INTRODUCTION

Increase of diversified online learners, educators need to understand how learners interact; therefore, they can provide more personalized instructions to engage learners in active social interaction. Digital learning vision suggests that emerging practices signal the need for more personal, social, and participatory approaches that support learners in becoming active users and co-creators of learning resources to control learning processes (Leone, 2013). Online learning from socio-constructivism and connectivism focuses on engaging learners in active social network interaction. Frequently, instructors lack of knowledge how online learners may interact in online instructions. Online learners' learning skills and behaviors are challenging for educators to foresee, particularly what skills may be related to certain social interaction behaviors. Without knowing the relationships, it is challenging for educators to provide relevant, and more personalized support to each individual learner.

Online discussion is one of effective learning activities in online instructions. Research (Klisc et al., 2017) found online discussion engages learners in critical thinking and more constructive leaner-learner interaction in addition to learner-content and learner-instructor interactions. Self-regulated learning skills are identified to be a critical skill to in online learning (Barnard-Brak et al., 2010). Current online learning research focuses the interaction on who interact with whom on what (postings). From social learning perspective, social network analysis (SNA) refines online interaction through understanding what role each individual plays and what relationships they build in online learning communication.

Horn and Fisher (2016) inspire research that pushes the understanding beyond the average learners and instead works to discover predictably effective paths for each individual. It's unclear how SRL skills may predict social network interaction. By predicting digital behavior would help educators to understand what works for specific learners in specific circumstances.

This study empirically investigated the following research question: How will self-regulated learning skills predict various aspects of students' role (i.e., in-degree, out-degree, betweenness centrality, closeness centrality, eigenvector centrality, reciprocated vertex pair ratio, & PageRank) in the social network of discussion board within online courses? The research hypotheses based on the theoretical expectations were that there were positive predictive relationships SRL skills and various aspects of students' role in the social network.

Self-Regulated Learning (SRL) and Online Discussions

SRL skills are critical success factors to online learning (Barnard-Brak et al., 2010). "Self-regulated learning is seen as a mechanism to help explain achievement differences among students and as a means to improve achievement" (Schunk, 2005, p. 85). Barnard-Brak et al. (2010) concluded that learners who were equipped with higher SRL skills demonstrated more positive in formal academic learning outcomes than those who do not present SRL behaviors. In addition, Chen and Huang (2014) concluded that online learners with higher SRL skills have better learning performances. Furthermore, Hesterman (2015) argued that competent SRL skills would lead to positive online learning. Students would benefit from educational interventions to improve SRL skills (Bambacas et al., 2013).

SRL refers to those active and initiative behaviors on the part of individuals to achieve their learning (Woolfolk et al., 2000). These metacognitive strategies and behaviors include goal setting, environment structuring, task strategies, time management, help seeking, and self-evaluation (Barnard-Brak, et al., 2010). Goal setting denotes setting personal learning standards for short and long-term learning goals while environmental structuring commonly conveys as how physical and digital environments may result in distraction, efficiency, and learning. Task strategies indicate few distractions for studying, taking notes, reading aloud, preparing questions, and pursuing extra work while time management indicates allocating, scheduling, and distributing time for learning. Help seeking designates how learner utilize human networks to obtain learning support whereas self-evaluation employs different self-reflections processes to ensure their learning meets their needs and goals.

SRL skills are vital to online discussions (Vighnarajah et al., 2009). With the adoptions of socio-constructivism, online discussions are integrated to bolster learning engagements (Johnson et al, 2017), critical thinking (Klisc et al., 2017; Richardson & Ice, 2010), social interaction (Sun et al., 2018), higher-order thinking (Darabi et al., 2013), cognitive engagement (Zhu, 2006), knowledge and community building (Schrire, 2006; Tirado et al., 2015), academic achievement (Msonde, & Van Aalst, 2017). Bai (2012) concluded that SRL facilitates critical inquiry in online discussions. SRL skills influence how learners may interact in online discussion (Lee & Lee, 2016). Moreover, engaging students in online discussions would improve SRL skills (Kramarski, & Mizrachi, 2006).

Social Network Interaction

Applying social network to examine learning interaction in online discussions provide a more profound understanding in interaction behaviors (Jo et al., 2017;

Tirado et al., 2015). Social Network Analysis (SNA) examining interaction goes beyond interaction frequency, and numbers and learner-learner interaction, learner-content interaction, and learner-instructors interaction. It investigates interaction, clusters/subgroups, social relationships, and social structures via network, centrality, graph theory in how learners connect, and respond, how influential, prominent, and prestigious their roles are, and what resources flow they facilitate. It is a relational analysis. In other words, how network participants connect, respond receive responses, the roles they function in networks, how influential, whom they connect to, and who connect to them are critical evidences. Researchers have applied SNA to examine and to understand online interaction patterns, social presence, cognitive presence (Wu et al., 2014), group cohesiveness, and knowledge co-construction (Heo et al., 2010). Based on SNA results, Kale et al. (2011) found online discussion participants were adversely influenced by more knowledgeable others while Enriquez (2008) denoted SNA focuses on relational effects of multiple technical and social arrangements and engagements that beyond the response relations.

Centrality

Centrality, in SNA, is a measure of the behavior and roles of individual within a network. It indicates the extent to which individual (vertex) interact with others in the network (Wasserman & Faust, 1994). SNA includes different interaction measurements, in-degree, out-degree, betweenness centrality, closeness centrality, eigenvector centrality, reciprocated vertex pair ratio, and PageRank. Similar to frequency, in-degree shows the numbers of communication ones receive while out-degree represents communication they make to others.

Betweenness centrality denotes the extent to which a person (vertex) lies between others in their network. It is a measure of the potential influence (Wasserman & Faust, 1994) arising from their position within the network through both direct and indirect pathways (Friedkin, 1991). People who have higher betweenness centrality is known as gatekeepers or bridges who can control the flow of information (Haas, 2009). Therefore, they have more potential to influence others (Friedkin, 1991) and have more influential power in the network. Their connections are not based on the frequency but the strategic location in the network. While betweenness centrality focuses on flow communication and connection, closeness centrality accentuates on distance communication and connection.

