# Exploring students' epistemic orientation, learning trajectories, and outcomes

Pakon Ko
Centre for Information Technology in Education
The University of Hong Kong
Hong Kong SAR, China
kopakon@hku.hk

Cong Liu
Centre for Information Technology in Education
The University of Hong Kong
Hong Kong SAR, China
conglc@hku.hk

Nancy Law
Faculty of Education
The University of Hong Kong
Hong Kong SAR, China
nlaw@hku.hk

Yuanru Tan
Department of Educational Psychology
University of Wisconsin-Madison
Madison, Wisoconsin, USA
yuanru.tan@wisc.edu

David Williamson Shaffer
Department of Educational Psychology
University of Wisconsin-Madison
Madison, Wisconsin, USA
dws@education.wisc.edu

## Abstract

The influence of students' epistemic orientations on their learning behavior and outcomes is well-documented. However, limited research explores students' epistemic orientations in terms of conceptual engagement and learning outcomes. This study, set within the context of higher education, examined the patterns of conceptual engagement among two performance groups and identifies differences in their epistemic orientations. Both epistemic network analysis (ENA) and ordered network analysis (ONA) methods were used. The results from the ENA revealed distinct trajectories and patterns of conceptual engagement between high-performing and low-performing students during different periods in their learning journey. High-performing students were able to establish a more interconnected and distributed epistemic network earlier than their low-performing counterparts. ONA results revealed that (1) high-performing students were more inclined to employ abstract theoretical concepts to address empirical concerns, doing so more frequently and earlier; and (2) low-performing students benefitted from forum interactions with high-performing students to expand their knowledge resources and engagement with theoretical constructs over time. These discoveries contribute to our comprehension of epistemic orientations in different learners. The implications of this study could help generate learning analytics that monitor students' conceptual engagement in forum discussion and provide feedback to guide the design of learning.

## CCS Concepts

• **Applied computing**; • **Education**; • **Interactive learning environments**;



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## Keywords

epistemic orientation, learning trajectory, ENA, ONA

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## 1 INTRODUCTION

It is broadly recognized that personal epistemology plays a pivotal role in learning, with a strong consensus that more sophisticated epistemic beliefs concerning knowledge and knowing foster improved learning processes and outcomes [1][2][3][4][5][6][7]. Similarly, the individual's epistemic orientation, which reflects their belief system regarding the nature and acquisition of knowledge [8][9] significantly influences their epistemic practices. These practices involve justifying, evaluating, and legitimizing knowledge [10]. Such orientation plays a crucial role in how students interact with knowledge and develop their understanding [11]. Epistemic orientation is defined as the individual's preferred approach to acquiring and utilizing knowledge [12]. A widely recognized taxonomy of epistemic orientations identifies three primary approaches: intuitive, empirical, and rational [11][12][13], reflecting inclinations to consider knowledge as inherently subjective, as grounded on systematic observation and experimentation, or on logical reasoning and evaluation of arguments as true or false respectively. Research has shown that teachers with intuitive or empirical orientations are more likely to design lessons that promote inquiry and conceptual change [14][15][16]. It has also been reported that students' epistemic orientations are related to their academic performance [11].

Concept learning, the process of organizing information and discerning patterns or distinctions, is crucial for individuals to apply knowledge effectively across different situations [17]. Epistemic orientation in concept learning, which reflects learners' preferred approach to acquiring and utilizing new ideas, plays a crucial role in shaping how they construct, refine, and apply knowledge when engaging with new concepts [18][19]. Within the domain of chemistry concept learning, an abstraction-focused epistemic orientation emphasizes the identification and extraction of underlying principles, promoting a more profound comprehension of the subject matter. On the other hand, an exemplar-driven, empirical epistemic orientation centers around forming conceptual representations rooted in the recall of specific examples and algorithms [18]. This differs from the construction of abstract generalizations that integrate and relate individual instances.

