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The impacts of network centrality and self-regulation on an e-learning environment with the support of social network awareness

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Abstract

An e-learning environment that supports social network awareness (SNA) is a highly effective means of increasing peer interaction and assisting student learning by raising awareness of social and learning contexts of peers. Network centrality profoundly impacts student learning in an SNA-related e-learning environment. Additionally, self-regulation behavior significantly influences online learning of students. However, exactly how network centrality and self-regulation influence learning behavior and effectiveness in an e-learning environment remains unclear. Therefore, this study investigates how both variables (ie, network centrality and self-regulation) impact student learning in an SNA-related e-learning environment. Analytical results indicate that the student group with high-level centrality and low-level self-regulation more significantly progresses in learning achievement than the other groups. The second finding shows the group also has the highest number of students asking for help, revealing they have the highest system utilization rate.

Introduction

Social network awareness

While raising the awareness of the learning and social activities of peers, social network awareness (SNA) is extensively adopted in e-learning as an effective strategy to promote the opportunities of informal learning, peer interaction and collaboration, as well as knowledge sharing (Cadima, Ferreira, Monguet, Ojeda & Fernandez, 2010; Chen, Hong & Chang, 2008; Dawson, 2008; El-Bishouty, Ogata & Yano, 2007; Yang, Chen, Kinshuk & Chen, 2007). A greater awareness and mutual cooperation among peers during learning positively affect on student motivation, subsequently elevating student's self-reflection capability towards learning (DiMicco, Hollenbach, Pandolfo & Bender, 2007).

With the emerging trend of an e-learning environment supporting SNA, Dabbagh and Kitsantas (2012) advocated that an e-learning system should extend to social network use in higher education, with the intention of using social awareness and interaction to share and engage in collaborative activities among peers. In addition to integrating SNA with an e-learning

Practitioner Notes

What is already known about this topic

- Students' self-regulated learning (SRL) ability positively correlates with learning achievement.
- Students' network centrality has correlation with learning achievement. Students with high centrality outperform students with low centrality on learning achievement.
- An e-learning environment with the support of social network awareness (SNA) can effectively promote the opportunities for peer interaction and collaboration.

What this paper adds

- The investigation focuses on whether both network centrality and SRL have significant influences on learning achievement and peer interaction in an SNA environment.
- This paper develops an SNA environment. A student is able to be aware of peer knowledge, social and activity context, which are used to raise the opportunities of peer reflection and interaction and to scaffold learning by peer assistance.

Implications for practice and/or policy

- The SNA environment particularly benefits the students with high-level centrality and with low-level SRL. These students have significant progress on learning achievement and have more frequent interaction with peers compared with other students.
- The SNA environment enhances these students' interest and motivation to spend more time on the system. Thus, they get more peer contexts and interaction from the system compared with other students, resulting in making significant progress in learning achievement.

environment, related works developed models based on social or knowledge context for recommending suitable candidates to help learners with their queries. Learners can then ask for assistance based on the candidate list. For instance, El-Bishouty *et al* (2007) proposed an ubiquitous e-learning system, which incorporated a prediction model based mainly on the proficiency level of candidates to recommend a qualified candidate for a help seeker. The provided awareness information mainly includes a helper's academic level, interests, physical location and the detected objects. Yang *et al* (2007) also devised a forecasting model to recommend candidates based on the trust and knowledge associations of peers. Trust association refers to the level of trust that a seeker has in a candidate, which is determined by previous interactions and contact (ie, request and response). Knowledge association refers to the level of proficiency of a candidate in terms of a specific knowledge domain. Cadima *et al* (2010) developed an SNA system that provides peer social status, which focuses on facilitating knowledge sharing. The system provides two information types visually: social network tie among community members and interaction pattern (including the number of contacts, number of knowledge receiving transfers and knowledge giving transfers). Chen *et al* (2008) developed a data mining method for social interactive networks, in which a prediction model based on peer's social status is used (including social position and interaction) to recommend appropriate peers for a help seeker.

Within an SNA e-learning environment, network centrality (ie, social network position) can markedly influence learning effectiveness (Cadima *et al*, 2010; Chen *et al*, 2008; El-Bishouty *et al*, 2007; Yang *et al*, 2007). Students with high centrality outperform those with low centrality on learning achievement (Cadima, Ojeda & Monguet, 2012). Central members in a collaborative social network tend to obtain high final grades (Cho, Gay, Davidson & Ingraffea, 2007). Lin and Lai (2013) also indicated that network centrality significantly influences both learning achievement and help-seeking behaviors. More specifically, learners with a high centrality are more likely to take advantage of the social network position to ask for assistance. Also, they easily become target helpers that peers seek. In sum, network centrality influences both learning effectiveness and help-seeking behaviors within an SNA environment.

