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Anatomizing online collaborative inquiry using directional epistemic network analysis and trajectory tracking

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Abstract

Accurate assessment and effective feedback are crucial for cultivating learners' abilities of collaborative problem-solving and critical thinking in online inquiry-based discussions. Based on quantitative content analysis (QCA), there has been a methodological evolvement from descriptive statistics to sequential mining and to network analysis for mining coded discourse data. Epistemic network analysis (ENA) has recently gained increasing recognition for modelling and visualizing the temporal characteristics of online discussions. However, due to methodological restraints, some valuable information regarding online discussion dynamics remains unexplained, including the directionality of connections between theoretical indicators and the trajectory of thinking development. Guided by the community of inquiry (CoI) model, this study extended generic ENA by incorporating directional connections and stanza-based trajectory tracking. By examining the proposed extensions with discussion data of an online learning course, this study first verified that the extensions are comparable with QCA, indicating acceptable assessment validity. Then, the directional ENA revealed that two-way connections between CoI indicators could vary over time and across groups, reflecting different discussion strategies. Furthermore, trajectory tracking effectively detected and visualized the fine-grained progression of thinking. At the end, we summarize several research and practical implications of the ENA extensions for assessing the learning process.

KEYWORDS

community of inquiry, epistemic network analysis, learning analytics, online discussion, trajectory tracking

Practitioner notes

What is already known about this topic

- Assessment and feedback are crucial for cultivating collaborative problem-solving and critical thinking in online inquiry-based discussions.
- Cognitive presence is an important construct describing the progression of thinking in online inquiry-based discussions.
- Epistemic network analysis is gaining increasing recognition for modelling the temporal characteristics of online inquiries.

What this paper adds

- Directional connections between discourses can reflect different online discussion strategies of groups and individuals.
- A pair of connected discourses coded with the community of inquiry model can have different meanings depending on their temporal order.
- A trajectory tracking approach can uncover the fine-grained progression of thinking in online inquiry-based discussions.

Implications for practice and/or policy

- Besides the occurrences of individual discourses, examining the meanings of directional co-occurrences of discourses in online discussions is worthwhile.
- Groups and individuals can employ different discussion strategies and follow diverse paths to thought development.
- Developmental assessment is crucial for understanding how participants achieve specific outcomes and providing adaptive feedback.

INTRODUCTION

Online inquiry-based discussion is an effective pedagogy for collaborative problem-solving and knowledge-building (Chiu & Hew, 2018; Han & Ellis, 2019; Sun et al., 2017). Much research has focused on approaches to analysing and understanding online discussions (Galikyan & Admiraal, 2019; Lämsä et al., 2020; Rolim et al., 2019). The community of inquiry (CoI) model, a well-established theoretical framework, identifies three essential elements for worthwhile online discussions: cognitive, social and teaching presence (CP, SP and TP) (Anderson et al., 1999, 2001; Garrison et al., 2001).

Based on the CoI model, existing methods for analysing online discussions include self-report scales (Arbaugh et al., 2008; Stenbom, 2018) and quantitative content analysis (QCA) (Garrison et al., 1999). While the CoI scale is convenient for collecting large-sample data, it only captures subjective and summative human perceptions unless conducted repeatedly. In comparison, QCA offers a more objective and process-oriented perspective. There are multiple methods for modelling coded discourse data in QCA, including descriptive statistics

(Galikyan & Admiraal, 2019), sequential mining (Lämsä et al., 2020) and network analysis (Rolim et al., 2019). Epistemic network analysis (ENA) has recently gained widespread attention for its unique assumption that learning elements are inseparable, and it is the collective configuration of elements that describes the status of a community (Rolim et al., 2019; Shaffer et al., 2016; Zhang et al., 2022).

Nevertheless, although ENA is a significant advancement, it has limitations in revealing the flow of online discussions. First, the standard ENA does not account for directionality in connections, and thus valuable information hidden within the flow between elements may be overlooked (Saint et al., 2020). For instance, while standard ENA can reveal connections between the exploration (EX) and the integration (IN) activities of CP, it cannot tell whether student discussions moved from EX to IN or IN to EX. Second, although the overall structural evolution of a community's epistemic networks can reveal the community's thought progression (Gašević et al., 2022), such trajectory analyses mostly remain in coarse granularity (eg, week-to-week progression). As the smallest meaningful segment in ENA, a stanza consists of a fraction of discourse data where 'elements present in the same stanza are conceptually connected, while elements in different stanzas are not' (Shaffer et al., 2016, p. 23). It is yet to be explored whether and how tracking the structural changes of epistemic networks at the stanza level could offer detailed and fine-grained insights into the progression of thinking in online discussions.

Therefore, this study aimed to advance the current ENA method by (a) incorporating information on the directionality of connections among elements and (b) developing stanza-based trajectory tracking. Based on a CoI-guided online learning course, we investigated how the proposed analytical advancements could enrich our understanding of online discussion strategies and dynamics.

THEORETICAL BACKGROUND

The community of inquiry model

Text-based online discussion has been a crucial component in various online education scenarios, including MOOCs (Chiu & Hew, 2018), blended learning (Han & Ellis, 2019) and inquiry-based collaborative learning (Sun et al., 2017). As learning-oriented online discussions typically have clear goals, such as problem-solving or knowledge-building (Tan et al., 2021), researchers have proposed various theoretical frameworks (eg, Cacciamani et al., 2018; Durairaj & Umar, 2015; Garrison et al., 1999; Gunawardena et al., 1997) to understand and assess the effectiveness of online discussions. Through carefully reviewing and comparing different frameworks, this study adopts the CoI model by Garrison et al. (1999) as the guiding framework. The CoI model not only encompasses the main elements of online discussions (i.e., cognitive, social and teaching presence) but has also been examined in numerous empirical studies (Garrison & Arbaugh, 2007; Kozan & Caskurlu, 2018; Stenbom, 2018).