Research evidence to-date shows the influence of epistemic orientations on students' learning outcomes, most of the research is conducted in the STEM education area, and primarily concerned with teachers' epistemic orientation and their pedagogical practices, often referred to as epistemic practices. Studies of concept learning in professional domains uncovered a further, practical epistemic orientation in addition to the theoretical and empirical orientations [11][18][20]. The practical orientation involves applying conceptual knowledge to real-world situations within the professional domain, including those related to prior professional experiences. The theoretical orientation tends to focus on understanding and engaging with abstract concepts and principles within the professional context. The empirical orientation tends to emphasize the use of systematic observations, along with specific examples and evidence, to represent concepts and principles [12][13][18][20][21]. This taxonomy offers a structured way to explore diverse epistemic orientations in concept learning.

Conceptual change research occupies an important area of research in the learning sciences since the mid-1970s when researchers recognized that students often held robust misconceptions that were very difficult to change [22]. This research started in the natural sciences, physics and biology, and was taken up later by researchers in psychology and then other humanities and social sciences disciplines. One major debate within the conceptual change research community is the extent to which naïve conceptions are fragmented or coherent [23]. If learners' naïve conceptions were more fragmented, then the process of learning would also entail a need for change in the systematicity and structure of their knowledge resources. Conversely, students who are more inclined towards a theoretical epistemic orientation may find it easier to achieve a deeper understanding in subjects that involve theories as a connected coherent system. In this study, we explore the extent to which students' learning outcomes and learning trajectories are related to their epistemic orientations. The findings would have important implications for learning design and learner support in learning domains that require the understanding and application of abstract theoretical constructs in addressing complex authentic problems.

## 1.1 Knowledge analysis as an approach to investigate learners' evolving conceptual understanding from a systems perspective

If we take learning to be a constructive process, the construction involves not only the specific content of the knowledge elements but also their organization. Bédard & Chi's [24] work shows that novice learners have different mental representations from experts. Novices generally rely on intuitions and context-dependent knowledge elements to construct their conceptual representations and may struggle to apply their understanding to unfamiliar situations [25][26]. Learning occurs when learners re-organize and re-integrate the relationship among their knowledge elements for the generation of normative concepts [27] held by experts. Moreover, everyday knowledge held by novices can partially contribute to their construction of formal understanding within a discipline domain.

We posit that investigating learners' epistemic orientation and how it may be associated with differences in the learning process will help us better understand how novice students navigate the pathway to establishing a more structured theoretical understanding that characterizes expert conceptualizations. Here we find diSessa's (1993) [28] Knowledge in Pieces (KiP) theory to offer a helpful framework to guide our investigation. KiP was originally developed in the context of analyzing learning phenomena in physics education and has since been used in investigations of learning in other disciplinary contexts [29] and teacher professional development [30]. The KiP theory considers all knowledge elements, including students' naïve conceptions, as knowledge resources [30] that form a conceptual ecology [31]. The knowledge elements serve as potential building blocks for making sense of phenomenon, solving problems or constructing new understanding. Context and students' prior conception play a very important role in how they utilize the knowledge resources when encountering a phenomenon [29]. Diversity among learners in the learning process can then be revealed by the differences in how learners activate and coordinate the knowledge resources in their discussion, explanation, or problem-solving within a specific context.

Knowledge analysis [29] is an approach to understanding learners' evolving conceptual understanding that is underpinned by the KiP theory. An important KiP principle is that intuitive knowledge is diverse, rich, and generative such that naïve, inaccurate knowledge could serve as seeds (or knowledge resources) for the development of more nuanced ways of knowing. Hence, the empirical set-up for the learning context, what and how learning data are captured, and how the data is to be analyzed to identify patterns in students' conceptualization are important research design aspects in knowledge analysis.

## 1.2 Epistemic frames and knowledge analysis

An important methodological challenge to knowledge analysis is the need to cater for different granularities in the pieces of knowledge resources. KiP entails the need for a multi-scaled approach [27] as the granularity of knowledge resources depend on the level and focus of investigation. Building on a systems perspective for understanding learning, epistemic frames [32] have been employed in the analysis of higher levels of knowledge structure to detect the development of professional practices among learners. Similar to KiP, epistemic frame analysis addresses learning through the association of knowledge resources.

