Empowering Learning Networks: Insights from Social Network Analysis in Inquiry-Based Discussions

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Abstract

This study investigated the dynamics of complex interactions within inquiry-based (IB) discussions by visualizing patterns using social network analysis. Researchers explored network measures when learners participated in inquiry-based discussions with Practical Inquiry Model (PIM) and non-PIM questions while playing the weekly moderator's role. The findings revealed that at the group level, purposefully designed IB discussions can create fairly cohesive, evenly distributed, and proportionally consistent networks. Discussions using both PIM and non-PIM questions resulted in a moderate level of interaction, as learners followed the specified requirements for the number of responses. While discussions with non-PIM questions appeared more interactive, discussions with PIM questions actually resulted in greater interaction, as evidenced by students exceeding the average number of required responses per student. The findings revealed that despite similar discussion prompts and discussion requirements in both PIM and non-PIM, the flow of information can vary based on how closely learners are connected. At the individual level, the results showed that learners' levels of participation, influence, and network positions fluctuated and shifted in each discussion. In addition, the results did not reveal any impact of the moderator's role on learner participation and interaction in discussions with both PIM and non-PIM questions. This study's findings can help researchers and practitioners design a well-distributed network to enhance learner interaction in inquiry-based discussions with the balance of PIM and non-PIM questions.

Keywords: inquiry-based learning, learner-learner interaction, practical inquiry model, social network analysis

Sadaf, A., Olesova, L., & Choi., H. (2024). Empowering Learning Networks: Insights from Social Network Analysis in Inquiry-Based Discussions. Online Learning, *28* (4), (200-227). DOI: 10.24059/olj.v28i4.4635

Inquiry-based (IB) learning has gained significant attention due to its potential to promote deeper engagement and higher-order thinking skills among students. IB learning is a pedagogical approach that emphasizes the importance of student inquiry, curiosity, and active participation in the learning process (Pedaste et al., 2015). Within online learning, IB discussions serve as a critical pedagogical approach, fostering an environment where students can collaboratively construct knowledge through dialogue and exploration (Garrison et al., 2001). Central to the efficacy of IB learning is the nature of questions used during discussions, which significantly influences the depth and breadth of student participation (Tawfik et al., 2020). Research has demonstrated that the types of questions posed in IB learning can significantly influence the dynamics of learner interactions (Ertmer, Author, & Ertmer, 2011; Sadaf & Olesova, 2017).

The Practical Inquiry Model (PIM), developed by Garrison et al. (2001), provides a structured framework for facilitating discussions. The framework comprises four phases of cognitive presence: triggering event, exploration, integration, and resolution, each designed to guide students through a systematic inquiry process. Cognitive presence is defined as "the extent to which learners are able to construct and confirm meaning through sustained reflection and discourse" (Garrison et al., 2001, p. 11). To help learners construct a new meaning, questions designed with PIM can guide learners through the phases of cognitive presence (Hosler & Arend, 2012; Sadaf & Olesova, 2017). Studies found that the use of PIM questions can lead to higher levels of cognitive presence (Darabi et al., 2011; Sadaf & Olesova, 2017) and non-PIM questions can help increase learner-learner interaction (Sadaf & Olesova, 2020).

Considering that learner-learner interaction is a social element where learners relate to each other through the network in online discussions, social network analysis (SNA) offers a methodological tool for examining the complex interactions within online learning environments (Alwafi, 2022; Castellanos Reyes, 2023; Jan et al., 2019). By visualizing and analyzing the patterns of learner interactions, SNA can uncover the underlying structure of communication networks, providing insights into the dynamics of learner engagement and collaboration (Borgatti et al., 2018). Studies where SNA was used to examine learners' cognitive presence found that in-degree centrality (IDC) or the number of messages learners received can be a significant predictor of academic performance (Jo et al., 2017) but it can be a poor indicator of cognitive presence itself (Shea & Bidjerano, 2010). At the same time, Shea et al. (2014) used SNA to analyze the knowledge building mechanism within the Community of Inquiry (COI), they found that students who ranked highest in cognitive presence were generally found near the center of the network.

The need for this study arises from the growing emphasis on collaborative learning in online education and the lack of understanding of how different types of IB questions influence interaction dynamics. Despite a few existing studies using SNA to examine cognitive presence during discussions, there is a need to understand the dynamics of complex interactions within IB discussions. By employing social network analysis, this research provides critical insights into how PIM and non-PIM questions shape the cohesiveness, distribution, and consistency of learner networks. Specifically, it is necessary to investigate how network measures change depending on discussion designs, both with and without PIM questions, at the group and individual learner levels. Understanding these interaction patterns is essential for educators to design more effective IB discussions, ensuring equitable participation and deeper engagement. This study addresses the gap in knowledge, offering practical implications for improving the quality and effectiveness of online learning environments.

Literature Review

Inquiry-based (IB) learning is rooted in constructivist theories of education, which posit that learners actively construct knowledge through their experiences and interactions (Bruner, 1961; Vygotsky, 1978). This approach encourages learners to ask questions, seek information, engage in critical thinking and discourse, thereby promoting deeper understanding and retention of knowledge (Hmelo-Silver et al., 2007; Lazonder & Harmsen, 2016). In online learning environments, IB discussions provide a platform for learners to collaboratively explore complex topics and develop higher-order cognitive skills (Garrison et al., 2001; Kanuka et al., 2007). IB learning is characterized by its emphasis on learner-centered exploration and investigation. Research has demonstrated that the types of prompts that the course instructors posed in IB learning can influence the dynamics of learner interactions (Olesova & Sadaf, 2024; Tawfik et al., 2020). For example, in our case these prompts are PIM (structured with four levels) and non-PIM (non-structured with the levels). The non-structured prompts, such as the non-PIM questions usually facilitate surface-level interaction, whereas structured prompts with the four levels such as the PIM questions can elicit deeper cognitive and metacognitive interaction (Sadaf & Olesova, 2017). That’s why when course instructors design prompts and use structured PIM-based questions, they help learners identify problems (first level), search for resources and perspectives (second level), and model potential solutions (third level), thereby fostering a higher level of cognitive presence to solve the problem (fourth level) (Garrison et al., 2001; Olesova & Sadaf, 2024).

Learner-Learner Interaction in Asynchronous Online Discussions

Asynchronous online discussion boards are used to help students interact with each other, build relationships, and feel connected (Castellanos-Reyes, 2021). Research shows that participating in these discussions often strengthens personal relationships among students (Lee & Martin, 2017; Xie & Ke, 2011). Students value these social interactions as they help them get to know each other and create a sense of community. However, not all learners approach the online discussions in the same way; some learners do not find discussions valuable for their learning or for making social connections (Lee & Martin, 2017). These differences in engagement may be because not all online discussions are designed in a way that learners find them valuable for their learning.

Online discussions that are purposefully pre-designed for learner-learner interactions have higher potential for learners’ positive experiences (Borokhovoski et al., 2012; Oyarzun et al., 2018). For example, online discussions where the prompts include detailed directions on expectations and outcomes tend to get higher learner-learner interactions (Sadaf & Olesova, 2017). Moreover, if online discussion design is based on theoretical principles, for example the PIM principles, this type of discussion may guide students throughout the purposefully pre-designed deep interactions. Learners just need to follow the structured discussion prompts designed with the four levels: triggering events level to understand the concept, exploration level to explore the concept, integration level to synthesize ideas to find a better solution, and resolution level to defend a new suggested solution. However, studies on structured discussion prompts usually examined learner-learner interaction either by using descriptive statistical analysis or any traditional statistical measurements. These studies provided mostly the surface information on the depth of interactions without understanding how cognitively deep connections learners created during interactions. One of the well-established approaches to dig into the depth of interactions proved to be the social network analysis (SNA).

