Analyzing the Role of Group Interactions in Deep Learning: Connectivity Patterns and Self-Regulated Learning in University Discussion Forums

Masami Yoshida [1], Anuchai Theeraroungchaisri [2]

[1] *Thailand Cyber University Project, The Ministry of Higher Education, Science, Research and Innovation, Thailand, 328 Si Ayutthaya Road Bangkok 10400, Thailand*
[2]*Faculty of Pharmaceutical Sciences, Chulalongkorn University, Thailand, 254 Phayathai Road, Patumwan District, Bangkok 10330, Thailand*

Abstract **– As online education continues to gain popularity, it is crucial to analyze the role of group interactions in facilitating individual deep learning. This study explored the connection structure of online discussion forum messages shared by university students. To elucidate the interrelationship between intrapersonal and interpersonal forms of learning in an online environment, messages were classified according to behavioral indicators, elements of self-regulated learning, and types of threshold concepts. To this end, exponential random graph models were employed to reveal the connectivity patterns. A total of 24 messages containing threshold concepts were identified. Notably, these threshold concepts were closely associated with self-reflection in the context of self-regulated learning. Homophily in connections was evident in the metrics pertaining to message content. Messages containing threshold concepts were distributed throughout the community without any noticeable clustering. The diversity of information available within the community highlights the students' propensity to access personally meaningful information. The community structure did not include an aggregated connection, which is reminiscent of the structure of social networking services. In contrast, the network exhibited a paired-connection structure that was highly conducive to explaining connections to academic content, thereby reinforcing conceptual transformations.**

Keywords **– Discussion forum, exponential random graph models, global education, self-regulated learning, threshold concept.**

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Corresponding author: Masami Yoshida,
Thailand Cyber University Project, The Ministry of Higher Education, Science, Research and Innovation, Thailand, 328 Si Ayutthaya Road Bangkok 10400, Thailand
Email: yoshida@thaicyberu.go.th

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1. Introduction

The proliferation of the Internet and the rapid progress of technology have rendered online learning a significant aspect of higher education, particularly in the aftermath of the COVID-19 pandemic [1]. However, as merely distributing information via an online system cannot guarantee satisfactory learning outcomes, educators must establish scholarly discussion environments that facilitate students' conceptual development [2]. In this context, asynchronous online discussion forums are considered especially beneficial in helping students overcome the absence of real-time dialogue. They foster the exchange of ideas without time constraints, providing students with sufficient time to reflect and elaborate on their thoughts [3]. Notably, a discussion forum provides a learning environment in which students can experience self-regulated learning (SRL) and engage interactively [4]. It is necessary to elucidate the substantive content of academic exchanges to ensure that they transcend mere participation.

When examining interactive learning, it is also essential to discern concepts and capabilities that will have a critical influence on future knowledge and practice [5]. Describing the processes by which students acquire deep academic knowledge is becoming increasingly important in higher education [6]. One established approach involves threshold concepts. This approach makes it possible to explore transformations in conceptual understanding and how they shape the knowledge acquisition [7]. One distinctive attribute of threshold concepts is that they enable students to comprehend specific phenomena within the domain under discussion [8]. Because acquiring threshold concepts is arduous and poses challenges for students, it is crucial to ensure that they have continuous access to learning materials. Online environments provide this accessibility [9].

In this manner, online scholarly communication offers the opportunity to transform individuals' conceptual understanding in accordance with the principles of SRL. To clarify the relationship between intrapersonal and interpersonal forms of learning in the online environment, this study adopts the following two pivotal perspectives.

1.1. Self-Regulated Learning in Online Discussions

Earlier researches have indicated that the online learning environment is recognized as a tool for scaffolding in support of SRL when learners can manage the learning process effectively [4], [10]. SRL involves the systematic process of setting learning goals, monitoring progress, and employing appropriate study strategies [11]. Another study has observed that students who demonstrate proficient SRL skills tend to achieve higher academic outcomes compared to those who struggle with self-regulation [12]. Self-regulation is strongly associated with academic satisfaction: students who can self-regulate effectively report higher levels of contentment in their academic pursuits [13]. Research has also revealed that students who are able to self-regulate their learning are more inclined to seek assistance when required [14]. Additionally, studies have demonstrated that using technology to enhance SRL can improve students' ability to learn from online sources [15].

