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A predictive study of students' social presence and their interconnectivities in the social network interaction of online discussion board

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Keywords

Learning community;
social interconnectivity;
social learning analytics;
social network analysis;
social presence.

Abstract

Effective online interaction is beyond interacting with whomever. The quality of social interconnectivity matters. Social presence plays a vital role in building an effective online learning community. This study empirically examined: how online social presence will predict various aspects of students' social interconnectivities (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 an online course? The predictive utility of social presence for all social network interconnectivity was supported, but reciprocated vertex pair ratio, so-called two-way interconnectivity was not. Social presence serves as a strong predictor for social interaction and interconnectivity. Learners with higher social presence are more likely to play distinguished roles of influencer, liaison, transmitter, social strategist, and prestigious figure of a community of learners. The findings would support online instructors to facilitate, guide, and support their students to navigate through the convoluted social interconnectivity effectively and continuously.

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Introduction

If the COVID-19 pandemic rendered us alone and lonely, forging instructional and social community building can combat the pall to accomplish learning physically alone but together through collaboration and interconnectivity. Ironically, most students are drawn to social interaction on social networking sites, while unfamiliar with social interconnectivity in a learning context that values the effectiveness of with whom to interconnect to reach goals and the roles played in networks to obtain resources. The core tenet of online interaction is beyond interacting with whomever. In fact, with whom to interact and how to interact may determine whether or not one remains alone. The quality of interconnectivity matters. Effective online learning does not occur in a vacuum. Gunawardena et al. (2016) perceived a seminal claim that learning is not purely a cognitive process, but also is emotionally loaded and situated within a social context.

Social presence plays a vital role in building an effective online learning community. The effectiveness of a learning community has been explored extensively, resulting in a considerable body of literature about online social presence and online learning. Holme (2016) saw the need for research to expand the understanding from descriptive analytics, to predictive and prescriptive analytics. In other words, the knowledge acquired in building a community from descriptive research is in hindsight and insight only, rather than foresight. Predictive social learning analytics would take a more proactive approach to address the needs of the learning network. They help to understand and influence the present and improve ongoing learning processes. Previous descriptive studies in social presence and learning community were understood from students' attributes (i.e. genders, ages, skills), perceptions (i.e. motivations, experiences, attitudes, degrees of satisfaction) via self-reported data, and communication notes content analysis which served as a reactive approach to comprehend the past and by understanding derived from these discernments, educators intend to influence the future.

Social learning analytics is a new affordance to research social presence and social interconnectivity behavior in online learning networks and communities. The increasing prevalence of learning analytic technologies make interconnectivity behavior data available to researchers. Tirado, Hernando, and Aguaded (2015) contended social learning analytics does not replace existing analyses. However, it does offer additional powers to enable educators to detect learning network development and to empower them to nurture and improve community building. These profound discoveries would continue grounding and validating theoretical suppositions of building effective learning communities. These positions were strengthened by researchers (Alhadad et al., 2015; Arroyo, 2016; Alhadad et al., 2015) that indicate predictive analytics are needed to understand online learning and instructions.

By examining social presence and learning community building in reference to the perspective of social interconnectivity as interaction behaviors would add an additional layer to support teachers and students to sustain

a positive social presence and build viable online learning networks and communities. The knowledge in social interconnectivity is predictive, prescriptive, and proactive rather than descriptive, reactive, or hindsight. Prior research has thoroughly applied descriptive and diagnostic analysis to comprehend the relationships between social presence and the learning community by analyzing posting contents and measuring perceptions. Understanding social presence's predictive power would advance educators' knowledge, skills, and practices to promote personalized, but yet social and collaborative learning, to nurture students' ideal interconnectivity behaviors in the process of building a learning community.

This study empirically examined the following research question: How will online social presence predict various aspects of students' social interconnectivities (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 an online course?

Social Learning Community

Social presence

Social presence, defined as the ability of participants in a community of inquiry (CoI) to project themselves socially and emotionally, as real people through the medium of communication being used, is critical to understand social sense in a learning community. More specifically, it represents the degree of feeling, perception, and reaction of being connected by digital communication to another intellectual entity (Tu & Mclsaac, 2002).

Social presence impacts learning

Research has documented how social presence induces learning impacts and how social presence interplays with learning outcomes. In an online discussion environment, Joksimovic (2015) attributed social presence as a predictor of students' final course grades. Their further inquiry showed social presence serves as an early detection of students at risk of failing courses. Derived from Topu's et al. (2018) study, social presence was not correlated with students' retention but was related to learning satisfaction and achievements (Cho & Tobias, 2016). Expectedly, social presence was found correlated with trust and learner-centered instructions respectively (Tseng et al., 2019). It should be noted that females with prior cyberbullying experiences are more likely to demonstrate a lower level of social presence, thus utilizing protective and equilibrated strategies of silencing and conflict avoidance coping in online discussion settings (Byrne, 2021). Furthermore, learning motivation was found a positive influence of social presence (Law et al., 2019).

Social presence impacts learning community

Online discussion activities are a commonly operated means to promote student comprehension of a topic

and to facilitate social knowledge constructions within a learning community building process (Cho & Tobias, 2016). Branching out from the impacts on learning outcomes, researchers propelled their investigations to the forefront in social presence and building social trust relationships in a collaborative learning environment (Tseng et al., 2019) in online discussion instructions. In fact, Oyarzun, Hancock, Salas, and Martin (2021) concluded the importance of social presence in building Col amid the COVID-19 pandemic for online graduate teacher education instruction. More importantly, students with higher social presence are more amenable to collaborative activities and to manifest higher level of loyalty in online team activities.