Closeness centrality is based on the premise that individuals in the network with the shortest paths to access other members of the network faster. High closeness centrality is connected to all others through smaller number of connections (Otte & Rousseau, 2002) and reflects the ease of communication and distance of resources between the members (Haas, 2009). Higher closeness centrality is also called broadcaster or transmitter.

Eigenvector centrality is the degree to which a participant is connected to other active participants. It measures a person's prominence based on the number of links it has to other nodes within the network. Those who are tied to more central individuals would have higher eigenvector centrality and are more prominent.

Reciprocated vertex pair ratio is ratio between ingoing and outgoing connections in directed relationships. It is the proportion of vertices that have a connection returned to them. Higher reciprocated vertex pair ratio denotes a person engages in more two-way interaction.

PageRank is a way to rank the prestige individuals in network by counting the number and quality of links to a person to determine a rough estimate of how important the role one plays in the network. The assumption is based on more prestigious person are likely to receive more connection from other network members. It is used to identify more prestigious and authoritative ones in networks. Bruun and Brewe (2013) found that course grade is correlated with PageRank.

Social Network Interaction and Discussion Board

SNA has been utilized as an effective tool to understand online discussion interaction (Sun et al., 2018). Lee and Lee (2016) observed the power of closeness centrality measurement in SNA over the number of posts in online discussion activity; and concluded the importance of a relational analysis to examine interaction in discussion board. In addition, by applying SNA, Sun et al. (2018) found participants used the online discussion forum resulted in more communication aimed at knowledge construction, while using the mobile instant-messaging app resulted in more social interactions. Furthermore, Jo et al. (2017) concluded in-degree and out-degree centralities in online discussion were able to predict students' course final grades.

Besides SNA, Stevens (2016) argued and conclude research examining online discussion interaction should apply sociograms (social graphs, network graphs) to examine interaction in online discussion because sociograms provide teachers a diagnostic dashboard with reference to learning activity, including discussion posts, logins, or learning objects accessed. Sociograms visualize complex sets of relationships as graphs of connected symbols and calculate precise measures of the size, shape, and density of the network as a whole and the positions of each element within it (Hansen et al., 2011). They serve as visual illustrations in helping people to explore and understand network structural characteristics, and to communicate specific information about the network to others (Huang et al., 2007). Sobieski and Dell'Angelo (2016) found sociograms reveal the complexity and change nature of relationships among students and inform classroom-based decision that support teaching and learning. Macfadyen and Dawson (2010) deployed SNA' sociograms as a diagnostic tool to identify students at risk of failure or drop-out. The diagrams generated provided teachers and students with a ready-made diagnostic tool that could highlight individuals who might be left out of important learning interactions, or others whose social position could be beneficial to their peers in the network. Liu and Tsai (2008) utilized sociograms to identify the network members with different social interaction behaviors in the network, centralized knowledge exchanging, distributed knowledge exchanging, impediments based on either limited individual ability, and partial knowledge exchanging.

In fact, Card et al. (1999) argued that social graphs or InfoViz theoretical structures include six aspects: Memory and processing capabilities, Information search paths, Pattern detection, Critical information, Inferences, and Data manipulations. By examining sociograms, ones may observe critical information that may be not easy to be observed in SNA results in numbers. Sociograms examining enables further and deeper insights into teaching and learning practices. Ones can visualize complex sets of relationships as maps (i.e., graphs or sociograms) of connected symbols and calculate precise measures of the size, shape, and density of the network as a whole and the positions of each element within it.

METHOD

Participants

In 2018, all thirty-three graduate online students (*N* = 33), enrolled in an upper graduate level online course, Creating Technology Learning Environment, participated in the online discussion board and responded to an online survey in a Southwestern U.S. four-year public university. The majority of them were female (*n* = 23, 69.70%), Caucasian (*n* = 25, 75.76%), and aged 26 years old and older (*n* = 32, 96.97%). More detailed demographic information of the participants is listed in Table 1.

Table 1
Demographic Information of Participants (N = 33)

Variable	Frequency	Percent
Gender		
Female	23	69.70
Male	10	30.30

Ethnicity		
Caucasian	25	75.76
African American	3	9.09
Latino	3	9.09
Asian and Pacific Islander	2	6.06
Age		
18 - 25	1	3.03
26 - 35	9	27.27
36 - 45	12	36.36
45 +	11	33.33

Research Design

The participants partaken in the required and graded online discussion activities which hosted on Nabble (https://nabble.com/), an online discussion platform. They were required to respond to the discussion questions posted by the instructor and required to respond to others' postings to engage in learner-learner interaction. The instructor participated and facilitated the online discussion throughout the two-week discussion period.

Measurement of Research Variables

Predictor variables. The online survey was revised from the Online Self-Regulated Learning Questionnaire (OLSQ) (Barnard-Brak et al., 2010) to measure students' self-regulated learning skills. In specific, self-regulated learning skills of the students were measured by the total scores of accumulated from all 40 items (see Table 2) on a 7-point Likert scale with 1 as strongly disagree and 7 as strongly agree. The participants completed the questionnaire in the first week of eight-week online instructions. In the validation study by Barnard-Brak et al, (2010), the Cronbach alpha coefficient was .92 and supported the internal consistency of the survey items. In light of the exploratory nature of the current study, the overall scores of self-regulated skills instead of the subscale scores were used as the predictor for various social network interaction scores.

Table 2
Online Survey Items of the Predictor Variable

Variable	Survey item
Goal setting	
I set standards for my assignment in online course.	
I set short-term (daily or weekly) goals as well as long term goals (monthly or for the semester).	