These findings imply that providing students with asynchronous online discussions and the resources essential for effective SRL can help them achieve better academic results. Notably, these competencies are particularly salient in the context of online learning, where students must manage their own learning without direct support from teachers [12], [16]. Table 1 depicts the codes that represent the SRL processes that manifest in the online learning process [17].

These SRL processes are effective in promoting deep learning and transforming students' conceptual understanding, which is necessary to achieve threshold concepts [18].

Table 1. SRL processes

Code	Process	Definition
GOAL	Goal setting	Online learning allows learners to set educational goals or sub-goals and exert the effort necessary to achieve them.
MONIT	Monitoring	Online learning allows learners to engage in metacognitive monitoring of their learning processes, which includes following up on their learning goals.
SELFE	Self-evaluation Help-seeking	Online learning allows learners to initiate evaluations of the quality and progress of their work. Online learning allows learners to ask other people (e.g., instructors or peers) for help or consult external resources.
ORGN	Organization	Online learning allows learners to initiate the overt or covert rearrangement of instructional materials (e.g., by taking notes or highlighting to identify key ideas).
STRAP	Strategic planning	Online learning allows learners to plan the sequence, time, and completion of activities related to their goals.
TIMEM	Time management	Online learning allows learners to allocate time to studying and other activities, make decisions, and form intentions about the effort they must exert.
SELFR	Self-reflection	Online learning allows learners to compare their performance to a standard (e.g., past performance, others' performance, or an absolute standard).

1.2. Threshold Concepts in Scholarly Discussions

The notion of the "threshold concept" emerged within the process of the UK's National Research Project on the Teaching and Learning Environment of University Students [19]. A threshold concept is always transformative: it changes one's understanding or interpretation of a topic. It is "akin to passing through a portal" or "conceptual gateway" that permits "thinking about something that was previously inaccessible" [20]. Threshold concepts can change students' understanding of possibilities, ideas, phenomena, concepts, or processes [21].

One essential consequence of comprehending a threshold concept is that one's perception of a subject shifts from complicated, obscure, and intimidating to open, accessible, and rewarding [22]. It is a sudden and drastic conceptual transformation that occurs in a student during a learning activity. The transformation involves epistemological nuances and ontological shifts of viewpoint, which elicit a student's conceptual development [23], [24]. Threshold concepts are a form of progress in one's learning, as they are gateways to understanding the critical content of a discipline [25].

Previous studies have reported on the effects of acquiring threshold concepts through communication [26], [27], [28], [29]. The online learning mode involves the exchange of information, which can cause a learner's concepts to change or evolve [3].

As a criterion for evaluation, Kiley and Wisker proposed the existence of various types of threshold concepts that emerge in scholarly discussion [30]. The framework denotes how learners attain a qualitatively different view of themselves or the relevant domain. Wisker further explained that writing a good literature review requires the crossing of a conceptual threshold, as it demonstrates the interpretation of theoretical perspectives in the domain. This interpretation implies the possibility of extracting threshold concepts from students' scholarly reports. Subsequently, six types of threshold concepts were proposed, addressing developmental trajectories of research concepts and skills (Table 2) [31].

Table 2. Types of threshold concepts [31]

Code	Type	Desirable competency	Important concept
TC1	Argument	Building a logical, cohesive scholarly argument	Framing an argument about a world issue
TC2	Theorizing	Recognizing when to bring theory into the study	Developing a theoretical framework
TC3	Framework	Gaining critical value from the material of a study	Data and materials review
TC4	Knowledge creation	Progressing from description to analysis	Competency in data collection
TC5	Analysis and interpretation	Credible, evidence-based analysis and interpretation	Analysis
TC6	Research paradigm	Contributing trustworthy high-quality research	Writing, characteristics, integrity and ethics

This paper uses this framework to comprehend the structure of the online learning environment and the academic community.

1.3. Methodological Framework: Exponential Random Graph Models (ERGMs)

The statistical analysis of networks should not be conducted using conventional approaches such as linear models [32]. Social network analysis represents a suitable methodology, with its most salient principle being that it enables researchers to see how "actors are located or 'embedded' in the overall network." This methodology facilitates the analysis of relationships between individuals, groups, teams, cliques, agencies, and organizations [33]. Discussion forums with threads are also directed towards exploration [34], [35]. Furthermore, perceiving these online learning interactions either as an artifact of the learning process or a product of learning can help identify how they should be examined [36]. It is imperative to meticulously examine students' interactions carefully to understand whether—and to what extent—learning is occurring.