Self-regulation

A self-regulated learner can play an active role in learning, setting task-oriented and proper goals, taking responsibility for their own learning, monitoring their own learning and maintaining their own learning motivation (Heikkilä & Lonkab, 2006; Schunk, 1994; Wang, 2011). As the e-learning environment is characterized as autonomous, the ability of learners to engage in self-regulation behaviors is construed as a crucial factor in successful online learning (Barnard, Lan, To, Paton & Lai, 2009). This ability is owing to the fact that online learning requires that learners are more disciplined; they also require considerable persistence and determination (Shea & Bidjerano, 2012). Kauffman (2004) and Wang (2011) also asserted that learners in an online learning environment must be highly self-regulated; otherwise, their learning effectiveness may be low. Moreover, Narciss, Proske and Koerndle (2007) demonstrated that self-regulation has a significant positive correlation with academic achievement in an e-learning environment. Furthermore, highly self-regulated students significantly outperform low self-regulated ones in learning achievement (Azevedo & Cromley, 2004).

The impacts of network centrality and self-regulation

As mentioned in the above two subsections, network centrality profoundly impacts student learning in an SNA e-learning environment. Meanwhile, self-regulation behavior also profoundly impacts student online learning.

In addition, some studies claimed that both the SNA and self-regulation may simultaneously influence learning behavior and achievement. For example, Barnard, Paton and Lan (2008) posited that learner perceptions of peer communication and collaboration (ie, SNA) and self-regulatory learning behaviors may partially determine learning achievement in an e-learning environment. According to Shea and Bidjerano (2012) and Zeidner, Boekaerts and Pintrich (2000), environmental conditions and social environment (ie, SNA) may affect the ability of learners in adjusting their learning behaviors to achieve the desired outcomes.

However, exactly how network centrality and self-regulation influence learning behavior and effectiveness in an SNA e-learning environment remains contentious. Restated, no empirical study and thorough analysis are available on this topic.

Research questions

In sum, despite the ability of network centrality and self-regulation to separately influence student learning, exactly how both of these variables impact an SNA e-learning environment has seldom been addressed. To address this topic, this study aims to answer the following research questions:

1. How do network centrality and self-regulation influence students learning in an SNA e-learning environment?
2. Whether these two variables affect student learning in an SNA e-learning environment.

While McManus (2000) investigated whether self-regulation and linearity (ie, hypermedia learning content presented in a linear manner) interact with each other in an online learning environment, this study focuses on whether self-regulation and network centrality interact with each other in an SNA environment.

Methodology

Questionnaire to measure the self-regulation level of a student

The questionnaire used in this study was revised from the questionnaire of Gordon, Dembo and Hocevar (2007), who posited that learners scoring high on the questionnaire had a high level of self-regulation during learning. The revised questionnaire includes 20 questions based on a 7-point Likert scale ranging from 7 (*strongly agree*) to 1 (*strongly disagree*). Five subscales are "self-monitoring" (seven items), "deep strategy use" (four items), "shallow processing" (four items), "persistence" (two items) and "environmental structuring" (three items). Questions 1–7 are related to self-monitoring. For example, consider Q1: before a quiz or examination, I plan how I will study the material. Questions 8–11 are related to deep strategy use. For example, consider Q8: I will check whether I understand new concepts or not. Questions 12–15 are related to shallow processing. For example, consider Q12: I try to memorize the steps to solve problems presented in the textbooks or in class. Questions 16–17 are related to persistence. For example, consider Q16: if having difficulty in understanding a problem, I go over it again until I understand it. Questions 18–20 are related to environmental structuring. For example, consider Q18: I arrange a place to study without distractions.

The Cronbach's alpha of the whole revised questionnaire is 0.81, and the Cronbach's alpha for each subscale is as follows: self-monitoring (0.84), deep strategy use (0.80), shallow processing (0.92), persistence (0.65) and environmental structuring (0.79).

Measuring the centrality level of a student

Network centrality can be further measured in terms of three indices: degree centrality (*DC*), closeness centrality or betweenness centrality (Freeman, 1979; Wasserman & Faust, 1994). Each index has its own specific definition for centrality. A node with a high centrality is generally in a more central position in a network. This study identifies an individual's network position by using the degree of indices. According to Cadima *et al* (2012), the *DC* of students is more significantly related to their learning performance than the other two indices.