Mokoena (2013) indicated effective discussion and social network interactions are increased by greater social presence. More specifically, sociability, social space, and group cohesion apply crucial weight with social presence (Akcaoglu & Lee, 2016). Xie's et al. (2017) research was driven by the meanings of an online learning community development through examining social presence, conflictual presence, and identity negotiation. Their interplay in digital learning networks is derivative of socially situated identity theory with discourse analysis. They noticed that students devised their social presence to function as facilitators and participants in the process of community development.

Social interconnectivity

Social interaction is an element of sociability while social interconnectivity is a deep-seated social fabric of learning networks and communities. Social network interconnectivity surveys the level of latitude and longitude threads to uncover how and whom learners connect with and to what degree to initiate networks to build learning communities and how networks and communities evolve. Hansen et al. (2011) concluded that studying network structure or social interconnectivity would create an advantage for educators to comprehend how students' social interactions and learning behaviors are impacted by learning network structure. Additionally, students' network positions may involve their accession of learning resources (Burt, 1995), and how students fashion their interconnectivity to shape their network and community structures. Understanding both social interaction and social interconnectivity pertaining to a structural perspective will galvanize educators into action to create an online learning community that is better poised to fashion effective online learning support for instructional improvement and to facilitate rapid progress of social interaction and interconnectivity.

Kent, Rechavi, and Rafaeli (2019) contended that examining social networks would elucidate learners' interconnectivity behaviors in learning networks and communities. Social network interaction goes beyond interaction frequency and numbers. It investigates interconnectivities via different network indices, such as betweenness, closeness, eigenvector, and PageRank centralities. These network indices indicate how learners connect, respond, receive, communicate, determine the quality of roles, and facilitate resource flow. Researchers drive their investigations to quality of connections, interconnectivity roles, and tasks

to understand the development of a learning community. Building on the cognizance of social interconnectivity, researchers harness rivers of social interactivity to grapple with the community of learners (Rook, 2018), learning community building (Msonde & Van Aalst, 2017).

By observing the positions each student achieves in networks, social network interconnectivity reveals the social network roles they play with the strengths of their interconnectivity. Suthers (2017) proffered that social roles in interconnectivity denote communication values, meaning, goals, and expectations.

Applying different network indices, Feng (2016) and Adalat et al. (2018) identified conversation starters, influencers, active engagers, network builders, and information bridges by computing in-degree, out-degree, and betweenness centralities. Hansen et al. (2011) applied the combination of metrics consisting of a network metrics, participation metrics and visualizations to discern each individual's social roles and how they were connected. These roles were called question people, answer people, and discussion starters by using in-degree, out-degree, average degree of neighbors, and clustering coefficient. From a communication facilitation perspective, Kim, Wang, and Ketenci (2020) characterized three leadership roles, full facilitator, transactional facilitator, and attractive facilitator. Their further explorations showed these roles were related to students' behaviors, cognition, and emotions. The social role can be applied to observe online instructor's interconnectivity behavior. Ouyang, and Scharber (2017) found instructors migrated social roles from a facilitator, an observer, to a collaborator to meet the instructional practice needs over time. Yen et al. (2019) utilized different network centralities to identify network roles in an online learning community, such as liaison, transmitter, social strategist, prestigious. Furthermore, the predictive utility reveals that learners with higher self-regulated learning skills tended to connect to others based on flow and distance of the connections (betweenness and closeness centralities), rather than on how prominent (eigenvector centrality) and prestigious (Page Rank) their connections were. In Shan and Wang's (2021) recent study on social presence and online collaboration, based on social network analysis data, they found people who initiated the collaborations played three key roles in the discussions, creative idea sharers, resource providers, and problem solvers/advice providers. Nevertheless, such initiating act did not result in improving the process of high-level collaboration.

Chen and Huang (2019) conducted a series of network analyses to understand students' interconnectivity propensity. They noted that students in the high prestigious group (in-degree centrality) demonstrated higher quality connections with denser and stronger interconnectivity (closeness and eigenvector centralities) within their own network. Namely, they tended to interact with others who have similar prestige. Intriguingly, high prestige students did not hold discussion facilitation interests delved from their betweenness centrality which was not significantly higher than their counterparts who evinced connections with them but were not reciprocated.

The exploration of social interconnectivity can be extended from individual to network and community levels. Kent, Rechavi, & Rafaeli (2019) studied how offline social capital may impact online social interconnectivities by examining different network parameters, such as network density, network diameter, network clustering coefficient, and network modularity. It was concluded that offline social capital negatively impacted online social interactions.

Social presence and interconnectivity in learning community Researchers began to probe how the social presence may pertain to social interconnectivity from a perspective of social network analysis in the context of a learning community. By using network centrality, Shea et al. (2014) concluded that social presence correlated with in-degree and out-degree centralities that indexed the incoming and outgoing interactions while Yassin et al. (2020) administered community density, as a social network community metric, to analyze how it is associated with social presence. Their findings revealed the students with higher social presence are associated with interaction intensity (network density) and their significant roles might be responsible for bonding networks and communities.

Researchers continued their examinations of relationships between different dimensions of social presence and various social interconnectivities. The interactive dimension of social presence was commonly found to be highly correlated with different centralities, such as in-degree, out-degree, betweenness, and closeness centralities. Satar and Akcan (2018) found the interactive facet of social presence is correlated with interactivity, prestigious role, and influence roles that were measured by degree, in-degree, and out-degree centralities. These findings coincided with Kovanovic et al.'s (2014) treatise that endeavored to understand the relationships between social presence and betweenness and closeness centralities. They found an additional three statistically significant correlations between interactive dimensions of social presence and betweenness, in-closeness, and out-closeness centralities while affective and cohesive dimensions of social presence showed weak or no correlations with network centralities.