Epistemic frames have been used in studies of professional learning and are contextually sensitive, depending on the nature of the communities of practices involved. The use of epistemic frames for knowledge analysis sheds light on how frame elements as knowledge resources become connected in the learning process and whether the patterns of connections take after the characteristics of professional practices [33]. Nash and Shaffer (2013) [34] studied the development of professional practice during game design practicum among a group of undergraduate students at a European arts school. The two scholars used epistemic frame trajectories across three meetings to uncover the development of students in a novice team as compared to their mentor. The connections between frame elements among the novice team changed over time and grew more like those connections in the mentor's configuration. Their study addressed the developmental process of professional epistemic practices by examining the changing networks of focal knowledge elements. The network analysis illustrated not only the quantity of knowledge resources employed but also the organization of these resources. There have been different methods for conducting network analyses to examine epistemic frames. Among these methods, Epistemic Network Analysis (ENA) [35] has been adopted in different studies for network analysis [36][37][38][39], and Ordered Network Analysis (ONA) [40] has emerged recently for providing additional information about the flow of responses in communication.

### 1.3 ENA and ONA

Both Epistemic Network Analysis (ENA) and Ordered Network Analysis (ONA) quantifies, visualizes, and interprets network data by identifying and measuring connections among elements within coded data and representing these relationships through dynamic network models [35][40]. ENA models the relational structure among coded elements by quantifying the co-occurrences of codes within a specified segment of data. ENA creates an adjacency matrix to capture code co-occurrences, and these matrices are then aggregated into a cumulative matrix that summarizes the frequency of co-occurrences across the data. For each unit of analysis in the data, ENA transforms its cumulative matrix into a high-dimensional adjacency vector, which is normalized to account for response length differences. Finally, a singular value decomposition (SVD) is applied to reduce the dimensionality of those vectors while preserving maximum variance. As a result, each unit of analysis' vector is represented as a point in a metric space. By tracking the locations of points, ENA allows us to visually track the trajectory of students' conceptual engagement in different defined time periods.

Building upon the theoretical background and analytical foundation of ENA, ONA accounts for the order of connections during both the modeling and visualization processes [41]. Specifically, ONA tracks the direction of connections by differentiating if a code appears as a response to other codes or vice versa. Hence, ONA can differentiate the pattern of conceptual initiation and responses among different learners.

Both ENA and ONA support statistical and visual analyses of differences in epistemic networks across various comparison groups. The dimensional reduction process results in ENA scores and ONA scores for each unit of analysis, which is then visualized by plotting it in the resulting lower-dimensional space. These scores, represented as points, can be used to conduct statistical comparisons between groups [40].

## 2 RESEARCH CONTEXT, RESEARCH QUESTIONS AND DATA

This study investigates whether and how students' learning outcomes in the context of a master's level course on digital technology and educational leadership may be connected to the students' epistemic orientations. A focal aim of the master's course was to help students (1) understand that the most important potential impact of digital technology use in education is to develop students' 21$^{st}$ century skills, which requires teachers and schools to engage in curriculum and pedagogical innovations, and (2) be able to apply several abstract theories and concepts to address the challenges in the initiation and scaling of such innovations.

While this course is in the field of education, it shares some similarities in the challenges encountered during the course of teaching with those in the conceptual change literature. First, students generally perceive the primary goals for integrating digital technology in the school curriculum as personalizing learning, making learning more efficacious and enhancing students' digital literacy, and the key leadership challenges as procuring the appropriate e-learning infrastructure and providing teachers with professional development to handle the technological nuances of technology integration. The second course aim listed above is most demanding as it requires students to adopt an ecological understanding of the education system as a hierarchically nested complex system, to see educational leadership as a multilevel design challenge, and to be able to apply design principles to achieve scalable technology-enhanced learning innovations in authentic educational contexts. The course design, which is detailed in the next section, comprises different learning tasks to provide students with diverse learning experiences to achieve the targeted outcomes. Of the different learning tasks, the online forum discussion was designed as a platform for the open exchange of ideas among students throughout the course. The forum data is thus considered as a rich and authentic data source to gauge students' changing conceptual understanding. In an earlier paper, Authors (2024) [42] reported on their exploration of students' focal conceptual engagement over time using ENA to analyze the forum data. The results show that students advanced in their understanding over time following the conceptual development in the course design. However, the analysis also uncovered significant diversity across groups and individuals. This current paper extends the previous work by exploring whether students' epistemic orientation relates to students' course learning outcomes.