Social Network Analysis in Asynchronous Online Discussions

SNA has been applied to multiple educational studies to examine asynchronous online discussions due to the availability of big data where the large amount of data stored in learning management systems (LMS). The history of SNA dates to the 1930s (Moreno, 1953) and only in 1954 it was coined as a term of "social network analysis" to understand complex social interactions in different fields including communication, economics, and education. SNA is an interdisciplinary approach to examine connections between learners. Social network is defined as a set of people, called nodes, who are interconnected by relations, called edges (Wasserman & Faust, 1994). To avoid heavy use of the SNA terminology in this study, we continue referring to the nodes as participants and edges as relations. The relations that connect people could represent several things depending on the purpose of each network. In online courses, students are usually connected through online interactions in discussion boards. Each online discussion board connects a set of students who form a social network for analysis. In our current study, it is one online course with six online discussions. SNA is based on the structure that includes the participants connected by relations and it can be explained at an individual or group level. The social network results can be visualized using a sociogram representing individual participants (i.e., dots) with the lines to represent interactions. The sociogram may represent other attributes by using different colors or shapes. At the individual level, each participant's individual position is measured with the social network centrality. Each participant has a degree of centrality, representing the total number of relations connected to the participant. In asynchronous online discussions, degree centrality is the total number of posts each participant made comments to peers or received responses from them. Degree centrality can be a reliable predictor of students' academic performance (Jo et al., 2017). Another SNA element is density or the number of relations present divided by the total possible number of relations (range: 0–1). Networks with higher density are more connected providing evidence of an established online community. Network centralization is another measure for internal network structure of how concentrated the connections in the discussions.

Studies have used SNA to investigate various aspects of online learning through interactional analysis, effectiveness of different technologies, identification of group structures, and the roles of students, lecturers, and tutors (Jan et al., 2019). Using the COI framework, SNA has been applied to study how participants interact in asynchronous online discussions (Joe et al., 2017), on blogs (Jimoyiannis & Tsiotakis, 2017), and through journal entries (Shea et al., 2014). These studies have looked into the relationships between all three presences, how learners are positioned within the networks, the effects of assigning instructional roles to students, and how group cohesion and a central figure can affect the quality of the learning process (Shea et al., 2013; Tirado et al., 2015).

The majority of the studies on the COI and SNA used a one-mode network that comprised two sets of participants, consisting of students and instructors. These studies explored interactions within directed and unweighted/weighted networks. The studies on the COI and SNA used network centralization as a measure of collective communication and overall cohesion or interpreted centralization in relation to social presence in the COI. The concept of density was used to measure social engagement or participation levels in the community. Some studies also involved clique analysis, which looks at smaller, tightly-knit groups within the larger network to understand knowledge sharing and communication patterns. Additionally, measures such as in-degree centrality (number of messages one receives) and out-degree centrality (number of messages one sends) were considered indicators of an individual's influence in terms of cognitive engagement and teaching presence in the COI. Degree centrality, which is based on the total number of messages one is involved with, was seen as a measure of an individual's ability to disseminate information and influence others within the COI (Jimoyiannis & Tsiotakis, 2017).

Shea and Bidjerano (2010) found that in-degree centrality is a poor indicator of cognitive presence, especially when applied to the tutor because the replies to the tutor were not of educational value. On the contrary, the out-degree centrality of the tutor was associated with initiation of productive exchange, a category of cognitive presence. Tirado et al. (2015) found that social presence was more prominent than cognitive presence in online discussion forums. Other studies have found positive relationships between network centralization, social presence and cognitive presence as well as between cognitive presence, knowledge construction, and active participation in the community. Cognitive presence was higher than teaching presence or social presence and, combined with cognitive presence and in-degree centrality was a significant predictor of academic performance corroborating the positive relationship between the two (Jimoyiannis et al., 2012; Shea & Bidjerano, 2010). However, as the studies still report different findings on the cognitive presence in asynchronous online discussions and they are not generalizable, it is important to examine specific parts of the learning process—for example, application of other SNA measures besides centrality in the COI. Therefore, this study aims to understand the interaction when IB discussions are designed with the PIM (structured) and non-PIM (non-structured) prompts, while also considering the effects of assigning moderator roles to students. This study will explore additional network measures beyond degree centrality, such as density, centralization, reciprocity, transitivity, and average path length at the group level; and betweenness centrality, closeness centrality, and eigenvector centrality at the individual level.

Purpose of Study

The purpose of this study is to investigate the dynamics of the complex interaction within IB discussions by visualizing patterns using social network analysis (SNA). By exploring PIM (structured) questions and non-PIM (non-structured) questions, the study provides valuable insights into the specific conditions, such as using moderator's roles that foster effective IB discussions. The use of SNA as a methodological tool allows for an analysis of interaction patterns and highlighting the structural characteristics of learning networks. The following questions guided our study:

1. What are the dynamics of inquiry-based discussions observed from network measures, for both PIM and non-PIM questions?

2. How do students engage in inquiry-based discussions, both with PIM and non-PIM questions, where students moderate the discussions?

Methods

Participants

A purposeful sample of 20 graduate students (10 males and 10 females) enrolled in an Instructional Design course were selected to participate in this study. The sample was included in the study because students were enrolled in the online graduate course and participated in the same online discussions. Although the discussions were graded as part of the course, students were informed that they had the right to opt-out by not signing a consent for being included in the study. All students agreed to participate in the study and signed the online Instructional Review Board (IRB) consent form.

The students ranged in age from twenty-one to forty-five years. Most (n = 18**)** had taken three or more online courses before participating in this study. All of the participants rated themselves as being either fairly or very comfortable with participating in online discussions. Their names are replaced with pseudonyms to maintain confidentiality.

Context of the Study

The course—Instructional Design—was offered over a 16-week semester and delivered via a learning management system, Canvas, in a Learning, Design and Technology program at a university in the southeastern United States. Students were required to engage in week-long discussions as part of their course grade. During the semester, there were 13 discussions on various topics. For each discussion, students were divided into two groups of ten students each to make the discussions more manageable. At the beginning of the semester, students were required to sign up to facilitate one of the discussions. For every discussion, there were two discussion moderators each facilitating one of the two groups. For this research, six discussions (three PIM-designed and three non-PIM designed) were analyzed. Figure 1 shows the order of PIM and non-PIM discussions and topics provided.

Figure 1

The Order of Questions Provided in All Six Online Discussions

For the PIM questions, discussions were structured with questions representing four levels of cognitive presence under two different threads. Students were required to respond to "triggering" and "exploration" questions the first half of the week (Monday to Thursday) within the first thread and comment on one other student's post. The purpose of asking triggering and exploration questions during the first half of the week was to first help students understand the nature of the problem and then explore relevant information to provide possible explanations. During the second half of the week (Friday to Sunday), students responded to "integration" and "resolution" questions within the second thread and commented on one other student's post. The purpose of asking questions at integration and resolution phases was to help students build on their initial discussion responses to create solutions of the problem and provide justifications for their solutions of the problem. In total, students were required to make at least four posts for one week—two initial posts and two comments on others.