I keep a high standard for my learning in my online courses.
I set goals to help me manage studying time for my online courses.
I don't compromise the quality of my work because it is online.
I set goals for my formal learning.
I set goals for my informal learning.
I apply online technologies to support goals.
I constantly search, evaluate, select, and reselect online technologies to reflect my current goals.

Environment structuring
I choose the location where I study to avoid too much distraction.
I find a comfortable place to study.
I know where I can study most efficiently for online courses.
I choose a time with few distractions for studying for my online courses.
I use mobile devices (smartphones, tablets, etc.) to help me to study.

Task strategies
I try to take more thorough notes for my online courses because notes are even more important for learning online than in a regular classroom.
I read aloud instructional materials posted online to fight against distractions.
I prepare my questions before joining in the chat room and discussions.
I work extra problems in my online courses in addition to the assigned ones to master the course content.
I build "people network" online to help me to learn.
I build "resources network" online to help me to learn.
I build and connect "tools/technologies network" online to help me to learn.
I manage online tools and technologies regularly to help me to learn.
I use online technologies to collaborate with others to help me to learn.

Time management
I allocate extra studying time for my online courses because I know it is time-demanding.
I try to schedule the same time every day or every week to study for my online courses, and I observe the schedule.
Although we don't have to attend daily classes, I still try to distribute my studying time evenly across days.
I frequently allocate small chunks of time to engage in just-in-case, just-in-time, and bite size learning.
I frequently allocate substantial chunks of time to engage in learning.

Help seeking

I find someone who is knowledge in course content so that I can consult with him or her.
I share my problems with my classmates online so we know what we are struggling with and how to solve our problems.
If needed, I try to meet my classmates face-to-face.
I am persistent in getting help from the instructor through e-mail.
I am persistent in getting help by using different devices (computers, mobile devices).
I am persistent in getting help by using different technologies (Twitter, social networks, etc.).

Self-evaluation
I summarize my learning in online courses to examine my understanding of what I have learned.
I ask myself a lot of questions about the course materials when studying for an online course.
I communicate with my classmates to find out how I am doing in my online classes.
I communicate with classmates to find out what I am learning that is different from what they are learning.
I use different technologies to reflect my online learning, such as online portfolio, personal blogs, Twitter, social media, etc.
I re-evaluate online tools and technologies that I used for my online learning after each online course I took.

Criterion variables. Criterion variables: Role in social network of online discussion board. Learners' network interactions was collected and analyzed through Social Network Analysis (SNA). SNA provided both quantitative (local and global metrics) and qualitative data (sociograms/network graphs). Local metrics (for vertex and edges) and global metrics (for overall network structure) were calculated. Based on these metrics, network graphs were created to have visual bird-eye views of the network.

The criterion variables were various measures of participants' roles in the social network of an online discussion board: (1) In-degree, (2) out-degree, (3) betweenness centrality, (4) closeness centrality, (5) eigenvector centrality, (6) reciprocated vertex pair ratio, and (7) PageRank. In the actual regression analyses, each of them was used as the criterion variable (i.e., the dependent variable) to be predicted by the total self-regulated skill scores of the students. They were generated with the social network analysis software of NodeXL (Aldhous, 2012; Smith et al., 2009) and store in an Excel file. Then the Excel file was converted into the SPSS data file for the subsequent regression analyses. Due to the nature of threaded discussion board, standard Reply network were integrated since the participants were required to reply to each other after replying to the discussion questions. Due to the nature of online discussion, one type of vertex (learner) was utilized as single-mode or unimodal network (person-to-person) data analysis. All 33 participants' and the instructor's postings were coded as directed and weighted edges into NodeXL Pro. Post-and-reply threaded message structure was analyzed. For example, if A replies to B, it is counted as one directed edge between from Vertex A to Vertex B. Vertex A is counted with 1 out-degree while Vertex B is counted with 1 in-degree. If one replies to the same participant multiple times, a stronger weighted ties or edges is created (Hansen et al., 2011). The instructor initiated the discussion topics first and the learners replied to them. In addition, the learners were required to reply each other.

Data Analysis

All the data analyses of the current study were implemented with the IBM SPSS Statistics 24.

Linear regression analyses. Linear regression analyses (Cohen et al., 2003; Norusis, 2012) were conducted to assess the predictive relationship between the predictor variable and each of the seven criterion variables, one at a time.

Assumption checking. The assumptions of normality and homogeneity of variances in linear regression analyses were assessed with the normal q-q plots and the scatterplots of standardized residuals (Cohen et al., 2003; Norusis, 2012).

Significance test. The *F* test of the R^2 (Cohen et al., 2003; Norusis, 2012) was conducted to assess the predictive utility of the predictor (i.e., self-regulated learning skills) for each criterion variable related to various aspects of role in social network of online discussion board. The alpha level in all the *F* tests was set at .05.

Effect size index. In each simple regression model, the R^2 (Cohen et al., 2003; Norusis, 2012) was computed to estimate the proportion of variance in a criterion variable predictable by the predictor variable.

RESULTS

Social Network Analysis

The online discussion network was examined in terms of network metrics (Table 5). Visualize network in directed network sociograms (see Figure 1-5) were created using the Harel-Koren Fast Multiscale layout algorithm (Harel and Koren, 2001) because it was relevant to analyze vertices' relationships in threaded discussion network (Hansen et al., 2010). Based on SNA results, the discussion network was considered as highly interactive. The network is composed of 33 learners and 1 instructor (vertices) and 487 interactions (directed edges). Maximum geodesic distance was 2.00 while average geodesic distance was 1.63. According to Milgram's experiment (1967), people in a network can be reached from every other person in 6 steps. The studied discussion network provided an ideal network learning space.