Degree centrality measures the prominence of members in a network, facilitating efforts to identify those who are the most active or most inactive (Wasserman & Faust, 1994). In the graph of a social network (ie, a sociogram), a node represents a member, and a link represents a tie that exists between the pair of members (Wasserman & Faust, 1994). In the real world, when member i recognizes member j as a close friend and vice versa, they have a close friendship (ie, node i and node j are connected). Thus, in this study, a friendship network within a community is represented by using an undirected graph rather than a directed graph.

The *DC* of a student is simply the number of other adjacent members. To normalize this index into the range between 0 and 1, the *DC* of student S_i, denoted as DC_i, is defined as follows:

$$DC_i = \frac{d_i}{M-1},$$

where d_i denotes the degree of node I, and M represents the number of nodes in the graph. Restated, d_i refers to the degree of student S_i, and M denotes the number of members in the sociogram. With community members selecting their existing friendships individually, the sociogram of the whole network for the community can be generated; the *DC* of each member can be further obtained as well.

Experimental design

This study adopted a preexperimental design method, ie, one-group pretest-posttest design. The experiment was administered to an undergraduate freshman year class consisting of 62 students using the proposed SNA system. Before the experiment, the initial self-regulation level and the initial centrality level of a student were measured according to the previous questionnaire and

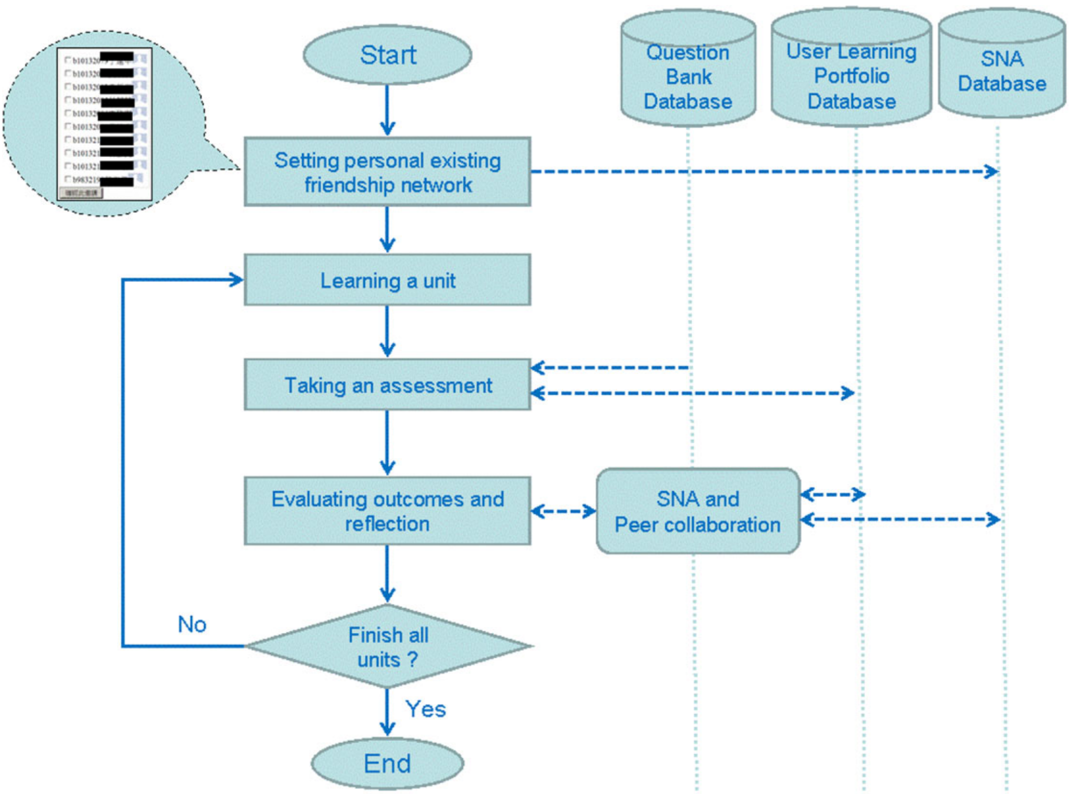

Figure 1: Experimental procedure

method, respectively. To thoroughly elucidate the impact of these two variables, students in this class were further divided into two groups based on these two variables. As for the initial self-regulation level, a student with an above-average questionnaire score was placed in the high-level self-regulation group, with the other students placed in the low-level self-regulation group. Similarly, as for the centrality level, a student with an above average *DC* value was placed in the high-level centrality group, with the other students placed in the low-level centrality group. In sum, subjects were divided into 2×2 groups according to their initial self-regulation and centrality levels.