For the non-PIM questions, students were presented with questions that required them to explore a specific aspect of the course material or a concept and then apply the knowledge to respond. Students interpreted the specific information (i.e., learning theories) and used that information to respond to the discussion questions. Students responded to two questions in one post during the first half of the week (Monday to Thursday) and then commented on three other students' posts during the second half of the week (Friday to Sunday). In total, students were required to make at least four posts for one week—one initial post and three comments on others.

Although the PIM and non-PIM questions both tend to facilitate student-student interaction and application-level responses, the way they were worded and structured were different. For example, PIM followed Garrison et al.'s (2001) PIM to create the question prompts and required student initial responses in two separate threads. On the other hand, non-PIM discussion questions represented a traditional discussion method of posting a response to one discussion prompt within one single thread and then replying to other students. Comparing these two types of question structures may provide more insight into how useful PIM and non-PIM questions are for wording and structuring initial question prompts to facilitate learner-learner interaction in online discussions.

Data Sources and Analysis

The original data in this study were collected from the asynchronous online course "Instructional Design," and, specifically the text-based discussion posts from the discussion board in the Canvas Learning Management System (LMS). Students' online discussion posts and replies were used to build the data sets necessary for the network analysis. The network analysis includes two data sets: node list and adjacency matrix. The node list represents each individual students' attributes (e.g., pseudonyms) that resemble conventional independent variables. The adjacency matrix represents interactional data (i.e., ties or replies between each student) and was used as a dependent variable. The collected data were transformed into the directed and weighted one-mode adjacency matrix dataset. A total of 307 online discussion posts were made during the six weeks, and students posted an average of 26 posts per week. The online discussions started from 19 nodes (i.e., students) and ended with 20 in week eleven and 18 in week twelve. We approached online communication as responses to peers, given that communication occurs when students reply to others' comments, promoting participation and interaction (Garrison, 2016). This type of communication indicated responses when students used a "reply" function instead of creating a new thread (Shea et al., 2010). We treated the post-reply as a sender and a receiver for interactional data to run the network analysis. Interactional data were collected from pairing students' replies to peers' comments in any discussion board for each of the six weeks. Twelve adjacency matrices were created, two discussion groups per week, each containing interactions between 10 students who participated in student-student interaction at least once over the six weeks.

The absence of a tie (reply) between a pair of students was coded as 0 and presence of a tie (reply) was coded as 1, respectively. The one-mode network represents the direction of who replied to whom (i.e., bi-directional). The adjacency matrices were bi-directional, meaning that the tie or reply that student A made to student B was different from the reply of student B to student A. Taking into account that not all 20 students created ties with peers, zeroes were used to account for absence of ties in each week. To analyze the one-mode network and compare network structures of six online discussions, we employed the iGraph package in R, examining network-level attributes and node-level centralities. Specifically, for network-level attributes, we employed five measures—density, reciprocity, transitivity, centralization, and average path length (APL)—to assess the overall cohesiveness, interactivity, distribution, and efficiency of networks. For node-level centralities, we considered four well-known centrality measures (i.e., degree, betweenness, closeness, and eigenvector) (see Table 1).

Table 1
A Network Analysis Framework

Category	SNA Measures	Description
Node-level	Degree	The number of adjacent edges a node has. [connection]

	Betweenness	The number of shortest paths going through a node. [mediator]
	Closeness	The number of steps required to access every other node from a given node. [efficiency]
	Eigenvector	The influence of a node (an actor) as the sum of the centrality of its connections [influence]
Network level	Density	The ratio of the number of actual relations to the number of all possible relations in a network [cohesiveness]
	Reciprocity	The ratio of mutual links to the total number of edges in a network [interactivity]
	Transitivity	The tendency of the nodes to cluster together (clustering coefficient). [interactivity, cohesiveness]
	Centralization	The distributional characteristics of a network. [distribution]
	APL	The average number of the shortest paths for all possible pairs of nodes: 0 (most evenly-distributed network) to 1 (most centralized network). [efficiency]

Results

RQ 1: Measures of the network in inquiry-based discussions

The results revealed that all six discussions (2 groups per discussion) fostered an inquiry process. In discussions with non-PIM questions, the average number of ties within a group per week, considering weights, was higher (26.5) than in PIM discussions (25), indicating a relatively greater engagement and idea exchange among students in non-PIM discussions. However, in discussions with PIM questions, students posted more than the required amount (average of 2.5 posts per student when 2 were required), whereas, in non-PIM discussions, students posted fewer than required discussion with non-PIM questions (2.65 posts per student when 3 were required). This suggests that students invest more effort, thus demonstrating greater social interactions and cognitive presence in discussions with PIM questions.

Students responded to at least two peers in all discussion groups, indicating active interaction and contributing to an ongoing, interconnected discussion environment. Notably, non-PIM2 group 1 (31) and PIM2 group 1 (31) discussions stood out with the highest levels of student participation, given the average ties of 26 (see Table 2). It seems that students in group 1 in both non-PIM2 and PIM2 discussions may have shown more interest in learning about the weekly discussion topic compared to students in group 2. Overall, our findings show that directed and structured discussions can facilitate ongoing and interconnected interactions in IB learning, particularly by generating higher engagement through PIM questions.

Table 2
The Network-Level Attributes of Overall One-Mode Learner-Learner Interaction in Weekly Discussions

Measure	PIM1		PIM2		PIM3		NonPIM1		NonPIM2		NonPIM3	
	G1	G2	G1	G2	G1	G2	G1	G2	G1	G2	G1	G2
# of participants	10	10	10	10	10	10	10	10	10	10	10	10
# of ties (regardless of weight)	20	21	26	21	20	20	18	27	**31**	20	24	26
# of ties (including weight)	25	23	**31**	24	23	22	21	28	**31**	26	26	27
Density	0.222	0.233	**0.288**	0.233	0.222	0.222	0.200	**0.300**	**0.344**	0.222	0.266	0.288
Centralization	0.123	0.111	0.173	0.235	0.185	0.123	0.272	0.160	0.173	0.123	0.074	0.235
Reciprocity	0.300	0.380	**0.538**	0.285	**0.400**	**0.500**	0.333	**0.518**	**0.516**	**0.500**	**0.521**	**0.615**
Transitivity	0.250	0.300	0.350	0.283	0.266	0.257	0.162	**0.416**	**0.551**	0.090	0.341	0.306
Average Path Length	2.477	2.133	**2.556**	2.417	2.242	**2.556**	**2.589**	**1.950**	**1.911**	**2.778**	2.367	2.100

