1994). It is more appropriate then to treat the I/C dimension as an indicator of the likelihood that a person or a group of people will behave in an individualistic or collectivistic way in various situations. Following Triandis’s argument, in the current study, the I/C dimension is considered an individual trait, and an individual’s I/C proclivity is operationalized as the likelihood that a person or a group of people will behave in an individualistic or collectivistic way.

Individuals with individualistic proclivities tend to belong to many groups. They consider interactions with others restricted to a particular purpose and time and experience little difficulty joining or leaving such groups on the basis of their ability to satisfy their goals and tasks (Triandis, Bontempo, Villareal, Asai, & Lucca, 1988). As for information sharing, we expect that individuals with individualistic proclivities are more likely to focus on the task at hand and on the value and quality of information. Hence, their information search would be more heterogeneous and open, because personal preferences and style, among other factors, guide their search. From these considerations, we hypothesize as follows:

Hypothesis 3: Individuals’ cultural proclivity will influence the way individuals seek information from within or across boundaries.

Information evaluation

Information-seeking is the first step in information exchange and knowledge transfer. To be used meaningfully, shared knowledge must be coupled with mechanisms for acquisition, retention, retrieval, evaluation, and the application of the information. In terms of information evaluation, studies suggest that people have a strong tendency to judge the value of information on the basis of the (often irrelevant) characteristics of information sources. Research on source credibility indicates that the perceived expertise and trustworthiness of the source influence the acceptance of information (Beebe & Beebe, 2005; Griffin, 1967). As mentioned previously, research on TM theory also suggests that individuals often rely on information from known sources because they believe that these sources have expertise (Yuan et al., 1986), especially in group settings (Palazzolo, 2005). This tendency applies even to what might be considered a prototypical information retrieval scenario. In a study about “desk officers” at the International Monetary Fund (IMF), for example, Harper (1999) concluded that it is the overall social texture of the information that determines its value.

With regard to CMC, the early prediction was that CMC participants would be more likely to judge the value of information according to the content value, referring to such factors as persuasiveness, novelty, validity, and accuracy. Because of the social-cues-filtered-out nature of CMC interactions, the contextual cues play less significant roles in the information-evaluation process (El-Shinnawy & Vinze, 1998). Consistent with this argument, the study of Constant, Sproull, and Kiesler (1996) discovered that people assigned higher values to information from “electronic weak ties” than to strong ties, since the weak ties provide more unique and locally unavailable knowledge. Soininen and Suikola (2000), however, showed that social aspects moderate almost every step of the information retrieval process, ranging from problem formulation to the evaluation of the retrieved items. Hence, we propose to test empirically the degree to which social factors influence the way individuals determine the value of information when they exchange information using CMC channels.

RQ1: Will school membership or pre-existing social relations influence the perceived quality of information?

Methods

Participants and procedure

To test the hypotheses and the research question, we conducted a field experiment in an educational setting. Undergraduate students taking an introductory communication classes at two universities (hereon they will be called U1 and U2) in two different geographical areas participated in this study. The total number of participants was 78 (30 from U1 and 48 from U2; 57 females and 21 males). At the beginning of the semester, instructors at both universities announced in class that an online collaborative learning exercise with students from another university would take place during the semester. In the middle of the semester, students were asked to participate in the
collaboration practice to find useful information about current issues in communication technologies. Participation in the practice was voluntary, and participants received extra credit.

An online discussion forum was developed and used for the exercise. Participants were provided with the web address, at which they had to log in to read and write messages. The collaboration exercise consisted of two phases, each of which lasted two weeks. During the first phase, participants attempted to find an online article describing current issues in communication technologies. In addition, they had to post a brief summary of the article together with its online address, so that other participants could visit the webpage and read the article.

During the second phase, students were asked to browse all the summaries posted by other students, select one or two summaries, read the original article by visiting the webpage, and then leave a reply with his or her own opinion about the article. Students were not allowed to leave a reply until the end of the first phase so that all postings could have an equal chance of receiving replies.