Tirado, Hernando, and Aguaded (2015) discerned the positive relationship between in-degree and network cohesion that suggested students who received more responses tended to situate themselves in a central location with higher network cohesion power. They extended their examination with Sequential Equation Modeling and found positive influences of network cohesion and indegree on social presence, especially interaction and cohesion dimensions.

Owing to matured knowledge in social presence and the advanced social interconnectivity analysis, examining the predictive power of social presence on students' interconnectivities through network centralities is opportune. By fathoming social presence predictability, teachers are empowered to galvanize their instructions to build a more cohesive learning community by facilitating each step of interconnectivity that students embark on online discussion instruction. Knowledge gained from such examinations would lead to better practices of personalized learning and

collaborative learning.

Method

Participants

Thirty-two graduate students (N=32) in an online educational technology course responded to an online survey prior to their participation in the online discussion board in a Southwestern U.S. four-year public university. One student did not respond to the survey. Most of the respondents were female (n=21, 65.63%), Caucasian (n=24, 75%), and aged from 26 to 45 years old (n=21, 65.63%). More detailed demographic information of the participants is listed in Table 1. The graded online discussions were instructor-led, asynchronous activities in which the students responded to the discussion questions posted by the instructor and others' postings.

Table 1: Demographic information of participants (N = 32).

Variable	Frequency	Percent
Gender		
Female	21	65.63
Male	11	34.37
Ethnicity		
Caucasian	24	75.00
African American	3	9.38
Latino	4	12.50
Asian and Pacific Islander	1	3.12
Age		
26 - 35	12	37.50
36 - 45	9	28.13
45 +	11	34.37

Measurement of research variables

Online social presence as the predictor variable

Online social presence was measured by the Computer-Mediated Communication Questionnaire (CMCQ) (Yen & Tu, 2008). In the CMCQ, there were 24 items on a 7-point Likert scale (i.e., 1 as strongly disagree to 7 as strongly agree) developed to measure a respondent's self-perceived intensity of online social presence in terms of (1) social context, (2) online communication, (3) interactivity, and (4) privacy. Total scores from 24 items (see Table 2) were used to measure online social presence in this study.

Prominence in social network of online discussion board as the criterion variables

Participants' social interaction in online discussion was analyzed via Social Network Analysis (SNA). SNA provided both quantitative (local and global metrics) and qualitative data (sociograms/network graphs). A reply from A to B was coded as one unique edge different from a reply from B to A due to the difference in the interaction direction. Both the local metrics of vertex and edges and global metrics of overall network structure were calculated. Then the network graphs of sociograms were created to get the visual bird's-eye views of the network.

Table 2: Questionnaire items of online social presence.

Interactivity

- Computer-Mediated Communication allows me to participate comfortably in activities with other.
- Computer-Mediated Communication allows me to communicate comfortably with my communication style.
- Computer-Mediated Communication allows me to respond to messages in a timely fashion.
- Computer-Mediated Communication allows others to respond to my messages in an acceptable time.
- Computer-Mediated Communication allows me to participate comfortably when I am familiar with the topics.
- Computer-Mediated Communication allows me to make important online contributions to activities involving others.

Social context

- Computer-Mediated Communication allows me to convey feeling and emotion.
- Computer-Mediated Communication allows me to carry on informal conversations.
- Computer-Mediated Communication allows me to build more positive social relationship with others.
- Computer-Mediated Communication allows me to build trust relationships.
- Computer-Mediated Communication allows me to perform social interactions.
- Computer-Mediated Communication allows me to communicate comfortably with one person or with multiple people.

Online communication

- Time delayed Computer-Mediated Communication allows me to easily express and understand communications.
- Real time Computer-Mediated Communication allows me to easily express and understand communications.
- Text-based Computer-Mediated Communication messages are easy to understand and to express.
- Computer-Mediated Communication allows me to communicate comfortably with my writing skills.
- Computer-Mediated Communication allows me to use my keyboarding skills comfortably.
- Computer-Mediated Communication allows me to be connected with others.

Privacy

- Computer-Mediated Communication allows me to be assured that my private messages will not be forwarded to the public.
- Computer-Mediated Communication allows me to be assured that my personal information cannot be obtained by others.
- Computer-Mediated Communication allows me to communicate in a private and confidential way.

- Computer-Mediated Communication allows me to reliably communicate to specific destinations.
- Computer-Mediated Communication allows me to be assured of privacy if it is accessed from secured areas (Homes, Office, etc.).
- Computer-Mediated Communication allows me to manage privacy.

Participants' prominence in the social network of online discussion board were measured by (1) in-degree, (2) out-degree, (3) betweenness centrality, (4) closeness centrality, (5) eigenvector centrality, (6) reciprocated vertex pair ratio, and (7) PageRank with the help of NodeXL Pro (Aldhous, 2012).

Degrees (in-degree and out-degree) are distinct measurements from frequencies. In-degree is 'the number of different individuals' from which one receives messages while out-degree is the number of individuals to which one replies. Contrarily, frequency is to measure 'the numbers of postings' that individuals conduct.

Betweenness centrality is a measure of the degree that a person is strategically situated between different networks. It purports the potential influence on the information flow between networks through both direct and indirect pathways (Friedkin, 1993). It can be used to identify a social role gatekeeper or a liaison. Closeness centrality observes the distance of connection and gauges the shortest paths to reach others more efficiently (Hansen et al., 2011). Higher degree of closeness demonstrates the role of an information transmitter, conveyor, and broadcaster.