Among the three building blocks of the CoI model, social presence indicates the extent to which participants feel belonging to the group, are willing to express themselves and can build social relationships (Anderson et al., 1999). Teaching presence refers to designing, supporting and moderating cognitive and social processes in online inquiries to achieve meaningful educational goals (Anderson et al., 2001). Cognitive presence stems from the practical inquiry model and describes four interconnected phases, namely triggering event (TE), EX, IN, and resolution (RE), through which meanings and knowledge are constructed (Garrison et al., 2001). With the support of social and teaching presence, one of the primary goals for CoI-guided online discussions is to develop from lower-order (i.e., TE and EX) to higher-order thinking (i.e., IN and RE) (Maranna et al., 2022; Stein et al., 2013).

The indicator-centred analysis

Research has adopted two approaches to assessing the effectiveness of CoI-based online learning: self-report scales and QCA. On the one hand, originating from the CoI model, Arbaugh et al. (2008) proposed a self-report instrument containing 34 items corresponding to different CoI indicators (eg, EX – 'I utilized a variety of information sources to explore problems posed in this course', p. 135). When using the self-report instrument, researchers would typically invite participants to report their perceived level of agreement with each item at the end of a learning activity. For example, Shea and Bidjerano (2013) measured and compared college students' perceived presence toward fully online and hybrid course delivery modes at the end of an academic year.

On the other hand, QCA focuses on textual data generated in online discussions and annotating units of analysis (eg, post, paragraph or sentence) with the CoI coding scheme (Garrison et al., 1999). The coding scheme consists of indicators for each CoI presence and their descriptions. Based on coded discussion data, the frequencies of indicators are counted to represent discussion dynamics. For instance, Galikyan and Admiraal (2019) applied the CoI coding scheme to examine pre-service teachers' online knowledge-building activities. Based on the percentages of the four CP phases, they assessed the levels of CP between different communities consisting of first- and second-year students. Moreover, aiming at improving the coding efficiency and extending the applicability of QCA for learning assessment, several studies have worked toward automated approaches by leveraging machine learning techniques (Ba et al., 2022; Hu et al., 2022; Kovanović et al., 2016; Zou et al., 2021).

Although traditional self-report scales and QCA approaches have revealed insights regarding the composition of online learning and the roles of CoI indicators, these two approaches are limited in uncovering learning progressions and guiding formative assessments (Csanadi et al., 2018). Moreover, while these two approaches focus on individual indicators, recent studies have argued that the spatial–temporal connections of elements could be more informative in representing online discussion patterns (Gašević et al., 2022; Rolim et al., 2019; Shaffer et al., 2016). For example, Rolim et al. (2019) demonstrated that connections between CP and SP indicators developed in different patterns for practicing and expert learners under the same scaffolding condition, suggesting that scaffolding may affect behavioural changes differently given learners' academic levels. This finding was not revealed by counting those indicators individually.

The connection-centred analysis

Unlike online forums, where multiple threads and topics develop simultaneously, CoI-guided online discussions typically have a guiding topic/question and are more focused and integrated. Participants' posts are generally under the umbrella of the designated topic and arranged chronologically. Previous studies have adopted sequential (Jeong, 2003; Lämsä et al., 2020; Wu & Hou, 2015) and network (Csanadi et al., 2018; Rolim et al., 2019; Shaffer et al., 2016) perspectives, respectively, to model the connections within textual data.

Sequential analysis aims to model the transitional relationship between events and identify unique chain reactions (Fan et al., 2022). It helps interpret learner behaviours in complex educational tasks. Several studies have utilized sequential analysis in online discussion contexts to understand student interactions (Jeong, 2003; Lämsä et al., 2020; Wu & Hou, 2015).

For instance, when researching critical thinking in group discussions, Jeong (2003) coded discussion data into 12 critical thinking events, computed transitional probabilities among events with sequential analysis, and explained the meanings of various transitions. Lämsä et al. (2020) emphasized the significance of sequential analysis in uncovering the temporal dynamics of learning processes.

Following the goal of slicing and dicing the learning process, recent studies have adopted a network perspective for modelling the complex interactions between learning elements (Elmoazen et al., 2022). Unlike sequential analysis, which emphasizes transitional features between a subset of elements, the network perspective stresses that the configuration of all elements defines the status of an individual, group or community (Shaffer, 2006). Based on this conception, researchers have devised and implemented ENA, a method for modelling and representing the dynamic co-occurrences of elements (Shaffer et al., 2016). Specifically, ENA is designed to analyse hand-coded discourse data by finding the associations between different codes. By accumulating the co-occurrences of codes within meaningful subsets of data (eg, seven continuous discussion posts), ENA generates network representations portraying the interconnectivity among the coded data. Based on the structures of these networks (eg, edge weights), it is possible to compare different patterns between the networks across groups or individuals. Furthermore, ENA allows for testing statistically significant differences by representing networks via their centroids (i.e., a network's centre of mass calculated from edge weights). Rolim et al. (2019) explored connections between CP and SP indicators in online communities of inquiry using ENA and demonstrated how pedagogical and time factors affected the connections. For instance, by comparing the networks of groups with and without additional scaffoldings, their study showed that the group with additional scaffoldings exhibited stronger connections between nodes of higher-order CP phases and SP indicators. Moreover, Csanadi et al. (2018) demonstrated that ENA was more advantageous than traditional indicator-centred analysis in accommodating the temporal nature of discourse data and revealing the developmental characteristics of collaborative learning.

Although the generic ENA has enriched our understanding of the temporal characteristics of online discussions, two methodological extensions could further strengthen ENA's affordance. Due to technical restraints, empirical studies have primarily employed ENA to examine non-directional co-occurrences among CoI indicators (Ba et al., 2022; Rolim et al., 2019). Researchers have suggested that incorporating directionality could clarify the detailed associations between elements (Fan et al., 2022; Saint et al., 2020). Directionality is particularly meaningful in online discussions as learners and groups shift non-linearly between cognitive phases and form diverse development paths (Garrison et al., 2001; Stein et al., 2007). Following this idea, recent studies have proposed ENA variants such as ordered network analysis where hourglass-shaped edges (i.e., two triangles pointing toward each other) are used to represent directional connections between nodes (Fogel et al., 2021; Tan et al., 2022). Specifically, the size and saturation of a triangle are proportional to the frequency of the corresponding directional connection. Meanwhile, as the smallest meaningful unit in ENA, a stanza provides a snapshot of a discussion's status based on the co-occurrences of codes in that stanza. Rather than directly accumulating the information in a collection of stanzas, it is worthwhile to consider whether and how tracking the structural changes of epistemic networks at the stanza level could offer additional insights into the progression of thinking in online discussions.