### 2.1 Course Design

The e-Leadership course followed a mission-focused inquiry (MFI) pedagogical approach [43]. At the core of this approach is a group inquiry project on a complex authentic problem that runs throughout the course. The project development is divided into several stages, and students need to apply a subset of concepts and/or skills for each stage of the project inquiry. Other learning tasks and resources are provided to support students' learning, guided by the Bloom's Taxonomy [44]. The course outline highlights three to four keywords each week that are important for addressing the particular stage of inquiry for that week. Table 1 presents the list of keywords for each week. The course also adopted a flipped learning design. Students were given corresponding Perusall®reading

**Table 1: Keywords highlighted in the eight sessions**

| Session | Keywords (KW) |
|---|---|
| 1 | digital competence (DC), 21st-century skills (CL21), AI Literacy (AIL), e-learning leadership (eLL) |
| 2 | knowledge ladder (KL), socioeconomic context (SoEC), ITEd policy (ITEd) |
| 3 | curriculum innovation (CI), pedagogical innovation (PI), ethical issues related to AIEd (EIAI) |
| 4 | innovation diffusion (ID), educational ecology (Eco), catalysts of coherence (CaCo) |
| 5 | sustainability (Sust), teacher design teams (TDT), teacher leadership (TL) |
| 6 | architecture for learning (AfL), design-based implementation research (DBIR), infrastructuring (Infr) |
| 7 | sociotechnical co-evolution (STCo), multilevel multiscale leadership (MLMS), community of Practice (CoP) |
| 8 | program evaluation indicators (ProE), pathways of innovation (Path), scalability (Scal), research practice partnership (RPP) |

assignments and a reading quiz related to the identified keywords. These two tasks aimed to help students master the remember and understand levels of outcomes.

During the synchronous class sessions, each group of students would be doing project presentations on their progress at each stage. The forum discussion was designated for students to share and debate ideas throughout the course. Students needed to meet a participation requirement of two postings per week, and at least one of the postings needs to be a response to another classmate's postings. These postings should include at least two of the set keywords in their weekly readings. They were encouraged to use hashtags to indicate these keywords in their posts. Confusions identified in the Perusall®reading assignments or significant issues arising from the forum discussion were followed up during the subsequent class session. In addition to the continuous coursework listed, students had to submit an individual essay assignment three weeks after the course ended. The essay could be a critique, or an application of a policy document related to AI in education, or a critical evaluation of a publicly accessible example of AI in education implementation in an educational institution.

## 2.2 Research questions

To address the research problem elaborated at the beginning of this section, this paper investigates two specific research questions:

RQ1: What were the developmental trajectories across different time periods during the course in terms of the students' conceptual focus for the low- and high- performing groups as revealed through ENA?

RQ2: What were the patterns of conceptual activation and responses among low- and high- performing learners in the discussion forum discourse across different time periods, as analyzed through ONA?

## 2.3 Participants and data sources

Data was collected from 24 postgraduate degree students enrolled in the master's course on *Digital Technology and Educational Leadership*" (*e-Leadership* for short) in a university in Hong Kong during the 2023-2024 academic year. The research was approved by the university and participants' consent was obtained before the investigation. Data sources included students' inputs in online discussion forums and records of their assignment performance. The messages posted by students in online discussion forums were used to analyze students' conceptual engagement in their learning process. These students were divided into high and low performing groups based on final individual assignment results. One student dropped out in the middle of the course and was not included in this comparative group analysis.