Note. G1 = Group 1, G2 = Group 2

<u>Density</u>

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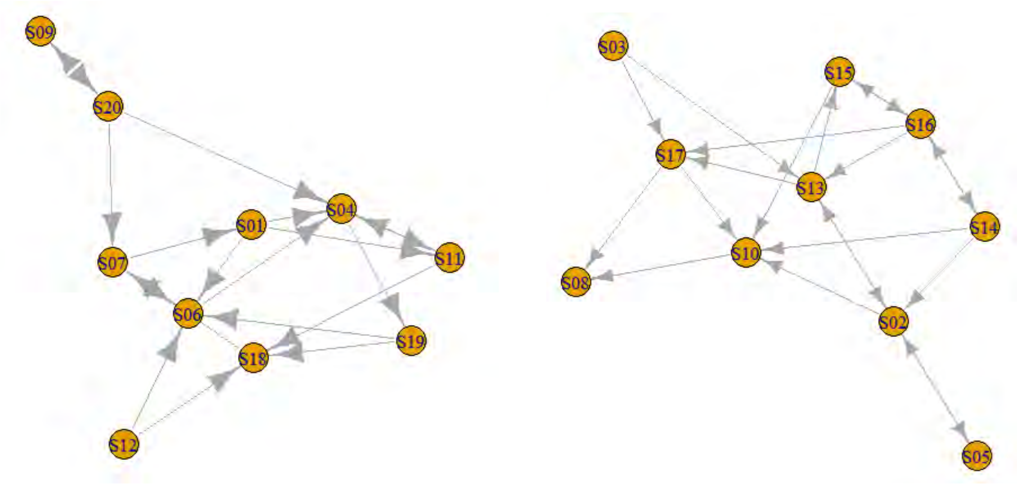
Figure 2

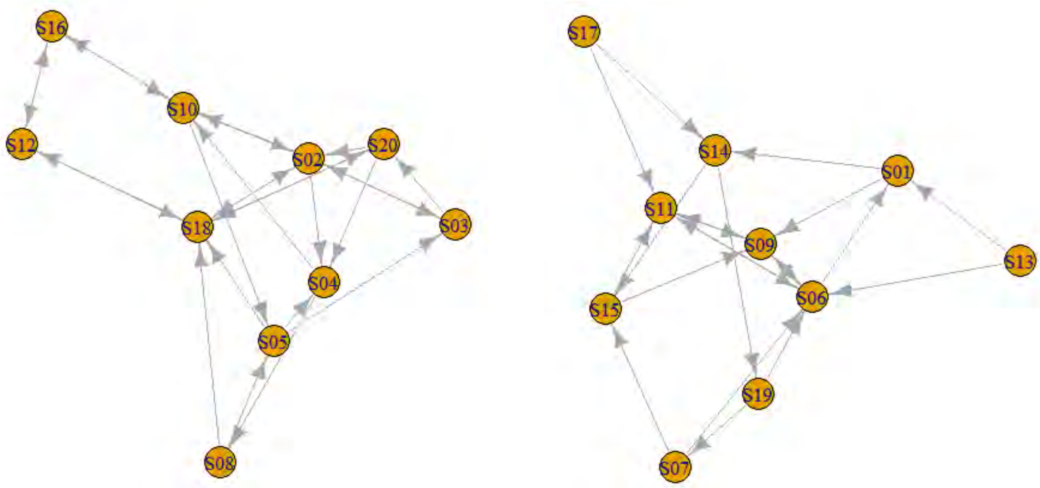
SNA in PIM 1 Group 1 and Group 2 Discussions (d = density)



Group 1 (*d* = .222) Group 2 (*d* = .233)

Figure 3

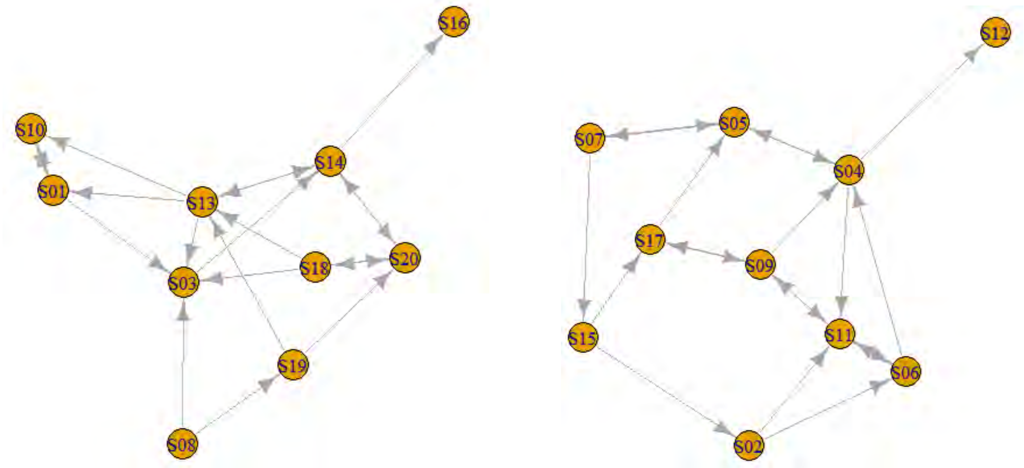
SNA in PIM 2 Group 1 and Group 2 Discussions (d = density)



Group 1 (*d* = .288) Group 2 (*d* = .233)

Figure 4

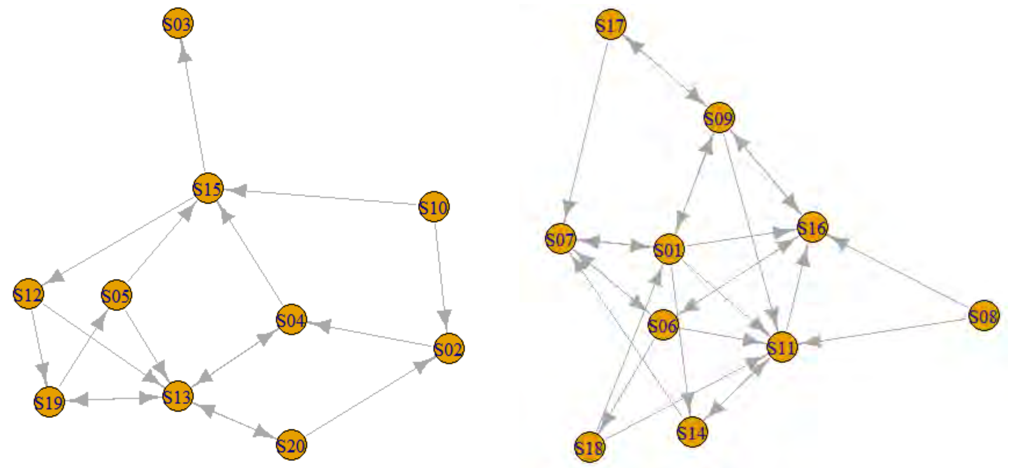
SNA in PIM 3 Group 1 and Group 2 Discussions (d = density)



Group 1 (*d* = .222) Group 2 (*d* = .222)

Figure 5

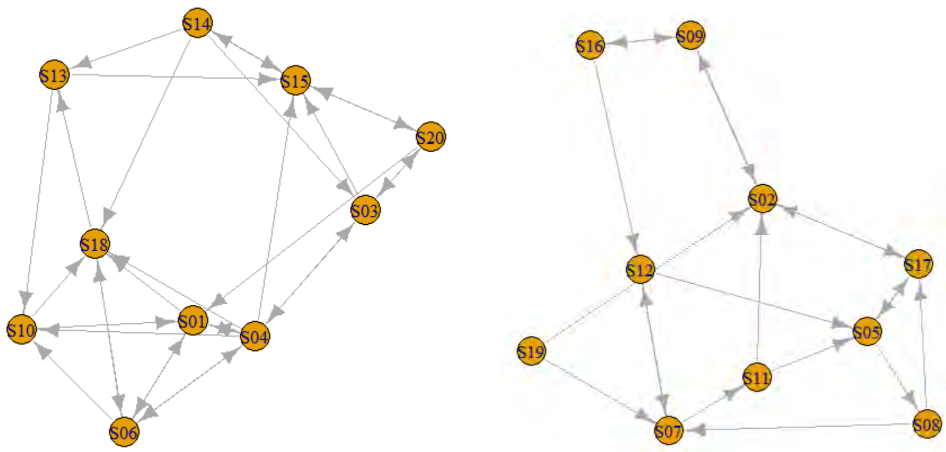
SNA in NonPIM1 Group 1 and Group 2 Discussions (d = density)