The Hammersley-Clifford theorem provides the joint probability density function that must be assumed by a Markov random field, in which any network model can be expressed within the exponential family encompassing the counts of graph statistics [37]. One tool based on this feature is the exponential random graph model (ERGM), a statistical model used for social network analysis that can elucidate the underlying mechanisms of structure production [38]. ERGMs enable one to assess how various properties of an observed network are associated with the probability of its occurrence [39]. ERGMs are popular among social scientists who seek to test hypotheses about networks [40]. Significantly, they are not simply a class of statistical models, but also a set of theoretical assumptions about social network structures; hence, they allow researchers to analyze network data in a robust, theoretically justified way [41]. ERGMs summarize the measure of network statistics of social graphs using the formula (1).

$$P_\theta(G) = ce^{\theta_1 z_1(G)+\theta_2 z_2(G)+\cdots+\theta_p z_p(G)} \quad (1)$$

The probability P of network G is computed within the range of 0–1. It represents the summation of the network statistics (represented as z in this expression), which are weighted appropriately using regression techniques by means of model parameters (θ) enclosed in an exponential function. Here, the constant c serves as a normalizing constant [42].

Each $\theta_i Z_i$ *(G)* is referred to as a "term," representing a single network statistic that contributes to the model. Each term adds one network statistic to the model.

ERGMs encompass an intricate arrangement of terms specifically designed to capture the social and structural processes relevant to social scientists, including social closure, connectivity, and other affiliation preferences. This allows ERGMs to exhibit the flexibility required for testing complex hypotheses within a multivariate framework [43].

Analysis was conducted utilizing the "ergm," "statnet," "ggnetwork," and "stargazer" packages for R (ver. 4.3.2; R Foundation).

1.4. Research Questions

This study examined university students who were engaged in message-sharing activities on an online discussion forum. The following four research questions were posed:

RQ1 How do SRL codes and threshold concepts appear in online communities?

RQ2 What are the remarkable structures of the community and how do they relate to threshold concepts?

RQ3 What distinguishes the structural characteristics of this scholarly community from those of a social networking site (SNS) community?

RQ4 What is the notable form in which threshold concepts are established within the community?

2. Materials and Methods

The dataset for this study was obtained from a Moodle discussion forum where university students engaged in knowledge exchange about world issues associated with the sustainable development goals. The course was exclusively presented online as an instance of emergency remote teaching during the COVID-19 pandemic. The Moodle virtual platform allowed students to communicate with their peers seamlessly and offered functionalities such as mobile accessibility and automated notifications for incoming responses.

For this study, a particular session was selected that required students to examine the macroeconomic conditions of a foreign country. During this session, 146 first-year undergraduate students from the faculties of literature, engineering, and nursing actively participated in a week-long online discussion spanning from April 19 to April 26, 2022. The discussion revolved around the assignment answers they submitted and their subsequent replies.

