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Peer interaction and social network analysis of online communities with the support of awareness of different contexts

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Abstract Although several studies related to social-context awareness (SA) and knowledge-context awareness (KA) argued that each (SA or KA) can individually enhance peer interaction in an online learning community, other studies reached opposite conclusions. These conflicting findings likely stem from different experimental settings. Most importantly, few studies have investigated the difference between the impacts of SA and KA under an identical experimental setting, which can be used to determine whether SA or KA better enhances peer collaboration. Restated, direct empirical comparisons of these two approaches are lacking. This work simultaneously investigates the impacts of SA and KA on quantitative and qualitative peer interaction and learning performance using the same experimental setting. Additionally, an underlying repeated-measurement design is applied to investigate peer interaction patterns and learning performance in SA and KA communities. Experimental results show that SA can stimulate more quantitative peer interaction than KA. However, both SA and KA have limited capacity to elicit qualified message content, even in a longitudinal experiment. Although the scores of SA and KA communities did not differ significantly on the first posttest, the SA community had significantly better learning performance on the second posttest, likely related to more extensive and frequent interaction among peers within the SA community.

Keywords Computer-mediated communication · Learning communities · Evaluation of CAL systems

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Introduction

Numerous studies have proven that computer-supported collaborative learning (CSCL) is an innovation that improves learning performance using modern information and communication technology (ICT). A CSCL environment typically offers tools that facilitate the sharing of information and ideas, as well as the distribution of expertise among group members (Lipponen et al. 2003). However, when members are reluctant to share knowledge, the efficiency of CSCL declines (Kimmerle and Cress 2008). Unfortunately, some studies reported that team members had poor motivation to share knowledge (Ardichvili et al. 2003; Yuan et al. 2005). Additionally, collaborative learners seldom establish productive interaction spontaneously in online communities (Dehler et al. 2011; King 2007).

Social-context awareness (SA) and knowledge-context awareness (KA)

Recently, awareness of the social context and knowledge context for peers has increased opportunities for informal learning, peer interaction and collaboration, and knowledge sharing (El-Bishouty et al. 2007; Yang et al. 2007). Increased peer awareness and assistance during learning positively affect student motivation and encourage self-reflection (DiMicco et al. 2007). Numerous studies have developed methods to increase context awareness for online learning communities. According to Janssen and Bodemer (2013), two common categories are peer social-context awareness (SA) (Cadima et al. 2010; Chen and Chang 2012; Janssen et al. 2007; Kimmerle and Cress 2008), and peer knowledge (or cognitive)-context awareness (KA) (Dehler et al. 2011; El-Bishouty et al. 2007; Engelmann et al. 2010; Sangin et al. 2011).

An SA provides students with information about group members' participation levels during collaborative processes, including information about social network positions (namely, close friends and central/peripheral positions in a social network) or social interactions (namely, messages sent, responses and participation rates) among participants. Moreover, previous SA studies focused on investigating its quantitative impact on peer interaction, such as analyzing the number of messages sent and received. For example, Cadima et al. (2010) devised an online SA system that visualizes social interactions is a community (knowledge transfer between givers and recipients) and sociogram (revealing social network positions of peers). The investigation by Cadima et al. measured network density and number of peer messages given and received to determine the degree of peer interaction. Chen and Chang (2012) proposed an online SA system that used a prediction model based on past social interactions among peers (namely, messages dealing with requests and responses) to recommend optimal candidates to whom (a requestor) can direct requests for assistance. Janssen et al. (2007) investigated the effects of visualization of participation during online collaboration during a historical inquiry task. The SA tool visualizes the number of messages sent by a member and their average length.

A KA provides students with information about the knowledge levels of group members, including 'who knows what' information in the knowledge dimension, as well as information relevant to knowledge expertise and experience. Most studies investigated the impacts of KA on peer interaction quality, including message quality. For example, Dehler et al. (2011) proposed a KA system that visualizes self-assessed knowledge as a reference, which allows peers to decide which questions to ask and which aspects or issues need explaining when discussing online materials. El-Bishouty et al. (2007) developed a ubiquitous learning system that identifies levels of peer self-assessed knowledge, and recommends qualified candidates to those seeking help. Engelmann et al. (2010) utilized a KA system, capable of visualizing constructed concept maps of peers. Members had to collaborate online to co-construct a concept map that dealt with which pesticides and fertilizers members should apply to protect and cultivate a spruce forest. Finally, Sangin et al. (2011) applied a KA system that visualizes knowledge levels of peers based on pre-test scores.

Research background and questions

However, several conflicting arguments have emerged. First, several SA-related studies argued that SA can enhance the quantitative peer interactions (Cadima et al. 2010; Chen and Chang 2012; Kimmerle and Cress 2008) because SA can regulate one's participation (Janssen et al., 2011), such that a learner may adopt a friendlier demeanor (Bodemer and Dehler 2011). For example, Chen and Chang (2012) demonstrated that an SA mechanism can increase the number of learning-related interactions. Their experimental group had three times more interactions than their control group. In contrast, some research attained contrary findings. For example, Janssen et al. (2007) discovered that the SA only partially motivates students to improve their engagement when coordinating a social activity. Although the experimental group of students in the work by Janssen et al. (2007) sent markedly longer messages (messages exceeding five words) than control group students, the number of short messages did not differ between the two groups. Second, several KA-related studies argued that KA can qualitatively enhance peer interactions (Dehler et al. 2011; Sangin et al. 2011) because KA information can guide learners' decisions regarding which questions they should ask and how questions should be answered (Dehler et al. 2011). For example, Sangin et al. (2011) showed that their experimental group (with KA) had better quality knowledge transfers than the control group (without KA). Additionally, the experimental group produced significantly more elaborate messages than the control group. In contrast, some researchers obtained contrary results. For example, Engelmann et al. (2010) demonstrated that no significant difference existed in the quality of communication and collaboration between the experiment group (with KA) and control group (without KA).

These two conflicting arguments likely stem from different experiment settings, including different awareness information, application fields, tasks, collaboration forms (asynchronous vs. synchronous), ICT, and evaluation measures and methods (Table 1). For example, in terms of using KA, Engelmann et al. (2010) visualized how the constructed concept maps of peers differed, while Sangin et al. (2011) visualized the level of prior knowledge of peers. These awareness tools and information are correlated with the degree of behavioral adaptation (Buder 2011). In terms of collaboration forms, Chen and Chang (2012) adopted asynchronous online Web messages, while Janssen et al. (2007) adopted synchronous online chatting. Chao et al. (2011) pointed out that different collaboration forms can lead to different learning behaviors and reactions. Hendriks (1999) also stated that different ICT applications can influence individual knowledge-sharing behavior.