Table 5:
Social Network Metrics

Global Network Metrics	Values
Graph Type	Directed
Vertices	34
Unique Edges	208
Edges with Duplicates	279
Total Edges	487
Self-Loops	50
Reciprocated Vertex Pair Ratio	0.47
Reciprocated Edge Ratio	0.64
Maximum Geodesic Distance (Diameter)	2
Average Geodesic Distance	1.63
Graph Density	0.24

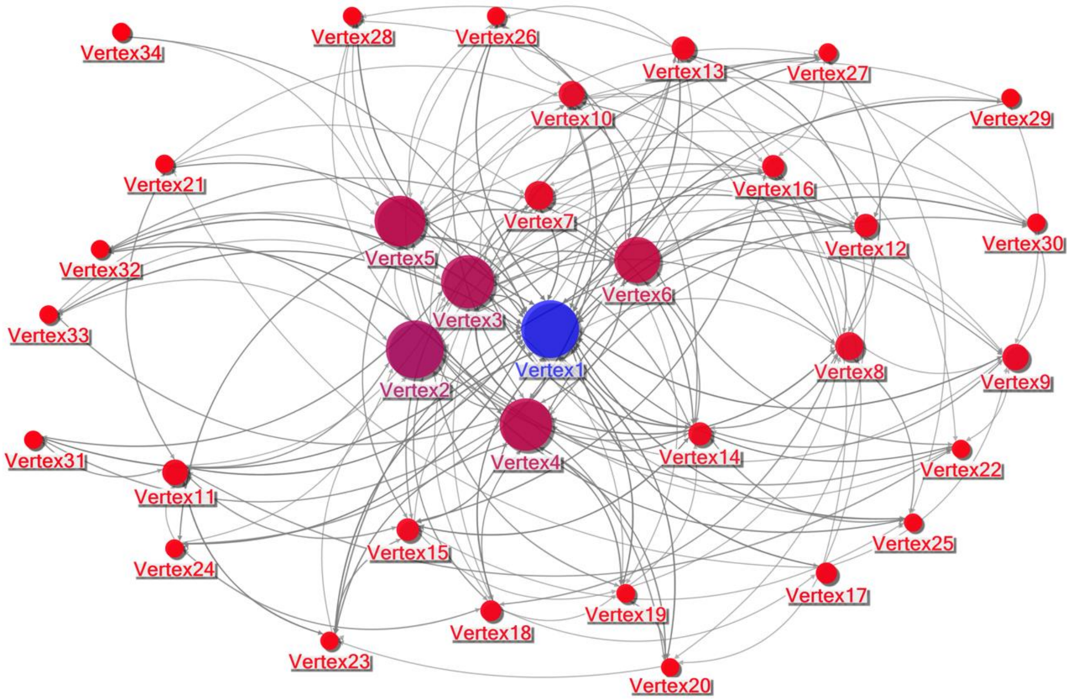

Figure 1. Vertex color-size & position based on betweenness centrality

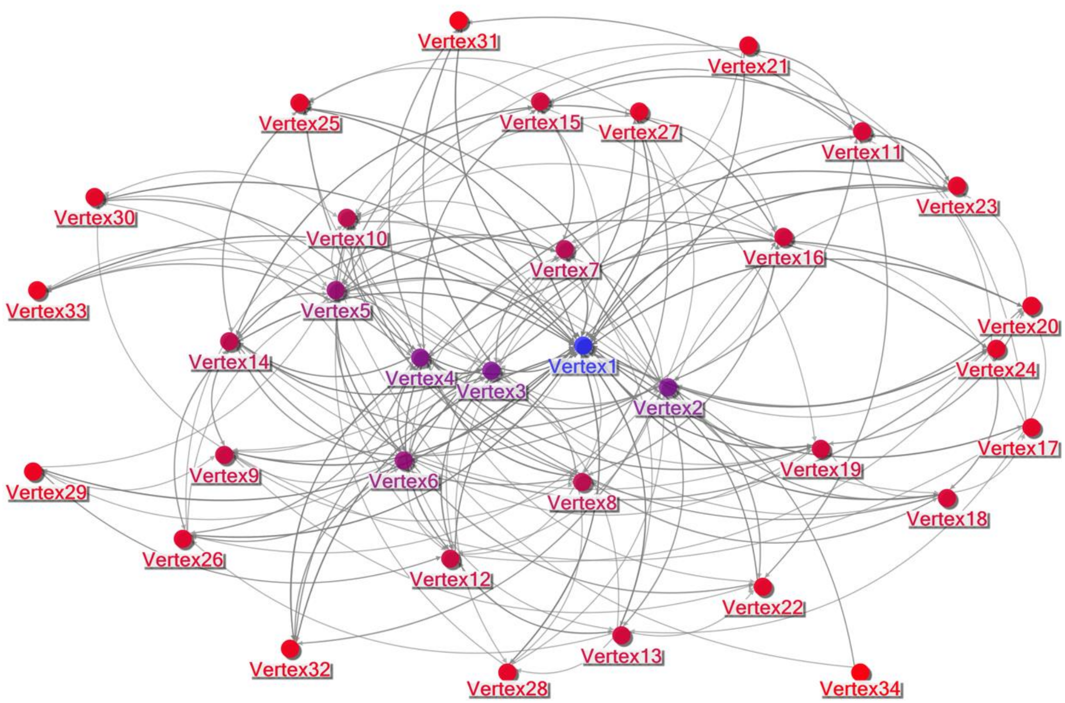

Figure 2. Vertex color-size & position based on closeness centrality.