Eigenvector centrality observes the quality and level of how individuals strategically connect to other more active or well-connected members (Zaki & Meira, 2014) (like prestige roles

with higher PageRank). These roles are referred to as social strategists or strategic connectors. PageRank is the value to which a participant is connected (inbound connection) by other active participants (de Keyser, 2012). A person holding a higher PageRank score is perceived by other active participants (higher eigenvector) as more prestigious or as potent peers of prestige. Reciprocated vertex pair ratio is the ratio between ingoing and outgoing connections in directed connections. 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.

Data analysis

Data analyses were conducted with IBM SPSS Statistics 24.

Linear regression analyses

The predictive relationship between the predictor variable of online social presence and each of the seven criterion variables was evaluated with linear regression (Cohen et al., 2003; Norusis, 2012).

Significance test

The F test of the R² was conducted to evaluate the predictive relationship of interest with the .05 as the alpha level.

Effect size index

The R² as the effect size index quantified the proportion of variance in a criterion variable by online social presence.

Results

Social network analysis

Inquiry of the online social network was accomplished through network metrics. Visual sociograms (see Figures 1-6) were created using the Frucherman-Reingold (Frucherman & Reingold, 1991) and the Harel-Koren Fast Multiscale (Harel & Koren, 2001) layout algorithms to identify structural patterns. The community (see Table 3) consisted of 33 learners, 1 instructor (vertices), and 487 total edges. Maximum geodesic distance was 2.00 while average geodesic distance was low (1.63), on the premise of Milgram Experiment's (1967) 6-step network distance. The community also exhibited a medium low level of connectivity (graph density = .24) that affirmed not all students interconnected with each individual while the community demonstrated medium interactive traits through two-way connections, reciprocated vertex pair ratio (.47) and reciprocated edge ratio (.64). Four distinguished clusters/networks were observed with low modularity (0.12) among them. Cluster 1 has the most students (12), while Cluster 4 has the least (4). Four networks have a wide range of reciprocated ratios that range from .14 - .80. Highly interactive networks (Cluster 1,

2, & 3) tend to demonstrate higher reciprocated interaction. It is noteworthy that despite low modularity revealed limited interaction among the emerged four networks, more than half of connections (262, 53.80%) were made as cross cluster interactions.

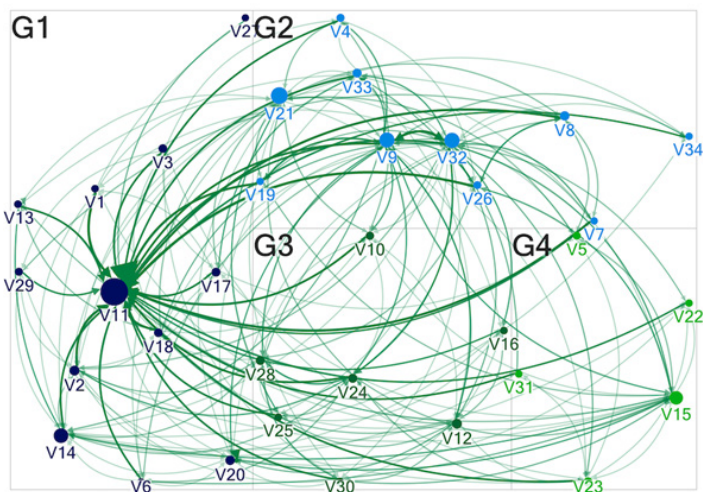


Figure 1: Clustered network. Note: the vertices were grouped by using the Clauset-Newman-Moore cluster algorithm (Clauset, Newman and Moore, 2004) and visualized in a network graph. The vertices were assigned with colors according to the clusters they belonged to. The vertex size is based on betweenness centrality.

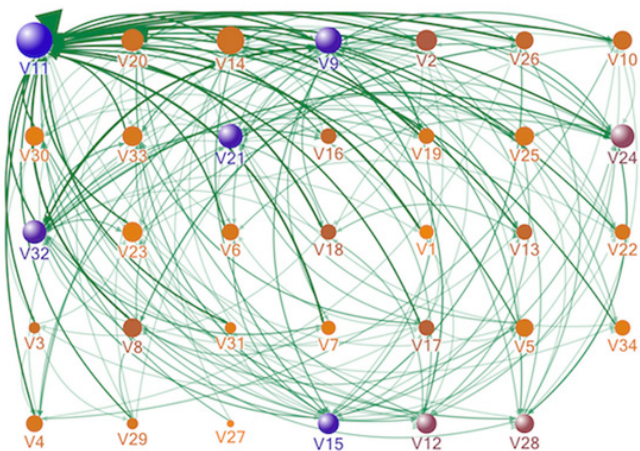


Figure 2: In-degree & out-degree centralities in a grid format layout. Note: vertex size is based on in-degree centrality. Vertex color and shape are based on out-degree centrality. The spear shape with blue color represent higher out-degree.