Few studies have investigated differences in the impacts of SA and KA under an identical experimental setting, which can be used to clarify which one better enhances quantitatively and qualitatively peer collaboration. Almost all studies that investigated the effects of SA or KA employed an experimental design that facilitates comparisons between situations in which group members can access an awareness tool and situations in which they cannot access such a tool (Janssen and Bodemer 2013) (Table 1). Thus, this research stream should start moving away relatively straightforward comparisons (e.g., comparing conditions with a tool and t1.1 **Table 1** The comparison between the SA- and KA-related works

	Type	Work	Awareness information	Application field and task	Collaboration forms	Evaluation method	Evaluation measures
t1.3	SA	Cadima et al. (2010)	Visualizing social network position, the number of knowledge given and received	Knowledge sharing and collaborative learning in multidisciplinary projects	Synchronous and asynchronous, including Email and video conferencing	Experiment group	Network density and satisfactory questionnaire
t1.4		Chen and Chang (2012)	Visualizing a candidate list which is generated based on past peer social interactions	Presenting a proposal of "integrating information technology into instruction"	Asynchronous (Web messages)	Experiment group (with SA) vs. control group (without SA)	The number of interaction messages and learning achievement
t1.5		Janssen et al. (2007)	Visualizing the number of messages sent and average length	Presenting a solution to a historical inquiry task	Synchronous (real-time chat)	Experiment group (with SA) vs. control group (without SA)	Sent message length
t1.6		Kimmerle and Cress (2008)	Visualizing the number of contributions within a group (group feedback) or the number of contributions of each member (individual feedback)	Calculating fictitious salesperson's salary	Asynchronous (Web message)	Control condition, group-feedback condition, and individual-feedback condition	Participation (contribution) rate
t1.7	KA	Dehler et al. (2011)	Visualizing peer self-assessed knowledge	Collaborative learning online materials of a subject called "biology immune system"	Asynchronous (Web message)	Experiment group (with KA) vs. control group (without KA)	The quality of questions and explanations
t1.8		El-Bishouty et al. (2007)	Visualizing peer self-assessed knowledge levels	Complete a task, called "personal computer assembling"	Synchronous, including real-time message	Experiment group	Satisfactory questionnaire
t1.9		Engelmann et al. (2010)	Visualizing the constructed concept maps of peers	Co-constructing concept map for a task of the botany subject	Synchronous, real-time talk using SKYPE software	Experiment group (with KA) vs. control group (without KA)	The quality of communication content
t1.10		Sangin et al. (2011)	Visualizing the prior knowledge levels of peers	Co-constructing concept map of the neural transmission subject	Synchronous, real-time talk using TeamSpeak software	Experiment group (with KA) vs. control group (without KA)	The quality of knowledge transfer and learning gain

without that tool) and conduct experiments that test which features of an awareness tool work under specific circumstances (Buder 2011; Janssen and Bodemer 2013). Alternatively, direct empirical comparisons of these two approaches are rare; that is, this study is the first that attempts to compare directly both approaches.

Additionally, most SA- and KA-related studies limited intervention durations, usually failing to effectively assess their effects (Dehler et al. 2011; Engelmann et al. 2010; Sangin et al. 2011). Wang (2011) posited that the positive effects of computer-assisted learning may be temporary. To improve our understanding of whether the effects of SA and KA are temporary warrants longitudinal research for an extended period; that is, the treatment period should be sufficiently long to identify certain tendencies in students' learning behaviors as familiarity with an environment typically improves over time (Aleven and Koedinger 2001).

Thus, this work contributes to literature in two important ways. First, this work simultaneously investigates the quantitative and qualitative impacts of SA and KA on peer interactions. Second, this work applies a repeated-measure design with seven tests and two posttests for one semester to identify the trajectories of peer interactions under SA and KA conditions. This work further develops individual SA and KA online systems. As suggested by Buder (2011) and Janssen and Bodemer (2013), this work uses an identical application field (e-commerce), collaboration method (asynchronous), and task (multiple-choice questions). Additionally, most SA studies failed to identify the effects of SA tools on individual achievement (e.g., Kimmerle and Cress 2008) or demonstrate achievement empirically (Janssen et al. 2007; Janssen and Bodemer 2013). The following are the three questions this study seeks to answer.

1) Do SA and KA communities differ markedly in quantitative peer interaction?
2) Do SA and KA communities differ markedly in qualitative peer interaction?
3) Do SA and KA communities differ markedly on the first and second posttest?

Method

The SA and KA online systems

The developed SA and KA systems are based on relevant literature. Both systems are based on asynchronous written texts, enabling learner groups to engage in multidirectional communication. This communication type helps promote participation, joint reflection and collaborative learning (Engel et al. 2013).

The developed SA system use three parameters: whether a peer is a close friend (Chen and Chang 2012); number of messages sent (Janssen et al. 2007; Cadima et al. 2010); and number of messages received (Cadima et al. 2010). A close friendship between two peers is established when both individuals admit that this characterizes their relationship. Figure 1a shows a snapshot of these three parameters for the three peers.

The developed KA system uses two parameters: prior knowledge level (Sangin et al. 2011); and current knowledge level (Engelmann et al. 2010). The former is determined by a pretest prior to collaboration, while the latter is measured using a series of tests conducted during collaboration. The current knowledge level of a peer