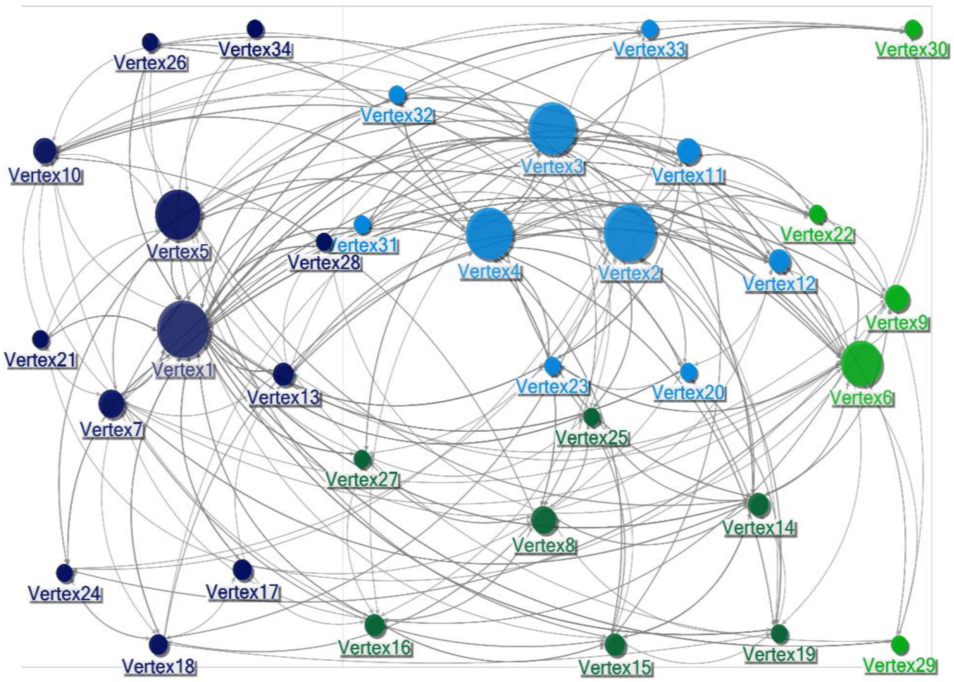

Figure 3. Clustered network based on closeness centrality.

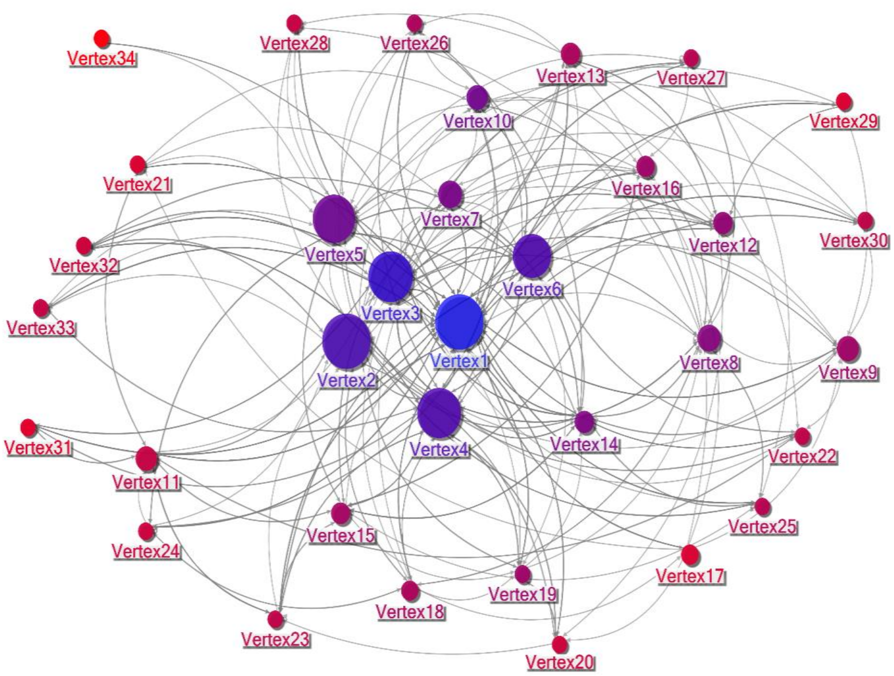

Figure 4. Eigenvector centrality based on the vertex colors & size.

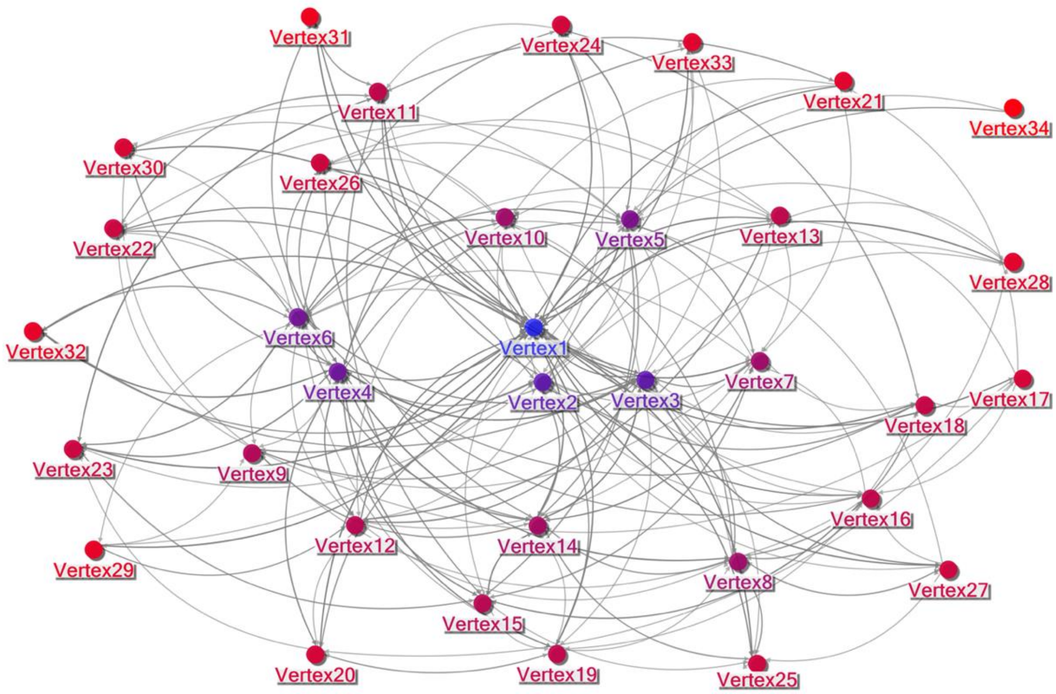

Figure 5. Vertex color-size and position based on PageRank centrality

The graph density value, which is the ratio of the observed number of ties divided by the maximum possible ties and might range between 0 and 1, was found 0.24. These dense networks are often communities of people who are aware of one another, and converse, communicate and interact often. Theoretically, if the number of the individuals are less, it is easy to get a high score. However, considering the length of the 8-week instruction period, the discussion network was considered as interactive. Reciprocated vertex pair ratio was found 0.47 while reciprocated edge ratio was found 0.64, which is considered as high and further supports highly two-way interactivity level.