Figure 1 illustrates the experimental procedure. Students first individually registered their personal information (eg, account, name and photo) and then set their existing friendship, as shown in the top-left part of Figure 1. The students enrolled in a computer science course called "Database Theory and Application—Microsoft Access 2007." The experiment used five units of the subject. Each unit underwent a corresponding assessment, and each assessment contained around 10~15 multiple-choice questions. While lasting for two months, the experiment was performed 2 hours weekly; five assessments were also conducted owing to the five experimental units. Upon completion of one-unit learning, students took the corresponding assessment in which quizzes were based on teaching material (eg, textbook and handouts). Students then received their outcomes as shown in Figure 2(a). For each incorrect question, students could click the corresponding button called "looking for peer assistance" to generate the candidate list as shown in Figure 2(b). These candidates all answered the question correctly. SNA was used during this phase. Restated, information regarding the social and learning context of each candidate was

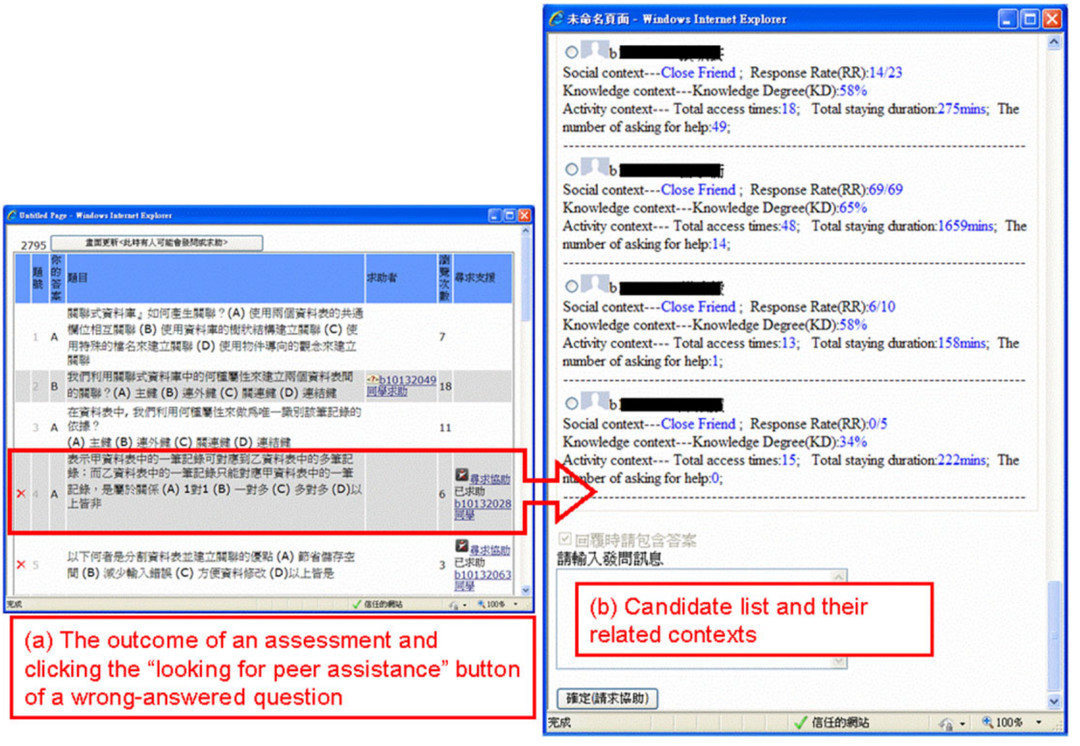

Figure 2: Social network awareness (SNA) supports and asking for assistance: (a) the outcome of an assessment; (b) candidate list

also displayed as described in the next subsection. Students could then select the desired helpers from the list and send help messages. Upon response to a request, the student (ie, help seeker) received a notification e-mail from the system, which contains a hyperlink linking to the new response. Additionally, a student could login the system to check new responses and review historical assessments.

Before the experiment, a pretest was also performed to measure background knowledge. To ensure pretest validity and reliability, the pretest was tested by 28 students. Next, inappropriate questions were removed according to the corresponding difficulty and discrimination levels, resulting in 19 multiple-choice questions and Cronbach's alpha of 0.79. To verify possible significant differences of participants in terms of learning achievement, a posttest was further conducted after the experiment. Finally, validity and reliability analyses of the posttest were handled in the same manner as that of the pretest, resulting in 35 questions with Cronbach's alpha at 0.82.