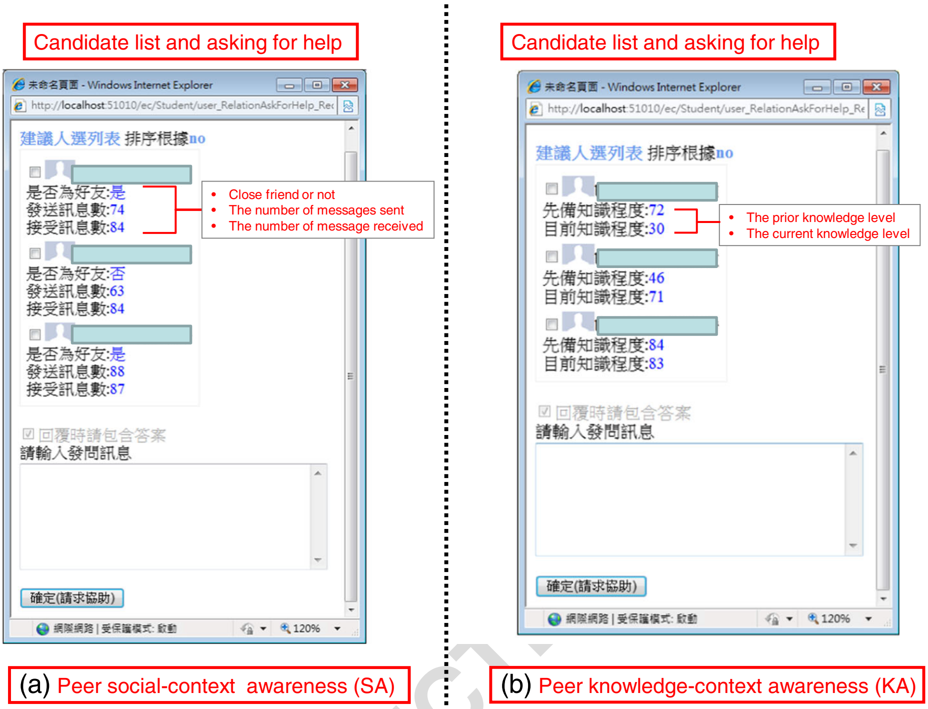


Fig. 1 The snapshots of the two different awareness systems

P_i, denoted as CKL_i, represents the performance of that peer after the first test. The variable CKL_i is defined as follows:

$$CKL_i = \left(\left(\sum_{j=1}^{N} \frac{\text{The number of questions that } P_i \text{ has correctly answered in the } j\text{-th test}}{\text{The number of questions in the } j\text{-th test}}\right) \div N\right) * 100$$

where N is the number of tests conducted to date. Figure 1b shows a snapshot of these two parameters for the three peers.

Research procedure

The study enrolled students in two first-year classes at a university: the first class had 58 students (12 males and 46 females) and used the SA system, while the second class had 59 students (14 males and 45 females) that used the KA system. Before the experiment, both classes were trained in and practiced using their systems for 1 week. Additionally, the research purpose and procedure were briefly presented for each class. During the experiment, both classes were instructed by the same teacher and followed the same schedules to eliminate confounding factors. The experimental subject was "Electronic Commerce," and had the following seven lessons: Basics of e-commerce; E-commerce strategy development; E-commerce applications; E-commerce transaction and security mechanisms; Infrastructure and technology; Social ethics; and E-business.

The experimental procedure had two stages (Fig. 2). At the start of the experiment, both classes registered in their systems. Students in the SA class preset their close friendship through the user interface; that is, a peer submits a request, after which others either accepts or rejects it; the results are then saved in the Social Network Database (SND) (upper right of Fig. 2). Additionally, students in both classes completed a pretest regarding background knowledge before entering the first experimental stage. The first stage consisted of learning lessons 1–3 and then taking the first posttest (i.e., midterm). Similarly, the second stage consisted of learning lessons 4–7 and then taking the second posttest (i.e., final term). The experiment's duration was one semester, 2 h each week, such that both classes completed seven tests.

The right part of Fig. 2 shows the procedure for learning one lesson. Both classes entered Step 1 and were taught face-to-face. Following Step 1, both classes started Step 2 and completed the test that corresponded to the lesson. Figure 3a shows one test question. The test contents were from the Question Bank Database (QBD) and test outcomes were saved in the Learning Portfolio Database (LPD). To establish the QBD, two teachers cooperatively edited the question banks, generating 23, 27, 28, 18, 22, 21, and 26 multiple-choice questions for lessons 1 to 7, respectively. Question content primarily originated from teaching materials. Subsequently, both classes entered Step 3 and reviewed test outcomes (Fig. 3b). Both classes viewed the same outcomes; that is, the results show only questions and answers, whether correct or not, yet do not show correct answers.

Notably, the peer collaboration mechanism (i.e. SA and KA) is activated in Step 3 ("SA or KA" block in Fig. 2), during which members can request assistance from peers. Specifically, for each incorrect answer, students in either class can click the button "looking for peer

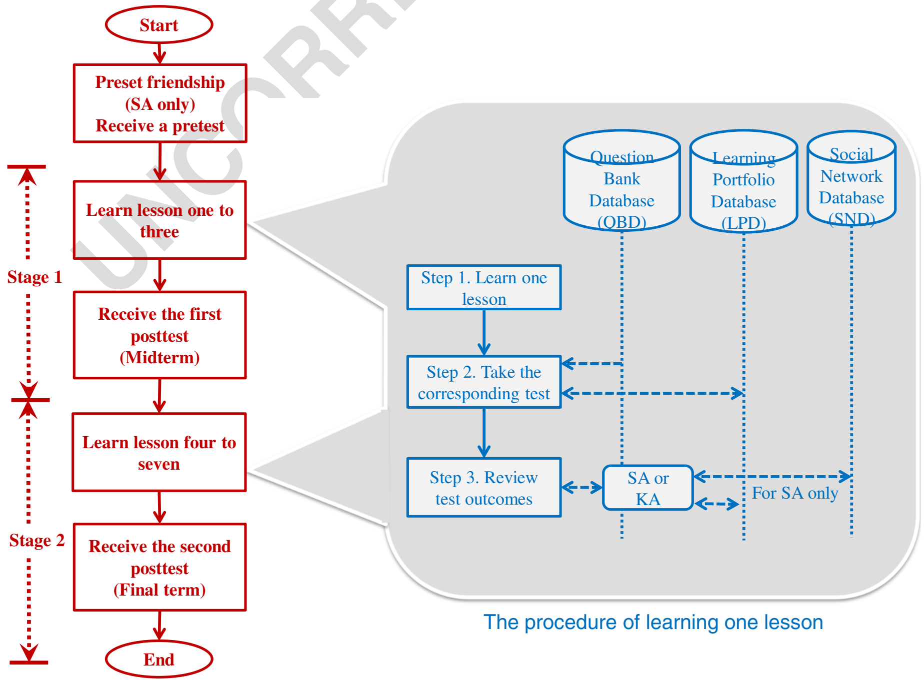


Fig. 2 The two-stage experimental procedure

Fig. 3 (**a**) The snapshots of one test question; (**b**) the snapshot of the outcome of a test

assistance" (Fig. 3b) to generate a candidate list. The candidate list is comprised of all members who correctly answered that test question. This ensures that both classes can rapidly identify those with the answers they seek. By clicking the button, both classes obtain different awareness information; that is, the SA class gets snapshots (Fig. 1a). The KA class, conversely, receives snapshots (Fig. 1b). At this point, a student can send messages requesting help based on the given awareness information. Students in both classes can obtain the correct answers from their helpers. Students in both classes can also login to their system to view the list of questions sent to helpers to see whether they have answered (Fig. 4a). Similarly, students from both classes can login to their system to view the list of questions originating from requestors to see whether new requests arrived, then reply when necessary (Fig. 4b). Notably, messages sent and received by both classes are stored in LPD for subsequent analysis of peer interaction. Since the systems facilitate question-related communication, students should rarely engage in the real world (e.g., printing questions or presenting questions in face-to-face discussions is inconvenient). Students in each class are strongly encouraged to use online communication (Heo et al. 2010).