Based on betweenness centrality and closeness centrality (see Figure 1 & 2), related tight crowd community structures were characterized by highly interconnected people with few isolated participants.

Participants in the network have strong connections to one another and significant connections that bridge between any sub-networks. To better see the interaction pattern, the vertices was grouped by using the Clauset-Newman-Moore cluster algorithm (Clauset et al., 2004) and visualized in a network graph (see Figure 3). Participants with higher betweenness centrality connect and fuse different sub-networks. Based on community structure classification (Smith et al., 2014), the network demonstrated a connected and unified tight crowd community structure.

Descriptive Statistics of the Research Variables

The descriptive statistics of the research variables are listed in Table 3.

Table 3

Descriptive Statistics of the Research Variables (N = 33)

Variable	*M*	*Mdn*	*SD*	*Min.*	*Max.*
Self-regulated learning skills	226.15	231.00	30.45	162.00	280.00
Role in social network					
In-degree	8.06	7.00	5.87	.00	32.00
Out-degree	7.88	6.00	5.33	2.00	23.00
Betweenness centrality	20.44	7.52	47.75	.00	264.90
Closeness centrality	.02	.02	.003	.02	.03
Eigenvector centrality	.03	.03	.01	.008	.07
Reciprocated vertex pair ratio	45	.40	.26	.00	1.00
PageRank	.97	.83	.51	.30	2.81

Note. Self-regulated learning skills were measured with 40 questionnaire items on a 7-point Likert scale.

Linear Regression Analyses

Self-regulated learning skills was the predictor in all linear regression models in the current study. The relevant statistics from linear regression analyses are listed in Table 4. The normal q-q plots and the scatterplots of standardized residuals did not suggest severe violations of the normality assumption and homogeneity of variances assumption.

Table 4

Seven Simple Regression Models with Self-regulated Learning Skills as the Predictor Variable (N = 33)

Criterion variable	*F*	*df1*	*df2*	R^2	*B*
In-degree	3.81	1	31	.11	.06
Out-degree	3.72	1	31	.11	.06

Betweenness centrality	4.55*	1	31	.13	.56
Closeness centrality	4.35*	1	31	.12	<.01
Eigenvector centrality	3.19	1	31	.09	<.01
Reciprocated vertex pair ratio	.29	1	31	.01	<.01
PageRank	3.97	1	31	.11	.01

Note. F = F test statistic; *df1* = regression degrees of freedom; *df2* = residual degrees of freedom; R^2 = squared multiple correlation coefficient; B = unstandardized regression coefficient.

$^{*}p < .05$

In-degree as the criterion variable. The results did not support the predictive utility of self-regulated learning skills for in-degree in online social network, $F(1, 31) = 3.81$, $p > .05$, $R^2 = .11$. In light of the size of R^2 close to the cutoff of a medium R^2 as .13 (Cohen, 1988) and the actual sample size in the current study, a post hoc power analysis was implemented with the GPower 3 program (Faul et al., 2007). As a result, the observed statistical power level was .50 and lower than the optimal .80 level (Cohen, 1988). Therefore, future studies with larger sample sizes may be advisable to further investigate the predictive utility of self-regulated learning skills for in-degree in online social network. In this particular sample, 11% of variance in in-degree was predictable by self-regulated learning skills.

Out-degree as the criterion variable. A predictive relationship between self-regulated learning skills and out-degree in online social network was not suggested by the results, $F(1, 31) = 3.72$, $p > .05$, $R^2 = .11$. According to the post hoc power analysis with the GPower 3 program (Faul et al., 2007), the observed statistical power level (i.e., .50) was lower than the optimal .80 level (Cohen, 1988) and rendered the future studies using larger sample sizes advisable. About 11% of variance in in-degree was predictable by self-regulated learning skills based on the value of R^2.

Betweenness centrality as the criterion variable. The predictive utility of self-regulated learning skills for betweenness centrality in online social network was supported by the results, $F(1, 31) = 4.55$, $p < .05$, $R^2 = .13$. The positive regression coefficient of self-regulated learning skills also suggested a positive predictive relationship between self-regulated learning skills and betweenness centrality. As a result, students with higher self-regulated learning skills were predicted to have higher betweenness centrality in online social network relative to the ones with lower self-regulated learning skills. The size of R^2 indicated a predictive relationship of medium strength (Cohen, 1988) and a 13% of variance betweenness centrality predictable by self-regulated learning skills.

Closeness centrality as the criterion variable. The results supported the predictive utility of self-regulated learning skills for closeness centrality in online social network, $F(1, 31) = 10.55$, $p < .05$, $R^2 = .12$. Moreover, a positive predictive relationship between self-regulated learning skills and closeness centrality was indicated by the positive regression coefficient of self-regulated learning skills. Accordingly, students with higher self-regulated learning skills were predicted to have higher closeness centrality in online social network relative to the ones with lower self-regulated learning skills. In light of the size of R^2, an approximately medium predictive relationship was suggested (Cohen, 1988) and 12% of variance in closeness centrality was predictable by self-regulated learning skills.