The present study

The present study aimed to address the research gaps and further advance existing research by adding directionality to connections in ENA as well as developing stanza-based trajectory tracking. For directionality, we devised an alternative visualization approach by connecting network nodes with double edges pointing in opposite directions. This approach offers an intuitive and straightforward representation of directional connections. Moreover, compared to existing ENA variants, we adapted a strategy from lag sequential analysis (LSA) to calculate and integrate transition probabilities between nodes in both directions. This integration leverages the strength of both ENA and LSA and enables us to identify representative patterns while reducing visualization complexity. The proposed extension is expected to visualize directional epistemic networks and highlight significant inquiry patterns. For trajectory tracking, this study adopted stanzas as the smallest meaningful modelling units. By calculating the co-occurrences of elements in each stanza, we obtained all stanzas' corresponding networks, projected the centroids of networks onto the ENA plane and tracked the movement of those centroids. This stanza-based trajectory tracking is expected to contribute more detailed insights into the progression of thinking in online discussions compared to the generic ENA and its other variants.

The following research questions (RQs) guided this study:

RQ1: To what extent can directional ENA identify different inquiry patterns?

RQ2: To what extent can stanza-level trajectory tracking identify different progressions of thinking?

METHODS

Research context

This case study focused on an online course about the role and function of adult education in society offered by a public research university in North America. This course consisted of 10 modules published on the university's learning management system. During each module, students studied reading materials, posted personal understanding and views and conducted inquiry-based discussions regarding typical cases or debates in adult education (eg, ‘Would you agree/disagree that education serves the purposes of fostering the dominant culture's way of living, thinking, and acting?’). Fifteen graduate students (9 females) with education-related backgrounds participated in this course. In three modules selected by the instructor, students were randomly divided into three 5-person groups for in-depth discussions. The three modules were distributed at this course's early, middle and late stages, which could reflect changes in group discussion strategies over time to a certain degree (Stein et al., 2013). The grouping was consistent across the three weeks. The groups' discussion texts were collected and analysed in this study.

Identifying CoI indicators with content analysis

We followed the traditional content analysis approach to identify the CoI indicators from discussion texts (Garrison et al., 1999). First, coding units were created by splitting student posts into sentences. While both post- and sentence-level content analysis have been adopted before (Shea et al., 2010; Stein et al., 2013), sentence-level coding could support interpretations at a finer granularity and was more suitable for this study. Following data pre-processing, two researchers with extensive experience in online learning and the CoI model manually coded the discussion texts through two stages (Table 1). At stage one, they coded 20% of the sentences cooperatively to familiarize themselves with the data and

TABLE 1 Coding scheme.

Presence	Code	Definition	Example
CP	TE	The initial question or topic that sparks a meaningful discussion	'What defines a literate member of our society?'
	EX	Active investigation and exploration of the triggering event	'The culture defines what the standard is that people should be learning'
	IN	Connecting and synthesizing information and ideas from the exploration phase	'So to summarize, you are suggesting that the culture that [Company B] created affected the way all those people were educated'
	RE	Reaching a shared understanding or solution based on exploration and integration	'Adult ed[ucation] prepares us for the present by offering classes in adult ed that relates to the world'
SP	SP	The expressions of connectedness and engagement with others in the online discussion environment	'I thought that was interesting'
TP	TP	The actions of facilitating, guiding and supporting the discussion process	'We're going to need to kind of bring all this together'

Abbreviations: CP, cognitive presence; EX, exploration; IN, integration; RE, resolution; SP, social presence; TE, triggering event; TP, teaching presence.

resolve potential disagreements. At stage two, the two researchers independently coded the remaining data. The inter-rater reliability measured by Cohen's kappa reached 0.95, which was near perfect (Cohen, 1960). Following stage two, the coders discussed and addressed the remaining disagreements. After data coding, descriptive statistical analysis was performed to show the primary distributions of CoI indicators in each discussion.

Detecting discussion patterns with directional ENA

Building standard ENA

This study performed standard ENA using the rENA package (Shaffer et al., 2016). To identify the co-occurrences of CoI indicators, a moving window (i.e., stanza) of 14 sentences was defined. As a discussion post (i.e., unit of information) on average contained around two sentences in our dataset, this window size could cover roughly seven units of information, which has been demonstrated to provide statistical discrimination between groups and support stable ENA interpretations in collaborative learning contexts (Ruis et al., 2019). By applying the moving window to the coded data, we obtained a collection of stanzas for each discussion (i.e., a unit of analysis). ENA then transformed each stanza into an adjacency matrix and represented each discussion by accumulating its adjacency matrices, which were subsequently restructured as high-dimensional vectors. Next, singular value decomposition was employed for dimensional reduction and projecting the discussions onto a two-dimensional plane. Based on the positions of discussions, an optimization routine was used to locate CoI indicators.

Embodying directions between ENA nodes

To account for the directional features between CoI indicators and maintain the assumption in ENA that all co-occurrences in a stanza were equally important, we counted the directional connections while building adjacency matrices for stanzas. Then, upon visualizing the epistemic networks, this study employed the NetworkX toolkit to portray the directional networks among nodes. For any two nodes, the directional networks utilized two curved arrows with varying thicknesses to indicate the direction and strength of connections.