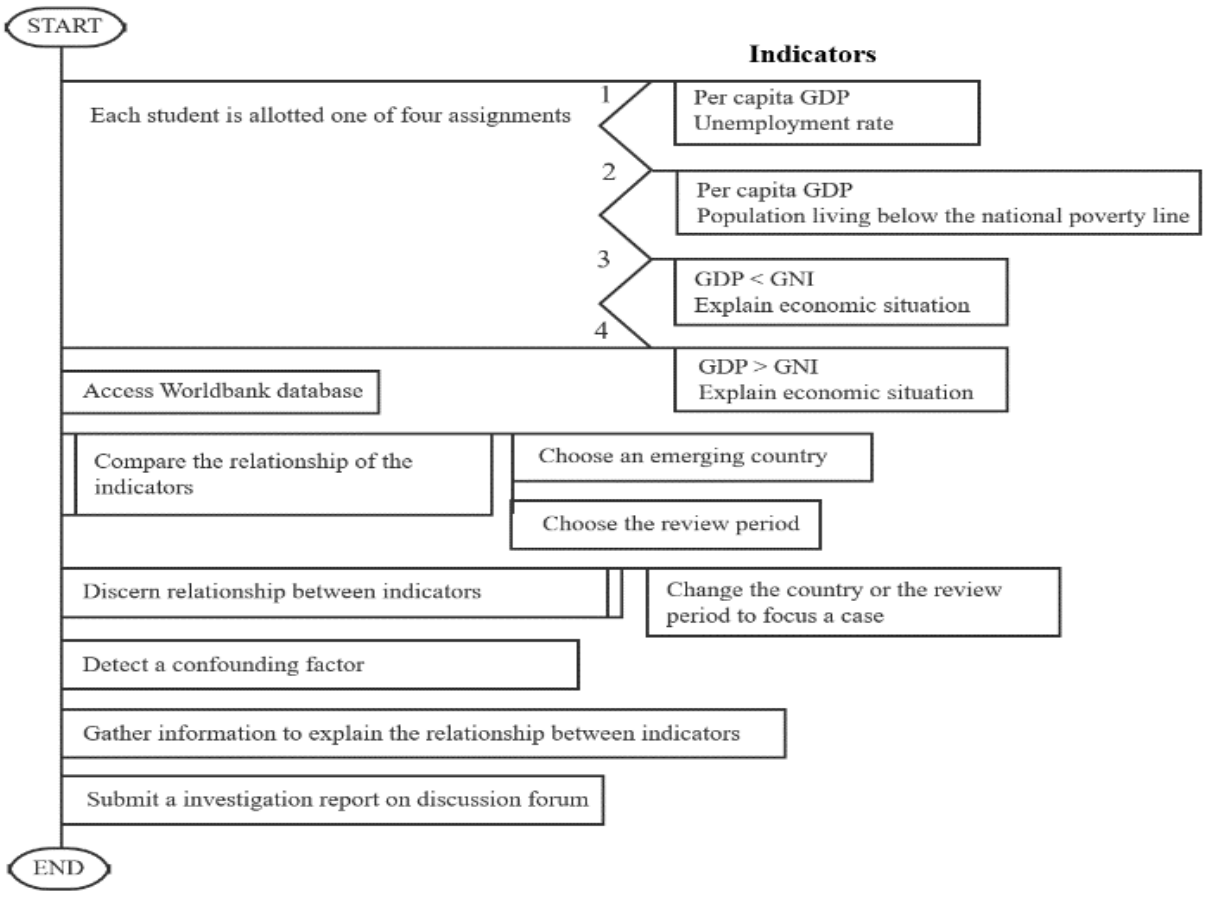

Figure 1. Problem analysis diagram showing the online learning flow

Each student was assigned following one of the four research tasks.

1. Select an emerging country. Compare the temporal shifts in its per capita GDP and unemployment rate. Investigate and explain the characteristics of that country's economic situation.
2. Select an emerging country. Compare the temporal shifts in its per capita GDP and the proportion of the population living below the national poverty line. Investigate and explain the characteristics of that country's economic situation.
3. Select an emerging country with a per capita GDP less than its GNI. Compare the temporal shifts in both. Investigate and explain the characteristics of that country's economic situation.
4. Select an emerging country with a per capita GDP larger than its GNI. Compare the temporal shifts in both. Investigate and explain the characteristics of that country's economic situation.

They were asked to explore a confounding factor and elucidate the differences between two global indicators sourced from the World Bank database. As this investigation was conducted during the first session of new students' first semester courses, it was not necessary to consider the influence of interpersonal relationships or knowledge from previous courses.

Given that exploring world issues presented a novel experience for these students, the assignments were meticulously designed to expose them to counterintuitive statistical phenomena and introduce unfamiliar aspects of foreign nations.

This instructional approach has been recognized as a thought-provoking strategy to engender engagement with threshold concepts [44]. Furthermore, acquiring the proficiency to identify confounding factors related to global indicators is reportedly a suitable challenging task for students to introduce them into deep learning [45]. The flow of online learning employed in this study is illustrated in Figure 1.

To process the analysis, the message records were collected, encoded, and classified in terms of the following metrics. Metric names and data types are presented in parentheses.

Concerning message content, the following four metrics were employed to assess the messages: item number of assignment (ITEM: categorical), country chosen by the student (COUNTRY: categorical), number of years covered by the survey (PERIOD: numerical), and the confounding factor between indicators (CONF: categorical).

Regarding the message attribute, the following eleven metrics were employed to measure messages: references (LINK: numerical), figures (FIG: numerical), characters (CHARA: numerical), SRL codes (GOAL, MONIT, SELFE, ORGN, STRAP, TIMEM, and SELFR: numerical), and threshold concepts (TC: numerical).

3. Results

The compiled dataset was introduced to analyze the metrics and examine their relationships with threshold concepts. A total of 367 messages from 146 students emerged from the discussion forum. Table 3 presents the numerical metrics of students.