Eigenvector centrality as the criterion variable. A predictive relationship between self-regulated learning skills and eigenvector centrality in online social network was suggested by the results, $F(1, 31) = 3.19$, $p > .05$, $R^2 = .09$. In the post hoc power analysis with the GPower 3 program (Faul et al., 2007) the observed statistical power level was .42 and call for large sample sizes in future studies. The size of R^2 suggested a weak predictive relationship (Cohen, 1988) and a 9% of variance in eigenvector centrality predictable by self-regulated learning skills.

Reciprocated vertex pair ratio as the criterion variable. The results did not support the predictive utility of self-regulated learning skills for reciprocated vertex pair ratio in online social network, $F(1, 31) = .29$, $p > .05$, $R^2 = .01$. The above conclusion was further corroborated by the negligible size of R^2.

PageRank as the criterion variable. A predictive relationship between self-regulated learning skills and PageRank in online social network was not suggested by the results, $F(1, 31) = 3.97$, $p > .05$, $R^2 = .11$. Based on the post hoc power analysis with the GPower 3 program (Faul et al., 2007), the observed statistical power level (i.e., .50) was low and indicated the utility of conducting more studies with larger sample sizes. Approximately, 11% of variance in in-degree was predictable by self-regulated learning skills based on the value of R^2.

DISCUSSIONS

The predictive utility of self-regulated learning skills for betweenness and closeness centralities was supported, but not for in-degree centrality, out-degree centrality, eigenvector centrality, PageRank, and reciprocated vertex pair ratio. Learners with higher SRL skills tend to connect to others based on flow and distance of the connections, rather than how prominent (eigenvector) and prestigious (PageRank) of their connections nor frequency of their postings (out-degree), received replies (in-degree), and reciprocated communication. These findings align with the literature that students with higher SRL skills more likely to apply metacognitive strategies, goal setting, environment structuring, task strategies, time management, help seeking, and self-evaluation (Barnard-Brak et al., 2010), and engage in active and initiative learning behaviors. Additionally, learners with greater SRL skills play more influential and collaborative roles in online discussion network. They, called as social connectors, tend to hold and tighten network to facilitate social interaction. They bridge different sub-groups and their removal from the network may have consequences to holding network together as a whole. This denotes that learners with higher SRL skills play a more facilitating roles focusing on communication dynamics between/among each individual learners and sub-groups in the discussion network. However, they are not necessary perceived as significant authority figures. The characteristics of the discussion network tend to exhibit more supportive and collaborative posting behaviors, and more connections to individuals in sharing information. Current literature showed that SRL skills are related each individual's metacognitive strategies, and behaviors, and positive learning outcomes, performance, and achievements. This study discerns higher SRL skills would lead to more social, interactive, connecting, and facilitating behaviors. In other words, students with higher SRL skills not just learn for themselves, they learn for and with the network community. They are community learners.

Influential Roles

From betweenness centrality perspective, learner with higher SRL skills present as bridges or gatekeepers and are located in strategic positions (see Figure 1) to actively facilitate and influence what information flows through the networks. They reflect the ease of communication and flow of resources between and among the learners. In addition, they function and fuse others and warrant learning resources flow effectively and efficiently. Furthermore, learners with higher SRL skills function as bridges among other sub-networks or clusters in the network (see Figure 3). They are the gatekeepers among the sub-networks; therefore, they situate as central roles in the network. Students with higher SRL skills likely set learning goals for the community, structure their learning environments within the discussion network, and apply learning strategies for communal. Interestingly, lower SRL skills associated with lower betweenness centrality more likely clusters with the instructor to form group cohesion. These learners likely value the interaction between them and the instructor higher than with peers. They see the instructor is main information provider rather than learning from peers. This group cohesive (Forsyth, 2010) with the instructor is based on the task relation since the discussion activity was required and graded. Additionally, lower SRL skills learners have the needs for cognitive closure (NFCC) (Kruglanski &

Webster, 1996) in their network learning since they may see online discussion as question and answer activities between them and the instructor.

While higher betweenness centrality controls the flow of communication, higher closeness centrality maneuvers the distance of communication. Closeness centrality is a measure of how long it will take information to spread from a given individual to all others in the network. Learners with higher closeness centrality incline to interact with different participants rather than more prestige or more interactive ones. This finding did not align with Lee and Lee's (2016) findings that concluded SRL level did not correlated with closeness centrality. These learners with higher SRL skills tend to manage their time efficiently to access learning resources, to structure their learning environments, and to obtain help and supports online. In addition, they are more likely constantly to reflect the efficiency of their learning environment structuring and time management in help or support seeking to ensure positive interaction experiences. They can be seen as transmitters or community learners because of their influential roles in distributing information in the network. This could be explained SRL skills cannot predict eigenvector centrality. In other words, learners with higher SRL skills are more likely to engaged in distributed knowledge exchange (shared exchange) rather than centralized knowledge exchange (single expert responder).

Connection Strategic

Although SRL skills cannot predict in-degree, out-degree, eigenvector centrality, PageRank, and reciprocated vertex pair ratio, it should be noted this reflects the characteristics of the network. Generally, in-degree, our-degree, betweenness, and closeness centralities positively correlated (Valente et al., 2008; Valente & Forman, 1998). When they are not or low correlated, likely it signifies unique characteristics about the network. Although learners with higher SRL skills tend to influence the flow communication and distance communication, their interaction is not necessary based on the frequency of their connections in the discussion board. In other words, they connect strategically in the network. Their connections are more crucial to the network flow and tend to tie to more social and active network members. Learners with lower SRL skills tend to make redundant connection and network crucial communication likely bypass them. In addition, they are embedded in cluster or sub-groups that is distant from the reset of network, particularly the more influential ones. This could be explained as they incline to learn for themselves, not necessary for the community. It should be noted that the learners with lower SRL skills demonstrated lower in-degree and out-degree. They are prone to meet the basic discussion requirements, respond to the discussion questions and reply to others, to earn satisfactory grade.