As shown in Figure 1, the design of the discussion forum allowed participants to recognize who replied to whose posting. When students left replies to the initial postings during the second phase, they were also asked to evaluate the quality of the information on a five-item scale (criteria included whether the information was unique, useful, interesting, of good quality, and recommendable to others) ranging from 1 to 7, one being “strongly disagree” and 7 being “strongly agree” ($\alpha = .86$). The rating scores were saved in a data file, and students did not have access to the scores at any time. The poster of a message was not allowed to rate his or her own message.

Figure 1. Setting of the discussion forum

Measurements

To test Hypothesis 2, two kinds of networks, social and information sharing networks, needed to be constructed. As for the social network, we conducted a social network survey before the experiment in which students were asked to report three to five names of their close friends. The closeness of each friend reported was measured on a seven-point Likert-type scale, one being “not close at all” and seven being “very close.” Students had access to the class rosters of the respective schools to aid them in recalling the names of their classmates. The resulting two social networks of each school (30 by 30 for U1 and 48 by 48 for U2) were merged into one 78 by 78 overall social network. Note that cross-school social relationships were not assumed in the final social network.

A 78 by 78 information-sharing network was constructed by identifying whether student $i$ wrote a reply to a message posted by student $j$. In other words, if student $i$ selected and read a message posted by student $j$ and wrote a reply to it, it was assumed that the two students have shared information. If students $i$ and $j$ shared information, the cell $ij$ was coded as 1; and if they did not share, as 0.

Hypothesis 3 concerns whether individuals’ cultural proclivity fosters within- or cross-boundary information-seeking. To test Hypothesis 3, we divided the information sharing network into two components, within- and between-school information sharing. As for the within-school information sharing network, information sharing between students in the same school was maintained, but all cross-boundary information sharing was coded as 0. Conversely, in the between-school information-sharing network, information-sharing between students from two schools was maintained, but all local information sharing was coded as 0. As a result, we constructed two 78 by 78 information-sharing networks, which contained within- and between-school information sharing, respectively.

Finally, individuals’ cultural proclivity (the I/C index) was measured on a seven-point Likert-type scale composed of eight items ($\alpha = .72$) developed and validated by Erez and Earley (1987). Examples of the items include “If the group is slowing down, it is better to leave it and work alone”; “To be superior a man must stand alone”; and “I would rather struggle through a personal problem by myself than discuss it with my friends.” A higher score on this scale indicates a higher individualistic proclivity. This measurement was administered on the social network survey as described above.
Analysis and results

Table 1 shows the descriptive results of the initial message postings and the I/C index scale. During the first phase of the social recommendation practice, 81 messages were posted. Of these, 30 messages came from U1 and 51 from U2. As for individualistic proclivity, no significant difference was found between the two schools ($F = 3.7, p > .05$).

<table>
<thead>
<tr>
<th></th>
<th>U1</th>
<th>U2</th>
<th>Total</th>
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<tbody>
<tr>
<td>Number of participants</td>
<td>30</td>
<td>48</td>
<td>78</td>
</tr>
<tr>
<td>Number of initial postings</td>
<td>30</td>
<td>51</td>
<td>81</td>
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<tr>
<td>Individualistic proclivity</td>
<td>4.6 (1.2)*</td>
<td>4.2 (1.3)</td>
<td>4.4 (1.3)</td>
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*Numbers in parentheses represent standard deviations.

During the second phase, 80 replies were posted. Of these, the number of within-school replies (i.e., U1→U1 and U2→U2) was 52 (65%) and that of between-school replies (i.e., U1→U2 and U2→U1) was 28 (35%), as shown in Table 2. To test Hypothesis 1, a chi-square analysis was performed. The results show that the difference between the numbers of cross- and within-school postings was significant ($\chi^2 = 7.5, df = 1, p < .01$), meaning that participants tended to write replies to messages from the same school, which supports Hypothesis 1.