Table 3. Numerical metrics – results

	PERIOD	**LINK**	**FIG**	**CHARA**	**GOAL**	**MONIT**	**SELFE**	**ORGN**	**SELFR**	**TC**
M	20.3	3.73	2.51	983	0.04	0.25	0.20	0.17	0.97	0.16
SD	4.15	1.58	1.10	397	0.23	0.56	0.46	0.43	0.88	0.40

After analyzing the correlations among all of the pairs of metrics and conducting a non-correlation test, the metric CHARA showed a significant association with several other metrics: LINK($r(144) = .601$, $p < .01$), FIG($r(144) = .292$, $p < .01$), GOAL ($r(144) = .279$, $p < .001$), MONIT ($r(144) = .409$, $p < .001$), ORGN ($r(144) = .343$, $p < .001$), and SELFR ($r(144) = .361$, $p < .001$). An increase in the number of characters used in a post coincided with a rise in qualities such as links, diagrams, and SRL codes. The community exchanges exhibited an aptitude for concentrating on scholarly discourse.

However, it is worth mentioning that the number of characters showed no correlation with SELFE or TC.

3.1. Analysis of Metrics for Messages

A total of 24 messages from 23 students pertained to threshold concepts. There were 238 occurrences of SRL codes. STRAP, TIMEM, and TCs 4-6 were not detected. Consequently, the difficulty of achieving threshold concepts was apparent.

After score normalization, a one-way ANOVA was employed, revealing a statistically significant difference in the mean scores of the metrics, $F(8, 1305) = 76.62$, $p < .01$. The post-hoc test (Tukey) indicated that TC had a significantly distinct mean score from all of the other assignment-related metrics.

Conversely, correlation analysis demonstrated that TC only exhibited a positive correlation with SELFR, $r(144) = .288$, $p < .001$.

A known principle, posited by Timmermans and Meyer, elucidates this correlation: encouraging reflective practice imbues threshold concepts into lessons [46].

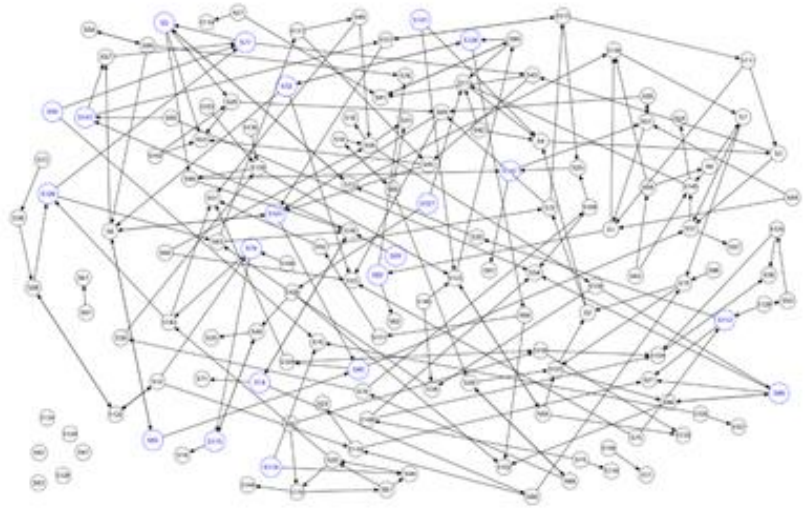

Figure 2. Social graph of the emergent community
Note. Larger nodes indicate students demonstrating threshold concepts

With regard to the categorical data, a total of 62 countries and 48 confounding factors were observed, demonstrating the diversity of the posts. The categorical data exhibited no relationships with the acquisition of threshold concepts.

These findings imply that acquiring threshold concepts occurs from scrutinizing others' messages and assessing their performance, irrespective of the content of one's own answers.