Nurturing vs. Authority

Eigenvector centrality and PageRank concern the quality of connections. One with higher scores tend to discern to connect more prominent (eigenvector centrality) learners and more prestige (PageRank). Eigenvector centrality provides a measure that incorporates both the number and quality of the connections an individual actor has formed. Establishing relationships to highly connected people in the network will provide greater access to resources than less connected peers (Newman, 2010). Learners with higher SRL skills did not have higher eigenvector centrality. It indicates they are not necessary to connect to more prominent learners. They incline to connect to disparate parts of the network based on flow (betweenness) and distance (closeness) of communication, rather than to connect to more prominent ones.

SRL skills did not predict PageRank. PageRank factors in directionality and connection weight; therefore, one with higher PageRank is considered as prestigious or holding authority. In other words, one with higher SRL skills does not demonstrate higher prestigious or authority. Although Zhu (2006) found SRL is related cognitive engagement, the participants in this study likely were drawn more to social connection rather than cognitive engagement. Learners with higher SRL skills did not necessary receive higher incoming posts or connections (in-degree) from highly influential ones. Network learners do not necessary to recognize learners with SRL skill as more prestigious, particular as information authority community members.

SRL skills cannot predict reciprocated vertex pair ratio. It signifies higher SRL learners did not necessary engage in two-way communication with the same discussion participants. While Sun et al. (2018) observed higher SRL is resulted in higher social interaction in online discussion activity, the participants in this study built their network in a broader sense, one-many or many-many interaction, rather than two-way one-to-one interaction. This implies learners with higher SRL skills may not necessary engage in two-way connection, rather than more facilitating network communications as a whole.

Roles

The literature may suggest that learners with higher SRL skills should demonstrate and behave actively in all social network roles. Based on the main findings of this study, one question raised. Is it necessary for all learners to pursue influential, prominent, and prestigious roles in social interaction in order to ensure effective learning? In fact, a healthy and effective learning community may be composed by different social network roles. This study concludes learners with higher SRL skills tend to connect to others based on flow and distance of the connections, rather than how prominent (eigenvector) and prestigious (PageRank) of connections. Each individual learner has his/her own learning goals and their own preferences to learn effectively; therefore, each learner should be encouraged to identify ideal roles to play in network. Namely, if learners with higher SRL skills, they will have wider ability and capability to select and play their ideal social role in learning community. From educator's perspective, it is critical for instructors and instructional designers to understand each individual learner's ideal goals and roles and provide personalized support to assist them prior the instructions and just-in-time supports. Effective online instructions should empower learners to personalize and customize their learning process. By knowing their SRL skills prior to the online instructions would help instructors and instructional designers to be better prepared to provide the personalized instructions and support.

Limitations

The limitations of this study should be noted in the online threaded discussion natures of this study. Social network analysis is based on relational relationships among learners and instructors. This study was conducted in a discussion community that the instructor facilitated the required and graded online discussions. Each online discussion instruction has unique characteristics that may prompt learners' different interaction behaviors and different network roles. Learners may perceive and act differently with or without instructors' presences.

This study examined social network interaction based on online threaded discussions. Social network interaction is not limited to online threaded discussions. Other interaction activities, such as e-mail, listserv, blogs, chat, SMS, social network sites (Facebook, Twitter, Instagram etc.), are relevant to social network interaction as well.

This study solely examined single-mode network (person-to-person). Social network analysis and SRL skills could be examined from the aspects of bimodal or multimodal networks. Besides learners as vertex or node, learners' demographics, each individual discussion thread/topics, different online discussion platforms (discussion board, blogs, social network sites etc.), or different discussion affiliations/groups can be applied for bimodal or multimodal networks to understand interaction behaviors.

Implications for Future Research

This study only examined social network roles in a single timepoint. The future study should examine learners' social network behaviors from temporal to observe how learners' social roles progress within three phases (forethought, performance, and self-reflection) of SRL (Zimmerman, 2002). By examining social interaction changed over time would help researchers to understand how learners' social network roles evolve throughout discussion activities, courses, or educational program etc.

In addition, future studies should examine and cross-examine other predictor variables, Community of Inquiry (teaching presence, cognitive presence, and online social presence), network social presence, mobile social presence, and online collaboration skills on different social network channels and platforms. Furthermore, by examining and cross-examining these predictor variables would help educators to understand how online community may progress in learning network. These further researches would guide educators for facilitating change, different approaches of participatory network mapping have proven useful.

CONCLUSIONS

This study observed the importance of SRL skills in predicting learners' digital social interaction behaviors. It enables further and deeper insights into online teaching and learning practice. The results assist educators to provide personalized guidance and support learners to navigate through online discussions. By understanding how SRL skills related to social interaction roles learners play would assist instructors to recognize each individual learner's needs and to provide personalized support. In addition, it would support instructors to nurture and to balance healthy and dynamic learning networks for the learning community. The findings help educators to prepare for network change, understand the effects of prior decisions and instructional activities, and cultivate crucial social and network relationships. In conjoining adaptive learning system with evidence-centered instruction, data-driven instructions, data-informed instructions, while real-time and contingency social network interaction data are collected, just-in-time personalization guidance could be delivered at any point in discussion activities. SNA sociograms and contingency graphs (Suther et al., 2010) can be deployed across a temporal axis and annotated to show direction of communication, connection, media, and collaborators. In addition, SNA results and sociogram should not be limited to teachers only. They can be used by academic staff to observe or give feedback, and by students to assist with self-monitoring. Students can reflect on their learning based on provided SNA information and sociograms that indicated their levels of social, cognitive, and behavioral engagements. In addition, students and teachers can communicate each other based on these presented to enhance and justify their learning and teaching throughout the period of social interaction. With applicable SNA data and graphic elicitation (Crilly et al., 2006), both teachers and students can achieve effective data-informed instructions and data-driven instructions.

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