SNA supports

In addition to helping students to self-reflect by understanding the social and learning contexts of peers, SNA attempts to scaffold student learning when encountering difficulties by peer assistance. A student uses SNA to foster informal learning communities surrounding the course topics, thereby extending a personal learning space to a social learning space (Dabbagh & Kitsantas, 2012). The proposed SNA reveals three contexts of each candidate: knowledge, social and activity contexts as shown in Figure 2(b). A candidate is a member who answered the question correctly. Here, some parameters are defined in advance as follows: C_i denotes the i-th candidate; M represents the number of members in a community; and n refers to the number of assessments already undertaken. The following discussion thoroughly explains the above contexts individually.

Social context largely determines whether a candidate is a close friend; the response rate of candidates is determined as well. The response rate represents the degree of willingness to help the others. The response rate of candidate C_i, denoted as RR_i, is defined as follows:

$$RR_i = \frac{\text{The number of requests for help that } C_i \text{ has responded to}}{\text{The number of requests for help that } C_i \text{ has received}}.$$

Knowledge context largely demonstrates a candidate's knowledge degree regarding a particular subject. The knowledge degree of candidate C_i, denoted as KD_i, represents how well the candidate has performed since first assessment began and is defined as follows:

$$KD_i = \left(\sum_{j=1}^{n} \frac{\begin{array}{c}\text{The number of questions that } C_i \text{ has correctly} \\ \text{answered in the } j\text{-th assessment}\end{array}}{\text{The number of questions in the } j\text{-th assessment}} \right) \div n$$

Activity context largely demonstrates a candidate's total review duration (in minutes), total access time and number of asking for assistance.

Data collection and analysis

This study examined how self-regulation level and centrality level simultaneously affect learning achievement in an SNA environment. Whether both the variables interact with each other for learning achievement was also verified using two-way analysis of covariance (ANCOVA). The analysis regarded self-regulation level and centrality level as the independent variables, posttest scores were viewed as dependent variables and pretest scores were taken as the covariate.

Additionally, different self-regulation levels and centrality levels were compared in terms of the number of help requests by using two-way analysis of variance (ANOVA). The self-regulation level and centrality level were used as the independent variables, and the number of help requests was used as a dependent variable. Moreover, the pattern of asking for help was analyzed by using the system to record the social message flow among peers. Two message flows are out-degree and in-degree. The former refers to a situation in which a student asks someone for assistance, whereas the latter implies that someone asks the student for assistance.

Results

Influence of self-regulation and centrality on learning achievement

Before analysis of two-way ANCOVA, the homogeneity of variance assumption and the assumption of the homogeneity of regression coefficients were tested. SPSS (SPSS Inc., Chicago, IL, USA) analysis demonstrated that the F values of the former and latter were 2.38 ($p > 0.05$) and 1.68 ($p > 0.05$), respectively. The results indicated that both homogeneity assumptions were not violated. Table 1 lists the two-way ANCOVA results. First, the pretest scores do not significantly impact the posttest scores ($F = 1.99$, $p > 0.05$). Both the self-regulation level ($F = 14.10$, $p < 0.05$) and centrality level ($F = 9.93$, $p < 0.05$) significantly impact the posttest scores. Least significant difference (LSD) PostHoc test results (Table 1) indicate that high-level self-regulation students significantly outperform low-level self-regulation students in terms of learning achievement ($F = 14.10$, $p < 0.05$). Meanwhile, according to the LSD PostHoc test results, high-level centrality students significantly outperform low-level centrality students in terms of learning achievement ($F = 9.93$, $p < 0.05$).

Table 1: Two-way ANCOVA on self-regulation and centrality (n = 62)

Source	*SS*	*df*	*MS*	*F-value*	*PostHoc*[a]
Pretest	87.58	1	87.58	1.99	
Self-regulation level	620.40	1	620.40	14.10*	High-level self-regulation > low-level self-regulation
Centrality level	436.92	1	436.92	9.93*	High-level centrality > low-level centrality
Self-regulation level* centrality level	213.34	1	213.34	4.84*	

*$p < 0.05$.
[a]Adjustment for multiple comparisons: LSD (equivalent to no adjustments).
ANCOVA, analysis of covariance; *df*, degrees of freedom; LSD, least significant difference; *MS*, mean square; *n*, the number of students; *SS*, sum of squares.