Table 4. Four models for positive relationships based on the ERGM results

	Dependent variable: Parameter estimate value (Parameter standard error)			
Terms	**Model 1**	**Model 2**	**Model 3**	**Model 4**
edges	-4.645***	-5.972***	-6.061***	-5.985***
Messages	(0.080)	(0.256)	(0.259)	(0.030)
nodecov.TC	0.226**	0.181*	0.098*	0.091*
Number of threshold concepts	(0.108)	(0.101)	(0.073)	(0.065)
nodematch.COUNTRY		1.586***	1.555***	1.285***
Same country		(0.232)	(0.233)	(0.187)
nodematch.ITEM		0.651***	0.631***	0.556***
Same assignment		(0.138)	(0.138)	(0.122)
nodecov.CHARA		0.001***	0.0004***	0.0003***
Number of message characters		(0.0001)	(0.0001)	(0.0001)
nodecov.SELFR			0.185***	0.162***
Number of self-reflection			(0.059)	(0.055)
mutual				2.620***
Reciprocal messages				(0.058)

Note. * p < *.1;* ** p < *.05;* *** p < *.01*

3.2. Analysis of Connections and Community Structure

Social Network Analysis (SNA) was employed to examine the connections among students more comprehensively. All of the message connections gathered were converted into nodes (representing students) and edges (representing messages). NodeXL Pro (version 1.0.1.511; Social Media Research Foundation), an SNA toolkit, was utilized to compute the metrics and generate a social graph (Figure 2).

Of the SNA metrics (e.g., betweenness centrality, closeness centrality, eigenvector centrality, page rank centrality, and cluster coefficient), only betweenness centrality exhibited a noteworthy correlation with TC, $r(144) = .284$, $p < .01$. This finding implies that students demonstrating threshold concepts were positioned along paths of vibrant information transmission. Students who posted message with threshold concepts were distributed throughout the community.

3.3. Exponential Random Graph Models (ERGMs)

The salient message connections were extracted using ERGMs, involving metrics as the determinants of establishing connections. Table 4 presents the selective mixing coefficients for four models including the statistically significant terms identified in this study. The parameter estimate value is the logarithmic odds of increasing the number of edges by one. A positive estimation value means that the probability of an edge between nodes increases when the number of terms changes by 1.

These four distinct models displayed the intricate architecture of the reciprocal connections, along with the terms pertaining to the content of the answers and SRL processes. Figure 3 visually depicts the interconnections of the ERGM terms employed in this scholarly investigation.

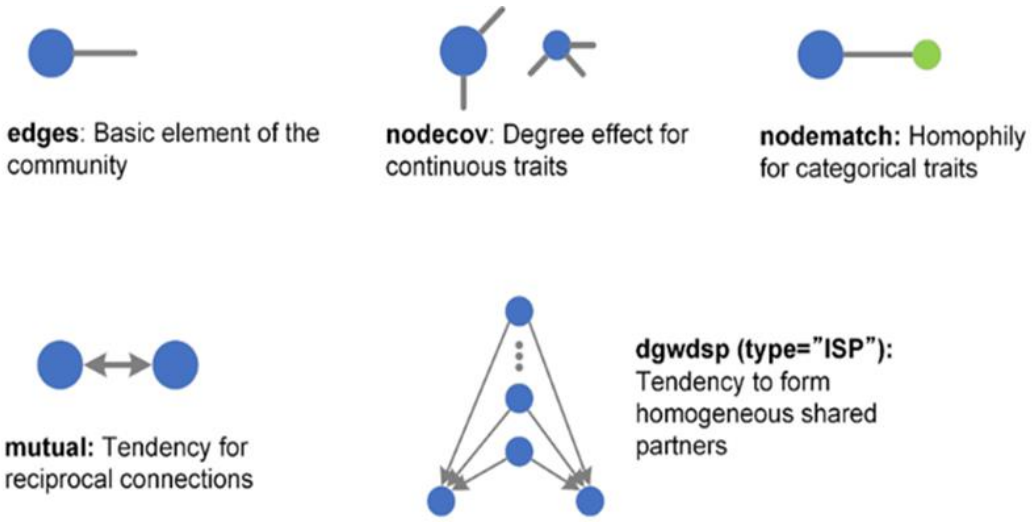

Figure 3. Diagrammatic guide to key terms used in this study

Model 1 is the baseline for the series of analyzes. The term "nodecov" denotes that students with higher scores for a continuous variable displayed a tendency to nominate more connections. The term "nodecov.TC" calculates propensity based on students' messages with threshold concepts in the discussion forum. The connection probability of Model 1 is calculated as 1.19%, indicating the difficulty of acquiring the threshold concepts in the community.

In Model 2, the term "nodecov.CHARA" represents the propensity to make connections with posts that contain long text messages.

Additionally, the dyadic covariate terms analyze the impact of node relationships on connectedness.