Principles of using multiple-choice tests

Multiple-choice tests are often accused of being less effective for learning than tests with open-ended questions. However, open-ended questions take more time and effort to evaluate learning performance and to give feedback because open-ended questions require greater assessment skills from teachers. Long delays in providing students with feedback may

Fig. 4 (**a**) The snapshots of the list of questions sent to helpers; (**b**) the snapshot of the list of questions originating from requestors

adversely impact student learning. This work uses multiple-choice questions to rapidly obtain scores that reflect the current knowledge level of students (KA information) and to rapidly give feedback to students.

To provide meaningful multiple-choice questions, the questions either had at least one correct answer or only one correct answer. A typical question with at least one correct answer was, "Which of the following are parts of Porter's Five Forces?" Of the four possible answers, at least one was correct. Figure 3a shows such a question type. The other question type, which has only one correct answer, provides plausible (competitive) alternatives, such that learners must determine why the correct answer is correct and/or why incorrect alternatives are incorrect (Little et al. 2012). For example, students answered a test question asking which alternative refers to "the value of a telecommunications network proportional to the square of the number of connected users of the system" (the correct answer is Metcalfe's law). Later, their recall of information pertaining to one incorrect alternative was enhanced only when the alternatives were competitive (e.g., "Moore's law" and "Gilder's Law," which are also prominent concepts for domain knowledge in e-commerce). Additionally, a posttest question was, "the number of transistors per square inch on integrated circuits doubled every year since their invention" (the correct answer is Moore's law). This strategy can stimulate students to determine the meaning of each alternative, not only remember which answer is correct.

To stimulate qualitative content in messages between peers, classes were encouraged to discuss their problems in detail when requesting help. Both classes were also advised that when responding to requests for help, feedback content should be substantive, such as (1) using examples when possible, (2) ensuring all relevant key terms and concepts were adequately addressed, (3) using directive information (e.g., information or page number) and (4) explain answers in language the students can understand (Pear and Crone-Todd 2002).

Measures

To answer research questions 1, 2 and 3, both systems recorded participant activities as logged data, including login time, message properties (requestor, replier, time and request and reply content), test scores, pretest scores, and posttest scores.

Quantitative interactive messages

To answer research question 1, the two message types are out-degree, which describes a student sending messages to peers to request help, and in-degree, which refers to a student receiving request-for-help messages from peers. Additionally, response rate of a student is defined as the number of help requests a student has responded to, divided by the total number of help requests that he/she has received. This work compares the number of out-degree messages and response rate for the two classes for each test. The response rate is only for students who received messages. Thus, the number of students involved for each test may be distinct and is probably less than the total number of students in a given class, since all students in a class rarely receive help.

Social network analysis

Social network analysis (SNA) is also applied to answer research question 1. The SNA uses a set of concepts and measures based on relatively standardized algorithms that can describe and explain participation and interaction structures (Engel et al. 2013; Reffay and Chanier 2003; Wasserman and Faust 1994). Many studies have applied SNA to online discussion sites and social network sites (Heo et al. 2010; Pfeil and Zaphiris 2009; Vrocharidou and Efthymiou 2012). For example, Heo et al. (2010) measured the densities of message posting, response, and reading in an online learning community.

This work employs three network measures—density (D), clique, and reciprocity (R) (Pfeil and Zaphiris 2009)—to capture the dynamics of a network structure for each test. Density identifies the degree to which interactions diffuse among peers (Hanneman and Mark 2005), as well as the degree to which a community is close knit (Ehrlich and Carboni 2013). Clique can identify the degree of sub-group cohesion and identify sets of members that are highly interconnected (Pfeil and Zaphiris 2009). Reciprocity can identify the extent of tie strengths within a community. A community generally functions better when most members engage in reciprocal interaction (Ehrlich and Carboni 2013). This work uses the following definitions and formulas to calculate these three measures.

Density is the ratio of existing connections within a network relative to all possible number of connections in the network (Pfeil and Zaphiris 2009; Wasserman and Faust 1994); $D=2L/g*(g-1)$, where L is the number of existing connections in the network and g represents the number of nodes (i.e., community members). A clique in a graph is a maximal complete sub-graph of three or more nodes (Wasserman and Faust 1994). Each clique member must be connected to all other clique members and no other network member is adjacent to all clique members (Pfeil and Zaphiris 2009). Reciprocity is the ratio of the number of reciprocal connections divided by that of all possible connections (Ehrlich and Carboni 2013;

Hanneman and Mark 2005; Pfeil and Zaphiris 2009); $R=2(\sum_{ij}X_{ij})/g*(g-1)$, where g represents the number of community members. If member i requests help and j responds, and vice versa, $X_{ij}=1$; otherwise, 0.

Notably, D and clique emphasize connections independent of their directions, while reciprocity emphasizes connection direction (Pfeil and Zaphiris 2009; Wasserman and Faust 1994). Restated, D and clique do not consider direction, but R does. In this work, a connection, in terms of D and clique, is undirected and thus is constructed between members i and j when the former requests help and the latter responds. However, in terms of R, a connection is directed and thus a connection between members i and j is reciprocated when the former requests help and the latter responds, and vice versa.

Social network analysis software, UCINET, calculates values for these three measures by importing relevant data retrieved from system databases (LPD in Fig. 2). Sociograms are generated using social network visualization software, NetDraw.

Qualitative interactive messages

To answer question 2, this work analyzed the length of each interactive message for each test. The average length of requesting help was calculated for each student in each test by dividing his/her total length of help requests accumulating every request by the total number of help requests that he/she has for that test. The length of help responses was handled the same. The calculation of average length of help requests (or responses) was only for students who requested help (or responded to requests).