Integrating transitional features into directional ENA

This study employed lag sequential analysis (LSA) to quantify the transitional probabilities in directional ENA. LSA was a classic sequential mining approach for identifying representative transitions among chains of events (Bakeman & Gottman, 1997). The term *lag* in LSA describes the relative positions between two events. For example, *lag* = *1* means the two events were adjacent while *lag* = *2* indicates a third event between the two target events. In the present study, we treated all indicator co-occurrences within the same stanza as adjacent transitions (*lag* = *1*) to keep in line with the co-occurrence assumption of ENA. After obtaining the accumulated directional adjacency matrices, we adjusted them to form the transition frequency tables. In each table, the rows contained the preceding indicators, and the columns denoted the following indicators. Subsequently, we calculated the transition probabilities by the relative frequency of transitions between indicators. To determine the significance of given transitions, the adjusted residual equation proposed by Bakeman and Gottman (1997) was employed:

$$z_{a\to b} = \frac{x_{ab} - y_{ab}}{\sqrt{y_{ab} \times \left(1 - n_{a+}/N\right) \times \left(1 - n_{+b}/N\right)}} \tag{1}$$

$$y_{ab} = \frac{n_{a+} \times n_{+b}}{N} \tag{2}$$

where x_{ab} and y_{ab} refer to the observed and expected number of transitions from an event a to b; n_{a+} and n_{+b} indicate the total frequencies of the a-th row and b-th column; N is the overall sum of frequencies in the table. As a result, the transition between two codes is deemed significant when the z-score is larger than the critical value of 1.96 ($\alpha = 0.05$). According to the LSA results, refined directional epistemic networks were generated by filtering out insignificant transitions.

Tracking the progression of thinking with stanza-level trajectories

In standard ENA, stanzas of a unit of analysis (eg, a discussion) are accumulated to represent the overall co-occurrence characteristics of that unit. ENA assumes that all indicators that occur within the same stanza are associated while cross-stanza co-occurrences are unrelated (Shaffer et al., 2016). This study tracked the progression of thinking in online discussions by treating stanzas as meaningful units and examining the path formed by projections of stanzas on the ENA plane. Specifically, as each stanza consists of indicators and their co-occurring relationships, a stanza network can be formed based on the positions of nodes determined in the standard ENA. According to the connections between nodes and their relative weights, we obtained projections of stanza networks by calculating the coordinates of the network centroids:

$$X_{stanza} = \frac{\sum_{i=1}^{n} \left(x_{node\ i} \times w_{node\ i}\right)}{\sum_{i=1}^{n} w_{node\ i}},\ Y_{stanza} = \frac{\sum_{i=1}^{n} \left(y_{node\ i} \times w_{node\ i}\right)}{\sum_{i=1}^{n} w_{node\ i}} \tag{3}$$

where $x_{node\ i}$ and $y_{node\ i}$ denotes coordinates of the i-th node in a given stanza and $w_{node\ i}$ indicates the number of times the i-th node is connected with other nodes in this stanza. Finally, we utilized NetworkX to visualize the locations of stanzas relative to the nodes and portrayed the developmental path of thinking by connecting the centroids of stanzas based on their order.

RESULTS AND DISCUSSION

Identified CoI indicators from content analysis

Based on the coding scheme, this study detected and counted the community of inquiry (CoI) model indicators in the three groups' online discussions (Table 2). As indicated by the sum of cognitive presence (CP), social presence (SP) and teaching presence (TP), group 2 was overall the most engaged, followed by group 1 and then group 3. The same trend also applied to the number of CP and higher-order thinking (HOT) indicators (i.e., the sum of integration and resolution), suggesting that group 2's discussions were also cognitively more engaged (Garrison et al., 2001; Stein et al., 2013). Among indicators in CP, exploration (EX) was the most frequently observed indicator in nearly all group discussions. In addition, regarding HOT indicators, integration (IN) has taken up the major proportion while resolution (RE) was rarely coded. Nevertheless, similar to previous understanding (Csanadi et al., 2018), descriptive statistics revealed limited information regarding the causes and processes of cognitive development.

Detected discussion patterns from directional ENA

Figures 1 and 2 present results from the directional ENA for each online discussion. To illustrate details of the epistemic networks, group 1's first discussion (i.e., G1-D1) was used as an example (Figure 1). The nodes of this network represented indicators from the CoI model, and their diameters were based on the number of occurrences. The frequencies that indicators co-occurred in the same stanza determined edge weights. Moreover, since we distinguished co-occurrences in different directions, any two nodes in the graph were connected by two edges. The node at the non-arrow end was the preceding indicator while the co-occurring node at the arrow end was the following indicator. For instance, the IN→EX connection indicated that IN co-occurred with EX, and IN was the preceding indicator.

TABLE 2 Number of CoI indicators in each group discussion.

Discussion	Group	TE	EX	IN	RE	HOT	CP	SP	TP
1	1	21	163	62	2	64	248	248	127
	2	10	270	73	4	77	357	234	126
	3	23	58	16	0	16	97	149	81
2	1	14	181	98	0	98	293	312	155
	2	9	323	145	16	161	493	224	157
	3	12	48	42	8	50	110	131	45
3	1	2	137	42	5	47	186	148	90
	2	4	245	145	15	160	409	234	161
	3	7	38	42	28	70	115	129	51

Abbreviations: CP, cognitive presence; EX, exploration; HOT, higher order thinking; IN, integration; RE, resolution; SP, social presence; TE, triggering event; TP, teaching presence.