The term "nodematch" refers to the propensity of students to nominate connections with peers who share a particular attribute. A developed and cohesive professional network of collaboration is often characterized as measured by homophily [47]. The terms of "nodematch.COUNTRY" and "nodematch.ITEM" denote the homophily in message content. In Models 2 and 3, the highest dependent variable scores are observed for homophily in a same country that is discussed in the messages. Thus, the messages in the community were focused on echoes of course content, and this supports a previous study in which students preferred content-focused digital sources [48].

Model 3 incorporates the term “nodecov.SELFR” to detect messages with self-reflection. The connection probability of Model 3 is calculated as 2.68%, indicating the propensity of connections pertaining to self-reflection within the community. Students had a triggering experience to acquire threshold concepts and then compared it with previous concept through online activities. This finding is in line with an earlier study, in which students who were given continuous point-of-need access to online resources acquired threshold concepts for organizing information and then gained different understandings [9].

Model 4 has two structural covariates. The structural covariates define the dependency structure used within the model to elucidate how the presence or absence of edges affects nearby edges. The first is a measure of “edge” density, which appears in all models and is mandatory for every ERGM estimate.

The second term, “mutual,” measures the likelihood of reciprocal ties, involving mutual exchange or interaction.

The positive and significant effects indicate existence of more mutual connections in this network than what one would expect from a random graph with 367 edges. Since “mutual” has a higher score, the probability of a connection is 21.9%, and the log odds of the connection increased by 1,841 times from Model 1 to Model 4. This proves a higher likelihood of paired connections in this community.

4. Discussion

RQ1 How do SRL codes and threshold concepts appear in online communities?

Threshold concepts were observed to have a significant propensity for emergence according to the analysis of the ERGMs (Table 4, Model 1). Four SRL codes appeared more frequently than threshold concepts (TC), as indicated in Table 3. Particularly noteworthy is self-reflection (SELFR), which exhibited the highest frequency among the SLR codes and had a significant correlation with threshold concepts (TC). An earlier study indicated this emergence of threshold concepts that was an individual outcome related to cognitive and motivational features of learning, such as being proactive and reflective about self-monitoring [49].

Furthermore, it is noteworthy that both threshold concepts (TC) and the SRL codes were more prevalent in the replies (TC: 100%, SRL codes: 94%) than in the assignment answers. Although perceived as individual competencies, they were predominantly manifested in distributed paired messages within the community. Also, this community has propensity that make it easy to create paired connections, shown in the high score of "mutual" (Table 4, Model 4).

To illustrate how conceptual transformation occurred through communication, a message was selected and an excerpt was provided as an example:

> Reply from S127 to S17, discussing Brunei, translated by the authors:
> I conducted an in-depth investigation and gave a comprehensive account of India. However, I did not discern any monocultural economic facets. Prior to reading your post, I held the notion that all nations would face the same impact from COVID-19. Nevertheless, your report enlightened me to the fact that Brunei's GDP is experiencing growth. As you expound, I could not have predicted that countries with robust monocultural economies would encounter fewer ramifications from COVID-19. Consequently, I am inclined to modify my perceptions henceforth, recognizing that not all countries have been affected by the pandemic equally.

A learner in a state of liminality undergoes a subjective shift, whether it be discursive, conceptual, ontological, or epistemological in nature [29], [50]. The student (S127) employed the theoretical lens of threshold concepts to derive the notion of monoculture. The cognitive process at this juncture was associated with prior research, confirming that discerning an entity from its context entails identifying it as a distinct “something” and attributing meaning to it [51]. Consequently, in this learning community, self-reflection (SELFR) surfaced and established a connection with communication. The occurrence of threshold concepts instigated profound learning experiences. These outcomes align with previous findings that threshold concepts are accompanied by a transformative shift in cognitive comprehension within the community [52].

RQ2 What are the remarkable structures of the community and how do they relate to threshold concepts?

During the analysis of the ERGMs, numerous terms were examined. Metrics pertaining to the assignments, threshold concepts (TC), and self-reflection (SELFR) were thoroughly scrutinized. They were associated with the country and item number of the assignment answers. Some examples demonstrating homophily in message content are shown in the following replies:

> Message from S28 to S16, discussing Indonesia, translated by the authors:
> I also reported on Indonesia, but it never occurred to me to explore the economy from the perspective of the declining birth rate and health system, thus expanding my horizons …

> Message from S65 to S8, discussing Turkey, translated by the authors:
> I researched the same country with the same item number, but I did not consider the topic of refugees at all so it was helpful. I mentioned the Gini coefficient, but since I did not investigate why it was rising, I have come to think that it might have something to do with the acceptance of refugees …

The collaborative relationships tend to be reciprocated, involving mutual exchanges or interaction. The community is proved to abound mutual connections in Model 4, and this finding adds to the fact that students pursued their scholarly interests in making connections within the community. On the other hand, nodes associated with threshold concepts were not involved in any cluster; rather, threshold concepts were distributed throughout the community.