Table 2: One-way ANCOVA on different level self-regulation groups (n = 62)

Self-regulation group	*Variable*	*Centrality level*	*Mean (SD)*	*F*
	Pretest			2.64
High-level self-regulation ($n = 31$)	Centrality level	High-level centrality	78.97 (1.50)	0.32
		Low-level centrality	77.64 (1.77)	
	Pretest			0.10
Low-level self-regulation ($n = 31$)	Centrality level	High-level centrality	76.56 (1.94)	12.86*
		Low-level centrality	67.43 (1.65)	

*$p < 0.05$.
ANCOVA, analysis of covariance; *SD*, standard deviation.

Table 1 also reveals a significant interaction between the self-regulation level and centrality level ($F = 4.84$, $p < 0.05$). Therefore, the simple main effect of the self-regulation level and simple main effect of the centrality level must be more closely examined as discussed in the following.

Simple main effect of the self-regulation level

Before one-way ANCOVA, testing was performed of the homogeneity of variance assumption (high-level self-regulation group: $F = 2.38$, $p > 0.05$; low-level self-regulation group: $F = 3.01$, $p > 0.05$) and the assumption of the homogeneity of regression coefficients (high-level self-regulation group: $F = 0.35$, $p > 0.05$; low-level self-regulation group: $F = 3.88$, $p > 0.05$). According to those results, all homogeneity assumptions were not violated.

Table 2 summarizes the one-way ANCOVA results. Within the high-level self-regulation group, centrality level does not significantly impact learning achievement ($F = 0.32$ $p > 0.05$). However, within the low-level self-regulation group, centrality level significantly impacts learning achievement ($F = 12.86$, $p < 0.05$). Within the low-level self-regulation group, students with high-level centrality attain a significantly better learning achievement than those with low-level centrality.

Simple main effect of the centrality level

Before one-way ANCOVA, testing was performed of the homogeneity of variance assumption (high-level centrality group: $F = 0.47$, $p > 0.05$; low-level centrality group: $F = 0.01$, $p > 0.05$) and the assumption of the homogeneity of regression coefficients (high-level centrality group: $F = 2.27$, $p > 0.05$; low-level centrality group: $F = 0.04$, $p > 0.05$). According to those results, all homogeneity assumptions were not violated.

Table 3 summarizes the one-way ANCOVA results. Within the high-level centrality group, self-regulation level does not significantly impact learning achievement ($F = 2.51$, $p > 0.05$).

Table 3: One-way ANCOVA on different level centrality groups (n = 62)

Centrality group	*Variable*	*Self-regulation level*	*Mean (SD)*	*F*
	Pretest			0.10
High-level centrality ($n = 31$)	Self-regulation level	High-level self-regulation	79.35 (1.15)	2.51
		Low-level self-regulation	76.51 (1.36)	
	Pretest			2.75
Low-level centrality ($n = 31$)	Self-regulation level	High-level self-regulation	77.68 (2.22)	13.16*
		Low-level self-regulation	67.06 (1.88)	

*$p < 0.05$.
ANCOVA, analysis of covariance; *SD*, standard deviation.

Table 4: Two-way ANOVA on self-regulation and centrality (n = 62)

Source	*SS*	*df*	*MS*	*F-value*	*PostHoc*[a]
Self-regulation level	160.08	1	160.08	26.76*	High-level self-regulation > low-level self-regulation
Centrality level	194.54	1	194.54	32.52*	High-level centrality > low-level centrality
Self-regulation level* centrality level	72.84	1	72.84	12.17*	

*$p < 0.05$.
[a]Adjustment for multiple comparisons: LSD (equivalent to no adjustments).
ANOVA, analysis of variance; *df*, degrees of freedom; LSD, least significant difference; *MS*, mean square; *SS*, sum of squares.

However, within the low-level centrality group, self-regulation level significantly impacts learning achievement ($F = 13.16, p < 0.05$). Within the low-level centrality group, students with high-level self-regulation attain a significantly better learning achievement than those with low-level self-regulation.

Influence of self-regulation and centrality on the interaction pattern
Before analysis of two-way ANOVA, the homogeneity of variance assumption was tested, and the F values were 1.01 ($p > 0.05$), indicating that the homogeneity assumption was not violated. Table 4 summarizes the two-way ANOVA results. The self-regulation level reaches significance on out-degree ($F = 26.76$, $p < 0.05$). On the other hand, the centrality level also reaches the significance ($F = 32.52$, $p < 0.05$). Furthermore, significant interaction occurs between the self-regulation level and centrality level ($F = 12.17$, $p < 0.05$) on out-degree. Therefore, the simple main effects must be further conducted as discussed in the following.