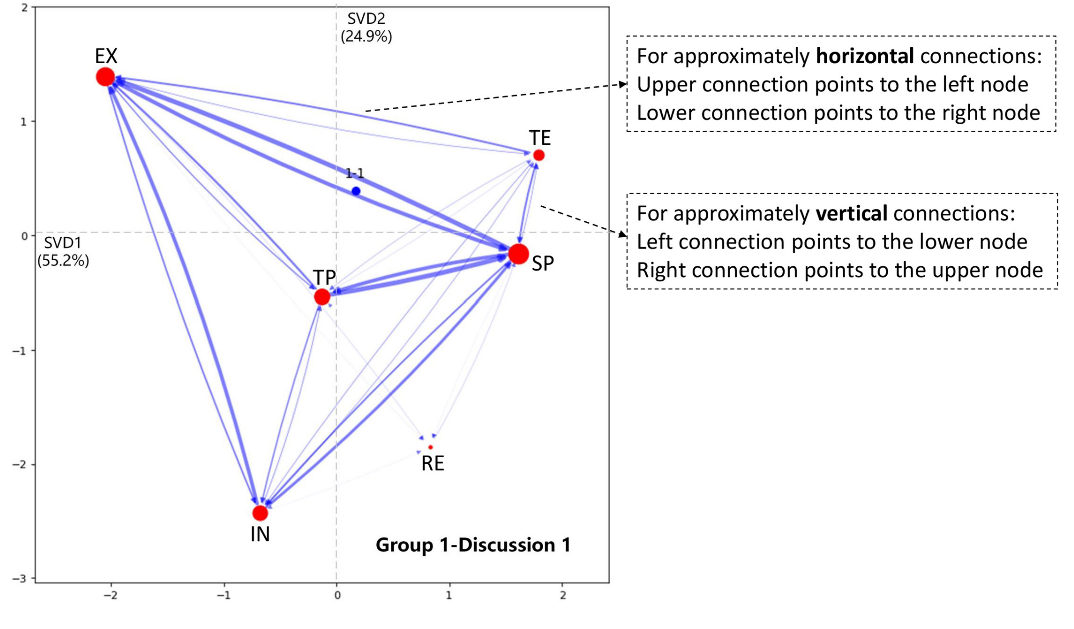

FIGURE 1 Directional ENA of group 1's first discussion.

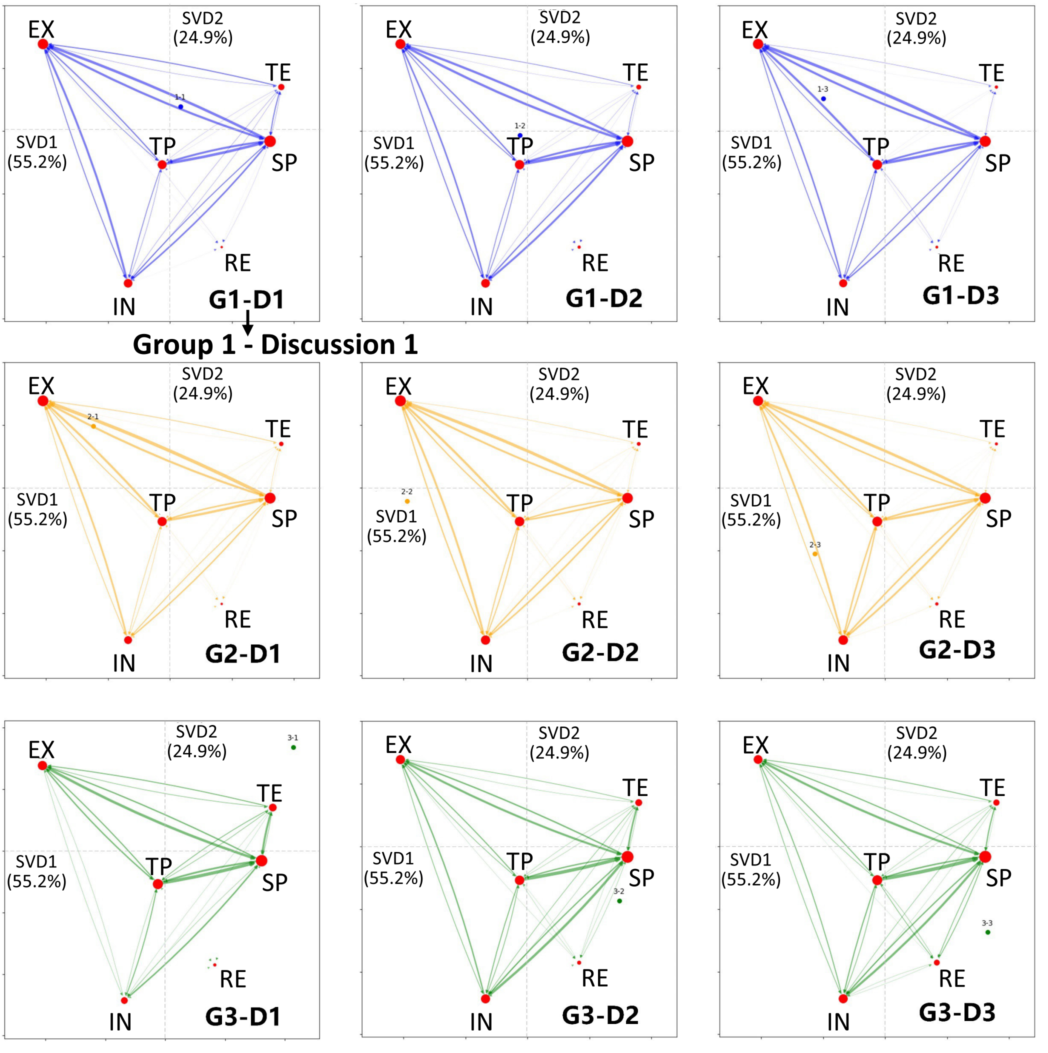

FIGURE 2 Directional ENA of the three groups.

As demonstrated in Figure 2, directional networks of the three groups were created and compared to uncover both within- and between-group differences. Since the nine networks were produced through the same directional ENA modelling, their node distributions and dimension interpretations were identical to discussion G1-D1.

In terms of within-group development, the connection between TE and EX in group 1 was dominated by TE→EX. This finding was expected since CoI-guided inquiries are generally initiated through TEs (eg, 'Is there a time when knowledge is no longer useful?') and followed by exploring information and ideas to resolve the target questions (eg, 'I mean someone is going to say that cursive is still useful.') (Garrison et al., 2001). Interestingly, progressing from the first to the third discussion, group 1 exhibited decreasingly fewer EX→TE connections, suggesting that this group was getting familiar with the question definition (Darabi et al., 2011). In other words, students in the first group became skilled in clarifying the contexts and scopes of TEs over time and thus did not need to revisit the questions. A similar pattern was also observed for the other two groups. This finding was in line with Stein et al. (2013) who indicated that time was a crucial factor for students to practice and acquire discussion skills. Another prominent within-group change was found in group 3 where connections involving RE increased throughout the three discussions. By the third discussion, there were bidirectional connections between RE (eg, 'Regarding the world to come, participate in a global society, make individuals more marketable.') and IN (eg, 'So, you got more literate in employment and profession.'), TP (eg, 'What defines a literate member of our society?') and SP (eg, 'I agree'). The multi-connections could be explained by the fact that the progression of thinking is not only a cognitive process but also involves active facilitation of inquiry activities (i.e., TP) and continuous social intercourses (i.e., SP), which fits the core claim of the CoI model (Garrison et al., 2001). Furthermore, it was presented in G3-D3 that while connections IN-RE and SP-RE each showed equal weights in both directions, connection TP-RE was unbalanced, with TP → RE being thicker than its opposite direction. This finding demonstrated the critical functions of TP in regulating and guiding the cognitive process (Hosler & Arend, 2012).