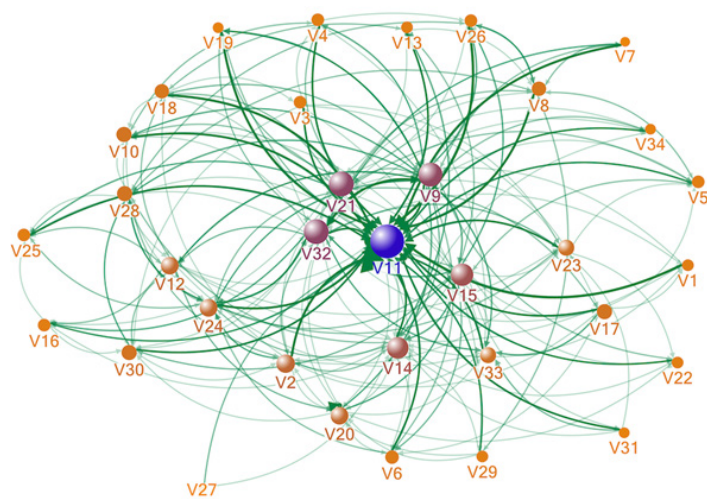


Figure 3: Vertex color-size & position based on closeness centrality in the Fruchterman-Reingold layout. Note: the vertex size and shape represent the degree of closeness centrality. The orange color and circle shape represent lower closeness centrality.

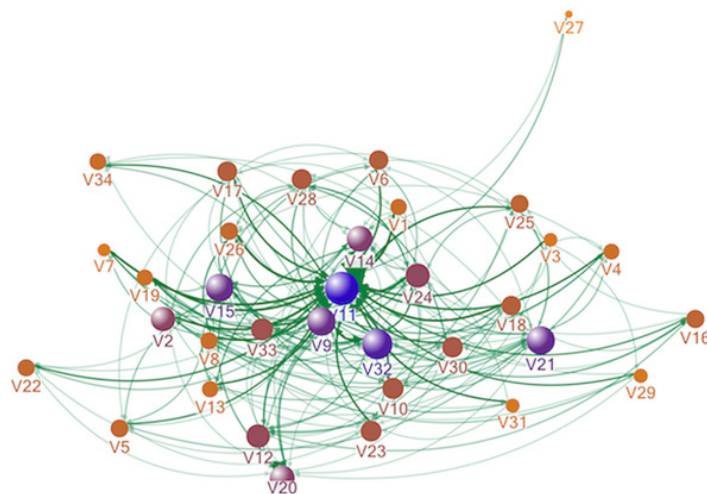


Figure 4: Eigenvector centrality based on the vertex color & size in the Harel-Koren Fast Multiscale layout. Note: The vertex color and shape represent the degree of eigenvector centrality. The blue-purple color and the spear shape represent higher eigenvector centrality.

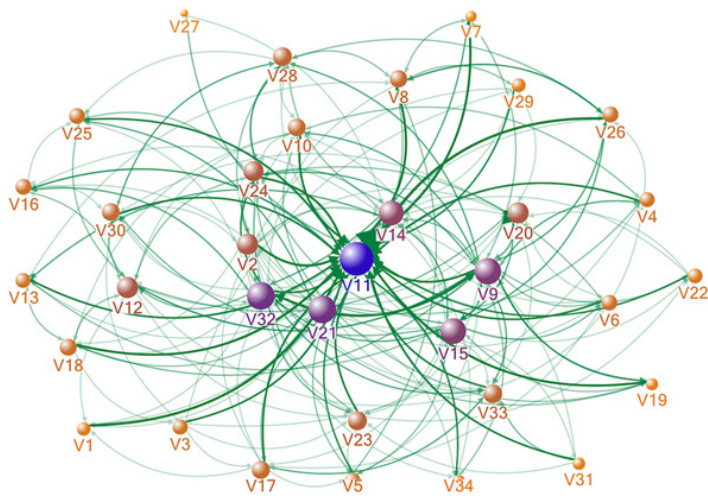


Figure 5: Vertex color-size and position based on PageRank centrality in the Fruchterman-Reingold layout. Note: the vertex color and shape represent the degree of PageRank. The blue-purple color and the spear shape represent higher PageRank.

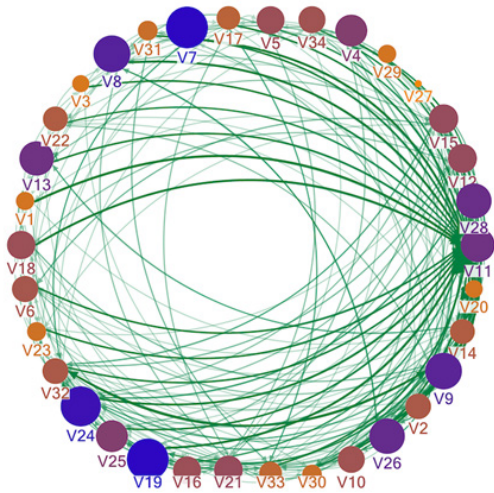


Figure 6: Vertex color-size and position based on Reciprocated Vertex Ratio in a circle layout. Note: the vertex color and shape represent the degree of eigenvector centrality. The blue-purple color and the spear shape represent higher eigenvector centrality.

The cross-cluster connections were examined further. More than one quarter of all outward (139, 28.54%) connections were conducted by Cluster 1 followed by Cluster 2's inward (109, 22.38) and outward connections (53, 10.88%) while the least was observed as Cluster 4 outward (25, 5.13%) connections (see Table 4).

Cluster 1 and 2 emerged as highly interconnected networks whereas Cluster 4 appeared as the lowest one (see Figure 7). Each cluster demonstrated distinguished and unique interconnectivity performances. Fashioning the same numbers of connections (edge = 172), both Cluster 1 and 2 manifested their connection preferences detected differently in cross-cluster inward and outward connections. In addition, Cluster 2 is distinct from Cluster 1 in liaison roles (size of the dots as betweenness centrality) that one participant dominated the inter-cluster information flow

Table 3: Global & cluster graph metric.