Simple main effect of the self-regulation level
Before analysis of one-way ANOVA, the homogeneity of variance assumptions was tested, and the F values for high-level and low-level self-regulation groups were 0.06 ($p > 0.05$) and 0.02 ($p > 0.05$), respectively, indicating that both homogeneity assumptions were not violated. Table 5 summarizes the one-way ANOVA results.

Within the high-level self-regulation group, centrality level does not significantly impact out-degree ($F = 3.36$ $p > 0.05$). However, within the low-level self-regulation group, centrality level significantly impacts out-degree ($F = 33.20$, $p < 0.05$), indicating that within the low-level self-regulation group, students with high-level centrality more frequently ask for assistance than those with low-level centrality.

Table 5: One-way ANOVA on different level self-regulation groups (n = 62)

Self-regulation group	*Variable*	*Centrality level*	*Mean (SD)*	*F*
High-level self-regulation ($n = 31$)	Centrality level	High-level centrality	3.78 (2.18)	3.36
		Low-level centrality	2.38 (1.93)	
Low-level self-regulation ($n = 31$)	Centrality level	High-level centrality	9.23 (2.80)	33.20*
		Low-level centrality	3.44 (2.72)	

*$p < 0.05$.
ANOVA, analysis of variance; *SD*, standard deviation.

Table 6: One-way ANOVA on different level centrality group (n = 62)

Centrality group	*Variable*	*Self-regulation level*	*Mean (SD)*	*F*
High-level centrality ($n = 31$)	Self-regulation level	High-level self-regulation	3.78 (2.18)	37.11*
		Low-level self-regulation	9.23 (2.80)	
Low-level centrality ($n = 31$)	Self-regulation level	High-level self-regulation	2.38 (1.94)	1.43
		Low-level self-regulation	3.44 (2.73)	

*$p < 0.05$.
ANOVA, analysis of variance; *SD*, standard deviation.

Simple main effect of the centrality level

Before analysis of one-way ANOVA, the homogeneity of variance assumptions was tested. Additionally, the F values for high-level and low-level centrality groups were 1.37 ($p > 0.05$) and 1.67 ($p > 0.05$), respectively, indicating that both homogeneity assumptions were not violated. Table 6 summarizes the one-way ANOVA results.

Within the high-level centrality group, self-regulation level significantly impacts out-degree ($F = 37.11$ $p < 0.05$). Notably, the mean of low-level self-regulation group ($M = 9.23$, standard deviation [SD] = 2.80) is significantly higher than that of the high-level self-regulation group ($M = 3.78$, $SD = 2.18$). Within the high-level centrality group, students with low-level self-regulation have a significantly higher number of asking for help than those with high self-regulation. However, within the low-level centrality group, self-regulation level does not significantly impact out-degree ($F = 1.43$, $p < 0.05$).

Discussion

This study first examines when the subjects were grouped by self-regulation. Within the high-level self-regulation group, centrality level is not significantly related to learning achievement as shown in the upper portion of Table 2. The group students are independent and capable of systematically using metacognitive, motivational and behavioral learning strategies (Wang, 2011; Zimmerman, 1990). The students proactively seek information from all available and possible channels including e-learning material, textbook, Internet browsing, teachers and peers when necessary; the necessary steps should also be taken to master it. For the students of high-level self-regulation group, the SNA system may just play one part of the channels to acquire the needed resources. This finding may explain why they do not significantly differ in the number of help requests as shown in the upper portion of Table 5. The SNA system has a limited capacity for the group, explaining why the group students do not significantly differ in learning achievement, even though they have different centrality levels.

Within the low-level self-regulation group, centrality level is significantly related to learning achievement as shown in the lower portion of Table 2. The proposed SNA system may offer a flexible and convenient approach for the group to acquire the need resources. Hanneman and Mark (2005) posited that students with a higher centrality imply that they have more directed ties with peers and, thus, has more resources and opportunities to obtain assistance than those with a lower centrality. Beauchamp (1965) also argued that members occupying central locations can be highly productive in communicating information. Thus, within the group, students with high-level centrality have a significantly higher number of requests for assistance than students with low-level centrality as shown in lower portion of Table 5. Within the group, students with a higher centrality are more likely to take advantage of the social network position to obtain related contexts of peers, help requests, peer interaction and collaboration than those with a lower centrality (Lin & Lai, 2013). Consequently, within the group, students with high-level centrality outperform those with low-level centrality in terms of learning achievement. This result also corresponds to the previous findings of Cadima *et al* (2012) and Cho *et al* (2007).