Concerning between-group comparisons, the directional ENA revealed that connection SP-EX in group 2 appeared mainly to be from SP to EX while group 3 had more EX → SP. Examining the discussion texts revealed that these two directions reflected different discussion patterns. Specifically, during the exploration stage, students in group 2 often started their posts by socially responding to others (eg, 'Cool', 'Right' and 'I am torn') and then presented their own thoughts and evidence (i.e., EX). On the contrary, although students in group 3 also responded to EX incidents, their responses were primarily social expressions without sharing their thoughts, which could lead to inefficient progression of thinking as demonstrated in Lee (2014). Another difference identified across groups was the TP-SP connection. While this two-way connection in groups 1 and 2 was relatively balanced, group 3 displayed much thicker TP → SP than SP → TP. Tracing back to the discussion texts, it was found that when students in group 3 were asked if they agreed with a statement (i.e., TP), they tended to simply agree (i.e., SP) without supplementing further thoughts. In contrast, when students in the other two groups faced the same situation, in addition to providing their responses, they were more likely to actively moderate discussions by clarifying statements or further seeking others' opinions (i.e., TP). According to the online discussion coaching framework proposed by Stein and Wanstreet (2013), the detected pattern in group 3 can be explained as students' lack of skills in conducting online inquiries.

Following the directional ENA, we performed LSA to filter out connections that failed to reach statistical significance. As depicted in Figure 3, a salient between-group difference after applying the LSA was that only group 2 maintained its overall network structures except for the connection TP-IN. This structure confirmed the essential role of TP in regulating both cognitive and social processes of online discussions (Garrison & Arbaugh, 2007; Ma et al., 2017). On the contrary, several connections in group 1 (eg, TP-IN) and group 2 (eg, EX-IN) were at least partially removed. As a result, the adoption of LSA has highlighted both within- and between-group differences. For example, group 2 only developed significant TP-IN bidirectional connections after the first discussion. Meanwhile, groups 1 and 3 only had IN → TP connections in discussions G1-D3 and G3-D1. Furthermore, while TP played an essential role in group 2 by being the centre of multiple bidirectional connections, TP in groups 1 and 3 was primarily linked to SP, indicating a focus of TP on social regulation.

Tracked progression of thinking from stanza-level trajectories

To further understand the progression of thinking in online discussions, we anatomized the standard (i.e., non-directional) epistemic networks by sequentially projecting the centroids of stanzas on the ENA coordinate system. In Figure 4, the second discussion of groups 2 and 3 was selected to illustrate the affordance of the stanza-level trajectory analysis. The

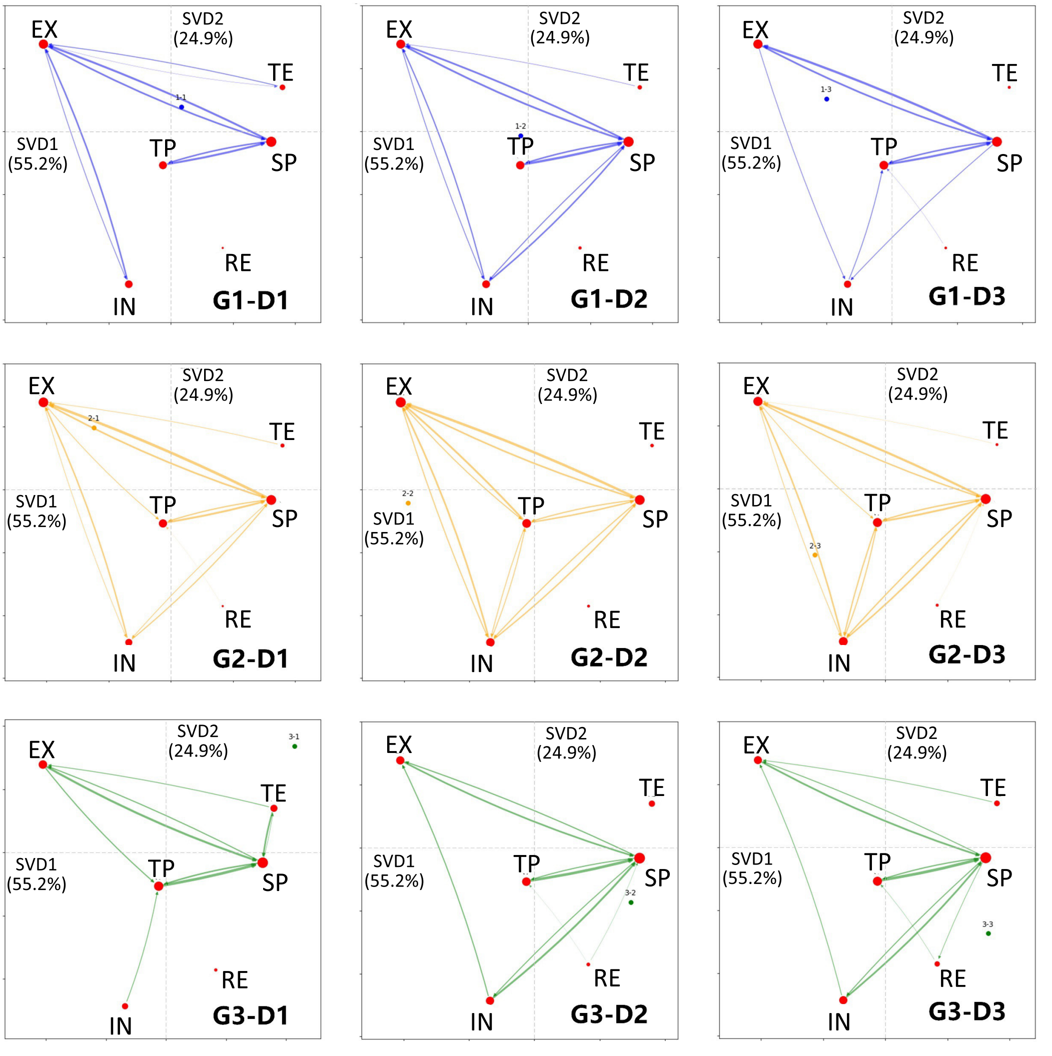

FIGURE 3 Integrating directional ENA with LSA transitional features.