Learning performance

To answer research question 3, this work used scores on the pretest and two posttests. Both classes took the same two posttests, both of which were based on teaching materials and online tests. The quizzes in the online tests directly reflected the course posttests. Thus, both classes were familiar with question type on their posttests. The online tests and posttests had few overlaps. Even though both question types were similar, posttest questions were not directly copied from online tests, thereby eliminating the problem of students memorizing questions and answers (Lin and Lai 2013a, b). Q3

To ensure pretest validity and reliability, two experts reviewed pretest content, which was then tested by 32 students. Inappropriate questions were then removed, resulting in 33 multiple-choice questions with a Cronbach's α of 0.78. Validity and reliability analyses of the two posttests were handled in the same way as those for the pretest, resulting in 36 and 38 questions with Cronbach's α values of 0.81 and 0.83, respectively.

Analyses

To answer questions 1, 2, and 3, multilevel analyses (MLAs) were applied to examine the condition effects on the out-degree, response rate, the content length, and learning performance. This technique addresses the statistical problem of non-independence often associated with CSCL studies (Kenny et al. 2006). Non-independence was determined in this work by computing the intra-class correlation coefficient (ICC) and its significance (Kenny et al. 2006) for all dependent variables. The coefficient indicates non-independence ($\alpha<0.05$) for all tests, justifying MLA for these data. The MLA compares deviance of an empty model and a model with one or more predictor variable(s) to compute a possible decrease in deviance. The latter model is considered better when deviance decreases significantly from the empty model (tested with a χ^2-test). Almost all reported χ^2-values were significant ($\alpha<0.05$) and therefore the estimated parameters of these predictor variables (i.e., effects of condition) were tested for significance (Janssen et al. 2007; Slof et al. 2013).

Results

Quantitative interactive messages

Not all students in each class requested help or were asked to provide help after all seven tests (Table 2). However, 66 % of students requested help in the SA class, exceeding the percentage of students who requested help in the KA class (46 %). Similarly, 90 % students in the SA class were requested to help, exceeding the proportion in the KA class (81 %). Obviously, more students participated and interacted with others in the SA class.

Table 3 shows the MLA for effects of condition concerning learners' out-degree and response rates for each test. In the first, second, and third tests, out-degree and response rate for learners in the SA class did not differ from those for learners in the KA class. However, significant effects were existed for out-degree on the fourth test (β=2.70, p=0.00), fifth test (β=3.30, p=0.01), sixth test (β=2.79, p=0.00), and seventh test (β=2.28, p=0.02); that is, learners in the SA class requested help more than learners in the KA class for these four tests. Significant effects also existed for response rates on the fifth test (β=0.57, p=0.03), sixth test (β=0.50, p=0.03) and seventh test (β= 0.55, p=0.00); that is, learners in the SA class had higher response rates than learners in the KA class for the last three tests. When all tests are taken as a whole, significant effects were found for both out-degree (β=21.63, p=0.02) and response rate (β=0.38, p=0.04). On average, learners in the SA class requested help more and had a higher response rate than learners in the KA class.

Additionally, the SA class had 1460 out-degree messages, of which 1144 were sent to close friends, resulting in roughly 78 % (1144/1460) of out-degree messages. On the other hand, the KA class had 698 out-degree messages, of which 325 were sent to close friends, resulting in only 46 % (325/698) of out-degree messages. To investigate this phenomenon in detail, MLA were applied to determine whether the ratios of out-degree sent to close friends differed significantly between the two classes, and whether ratios of in-degree originating from close friends differed significantly between the two classes.

Table 4 shows MLA results for condition effects. Significant effects existed for the ratio of out-degree sent to close friends (β=0.50, p=0.00) and for the ratio of in-degree sent from close friends (β=0.40, p=0.00); learners in the SA class had a significantly higher ratio of out-degree sent to close friends and a higher ratio of in-degree sent from close friends than learners in the KA class.

Table 2 Statistics for the ratio of individuals requesting help and being asked for help

Class	The ratio of requesting help (the number of students who have requested help / the total number of students)	The ratio of being asked for help (the number of students who have been asked for help / the total number of students)
SA	66 % (38/58)	90 % (52/58)
KA	46 % (27/59)	81 % (48/59)

Table 3 Multilevel analyses for effects of condition concerning learners' out-degree and response rate

Activity	Type	SA class		KA class		Effects of condition		
		N	M (SD)	N	M (SD)	$\chi^2(1)$	β	SE
1st test	Out-Degree (Asking)	58	4.10 (6.12)	59	3.47 (5.45)	0.34	3.78	0.53
	Response rate	38	0.66 (0.42)	32	0.67 (0.44)	0.02	0.67	0.05
2nd test	Out-Degree (Asking)	58	2.86 (6.85)	59	2.58 (4.86)	0.07	2.71	0.55
	Response rate	36	0.60 (0.47)	26	0.57 (0.48)	0.05	0.58	0.06
3rd test	Out-Degree (Asking)	58	4.72 (7.04)	59	3.34 (6.50)	1.22	4.02	0.69
	Response rate	37	0.55 (0.49)	35	0.44 (0.49)	0.88	0.49	0.05
4th test	Out-Degree (Asking)*	58	4.55 (6.90)	59	0.86 (2.51)	14.81	2.70	1.84
	Response rate	37	0.64 (0.44)	20	0.45 (0.48)	2.28	0.56	0.09
5th test	Out-Degree (Asking)*	58	4.74 (7.93)	59	1.88 (3.95)	6.11	3.30	1.43
	Response rate*	34	0.68 (0.40)	26	0.44 (0.50)	4.13	0.57	0.11
6th test	Out-Degree (Asking)*	58	3.90 (5.43)	59	1.69 (3.34)	6.99	2.79	1.10
	Response rate*	37	0.62 (0.42)	26	0.37 (0.45)	4.62	0.50	0.12
7th test	Out-Degree (Asking)*	58	3.16 (5.14)	59	1.42 (3.37)	4.64	2.28	0.86
	Response rate*	24	0.75 (0.38)	23	0.34 (0.45)	11.58	0.55	0.20
Total	Out-Degree (Asking)*	58	28.03 (37.67)	59	15.25 (24.54)	4.74	21.63	6.39
	Response rate*	53	0.45 (0.41)	50	0.31 (0.37)	3.88	0.38	0.07

* $p<.05$

Social network analysis

The number of connections and density within each class were computed following each test. Table 5 lists the seven values for number of connections and density for each class; Fig. 5a and b, respectively, show trends for connections and density. Obviously, the SA class exhibited sharper growth than the KA class in terms of number of connections and density during the experimental period. Ultimately, number of connections and density for the SA class were almost double those of the KA class.