Metrics	Global Network	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Vertices	34*	12	10	7	5
Total edges	487	172	172	84	59
Reciprocated	.47	0.37	.67	.54	.14
Vertex Pair Ratio					
Reciprocated	.64	0.54	.80	.70	.25
Edge Ratio					
Maximum	2	2	2	2	2
Geodesic Distance (Diameter)					
Average	1.62	1.42	1.32	1.18	1.04
Geodesic Distance					
Graph Density	.24	.31	.44	.48	.40
Modularity	.12	-	-	-	-

*Thirty-three students and one instructor.

Table 4: Global cross-cluster direct (inward & outward) connections (total edges = 487).

Clusters	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cross-Cluster Inward Total
Cluster 1	123 (25.26%)	25 (5.13)	14 (2.87%)	10 (2.05)	49 (10.06)
Cluster 2	71 (14.58%)	63 (12.94%)	26 (5.34%)	12 (2.46%)	109 (22.38)
Cluster 3	38 (7.08%)	16 (3.29)	27 (5.54%)	3 (0.62%)	57 (11.70%)
Cluster 4	30 (6.16%)	12 (2.46%)	5 (1.03%)	12 (2.46%)	47 (9.65%)
Cross-Cluster Outward Total	139 (28.54%)	53 (10.88%)	45 (9.24%)	25 (5.13%)	487 (100%)

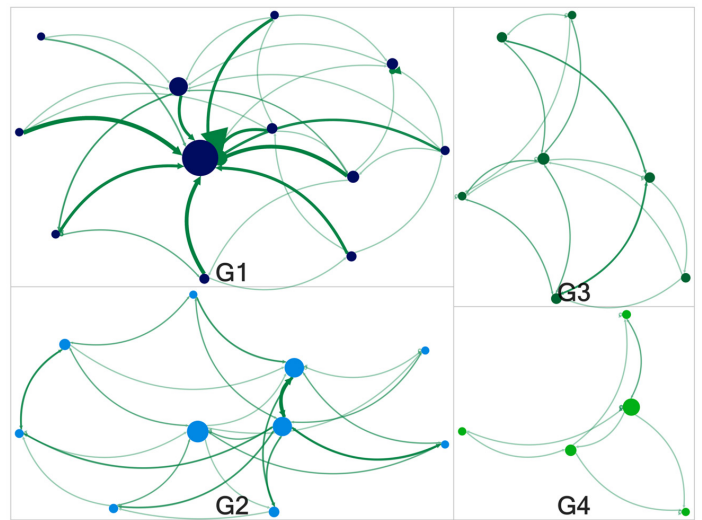


Figure 7: Four Clusters' internal interconnectivity with weighted edges. Note: G1: Cluster 1 & G2: Cluster 2. The size of the dots represents the strengths of betweenness. The color of the dots represents clusters. The width of the edges represents the degree of connections between two vertices.

while Cluster 2 depended on three participants, rather than falling one person. It should be noted that Cluster 3 and 4 lacked a dearth of liaison role to facilitate communication flows within the networks.

The further inquiry on the characteristics in internal cluster level elaborated unique insights. Figure 8 illustrated each cluster's interconnectivity preferences. Cluster 1 channeled almost three quarters (123, 71.51%) of its total connections

as internal which is the highest within all clusters that resulted in the lowest external connections (49, 28.49%). Contrarily, Cluster 2 devoted nearly two-thirds of its total connections toward external, Cluster 3 evidenced similar interconnectivity patterns. It is compelling to note that Cluster 4 appeared as the lowest in interconnectivity, but it tended to conduct the highest percentage (47, 79.66%) to connect with other clusters.

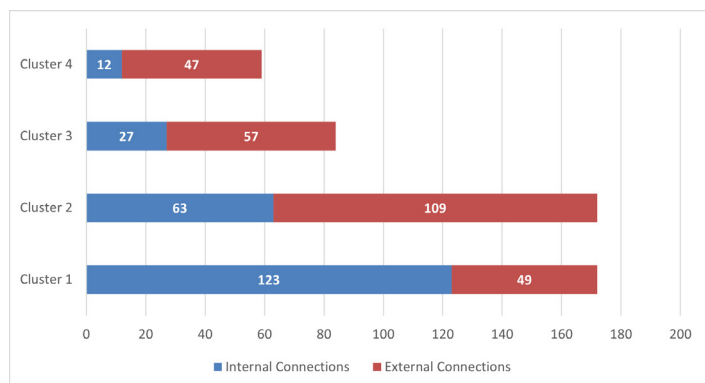


Figure 8: Cluster internal & external connections (total edges = 487).

Descriptive statistics of the research variables

The descriptive statistics of the research variables are listed in Table 5.

Table 5: Descriptive statistics of the research variables (N = 32).

Variable	<i>M</i>	<i>Min</i>	<i>SD</i>	<i>Min.</i>	<i>Max.</i>
Online social presence	133.50	137.50	19.50	98.00	168.00
Prominence in social network					
In-degree	8.44	8.00	6.00	.00	32.00
Out-degree	8.28	6.00	5.82	2.00	23.00
Betweenness centrality	23.39	7.66	49.65	.00	264.91
Closeness centrality	.02	.02	.003	.02	.03
Eigenvector centrality	.03	.03	.14	.008	.07
Reciprocated vertex pair ratio	.46	.41	.26	.00	1.00
PageRank	1.01	.85	.54	.30	2.81

Note: online social presence was measured with 24 questionnaire items on a 7-point Likert scale.

Linear regression analyses

All the relevant statistics from linear regression models with online social presence as the predictor variable are listed in Table 6.