second discussion was chosen because it was in the middle of the course when students were relatively familiar with the discussion process and the most engaged. In the trajectory graphs, except for the CoI nodes (eg, TE), each dot represents the centroid of a stanza. The number next to a dot indicates its temporal order. For grouped numberings such as [6, 18, 26], they indicated that multiple stanzas at different time points shared the same centroid and had the same or similarly portioned network structure (Shaffer et al., 2016). Additionally, to ensure visualization clarity, we evenly split each discussion into three sub-figures based on the total number of stanzas.

Several observations could be made from the comparison between G2-D2 and G3-D2 trajectories. Regarding the overall distributions of stanzas, while the starting and ending points for the two groups were close, stanzas in G2-D2 were spread more evenly along the horizontal and vertical spaces of the ENA plane. On the contrary, the G3-D2 trajectory hovered over the lower section near IN, RE and TP. This difference indicated group 3's relative lack of focus on the problem definition and information gathering phases of online

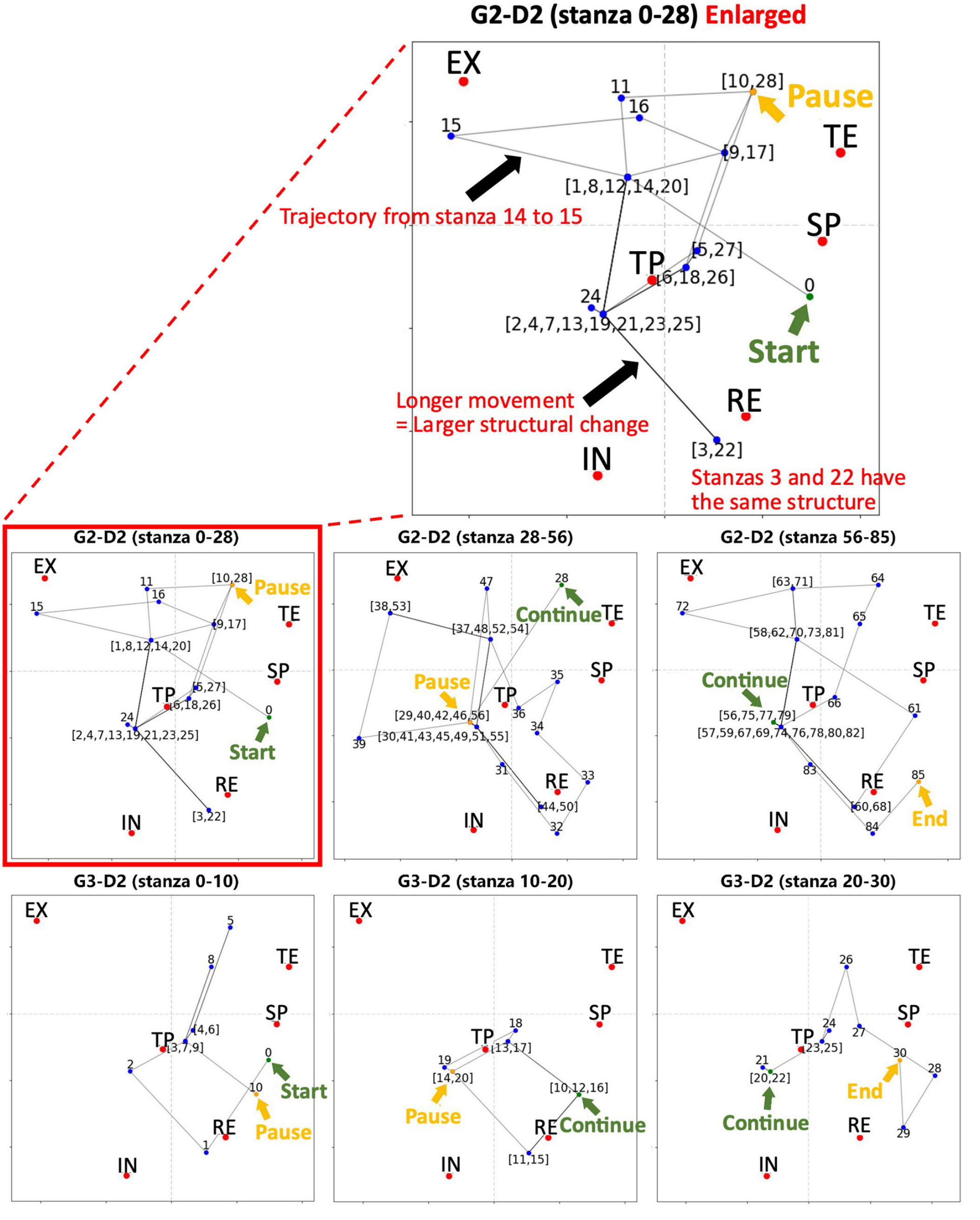

FIGURE 4 Development trajectories for Group 2-Discussion 2 (upper subfigures) and Group 3-Discussion 2 (lower subfigures).

discussions, which could be explained in two ways. On the one hand, group 3 might want to complete the discussion task as soon as possible and thus engage less in gathering information or critical thinking (i.e., EX). On the other hand, it could also be that participants of group 3 were very familiar with the discussion topic. As a result, they could efficiently come up with a mutually agreed solution instead of spending much time exploring. In either case, the trajectory analysis revealed a need for instructors to pay attention and ponder on possible causes.