Group 1 (*d* = .200) Group 2 (*d* = .300)

Figure 6

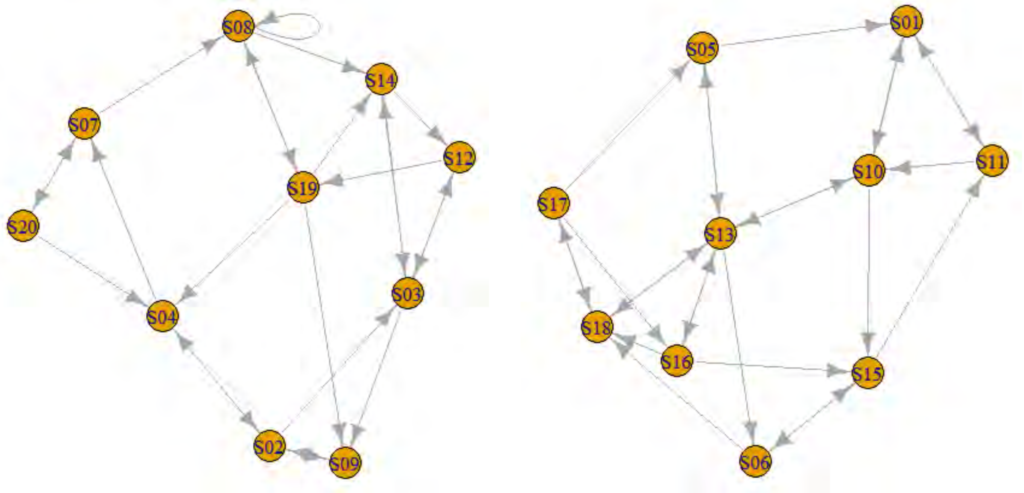
SNA in NonPIM2 Group 1 and Group 2 Discussions (d = density)



Group 1 (*d* = .344) Group 2 (*d* = .222)

Figure 7

SNA in NonPIM3 Group 1 and Group 2 Discussions (d = density)



Group 1 (*d* = .266) Group 2 (*d* = .288)

<u>Centralization</u>

Centralization measures the degree of distribution within the network. In our study, Non-PIM1 Group 1 exhibited relatively high centralization (0.272), indicating that the discussion was focused on a few individuals. In contrast, PIM3 Group 1 showed the lowest centralization (0.074), suggesting a more evenly distributed discussion within the group. Despite these two group discussions, all weekly discussions showed a low centralization score overall, indicating an equal distribution among students. It seems that in the IB discussions, the focus was not on just a few participants but rather on fostering equal participation from the entire group.

Reciprocity and Transitivity

Reciprocity and transitivity indicate the degree of connection and interactivity within the network. Among these discussions, non-PIM2 and non-PIM3 displayed the highest level of interactivity, as evidenced by a reciprocity score for non-PIM2 (0.516 for group 1 and 0.500 for group 2) and non-PIM3 (0.521 for group 1 and 0.615 for group 2). This suggests that in the non-PIM2 and non-PIM3 discussions, participants were highly engaged in mutual exchanges, indicating a strong level of direct interaction and responsiveness between pairs of learners. At the same time, non-PIM1 Group 2 and non-PIM2 Group 1 displayed the highest level of interactivity between more than two learners, as evidenced by a transitivity score of 0.416 for non-PIM1 and 0.551 for non-PIM2. This indicates that the non-PIM1 Group 2 and non-PIM2 Group 1 discussions had a significant level of clustering, where participants formed interconnected groups, leading to a cohesive and collaborative environment with multiple participants engaging collectively.

Average path length (APL)

Average path length (APL) gauges the efficiency of information flow within the network, calculated as the average number of steps along the shortest paths between all possible pairs of network nodes. Analyzing the efficiency of information flow, most networks showed similar patterns. Among the six discussions, non-PIM2 Group 2 had the highest APL of 2.778. A higher APL implies that participants were more distantly connected, leading to less efficient information flow and potentially slower dissemination of ideas. This suggests that it took longer for information to pass from one participant to another within this network. In contrast, the APL of non-PIM2 for group 1 was the lowest, indicating relative ease of information flow via interactions among participants in this specific network, allowing information to flow more efficiently and rapidly between them. This finding shows that even when students received the same discussion prompts and requirements, the flow of information can vary based on how closely participants are connected. In our examples, the same non-PIM2 discussion on the topic of learning objectives produced two opposite results.

RQ 2: Learner-learner interaction in inquiry-based discussions

The results for *the second question* revealed that students' participation in discussions designed with non-PIM questions was slightly higher (average degree centrality = 0.533) than in PIM discussions (average degree centrality = 0.439). However, this difference was due to the requirement for students to make three responses in non-PIM discussions compared to two in PIM discussions. As discussed earlier, the average number of responses per student was higher in PIM discussions because students exceeded the required number of responses. Student moderators in each group did not always exhibit a higher degree of centrality.

Degree Centrality

At the individual level, degree centrality measures the number of its adjacent edges (relations), including students' postings and replies received from other students. The results revealed that individual levels of participation fluctuated in each discussion. For instance, while most of the students changed their levels of participation from low to high and vice versa, S14's level of participation stayed almost equal throughout all six discussions (see Table 4). On the contrary, S13 also showed a very high level of participation in discussions except for non-PIM2 and PIM2. S13's participation in the first and third discussions was very high for non-PIM and PIM. It seems this inconsistency of participation shows that students' levels may have been impacted either by their own decision to take some break between discussions or the grades. Another interesting pattern is for S10, who was active in the middle of four discussions while maintaining low participation during the first and the last discussions.

We also checked if the students' moderator's role impacted their level of participation. Table 4 shows students marked with the stars, which means their moderator's responsibilities during that specific discussion. We expected that the moderator's role could help increase the level of participation, but based on our findings, we can't reveal any consistent patterns for this question. The moderators' role actually did not impact the level of participation much, except for two students: S04 (non-PIM2) and S18 (PIM2).