This study also examines when the subjects were grouped by network centrality. Within the high-level centrality group, self-regulation level is not significantly related to learning achievement, although the mean of high-level self-regulation is slightly higher than the mean of low-level self-regulation as shown in the upper portion of Table 3. Within the group, students with low-level self-regulation are significantly higher than students with high-level self-regulation in terms of the number of help requests as shown in the upper portion of Table 6. This finding may be owing to the fact that the SNA system is only one of several valuable channels for these high-level self-regulation students to acquire the needed resources. Conversely, the SNA system is a flexible and convenient approach for these low-level self-regulation students to acquire the needed resources, explaining why they used the SNA system more frequently. Consequently, within the high-level centrality group, the students with low-level self-regulation obtain more substantial benefits than those with high-level self-regulation, resulting in that they do not significantly differ in terms of learning achievement.

Within the low-level centrality group, self-regulation level is significantly related to their learning achievement as shown in the low portion of Table 3. Within the group, the students with low-level self-regulation do not significantly differ from those with high-level self-regulation in terms of the number of help requests as shown in the lower portion of Table 6. Cadima *et al* (2012) posited that students in the low-level centrality group are unlikely to take advantage of the social network position to seek assistance from peers. Within the group, a self-regulated learner and a non-self-regulated learner do not significantly differ in the help-seeking behavior (eg, asking peers to give a more detailed answer or explanation). Consequently, the SNA system has a limited capacity for the group. Self-regulation level completely determines learning achievement (Narciss *et al*, 2007; Schunk, 1994). Thus, within the group, our results demonstrate that high-level self-regulation students outperform low-level self-regulation students in terms of learning achievement. This result also corresponds to the previous findings of Azevedo and Cromley (2004).

Conclusions

An emerging trend has been the role of e-learning environment in supporting SNA. Network centrality profoundly impacts student learning in an SNA e-learning environment, whereas self-regulation behavior significantly influences online learning. This study examines whether within an SNA environment, difference in level of network centrality and difference in level of self-regulation significantly influence learning achievement and peer interaction. The first finding showed that the SNA system especially benefits the group which consists of students with high-level centrality and with low-level self-regulation. The group has more significantly progressed in learning achievement than other students. Meanwhile, the group also has the highest number of help requests.

According to McManus (2000), highly self-regulating learners learn poorly in mostly linear web-based hypermedia learning environments where they have few choices. Meanwhile, low self-regulating learners learn poorly in highly nonlinear web-based hypermedia learning environments where they are given too many choices. An online environment with regular and predetermined learning procedures, such as the proposed SNA, appears to be more appropriate for low self-regulated learners than for highly self-regulated ones. Additionally, although having the predetermined learning procedure (Figure 1), the SNA system enables learner to become aware of social, knowledge and learning activity contexts of peers and enhance the opportunity of discussing and exchanging ideas with peers during the learning process. Lin and Lai (2013) have demonstrated that students with high-level centrality on an SNA system take advantage of their network position to be aware of peer learning contexts, to more frequently interact with peers (eg, asking for help and easily become target helpers that peers seek) and utilize the SNA system more frequently. Additionally, Shea *et al* (2012) also claimed that frequent questions by peers in online discussion boards can add students' responsibility and heighten their self-regulatory behaviors. Above-mentioned literature corresponds to the finding of this study that the proposed SNA system especially benefits the group (ie, the students with low-level self-regulation and with high-level centrality). Owing to the provision of SNA function, the group contacted the system and interacted with peers more frequently and thus have more opportunities to realize their own contradictive thought and refer to the distinct assumptions of others when encountering problems. The iterative learning process (Figure 1) helped the group to cement their knowledge and reflect on their overall learning experience. All above are conducive to enhance their learning achievement.

This study did not thoroughly analyze the response messages of help requests. However, though the system log, we observed that the average response rate reaches 90% approximately. Nearly every response message contains the correct answer and explanation for help seeker reference. Additionally, some response messages also contain encouraging words (eg, being persistent) or chitchat words (eg, my answer is correct because of my good fortune). These informal messages may also play an important role in motivating and scaffolding peer learning. Despite its contributions, this study has certain limitations. Although the online system is the primary mode of communication among students, additional peer communication outside of the system is still likely to have occurred (Dawson, 2008). However, whether communication exchanges external to the SNA system substantially affect the evaluation results warrants further study.

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