Meanwhile, compared to the relatively straightforward trajectory of G3-D2, G2-D2 presented a much more complex development path with widely distributed dots and constant back and forth between dots. Notably, G2-D2 gradually generated more and more stanzas in the third quadrant (i.e., lower left) of the graph as the discussion progressed. In terms of movements of stanzas, we found that G2-D2 stayed in the upper middle section during the beginning of the discussion (i.e., stanza 0–28) and worked its way down to locations closer to IN and RE. Nevertheless, the G2-D2 trajectory often returned to the middle section along the vertical dimension instead of remaining in the bottom section. During this process, SP and TP played essential roles. Specifically, many stanza projections were in the middle section along the vertical axis which is closer to TP. Besides, group 2's trajectory repeatedly past projections close to SP and TP while progressing toward higher-order thinking indicators. The trajectory analysis further confirmed the importance of SP and TP in supporting cognitive development (Ma et al., 2017; Rolim et al., 2019). Furthermore, since the distance between projections indicated the degree of difference in network structures, the trajectory analysis could also demonstrate the magnitude of changes in discussion behaviours. Concerning the magnitude of a single movement, G2-D2 was found to have more long-distance movements (eg, stanza 38 → 39 and stanza 61 → 62) than G3-D2, indicating that structures of stanzas in G2 often changed more significantly. According to the CoI model (Castellanos-Reyes, 2020; Garrison et al., 1999), worthwhile online discussions feature continuous and circular interaction between personal meaning and shared knowledge. Therefore, the transition distance also suggested that group 2 has demonstrated a more dynamic knowledge-building process. That being said, a trajectory with many large-distance movements might also be interpreted as a less systematic learning process. Clarifying the desirable intensity and frequency of interactions between CoI constructs remains an issue.

IMPLICATIONS AND LIMITATIONS

Implications of extended epistemic network analysis

In terms of research implications, previous studies under the scope of the CoI model have been evolving from focusing on the characteristics of individual indicators (Galikyan & Admiraal, 2019) to the associations and connections between elements (Ba et al., 2022). However, there was limited understanding of the meanings of directions underlying indicator co-occurrences. By implementing the directional ENA, this study demonstrates that indicators co-occurring in opposite directions can reflect different discussion patterns and strategies (eg, the SP → EX connection in G2 and EX → SP in G3). Moreover, the weight of directional connection can also vary during the process of an online course given learners' accumulated skills and experience. Hence, the identified directional information is valuable in deepening our understanding of the fine-grained and dynamic associations between CoI indicators during the process of learning. Besides, due to differences of discussants in prior knowledge, learning preferences, personalities and more, each online discussion may unfold differently and present various developmental paths. The stanza-based trajectory analysis enables researchers to trace the cognitive development and explain the causes of different learning outcomes. For example, when learners are highly homogeneous regarding a discussion topic, their group trajectory may develop quickly toward the resolution phases without having sufficient critical examination of ideas. Beyond the CoI model, the proposed ENA extensions are also meaningful regarding their flexible implementations.

That is to say, both the directional ENA and trajectory analysis can be carried out together with ENA in many different contexts.

Practically, the proposed extensions of ENA can potentially enhance developmental and formative assessments of online inquiry-based learning by modelling the fine-grained development trajectory of discussions and detecting the detailed discussion patterns revealed by directional connections of indicators (Gašević et al., 2022). For example, from visualizations of directional ENA, instructors may spot certain groups with unbalanced connections between theoretical indicators. Then, based on their pedagogical knowledge and teaching experience, instructors can swiftly trace back to the corresponding discussion texts and diagnose the causes of problematic connections. Furthermore, the diagnosed causes can support instructors to provide learners with accurate and adaptive feedback (Stein et al., 2013). Similarly, the trajectory analysis is promising in offering an overview of the thinking progression. Ideally, learners in a community of inquiry should progress toward higher-order thinking through iterative cognitive and social intercourses. However, if a group's trajectory is overly distributed around specific indicators, this may indicate potential deficiencies. In this case, instructors can follow the trajectory in order to identify where discussions may go off track and provide precise guidance and coaching to learners.

Limitations and future research

Several limitations and future directions should be noted in this study. First, the size of a stanza is a critical factor in ENA, defining the range of meaningful co-occurrences. The stanza size is not only associated with epistemic networks but also affects the granularity of trajectory analysis. While we used a stanza size of 14 sentences, there has been no consensus regarding the most appropriate stanza size. The optimal stanza size may vary by topic and context. Future studies are suggested to examine how different stanza sizes will affect the modelling and interpretation of directional ENA. Second, the trajectory analysis and visualization incorporated all stanzas. While this decision allowed us to track cognitive development accurately, it also resulted in relatively complex visualizations. Future studies can investigate whether sampling methods can be applied to balance the complexity of visualizations and the accuracy of trajectory modelling. Third, since this study aimed to evaluate the affordance of ENA extensions in detecting behavioural differences between discussion groups, we focused on cognitive development and simplified social and teaching presence. Upon validating the proposed analytics, we plan to expand the research scope by incorporating indicators of social and teaching presence to further assess the online discussion dynamics. Lastly, while one of the goals of the proposed approaches is to support instructors, we need to acknowledge the challenges instructors may have in interpreting the analysis results. We plan to implement the ENA extensions in different contexts to reduce these challenges, and design user-friendly and generalizable interpretations to accompany the visualizations.

CONCLUSION

To summarize, this study devised and examined methodological extensions for ENA in mining the fine-grained behavioural patterns and developmental trajectories of online inquiry-based discussions. The findings demonstrate that both the directional ENA and trajectory analysis can advance the generic ENA and offer insightful patterns of online discussions. Moreover, from the perspective of developmental assessment, the proposed extensions offer stakeholders a unique perspective to identify and understand learning strategies in collaborative problem-solving.

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CONFLICT OF INTEREST STATEMENT

We have no known conflict of interest to disclose.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ETHICS STATEMENT

Appropriate ethical approval was reviewed and granted. A Funding Information section is provided.

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