Table 3
Students by Weekly Discussion in Groups (PIM and Non-PIM)

PIM1 Group 1	**PIM2 Group 1**	**PIM3 Group 1**	**Non-PIM1 Group 1**	**Non-PIM2 Group 1**	**Non-PIM3 Group 1**
S01	S02	S01	S02	S01	S02
S04	S03	*S03***	S03	S03	S03
S06	S04	S08	S04	*S04***	S04
S07	S05	S10	S05	S06	S07
S09	S08	S13	S10	S10	*S08***
S11	S10	S14	S12	S13	S09
S12**	S12	S16	S13	S14	S12
S18	S16	S18	S15	S15	S14
S19	*S18***	S19	*S19***	S18	S19
S20	S20	S20	S20	S20	S20
Group 2	**Group 2**	**Group 2**	**Group 2**	**Group 2**	**Group 2**
S02	*S01***	S02	S01	S02	S01
S03	S06	S04	*S06***	S05	*S05***
S05	S07	S05	S07	S07	S06

S08	S09	S06	S08	S08	S10
S10**	S11	S07	S09	S09	S11
S13	S13	S09	S11	S11	S13
S14	S14	S11	S14	S12	S15
S15	S15	S12	S16	*S16***	S16
S16	S17	*S15***	S17	S17	S17
S17	S19	S17	S18	S19	S18

** Discussion weekly moderators per each group

Table 4
Students' Degree Centrality by Weekly Discussions (PIM and Non-PIM)

Students	**PIM1**	**PIM2**	**PIM3**	**Non-PIM1**	**Non-PIM2**	**Non-PIM3**
S01	0.444	0.444**	0.444	0.889	0.778	0.556
S04	0.667	0.556	0.667	0.444	1.000**	0.556
S06	0.667	0.889	0.444	0.667**	0.778	0.444
S07	0.556	0.333	0.333	0.667	0.556	0.444
S09	0.222	0.667	0.556	0.778	0.444	0.444
S11	0.444	0.667	0.667	0.889	0.333	0.444
S12	0.222**	0.444	0.111	0.333	0.444	0.444
S18	0.444	0.889**	0.444	0.333	0.778	0.667
S19	0.333	0.333	0.222	0.444**	0.222	0.667
S20	0.444	0.556	0.556	0.333	0.556	0.333
S02	0.667	0.889	0.333	0.333	0.667	0.556
S03	0.222	0.444	0.556**	0.111	0.667	0.667
S05	0.222	0.556	0.556	0.333	0.556	0.444**
S08	0.222	0.333	0.222	0.222	0.333	0.667**
S10	0.556**	0.667	0.333	0.222	0.556	0.667
S13	0.667	0.222	0.778	0.889	0.444	1.000
S14	0.444	0.444	0.667	0.444	0.556	0.556
S15	0.444	0.444	0.333**	0.556	0.778	0.556
S16	0.667	0.444	0.111	0.778	0.333**	0.556
S17	0.556	0.222	0.444	0.333	0.556	0.444
Average	0.456	0.5223	0.439	0.499	0.543	0.556

The degree centrality analysis at the individual level provides insights into the varying participation patterns within online discussions. The results revealed fluctuating levels of participation among students, with some participants showing consistent engagement across multiple discussions while others had more variable participation.

Betweenness Centrality

Betweenness identifies students who lie on the shortest paths between other students, taking a mediation role. The top mediator changed in each discussion (S13 → S16** moderator → S13 → S11 → S18** moderator→S14), but some students consistently served as mediators throughout. S04 was among the top five mediators in five discussions, while S15, S07, S02, and S13 were among the top five mediators in three discussions, highlighting their importance in maintaining the network's connectivity (Table 4). This indicates that although the primary mediator role shifted, these students frequently acted as bridges, ensuring the efficient flow of information and interactions within the network. Among these top five mediators, S15 was the most efficient in sharing the information during the moderator's week as well. S04, S16, and S18 showed similar efficiency during their moderation week compared with regular weeks. Other students showed no efficiency in spreading the information during their moderation week.

Table 5
Students' Betweenness Centrality by Weekly Discussion

Students	PIM1	PIM2	PIM3	NonPIM1	NonPIM2	NonPIM3
S01	0.106	0.328	0.083**	0.176	0.141	0.054
S02	0.173	0.292	0.099	0.083	0.287	0.227
S03	0.000	0.015	0.176	0.000**	0.073	0.190
S04	0.245	0.142	0.280	0.208	0.237**	**0.340**
S05	0.000	0.069	0.259	0.056	0.236	0.069**
S06	0.203	**0.337**	0.125	0.000**	0.063	0.069
S07	0.185	0.017	0.229	0.162	0.319	0.211
S08	0.000	0.051	0.000	0.000	0.160	**0.113****
S09	0.000	0.021	0.185	0.171	0.132	0.072
S10	0.028**	0.212	0.000	0.000	0.058	0.251
S11	**0.787**	0.209	0.125	0.097	0.194	0.070
S12	0.000**	0.084	0.000	0.160	0.132	0.146
S13	0.194	0.000	0.218	**0.299**	0.098	**0.433**
S14	0.060	0.299	**0.313**	0.028	0.081	0.083
S15	0.123	0.052	0.219	**0.285****	0.206	0.116
S16	0.174	0.021	0.000	0.231	**0.556****	0.070
S17	0.095	0.000	0.139	0.007	0.118	0.049
S18	0.027	**0.363****	0.034	0.007	0.125	0.185

S19	0.093	0.146	0.069	0.111**	0.000	0.252
S20	0.097	0.104	0.120	0.083	0.056	0.028
Average	0.130	0.138	0.134	0.108	0.164	0.151

Closeness Centrality

Closeness centrality identifies students who tend to interact directly with most students and spread information efficiently through a network. The students who directly interacted with the most students changed in each discussion (S16 → S02 → S13/S14 → S01 → S04** moderator → S13), demonstrating a dynamic shift in who had the highest closeness centrality (see Table 6). S13 and S10 were involved in two discussions where they directly interacted with most students and efficiently spread information. S19 and S20 were among the top five in four discussions, suggesting their strong and consistent presence in the network and their effectiveness in disseminating information. Among the top active participants, only S04 increased direct interaction during her moderation week. This finding shows that moderator's role did not impact on closeness centrality in terms of direct interaction with peers. In addition, the type of discussion prompt also did not impact on closeness centrality.

Table 6
Students' Closeness Centrality by Weekly Discussion

Students	**PIM1**	**PIM2**	**PIM3**	**NonPIM1**	**NonPIM2**	**NonPIM3**
S01	0.545	0.500**	0.368	0.667	0.529	0.409
S02	0.471	0.562	0.375	0.333	0.348	0.474
S03	0.444	0.391	0.438**	NaN	0.563	0.409
S04	0.462	0.474	0.474	0.400	0.750**	0.450
S05	0.333	0.450	0.321	0.444	0.296	0.500**
S06	0.545	0.438	0.391	0.615**	0.563	0.450
S07	0.400	0.467	0.375	0.533	0.400	0.450
S08	NaN	0.450	0.450	0.450	0.348	0.450**
S09	0.267	0.269	0.429	0.615	0.333	0.346
S10	0.500**	0.474	0.233	0.391	0.409	0.563
S11	0.429	0.350	0.333	0.471	0.421	0.409
S12	0.467**	0.375	NaN	0.400	0.364	0.450
S13	0.500	0.444	0.636	0.421	0.474	0.642
S14	0.571	0.538	0.636	0.444	0.600	0.375
S15	0.444	0.318	0.450**	0.381	0.474	0.409
S16	0.615	0.333	Nan	0.533	0.364**	0.563
S17	1.000	0.500	0.429	0.421	0.333	0.474
S18	0.250	0.500**	0.583	0.500	0.474	0.450

S19	0.500	0.500	0.533	0.421**	0.429	0.600
S20	0.500	0.529	0.500	0.320	0.529	0.333
Average	0.486	0.443	0.442	0.461	0.450	0.460

Note. NaN is short for "Not a Number." NaN values represent undefined or unrepresentable results from certain mathematical operations. Mathematical operations involving a NaN will either return a NaN or raise an exception. Comparisons involving a NaN will return False.