The sociograms of each class are illustrated individually following the completion of all tests. Figures 6 and 7, respectively, show the sociograms of the two classes. Apparently, the sociogram of the SA class (Fig. 6) was denser than that of the KA class (Fig. 7). Additionally, the sociogram of the SA class (Fig. 6) had fewer isolated members than the sociogram of the KA class (Fig. 7). Analytical results show that the SA class is linked to a denser network of members and with stronger inclusiveness (fewer isolated members) than the KA class.

Table 4 Multilevel analyses for effects of condition

Degree type	SA Class		KA Class		Effects of condition		
	N	M (SD)	N	M (SD)	$\chi^2(1)$	β	SE
The ratio of out-degree sent to close friends*	38	0.79 (0.27)	34	0.22 (0.25)	79.86	0.50	0.19
The ratio of in-degree sent from close friends*	53	0.60 (0.35)	50	0.20 (0.27)	39.31	0.40	0.19

* $p<.05$

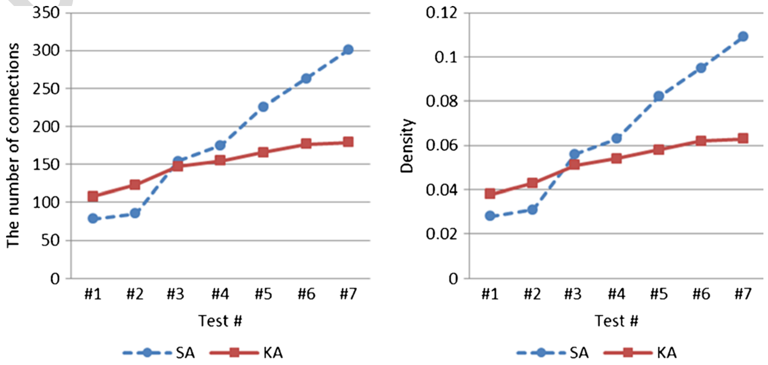
Table 5 The number of connections and density for each class

Test	The SA class		The KA class	
	The number of connections	Density	The number of connections	Density
#1	78	0.028	108	0.038
#2	85	0.031	123	0.043
#3	154	0.056	147	0.051
#4	175	0.063	155	0.054
#5	226	0.082	166	0.058
#6	263	0.095	177	0.062
#7	301	0.109	179	0.063

The number of cliques within each class was calculated following each test. Figure 8a shows the trend of cliques in both classes during the experiment. Initially, the SA class had fewer cliques than the KA class. However, during the experimental period, the SA class had a marked increase in number of cliques. In the end, the SA class had significantly more cliques than the KA class. Reciprocity within each class was calculated following each test. Figure 8b shows the trend of reciprocity for the classes. During the experiment, reciprocity for the SA class accelerated faster than that of the KA class. In the end, the SA class had more reciprocity than the KA class.

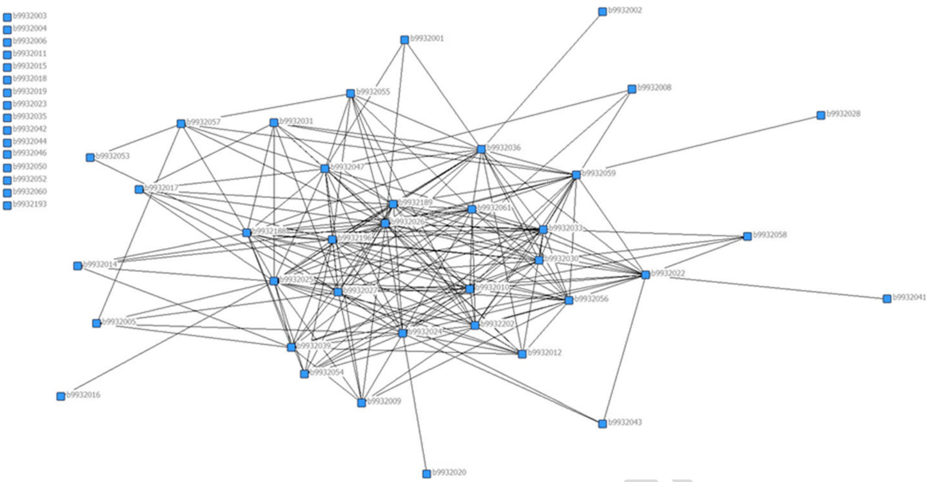
Qualitative interactive messages

Table 6 shows MLA results for condition effects in terms of length of messages requesting help and response messages for each test. The length of messages requesting help and length of response messages did not differ significantly between the SA class and KA class for all tests. The request and response messages for both classes were similarly short. Manually assessing the content of request and response messages shows that both classes focused primarily on correct answers. Specifically, most request messages for both classes contained simple courtesies or playful requests (e.g., "please help me"), or no words while most response



(a) Left part: the trend of connections; (b) Right part: the trend of the density

Fig. 5 (**a**) *Left part*: the trend of connections; (**b**) *Right part*: the trend of the density



Q4 **Fig. 6** The SA class –sociogram

messages for both classes contained correct answers with encouragement (e.g., my answer is correct because of my good fortune), and smile icons. In sum, request messages for both classes for specific questions or options were rare and response messages dealing with detailed explanations were thus scarce.

Learning performance

First, independent samples t-test results for the pretest of the SA class (mean = 33.13) did not differ significantly from that of the KA class (mean = 39.86) (t=1.82, p>.05). The backgrounds of students in the two classes were not significantly different.