In-degree as the criterion variable

The results supported social presence as a predictor for in-degree in an online social network, $F(1, 30) = 7.67$, $p < .05$, $R^2 = .20$. Also, the positive regression coefficient of social presence suggested a positive predictive relationship between social presence and in-degree. Therefore, students with higher social presence tended to have more in-degree connections in online social network. Namely, the participants with higher social presence would receive more in-bound connections from other participants. The size of R^2 suggested a predictive relationship of medium strength

Table 6: Seven simple regression models with online social presence as the predictor variable (N = 32).

Criterion variable	<i>F</i>	<i>df1</i>	<i>df2</i>	<i>R</i> ²	<i>B</i>
In-degree	7.67*	1	30	.20	.14
Out-degree	10.56*	1	30	.26	.15
Betweenness centrality	7.31*	1	30	.20	1.13
Closeness centrality	10.55*	1	30	.26	<.01
Eigenvector centrality	11.84*	1	30	.28	<.01
Reciprocated vertex pair ratio	.30	1	30	.01	<.01
PageRank	10.62*	1	30	.26	.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.
* $p < .05$

(Cohen, 1988) and a 20% of variance in in-degree accounted for by social presence.

Out-degree as the criterion variable

Social presence was found to be related to out-degree in online social network, $F(1, 30) = 10.56$, $p < .05$, $R^2 = .26$. In addition, the relationship between them was positive according to the positive regression coefficient of social presence. Accordingly, students with higher social presence were expected to have higher out-degree in online social network in comparison with the participants of lower social presence. The R^2 supported a strong relationship (Cohen, 1988) and a 26% of variance in out-degree accounted for by social presence.

Betweenness centrality as the criterion variable

The predictive utility of social presence for betweenness centrality in online social network was supported by the results, $F(1, 30) = 7.31$, $p < .05$, $R^2 = .20$. The positive regression coefficient of social presence also suggested a positive predictive relationship between social presence and betweenness centrality. As a result, students with higher social presence were predicted to have higher betweenness centrality in online social network relative to the ones with lower social presence. Namely, higher social presence would play stronger liaison or facilitator roles. The size of R^2 indicated a predictive relationship of medium strength (Cohen, 1988) and a 20% of variance betweenness centrality predictable by social presence.

Closeness centrality as the criterion variable

The predictive utility of social presence for closeness centrality in online social network was supported, $F(1, 30) = 10.55$, $p < .05$, $R^2 = .26$. The positive regression coefficient of social presence also suggested a positive predictive relationship between social presence and closeness centrality. As a result, students with higher social presence were more

likely to have higher closeness centrality in an online social network. The participants with higher social presence would play a stronger role as an information transmitter role. The R^2 supported a strong predictive relationship (Cohen, 1988) with 20% of variance in closeness centrality accounted for by social presence.

Eigenvector centrality as the criterion variable

The results supported a predictive relationship between social presence and eigenvector centrality in an online social network, $F(1, 30) = 11.84$, $p < .05$, $R^2 = .28$. Also, the above predictive relationship was positive. Therefore, the students with higher social presence would have higher eigenvector centrality in the online social network. Specifically, they were more likely to strategize their interconnectivity with more prominent or prestigious participants. The R^2 also suggested a strong predictive relationship (Cohen, 1988) with a 28% of variance in eigenvector centrality accounted for by social presence.

Reciprocated vertex pair ratio as the criterion variable

The predictive relationship between social presence reciprocated vertex pair ratio in online social network was not supported, $F(1, 30) = .30$, $p > .05$, $R^2 = .01$. The above finding was further corroborated by the negligible size of R^2 . Accordingly, the participants with higher social presence were not necessarily to engage in more two-way interconnectivity.

PageRank as the criterion variable

The predictive utility of social presence for PageRank in an online social network was supported by the results, $F(1, 30) = 10.62$, $p < .05$, $R^2 = .26$. Furthermore, the positive regression coefficient of social presence suggested a positive predictive relationship. So students with higher social presence were more likely to have PageRank in an online social network. Namely, the participants with higher social presence were more likely to play prestigious roles in the networks and to be perceived by others as influential figures in the networks. The R^2 suggested a strong predictive relationship (Cohen, 1988) with a 26% of variance in PageRank accounted for by social presence.

Discussions

The predictive utility of social presence for all social network interconnectivities was supported. Namely, social presence serves as a strong predictor for social interaction and interconnectivity. Learners with higher social presence more likely play distinguished roles of influential (in and out degrees centralities), liaison (betweenness centrality), transmitter (closeness centrality), social strategist or strategic connector (eigenvector centrality), and prestige with resources (PageRank) as an engaged and informed peer or a community of learners. They stress the quality of connections by interacting with others tactically in posting

and receiving more discussion responses, linking different networks, connecting with more diversified people, and relating with prominent and prestigious learners. Students who demonstrate higher social presence would forge their social interaction and interconnectivity to build stronger connected learning networks and learning communities. This points out the importance of competency of students' social presence if the learning community is critical of online instruction. The ability to prepare students with competent social presence depends on instructional capacity that would enable students to harness their ability of social interaction and interconnectivity. The findings of this study can be deduced from three areas: 'social catalysts' as community learners; 'active, interactive, and diversified connectors' imbued with a 'sense of community.'

Social catalysts: Community learners & community learning
The students with higher social presence are more likely to perform as social catalysts that drive the evolvement of learning community and community learning. They extend the effectiveness of their social learning transcend themselves. Predicated on the power of betweenness centrality, learners with higher social presence serve as liaisons, are located in strategic positions and actively facilitate information flows through the networks. They tend to situate in a central location to ensure the information flow between or among different networks. Students with higher social presence marshal their interconnectivities to connect all class community members and to ensure the networks and the community are well resourced. The effect of interlinking different networks would promote a better community building and sustaining. In fact, when liaisons or connectors missing in a community, it created a structural hole (Burt, 1995), a gap between or among networks. The students with higher social presence are crucial to fuse different networks to build and to sustain a healthy learning community.