<table>
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<tr>
<td>From</td>
<td></td>
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<tr>
<td></td>
<td>U1</td>
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<tr>
<td>U1</td>
<td>22</td>
</tr>
<tr>
<td>U2</td>
<td>18</td>
</tr>
<tr>
<td>Total</td>
<td>40</td>
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To test Hypothesis 2 and 3, we ran multivariate $p^*$ (MVP) logistic network regression analyses (Wasserman & Pattison, 1996). The benefit of using MVP analysis is twofold. First, MVP treats a pair of actors $i$ and $j$ as a single case, which dramatically increases the number of cases from $N$ to $N*(N - 1)$ ($78*77 = 6,006$ in the case of this study) and thus the power of the analysis. Second, MVP analysis allows the dependent variable to be in a matrix format and the independent variables in vector and matrix formats. In other words, attributes such as individuals’ cultural proclivity and networks such as a social network can be used as independent variables simultaneously. Because it is beyond the scope of the current study to review MVP analysis in detail, readers are referred to previous studies (e.g., Monge & Contractor, 2003; Wasserman & Pattison, 1996).

Based on the hypotheses and research question, we developed two MVP regression models. In the first model, the within-school information-sharing network was used as the dependent variable. The social network and individuals’ cultural proclivity were entered as independent variables. In the second model, the between-school information-sharing network was used as the dependent variable. Note that although the social network was used as an independent variable, it should not affect the dependent variable (i.e., between-school information exchange), because there were no pre-existing between-school social relationships. To control for gender effects, we entered participants’ gender as a control variable in both equations. For analysis, we used MultiNet (Richards & Seary, 2005), which reports the model fit in the form of $-2\text{Log (likelihood)}$, the “badness of fit,” meaning that the smaller the value, the better the result.

When performing MVP analysis with MultiNet, the fit of each research model was compared with those of basic network models in which inherent structural properties of the network (e.g., choice, reciprocity, and transitivity) were used as independent variables (Monge & Contractor, 2003). Note that the inherent structural properties used in basic network models are different from the exogenous attributes of network nodes used as independent variables in the research models. We fitted the basic network models in which various combinations of inherent properties were entered. We then compared the results with the fit of each research model to determine which had the best output. In other words, we tested whether the observed network patterns are determined by inherent endogenous attributes of a network or by exogenous attributes of network nodes (e.g., in-out group categorization).
First, we examined the basic network models. All of the basic models tested produced \(-2\log (\text{likelihood})\) values larger than 550. In addition, none of the endogenous properties used in basic network models were significantly associated with the dependent variables. Second, we fitted two research models, and the results are presented in Table 3. As Table 3 shows, the research models produced significantly smaller \(-2\log (\text{likelihood})\) values (within-school: 363.816; between-school: 457.028) than all of the basic models (> 550). These results illustrate that the research models explained the participants’ information-seeking behavior substantially better than did the models with inherent network properties. This means that the observed results of the information-seeking networks were not due to the structural tendencies of the networks but rather the effects of independent variables utilized in this study. Hence, we concluded that the two research models composed of exogenous attributes were parsimonious and appropriate models for use in the current study.

As shown in Table 3, male students, unlike female students, preferred local information sharing, but this difference was not observed for between-school information sharing. Individuals’ pre-existing social networks significantly increased local information sharing as predicted by Hypothesis 2, but they did not influence between-school information sharing as expected. Participants’ individualistic proclivity did not influence within-school information sharing, but significantly increased between-school information sharing, which is consistent with Hypothesis 3.

| Table 3. Results of \(p^*\) Logistic Regression Analysis |
|--------------------------------------|-----------------|-----------------|
| Dependent Variables                  | Within-school   | Between-school  |
| Gender (female = 0, male = 1)         | 1.88**          | -9.62           |
| Social network                        | .354**          | -9.05           |
| Individualistic proclivity            | .037            | .492**          |
| Model Fit \([-2\log(\text{Likelihood})]\) | 362.816         | 457.028         |