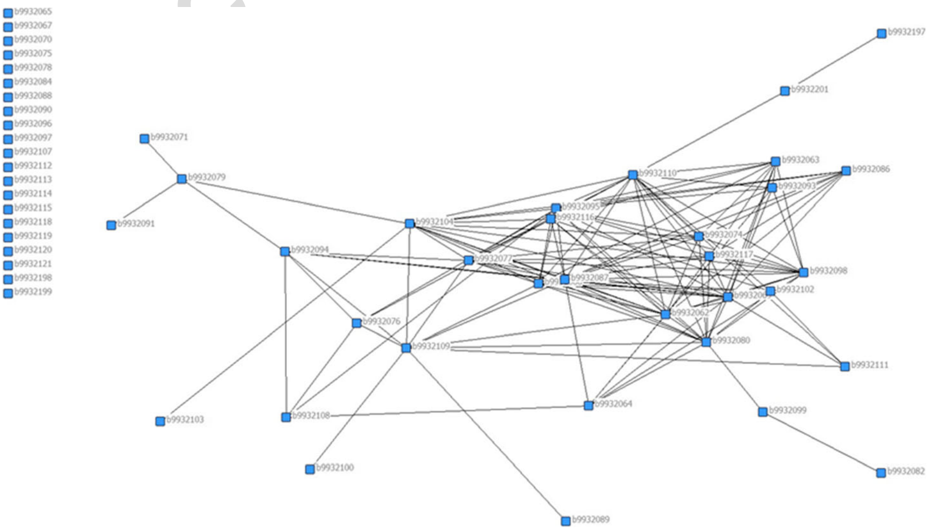


Fig. 7 The KA class –sociogram

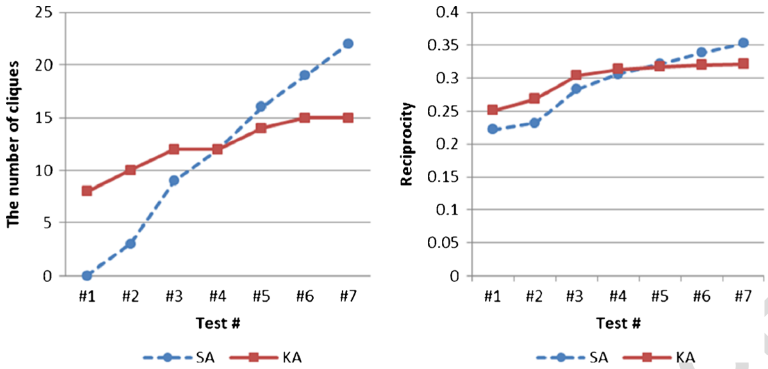


Fig. 8 (**a**) *Left part*: the trend of the number of cliques; (**b**) *right part*: the trend of reciprocity

Table 7 shows the MLA for condition effects concerning learners' scores on each test and learners' scores on posttests. The MLA show there no significant effects existed for scores on all tests, except for the 7th test. The two classes had no significant effect on midterm but had a significant effect (β=75.43, p=0.00) on final term. Students in the SA class had better learning performance on the final term than learners in the KA class.

Table 6 Multilevel analyses for condition effects in terms of the length of messages

Activity	Message type	SA class		KA class		Effects of condition		
		N	*M* (*SD*)	*N*	*M* (*SD*)	$\chi^2(1)$	β	SE
1st test	The length of request	30	2.35 (2.65)	28	3.54 (4.03)	1.73	2.93	0.59
	The length of response	29	19.84 (23.42)	23	12.13 (6.67)	2.34	16.17	3.85
2nd test	The length of request	19	2.05 (3.15)	15	1.72 (2.98)	0.09	1.90	0.52
	The length of response	23	13.12 (10.61)	16	14.73 (11.82)	0.20	13.78	1.76
3rd test	The length of request	23	1.86 (3.37)	17	0.79 (1.99)	1.34	1.38	0.52
	The length of response	21	11.83 (6.01)	17	11.58 (10.76)	0.01	11.72	1.35
4th test	The length of request	24	1.36 (2.54)	10	1.05 (2.61)	0.11	1.27	0.42
	The length of response	26	13.36 (9.15)	10	10.20 (2.01)	1.15	12.40	1.43
5th test	The length of request	22	0.83 (1.68)	12	0.87 (2.25)	0.01	0.84	0.32
	The length of response	24	11.12 (2.24)	12	9.97 (1.78)	2.48	10.63	0.56
6th test	The length of request	26	0.67 (1.84)	16	0.37 (1.02)	0.36	0.56	0.24
	The length of response	27	11.45 (3.47)	11	13.59 (13.21)	0.62	12.07	1.22
7th test	The length of request	26	1.52 (3.33)	12	0.14 (0.35)	2.09	0.95	0.67
	The length of response	20	11.41 (3.66)	9	9.34 (2.79)	2.38	10.55	1.02
Total	The length of request	38	1.35 (2.06)	34	2.19 (3.15)	1.80	1.76	0.41
	The length of response	38	13.39 (7.73)	29	12.35 (7.86)	0.29	12.94	0.94

* p<.05

Table 7 MLA for condition effects concerning the learners' scores on each test and posttests

Activity	SA class (N=58)	KA class (N=59)	Effects of condition		
	M (SD)	M (SD)	$\chi^2(1)$	β	SE
The 1st test	39.93 (20.91)	34.22 (22.21)	2.04	37.06	2.85
The 2nd test	39.48 (21.84)	33.75 (26.82)	1.62	36.59	2.86
The 3rd test	36.38 (16.83)	36.56 (22.54)	0.00	36.47	1.81
Midterm (posttest #1)	68.31 (15.55)	67.73 (16.73)	0.03	68.01	1.49
The 4th test	35.59 (16.43)	36.15 (26.88)	0.02	35.87	2.05
The 5th test	30.50 (19.70)	36.92 (23.24)	2.85	33.71	3.20
The 6th test	48.93 (20.39)	43.14 (28.45)	1.59	46.01	2.89
The 7th test*	59.36 (22.93)	50.24 (27.38)	3.81	54.78	4.56
Final term (posttest #2)*	80.46 (13.44)	70.00 (16.43)	14.16	75.43	5.26

* p<.05

Discussion

During the first stage (i.e., period before the midterm), the two classes had similar out-degree and response rate for the first, second, and third tests. The network measures (i.e., density, the number of cliques, and reciprocity) of the SA class had patterns that resembled those of the KA class. Additionally, both classes used short messages for help requests and responses, and message content for both classes favored the use of words indicating support, not those indicative of meaningful knowledge exchanges. The two classes did not differ significantly in midterm scores.

During the second stage (i.e., period between the midterm and final term), the number of peer connections, network density, number of cliques, and reciprocity of the SA class accelerated faster than those of the KA class. Over time, the social awareness gradually fermented within the SA community. The SA class had denser connections and exhibited a broader interaction network with stronger inclusiveness (fewer isolated members), and had a higher number of interactive messages than the KA class. Subsequently, the SA class had significantly more help requests and a higher response rate than the KA class in the fifth, sixth, and seventh tests. Additionally, the SA class had a higher ratio of out-degree sent to close friends and a higher response rate than the KA class, as well as more subgroups, more reciprocal and stronger connections (Ehrlich and Carboni 2013). While most requests can elicit friendly responses, SA members tended to respond more frequently and enjoy bilateral relations (Pfeil and Zaphiris 2009), resulting in a positive cycle of interaction among SA members. These phenomena facilitate sustained connections among community members by enhancing feelings of belonging. The sense of belonging helps students when engaging in knowledge acquisition (Dawson 2008) and learners can easily carry on coherent discussions in a SA environment (Erickson and Kellogg 2000).