These nodes were wired within the community and located in advantageous positions for accessing information.

RQ3 What distinguishes the structural characteristics of this scholarly community from those of a social networking site (SNS) community?

A prior investigation disclosed that 12.1% of Tweets from 113 users engaged with threshold concepts in a scholarly community on X (former Twitter) [53]. This study found that there were fewer messages related to threshold concepts. Considering the different environments, messages on X—even during academic exchanges—are characterized by their brevity and casualness. It was easier for students to express their experiences on X and thus acquire threshold concepts. Furthermore, numerous tweets of students responding to each other's threshold concepts.

On the other hand, the discussion forum in this study had fewer posts because a great amount of information is conveyed in each. However, the analysis of the ERGMs yielded noteworthy results, as "mutual" received the highest estimate value, suggesting that the community fostered reciprocal connections rather than serving solely as a platform for information acquisition by individuals (Table 4, Model 4). Despite the presence of mutuality, the term "triangle" denoting connected three nodes was not significantly present (*Estimate* = .435, $p > .1$) like it is in SNS communities [54], [55]. This triadic closure typically refers to the degree of closely connected clusters [56]. This suggests the absence of intimate clusters within the community. In contrast, the term "dgwdsp type = ISP" was found to be significantly present (*Estimate* = -0.266, $p < .01$), indicating that different students had access to the same students (Figure 3).

This is a noted structure of discussions focused on scholarly interests.

RQ4: What is the notable form in which threshold concepts are established within the community?

Whereas the non-comprehensive nature of the connections related to threshold concepts, it is evident that students had similar academic and informational interests. Actually, homophily was observed concerning the metrics associated with assignment answers (Table 4, Model 2). This finding can account for why only self-reflection (SELFR), among the various SRL codes, had a high propensity score (Table 4, Model 3). In other words, a learning strategy that promotes self-reflection based on the information of others can lead to the achievement of threshold concepts.

The following message illustrates a concrete case of how threshold concepts were established in the community:

> Message from S77 to S43, discussing Cyprus, translated by the authors:
> I was aware that Japan and China have corporate factories in Southeast Asian countries, but I had never encountered the information that more and more companies were establishing bases on the small island of Cyprus. It was found that they do not refuse to set up a base simply because of the difficulty of transporting goods to and from an island country, but take the safety and language of the land into consideration …

Writing assignments that ask students to summarize a complicated process in their own words may certainly inform about students' understanding [57]. Similarly, responding to an assignment answer, in which information about the change or transformation of the student includes subjective sentences. Using the online discussion forum to exchange comments, learners articulated threshold concepts and self-reflection in a natural manner. The target course involved the preparation and participation within a formal discussion and includes the design of assignment that allowed students to showcase in the shared knowledge of individual answers and replies, using the discipline-specific epistemes to explore concept.

5. Conclusion

This study analyzed connection data from messages in an online forum to examine students' deep learning. Social network analysis and ERGMs were used to elucidate the connection structure and the intricate nature of the learning community, including reciprocating connections, activity spread, and homophily.

The messages demonstrated how the self-reflection process and threshold concepts worked together within the community, facilitating higher-order learning. Information diversification within the community allowed students to encounter information that they personally regarded as important. The catalysts for acquiring the threshold concept were the comprehensive peer reports. Although self-regulated learning and threshold concepts are individual competencies, they manifest in paired interactions within the community. Students who expressed threshold concepts proceeded to develop paired communication to enhance their understanding. These paired students' interactions created an audience and presence within the community.

Moreover, overall community prioritized scholarly interests in their messages, leading to information diversification and focus on the scholarly content. This enhanced their reflection through mutuality. To summarize, the feature of the discussion forum provided a rational learning environment that facilitated self-reflection and conceptual transformation among students.

Ethical concerns

In this study, all students are identified using numbers created specifically for this article. They provided informed consent to analyze their activity data. All procedures in this study were executed in accordance with the ethical standards of the institution and complied with the 1964 Declaration of Helsinki and its subsequent amendments.

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