** \(p < .01\).

For RQ1, we tested the degree to which social contexts influenced the evaluation of information. As mentioned, when students replied to postings, they were asked to assess the quality of the information provided by the postings. Using the rating scores, we ran ANOVA tests to examine whether postings from the same school received higher scores than others. The results showed that the participants did not differentiate the value of the information according to whether the information provider was within their social network (\(M_{\text{within}} = 4.98, SD = .86, M_{\text{out}} = 4.65, SD = .94, F = 2.40, p > .05\)) or at the same school (\(M_{\text{same}} = 4.69, SD = .86, M_{\text{diff}} = 4.93, SD = .90, F = .914, p > .05\)).

**Discussion**

In this study, we examined the process of collaborative information sharing through CMC within and across different locations. Overall, this study’s findings demonstrated the socially bounded nature of computer-mediated information-sharing and -seeking behaviors. More specifically, we found that three factors significantly influenced the way individuals seek and exchange online information in a collaborative learning environment: 1) the group level in-out group categorization, 2) the relational level social network, and 3) the individual-level cultural proclivity.

At the school level, we hypothesized that online information-seeking behavior would be significantly affected by the in- and out-group categorization. The result of the chi-square test clearly illustrated that participants’ social categorization behavior supported Hypothesis 1. School membership increased the tendency of within-school information sharing and decreased that of between-school information sharing. The results imply that participants in the study preferred information from local sources to that from external sources. At the relational level, we hypothesized that online information-seeking behavior would be significantly affected by pre-existing social relationships. MVP analysis results show that pre-existing social networks are closely related to within-school information sharing, which supports Hypothesis 2. Taken together, these results demonstrate the socially bounded nature of online information sharing in a distributed educational setting.

Previous research has reported that the type and quality of information acquired through interpersonal networks is inversely related to the strength of ties (Granovetter, 1973). In this study, we measured the strength of pre-existing social ties and found that their influence on online information seeking arose more significantly from strong social ties instead of weak ties. This finding is consistent with the contention that the volume and extent of communication
are the basis of knowledge transfer (Sarker, Sarker, Nicholson, & Joshi, 2005). It has been hypothesized that frequent communication decreases misunderstanding and increases interaction, which leads to the creation of shared meaning and knowledge transfer. This suggests that strong interpersonal ties tend to influence individuals’ online information-seeking behaviors. The results of this study imply that information is “sticky” (Szulanski, 1996) and captive in strong social ties, even in a virtual setting, implying further that individuals are motivated to seek information from groups within the “fault lines,” since they may seem to be more accessible, relevant, and trustworthy.

These results indicate that distributed learners may need to overcome and transcend their social boundaries in order to achieve successful learning. In doing so they would benefit more from online information seeking by exploring various information sources in order to acquire information from different and novel perspectives. Practitioners, especially in education, should be aware of the socially bounded nature of information sharing and the potential weakness of online information sharing. Consequently, they should try to foster cross-boundary information sharing so that more diverse and valuable information can be exchanged. For instance, providing an anonymous information exchange condition in the design of collaborative learning systems may be a useful option to minimize the influences of such subgroup identifications.

At the individual level, although individuals with high collectivistic proclivity (i.e., low individualistic proclivity) did not prefer within-school information sharing, we found that individuals with high individualistic proclivity tended to seek out information from outside the boundaries, which supports Hypothesis 3. This result supports the contention of this study that individuals’ cultural proclivities affect CMC collaboration, at least to the extent that people with a more individualistic nature are more inclined to seek out information from sources outside of their social boundaries.