In terms of message quality, using average length of messages to measure message quality appears to be a relatively crude and shallow indicator. To thoroughly investigate message quality, other measures that are more germane should be used. For example, a systematic message-coding schema (Dehler et al. 2011; Sangin et al. 2011) should be adopted and the issue of whether different conditions have significantly different quality can then be investigated. However, the analytical results of message length and manual observation shows that messages for both classes were short and of poor quality even experiencing seven tests. Even though both classes were encouraged to raise substantive questions and responses for comprehending the puzzles and to pass the posttests, neither SA nor KA elicited such messages. In addition to polite or playful greetings, message requesting help simply requested correct answers without specifying what issues needed to be addressed.

This longitudinal study shows that over time, SA could improve the quantity of messages, but had limited effects in enhancing message quality. In contrast, KA had limited impact on both message quantity and quality. Although both classes had similar patterns (i.e., short messages) for all tests, extensive peer interactions and intensive message transfers within the SA class seemed to contribute that superiority of the SA class on the final term (Janssen et al. 2007; Lin and Lai 2013b).

Although Sangin et al. (2011) provided learners with KA information about peers' pretest scores for prior knowledge, their analytical results demonstrated that students who used the KA tool had more in-depth discussions and negotiate their information more often for open-ended questions (i.e., constructing a concept map) (Janssen and Bodemer 2013). Even with more awareness of knowledge levels (i.e. pretest scores and current knowledge levels), the proposed KA system had limited capacity to enhance message quality. One likely reason for the conflict in findings by this study and by Sangin et al. (2011) is question type. Multiple-choice questions mainly deal with factual knowledge, interpretation, or inference rather than higher-level skills (e.g., organizing and expressing ideas open-ended questions often require). Multiple-choice questions likely encourage a situation in which most learners are only concerned with the correct answers, not with why alternatives are incorrect. Thus, students may only be concerned with how to swiftly access correct answers; any other concerns and explanations may appear unnecessary. The SA information may implicitly indicate which answers can be accessed more easily and swiftly, resulting in the finding that SA was superior to KA. Consequently, the finding that SA was superior to KA may be changed when question type is changed from "multiple-choice" to "open-ended." When using "open-ended questions" (e.g., concept maps or essay questions), which do not have standard correct answers, requesters obtain either high-quality or low-quality (i.e. either elaborated or non-elaborated) responses, not correct answers when helpers respond. Students using KA then have more opportunities to acquire high-quality responses than students using SA since KA allows students to easily locate peers who have domain knowledge; that is, KA is possibly superior SA when message quality is the focus. However, whether KA is superior SA for message quantity requires longitudinal observations. A possible scenario is one in which SA is weaker in located knowledgeable peers, such that those requesting help may not acquire high-quality knowledge, leading to a situation in which students may, with the passing of time, become less interested in using SA. Thus, a future study can investigate how different question types influence message quantity and quality within a KA or/and SA environment.

Conclusions

This work simultaneously investigates the impacts of SA and KA on the quantity and quality of peer interactions, and learning performance using an identical experimental scenario: e-commerce with asynchronous collaboration and multiple-choice questions. Additionally, this work applies a repeated-measure design (i.e., seven tests and two posttests) for one semester to identify the trajectories of peer interaction and learning performance under SA and KA.

Experimental results show that the number of interactive messages by the SA community significantly exceeded that by the KA community in the second stage of the experiment, even though the difference in the first stage of the experiment was not significant. The network measures for the two communities for the seven tests also show that SA can effectively stimulate more peer interaction over time (i.e., denser communication network and fewer isolated members), compared with KA. Additionally, the SA community had more cliques and reciprocity, indicating that peer relations within the community were more bilateral and stable, possibly because most counterparts of SA members are close friends. In summary, SA effectively stimulates more extensive and frequent peer interaction in a progressive way, compared with KA. However, SA and KA have limited capacity to elicit qualified interactive messages even after both classes experienced seven tests. Finally, although scores for the two communities did not differ significantly on the first posttest, the SA community had significantly better learning performance on the second posttest, possibly related to more extensive and frequent peer interaction within the SA community.

Additionally, Janssen and Bodemer (2013) noted that one trend in group awareness research is that researchers typically focus on either KA or SA. However, one may argue that for effective collaborative activities, both forms (SA and KA) are required. Users should be able to perceive and compare social and knowledge patterns of activity within their models of work and interaction (Soller, Martínez, Jermann, & Muehlenbrock, 2005), mustering both epistemic and social resources to collaboratively build knowledge. In fact, some related work using a group awareness tool that provides users with both types of awareness information has been proposed. For example, El-Bishouty et al. (2010) developed a ubiquitous learning system that provides information about the knowledge context and social context and analyzed messages exchanged between members. Castillo and Ayala (2010) proposed a collaborative learning architecture that supports social-context and knowledge-context awareness in a mobile learning community. Lin et al. (2013c) developed an online test system that is aware of social and knowledge contexts for peers when requesting help for test problems. Again, these studies demonstrated that their systems were superior by comparing situations in which group members have access to a tool with both forms of awareness and situations in which they do not have access to such a tool. However, the most critical issue for research is to investigate how knowledge (i.e., cognitive) and social awareness interact (Janssen and Bodemer 2013). This work addresses the individual impact of SA and KA on the quantity and quality of messages in the same experimental setting. In other words, when using both forms of awareness, studies should focus on whether both can simultaneously and effectively enhance message quantity and quality or whether one form is redundant and can be replaced by another form under their experimental setting.

Finally, context awareness (i.e., SA or KA, or SA and KA) has room for further exploration (Buder 2011). Barnard et al. (2009) claimed that learners' perceptions of peer communication and collaboration (i.e., context awareness) and an individual's self-regulation may partially determine learning behavior and achievement in online collaborative environments. Shi et al. (2013) stated that the relationship between context awareness and individual self-regulation is an important issue that remains inadequately understood. Accordingly, how context awareness influences individuals with different levels of self-regulation in terms of learning behavior and effectiveness will be fruitful direction for future research.

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