The analysis of closeness centrality in online discussion networks reveals the key roles of certain students in efficiently spreading information and interacting directly with others. The top student with the highest closeness centrality varied across discussions, showing a dynamic pattern of interaction.

Eigenvector Centrality

Eigenvector centrality identifies students who have the most influence on a network. According to Eigenvector centrality, S06 and S08 emerged as the most influential participants in the PIM1 discussion. S06 and S04 were influential in the PIM2 discussion, while S18 and S09 held the most influence in non-PIM2 and non-PIM3. Additionally, S10 and S04 demonstrated influence in PIM3, and S13 and S16 were influential in non-PIM1, indicating their strong presence and influential connections in that particular network (see Table 6). Similarly to our previous findings above, the moderator's role did not impact eigenvector centrality.

Table 7
Students' Eigenvector Centrality by Weekly Discussion

Students	PIM1	PIM2	PIM3	NonPIM1	NonPIM2	NonPIM3
S01	3.38e-01	3.043256e-01**	8.203401e-01	0.5763093	0.7852098	0.6033742
S02	7.50e-01	0.8838055	0.04065683	2.414151e-01	7.633776e-01	0.6033398
S03	8.23e-17	0.4152944	3.765795e-01**	8.240300e-02	0.3961764	0.7886275
S04	9.604365e-01	**1.0000000**	**1.00000000**	4.313047e-01	0.6486145**	0.4819423
S05	3.750000e-01	0.4177620	0.58802265	2.513618e-01	3.182942e-01	0.4827785**
S06	**1.000000e+00**	**1.000000e+00**	0.30525928	0.5949884**	0.7976628	0.5877753
S07	7.880866e-01	8.577363e-03	0.24134623	0.6905039	1.416258e-01	0.2935136
S08	**1.000000e+00**	0.3190725	3.617738e-17	0.0000000	1.112630e-01	0.5180756**
S09	0.000000e+00	8.883795e-01	0.36710048	0.7375168	**1.000000e+00**	**1.0000000**

S10	8.125000e-01**	0.9902284	**1.000000e+00**	4.692064e-17	0.6045305	0.7340529
S11	5.581430e-01	5.840539e-01	0.70308533	0.9324239	4.950671e-02	0.4534541
S12	1.416791e-17**	0.4605095	0.41043697	8.240300e-02	2.938913e-01	0.6140617
S13	5.000000e-01	2.103968e-17	1.050512e-01	**1.000000e+00**	0.3982627	0.9752075
S14	1.250000e-01	9.261405e-02	2.286304e-01	0.5310126	0.2151768	0.7196502
S15	3.750000e-01	3.079514e-02	0.0990574***	2.371788e-01	0.6565462	0.6518964
S16	2.500000e-01	0.6098266	8.909744e-02	**1.0000000**	6.991202e-01**	0.4827785
S17	3.750000e-01	2.103968e-17	0.19132843	0.2595758	5.671585e-01	0.3612401
S18	4.171115e-01	0.8334488**	4.093854e-02	0.2094116	**1.000000**0	**1.0000000**
S19	4.126582e-01	2.818482e-02	0.000000e+00	7.234891e-01**	4.281235e-17	0.4609245
S20	0.000000e+00	0.5309487	1.050512e-01	6.948598e-01	0.3450199	0.1194975
Average	4.52E-01	4.70E-01	3.36E-01	4.64E-01	4.90E-01	5.97E-01

The distribution of influence across different participants and discussions suggests that the role of influential participants can vary depending on the discussion context. Different students emerged as key influencers in different discussions, indicating a dynamic and context-dependent distribution of influence. The identification of S06, S08, S18, S04, S09, S10, S16, and S13 as key influencers highlights their pivotal roles in shaping the discussions. Their high eigenvector centrality scores suggest they are not only central to the network but also have the ability to impact the interactions and engagement of other participants.

Discussion

The dynamics of learner-learner interaction in inquiry-based discussions

The analysis of interaction and participation levels in online discussions revealed that all six discussions (12 groups) fostered an inquiry process, characterized by consistent density, decentralized participation, and increasing interactivity over time. This indicates that directed and structured discussions can facilitate ongoing and interconnected interactions in IB learning.

The overall density levels were not excessively high in any of the discussions, suggesting that while there were connections among participants, the networks did not exhibit a very high degree of cohesiveness or interconnectedness. While moderate density is beneficial, suggesting a balanced interaction pattern, there might be opportunities to enhance engagement further by encouraging broader interactions. However, if we compare density in our study with Jo et al.'s (2017) findings, we can state that IB discussion can enhance consistent and stable interaction throughout the course starting from the first week up to the end. For example, Jo et al. (2017) found that density in their study increased from 0.034 to 0.334 by the end of the course. Density in our study was 0.200 for group 1 and 0.300 for group 2 during the first non-PIM discussion and it was 0.222 for both groups during the last PIM discussion. According to Shea et al. (2010) density also can be used as a good proxy for understanding the development of social presence. Based on the results of our study, we can conclude that social presence was consistent throughout all six discussions (12 groups). Interacting with at least 30% of the group can be counted as a medium to high level of social interaction. In addition, Satar and Akcan (2018) in their study stated that interpretation of density scores should be done with consideration of the network size, centralization, and subgroups. Smaller groups tend to have higher density scores because there are fewer potential ties and the chances that the network will reach full potential is high. Similar to our findings of density of 0.22 for the group of 10 students, Satar and Aksan (2018) found density of (0.15 and 0.22) was a more cohesive network.

The analysis further revealed that all six discussions with 12 groups were equally distributed, as indicated by the low score of centralization. This indicates that the discussions were evenly distributed in terms of participant interactions, rather than being dominated by a few individuals, the discussions fostered active participation from the entire group. This equal distribution of interactions suggests an inclusive and collaborative environment, where many participants contributed to the discourse. These findings highlight the effectiveness of the IB discussion design in promoting widespread engagement and preventing the concentration of interactions among a few central figures. However, Shea et al. (2010) found that measures of centrality appear to be relatively poor indicators of productive interactions, especially when applied to what might be considered a very central participant, the instructor in their case and a moderator in our study. Shea et al. (2010) concluded that the measures in terms of the number of responses generated by an actor (student) in a network, appears to be a better indicator of the interactions. In their study, they analyzed instructor comments on specific content issues and concerns that students were required to respond to. Similarly, Joe et al. (2017) in their study found that centralization decreased from the early to late stage. At the beginning of the course, everyone received messages equally but then with time, some students received responses intensively. In other words, those students had authority, and it created a centralization phenomenon in the social network (Joe et al., 2017). Our findings suggest that IB pre-designed discussions can provide an equally centralized environment throughout the course.

In terms of reciprocity and transitivity, the results revealed that most discussions showed an increasing degree of mutual interactions between pairs of learners as well as within groups over time. Ouyang and Scharber (2017) found reciprocity and transitivity in the network of 21 graduate students tend to increase over time, showing that students formed an interactive and cohesive community as the course progressed. However, Ouyang and Scharber (2017) analyzed the network facilitated by the course instructor not by students as moderators. Other studies found that low-level reciprocal interactions or discussions dominated by a few students (Zhang et al., 2018; Giannini-Gachago & Seleka, 2005). Our findings highlight the varying interaction patterns and levels of cohesiveness among the discussions, offering insights into the effectiveness of IB questions in fostering interactive online discussions.