The finding that people with high individualistic proclivities (i.e., low collectivist proclivity) tend to seek out information across school boundaries can be explained by the fact that highly individualistic people value their own goals and self-actualization over group goals. In other words, for those with high individualistic proclivities, achieving their goal is more important than following group norms, and thus as long as they believe that it is helpful to acquire more diverse and valuable information, they are willing to cross borders to fulfill their needs. Previous research has examined the affects of individual characteristics such as information processing styles (Jones et al., 2003), personality type (Sadler-Smith & Riding, 1999), and outcome expectations (Cho & Lee, 2008) on students’ information-seeking and learning behaviors. This study contributes to this line of education research by identifying another important, but relatively unexplored individual characteristic such as cultural proclivity and by specifying how this particular factor influences information seeking in the context of CSCL.

This result is consistent with the recent finding that individuals from an individualistic country tend more often to accept information from out-group members than people from a collectivistic country (Cho & Lee, 2008). The previous study, however, operationalized culture as a trait of people from a certain country, assuming that individuals in a nation as homogeneous. In this study, culture is considered a trait of an individual through which to investigate potential inconsistencies in behavioral patterns at the micro-level. The results of this study illustrate that the approach of the current study was appropriate and that individuals in a nation do vary in regard to cultural proclivity, which significantly affects their online information-seeking behavior. Hence, practitioners should be aware of different levels of preference to outbound information seeking at the individual level and its influence on information-seeking.

Finally, we tested whether social context influences the way individuals evaluate the value and quality of information. The results showed that individuals did not differentiate the values of information according to whether the source of the information was within their social network or school, which has an interesting research implication. On the basis of our findings, we suggest that social context can strongly influence information sharing in the information acquisition stage but not necessarily in the evaluation stage. This proposition underscores the scope of social influence on the information-sharing process. Individuals may rely on social and contextual heuristic cues to choose information in a large information space. Once they have the information in their hand, however, the assessment of the quality of information is not necessarily influenced by social context. It seems that information processing is a multi-step process, coupled with mechanisms for the acquisition, retention, retrieval, evaluation, and application of information. Researchers need to be aware of the multi-step nature of information processing and try to examine in what manner and to what extent social context affects the different steps of collaborative learning.
Conclusion

Many researchers have touted the power of CMC-based collaborative learning to facilitate cross-border information transfer by extending a person’s reach across the boundaries of time, space, and hierarchies (Starr, 1997). However, this study’s findings suggest that individuals do not necessarily benefit from “the usefulness of electronic weak ties” (Constant et al., 1996). At the very least, the results of this study indicate that information does not move across social network boundaries as readily as previously thought. The results demonstrate that computer-supported collaborative learning should be regarded as a social process and that teachers should be aware of the importance of social context when implementing CMC tools in educational settings.

We believe that the findings of this study make a significant academic contribution to the understanding of online information-seeking behaviors and the factors affecting such behaviors. To our knowledge, research empirically testing the effects of individuals’ cultural proclivity on computer-mediated information-seeking behaviors has been rare. We also discovered that, despite the socially bounded nature of CMC information exchange, the social values attached to the information exchange seldom influence the evaluation of information.

This study’s findings also have practical significance. As mentioned before, we suggest that understanding how individuals’ cultural proclivities and social roles affect CMC-based information processing can offer important insights into how technology can be effectively deployed in various settings. For instance, designers and managers of computer-mediated collaboration practices, such as virtual teams, need to be more proactive when members are engaged in distributed collaborative tasks. For instance, more incentives or rewards for cross-border information sharing can be given to participants with a collectivist proclivity.

This study has some limitations. It confined its focus to a set of variables of interest such as individuals’ cultural proclivity and the social roles in their social network. As a result, other relevant factors such as task characteristics, communications between information source and receiver, and technological features of the CMC environment were not incorporated in model testing. Participants in this study performed a rather simple task within a relatively short period of time. Hence, future research should examine whether the findings of this study can be replicated when distributed learners engage in a more complex learning task (e.g., problem solving) for a longer period of time. As identified by Cross and his colleagues (2001), information sharing provides at least five different types of benefits: solution, legitimatization, meta-knowledge, problem solving, and validation. Future studies should incorporate different types of information and tasks in order to verify the implications of the current study.

References