Paradoxically, despite their altruistic role, students with higher social presence also have been perceived by other network learners as prestigious figures (PageRank) who post meaningful and informative messages and perceived as resourceful students by their peer; therefore, others, particularly the ones (social strategists with high eigenvector scores) tend to connect to them. These students with comparative advantages hold impacting power on the level of the socially constructed knowledge in networks. This suggests that they tend to believe learning 'from' the community is as effective as learning 'with' the community by facilitating learning networks, videlicet, they are a community of learners. Students leveraged with higher social presence would likely fuse and catalyze the learning resources from different learning groups and networks that they receive and transform themselves into more innovative learners. Burt (2004) explained this phenomenon as "opinion and behavior are more homogenous within than between groups, so people connected across groups are more familiar with alternative ways of thinking and behaving..." (p. 349–50). In other words, to become better-resourced learners, these students shifted their thinking and behaviors from interaction to diversified and crossed groups and network interconnectivity.

Active, interactive, and diversified connectors

The higher social presence learners show a propensity of actively, and interactively interconnecting with more diversified network learners. They unify others and warrant that learning resources flow effectively and efficiently (closeness centrality). Learners with higher social presence are a community of learners who are aware of one another, and converse, communicate and interact actively, interactively, and strategically. In addition, they tended to be senders and receivers in responding to others more (out-degree) and received more postings (in-degree), but it's not necessarily a two-way interaction with the same people they responded to (reciprocated vertex pair ratio).

Furthermore, higher social presence can predict eigenvector centrality that concerns the quality of connections. These learners, as social interaction strategists or strategic connectors (eigenvector centrality), tend to discern to connect with more prestigious (PageRank) learners. To them, it's critical to establish relationships with prestigious people who will provide greater access to learning resources. They acquire strategic roles that strengthen networks and support network interactions through social dynamics.

Community sense

Students with higher social presence carry a broader sense of a learning community that is not necessary to be grounded in one-to-one interaction but rather in intricate many-to-many interactions and connections. This could be reflected in social presence and couldn't serve as a predictor for reciprocated vertex pair ratio that denote a ratio of mutual communication. The students made nearly half of interaction as two ways, while reciprocated vertex pair ratio and reciprocated edge ratio are .47 and .64. It should be noted that the Cluster/Network 2, a highly interconnected one with light blue circles in Figure 1, showed their reciprocated pair ratio and reciprocated edge ration as .67 and .80. Despite their highly interconnected nature, they did not reach an extremely high pair ratio (1.00). They underline the effective interactions as many-to-many interconnection which facilitates more organic network and community building ensuring that networks and community grow with all learners and all learners benefit from such beneficent social acts of camaraderie.

Implications

This study evinced that social learning analytics are attainable to understand imperceptible students' social interconnectivity in online learning networks and community. Previous research has accomplished diagonalizing what happened in online discussion activities. This study concluded online social presence is a strong predictor to detect students' social interconnective roles in an online discussion activity. Before online discussion activities proceed, instructors could survey and measure students' competency on social presence and foresee their possible social interconnective behaviors. The findings from this study would support online instructors to facilitate, to guide, to help their students to navigate

through the convoluted social interconnectivity effectively and continuously, particularly just-in-time personalized supports that would facilitate individual student's rapid social interconnectivity progress while they monitor the discussion activity. Such power would lead to increased learning efficiency, effectiveness and better learning outcomes.

Limitation

The limitation of this study is that interaction data were obtained from online discussions. It does not include other digital communication, such as emails, real-time messages, and any other backchannel postings. Furthermore, the online discussion activities were required, graded, and instructor-led. The instructor facilitated the discussion on a regular basis to reflect the uniqueness of online instructional design and teaching.

Future studies

Future studies could fruitfully explore the development and the evolvement of learning networks and communities and how online social presence may moderate these evolvments over time. Such longitudinal studies could offer researchers further systematic inquiries on how students' social presence may facilitate online learning networks and communities may initiate, develop, sustain, or diminish throughout the entire instructional communication period. Obtaining these facts could serve as critical information for instructors to provide more effective and just-in-time support to each individual and community. In addition, future research should evaluate the potential effects of inter-social roles since humans play multiple social roles in a social learning context. Advantageous research questions for future research that can be derived from how cross-referenced social roles may be observed by students' online social presence? Moreover, future research should examine and cross-examine other predictor variables; e.g. cognitive presence, teaching presence, and different social network interactions, social network sites, and collaboration.

Conclusions

Online social interaction and interconnectivity are too complicated for any human to keenly detect due to their dynamic nature. This study noted the importance of social presence and its predictive power on social network interaction. The results would assist educators to develop a model to provide personalized guidance and support learners to navigate through digital network interaction. With these valuable data in hand, while real-time social network interaction data is collected, just-in-time personalization guidance of discussion activities could be delivered at any given point for learning adjustment and improvement. From a social learning analytic perspective, this knowledge and these skills in designing and delivering online discussion activities pave a new direction for educators in learning engineering and data-driven instructional design and teaching. Instructional designers and teachers should secure competent knowledge and skills in data-driven

decision making to address the dynamic and intricate human interactions and interconnectivity. This knowledge would permit educators to obtain better skills to benefit students in building a sustainable learning community. More specifically, online learning would no longer be a friendless endeavor. The impacts of COVID-19 on online, or remote learning will continually motivate educators to ask broader questions of the quality of social interconnectivity becoming part of contentious discussions.

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