The analysis of Average Path Length (APL) in the discussion networks provided insights into the efficiency of information flow among participants. Discussions with both PIM and non-PIM questions exhibited similar APL, indicating that information transfer within this network took an equal path between participants. These findings highlight the varying network structures and their impact on the dynamics of online IB discussions. While we expected that the discussions with PIM questions might take in slower communication and less cohesive discussions because of their structured nature, the results indicated that the type of discussion prompt or student's moderator role did not change the flow of the information between students.

Individual students' participation in inquiry-based discussions

The degree centrality analysis at the individual level provides insights into the varying participation patterns within online discussions. The results revealed fluctuating levels of participation among students, with some participants showing consistent engagement across multiple discussions, while others had more variable participation. These findings underscore the importance of understanding individual participation dynamics to design more effective and inclusive IB learning environments that cater to diverse student engagement patterns. As students in our study were also assigned moderator roles, we expected higher degree centrality for them. Our findings are different from what Shea et al. (2013) found when analyzing student facilitators. Shea et al. (2013) found that student facilitators demonstrated more prominent network positions for degree centrality than the rest of the class. However, our findings are similar to Xie et al. (2018) who found that student moderators were not the most central nodes. This means that other students emerged as leaders and SNA can bring them into focus (Xie et al., 2018).

Further analysis of betweenness centrality in the discussion networks reveals the critical roles of certain students in facilitating communication. While the top mediator varied across discussions, some students consistently served as key mediators. This result indicates that although the primary mediator role shifted, these students frequently acted as bridges, ensuring the efficient flow of information and interactions within the network. Understanding these mediation roles can help in designing more effective online discussions by identifying and supporting key facilitators who enhance network connectivity and communication. The analysis of closeness centrality in online discussion networks reveals the key roles of certain students in efficiently spreading information and interacting directly with others. The varying top interactors across discussions suggest that different students took on prominent roles in directly interacting with many participants, depending on the specific context or topic of the discussion. On the other hand, the consistent presence of a few students among the top interactors highlights their pivotal roles in maintaining efficient communication channels within the network. Their high closeness centrality suggests they are central figures in facilitating quick information spread and engaging directly with many participants. Long and Koehler (2021) in their study on expert and novice facilitators found that betweenness and closeness were above the mean and median showing that facilitators played an essential role in connecting different students and transmitting information quickly. However, our study did not find any evidence of moderators' role in connecting students in the network.

The analysis of eigenvector centrality in online discussion networks provides insights into the most influential participants. The distribution of influence across different participants and discussions suggests that the role of influential participants can vary depending on the discussion context. Different students emerged as key influencers in different discussions, indicating a dynamic and context-dependent distribution of influence. Although these students were identified as key influencers and highlighted their pivotal roles in shaping the discussions, their high eigenvector centrality scores suggest they are not only central to the network but also have the ability to impact the interactions and engagement of other participants. These findings highlight the varying distribution of influence across different discussions and the central roles of these key participants.

Limitations and Future Research

When interpreting our results, it is important to recognize the limitations of our study. This study is limited in generalizability of findings due to small sample size and participants representing a purposeful sample from only one course, program and university. Future research should explore the applicability of these findings across diverse educational settings, including different age groups, subject areas, and cultural contexts. This will help in understanding the generalizability of the results and tailoring IB learning strategies to various learning environments.

Additionally, the study revealed no significant impact of the moderator's role on learner participation and interaction. However, the dynamics of moderation and facilitation in online discussions can be complex and multifaceted. The study did not look into the specific strategies employed by moderators or their interactions with learners. Differences in moderation styles, the frequency of moderator interventions, and the timing of feedback could have influenced the outcomes but were not thoroughly examined. Researchers can explore different moderation strategies and their effectiveness. Investigating how varying levels of moderator intervention, from minimal to active facilitation, impact discussion quality and learner engagement can provide valuable insights for designing optimal moderation practices. Additionally, exploring the impact of different instructional strategies to facilitate PIM and non-PIM questions on the dynamics of learner-learner interactions could provide insights into optimizing online discussions.

Finally, the study used social network analysis to visualize interaction patterns and measure network attributes such as cohesiveness, distribution, and consistency. However, these metrics provide a limited scope of understanding the full complexity of learner interactions. Integrating quantitative social network analysis with qualitative methods, such as content analysis of discussion transcripts, can provide a richer understanding of the interaction patterns and the nature of discourse within IB discussions. Future research should leverage mixed-methods approaches to gain comprehensive insights into learner interactions and their implications for learning. By addressing these areas, future research can build on the insights provided by this study, contributing to a deeper understanding of IB learning and the optimization of online learning environments through effective discussion designs and network configurations.

Conclusion and Implications

This study offers significant insights into the dynamics of learner interactions within IB discussions, highlighting the impact of different question designs and the role of moderators. Results revealed that purposefully designed IB discussions, whether using PIM or non-PIM questions, can create cohesive, evenly distributed, and proportionally consistent networks with equal participation and contribution. In this regard, balancing the use of PIM and non-PIM questions can optimize students' learning experience. Instructors might start with non-PIM questions to build a base of knowledge and then progress to PIM questions to deepen understanding. A balance between both PIM and non-PIM questions in IB discussions may optimize learning outcomes by supporting both in-depth exploration and efficient knowledge sharing.

Furthermore, results revealed that discussions with both PIM and non-PIM questions resulted in a moderate level of interaction, which indicates that learners generally adhered to the specified response requirements. This adherence highlights the effectiveness of structured guidelines in maintaining social interactions. Although clear guidelines and response requirements are essential in maintaining a moderate level of interaction, educators can also encourage students to exceed minimum requirements, to promote deeper engagement. While higher interaction requirements for non-PIM questions, discussions with PIM questions promoted more extensive discussions, as evidenced by students exceeding the average required responses. Educators may consider incorporating PIM questions into their discussion designs to foster deeper and more meaningful interactions. The structured nature of PIM questions can lead to higher engagement and richer discussions.

At the individual level, learners' participation, influence, and network positions shifted in each discussion. This fluctuation suggests that the dynamic nature of online discussions can influence individual engagement and leadership roles. In addition, the study found no significant impact of the moderator's role on learner participation and interaction in discussions with both PIM and non-PIM questions. This indicates that the design of the discussion prompts and the structure of the interaction play a more critical role than the presence of a moderator. Since the moderator's role did not significantly impact interaction, educators might focus more on designing effective discussion prompts and creating a supportive environment that encourages self-regulated learning and peer-to-peer interaction. On the other hand, recognizing and supporting key facilitators—students who play crucial roles in communication and information flow—can enhance discussion effectiveness. Strategies might include assigning specific roles to these facilitators, providing training or better facilitation guidelines/resources to boost their mediation skills, and designing discussions that leverage their influence. By fostering an environment where key facilitators are empowered and all students are encouraged to participate, IB discussions can become more dynamic and effective.

This study contributes to the growing body of literature on IBL and SNA in education. By providing a detailed analysis of interaction patterns and network attributes, it offers valuable insights into how educators and practitioners can design and implement IB discussions to maximize student participation and engagement. The findings underscore the potential of PIM and non-PIM questions in creating effective learning networks, paving the way for further research and practical applications in diverse educational settings.

Declarations

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The authors assert that approval was obtained from an ethics review board (IRB) at the University of North Carolina at Charlotte. The authors declared that no financial support for the research, authorship, and/or publication of this article was received.

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