# 3 METHOD

Quantitative ethnography was adopted in this study. This methodology integrates both qualitative and quantitative methods in the research process [45]. Qualitative data was coded and transformed to quantitative data for the subsequent statistical and network analysis. Then, qualitative data was examined together with the results of the quantitative analysis for the interpretation.

Students were grouped into a high performance and a low performance group based on their individual final assignment scores, with 13 and 10 students respectively in the two groups. The t-test results with unequal variance indicated that the means of the two groups are significantly different from each other (see Table 2). The groups will be referred to as high and low groups for short.

## 3.1 Data transformation

The instructor-identified keywords listed in Table 1 can be considered as codes in the context of data analysis in this study as we need to identify all instances when the meaning of the discussion text was similar to those highlighted in the course outline. This process was done manually due to the conceptual nature of the task and the lack of a validated dictionary. The forum had 39,198 words in 390 posts. One team member highlighted and collated textual expressions, which were then independently reviewed by two members to match with the 26 codes. They resolved differences and created a consolidated list, which the class teacher approved with few exceptions. This consolidated list of textual expressions matched to the 26 codes were then used to construct Excel formulas for counting code occurrences and co-occurrences in each post. This was inspired by the procedure adopted by Moraes et al. [46] for the automated generation of codes. The details of the coding process were reported in [42]. The coded data was then used to identify the occurrences and co-occurrences of the 26 keywords in each post.

**Table 2: Independent Samples Test for the final assignment results of the two groups**

| Group | Mean | StandardDeviation | Levene's Test for Equality of Variances | | The t-test with unequal variance | |
|---|---|---|---|---|---|---|
| | | | F | Sig | t | Sig (2-tailed) |
| Low | 13.650 | 2.812 | 6.659 | 0.017 | -5.431*** | 0.000 |
| High | 18.885 | 1.341 | | | | |

[a] $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

## 3.2 Network Analysis

The web-ENA[1] was used to generate network models of different performance groups at different time periods to approximate trajectories. In both ENA and ONA analyses, we identified all lines of data related to an individual participant as the units of analysis. A stanza was defined by threads as students interacted with each other around the same topic in a thread. A moving window of four was used as four is representative of how many lines students normally refer to certain concepts in the data. While the total number of students (units of analysis) was 23, the network analysis had high stability. In ENA, stability is primarily concerned with data variance and the number of units of analysis, rather than solely with participant numbers. In our study, the number of units of analysis is smaller than the number of codes. However, the ENA points used in our t-test meet standard criteria for valid comparisons. The goodness of fit measures for the x-axis are 0.91 (Pearson) and 0.87 (Spearman), and for the y-axis are 0.89 (Person) and (0.89 (Spearman), indicating that stability is not a concern.

The course comprised eight weekly sessions, spanning 7 weeks from session 1 to session 8. The trajectory analysis focused on the changes in configurations of conceptual engagement in the 26 keyword concepts (Table 1) across three periods of the course. A week-by-week analysis reported in another related paper [42] showed that the mean of week 1 was notably distinct from other weeks. The means of weeks 2-4 clustered together, as did the means of weeks 5-7. The analysis results using this categorization also indicate that the means of these three phases were significantly different from each other. We thus report students' epistemic trajectories over the three periods: onset (week 1), midway (weeks 2-4), and final (weeks 5-7).

In order to highlight the epistemic orientations of the students' activation and responses in the ONA, we further categorized the keywords into thematic categories according to their content and epistemic orientation, based on the course's conceptual content (e-leadership and scalability of technology-enhanced learning innovations), with closely connected keywords in each category. Of the 26 instructor-selected keywords (see Table 1), two (EIAI & ProE) were not specifically connected to the theme of e-leadership. The remaining keywords were grouped into 8 thematic categories (see Table 3). Two of the categories were *empirically oriented* concepts related to educational concerns (CLO21) and contexts (ESC) respectively. Three were *practically oriented* and concerned with implementation (eLL, LI, ECOS), while the remaining three were *theoretically oriented* conceptualizations of the solution (SDesT, SDesP, and InnoT). ONA was used to uncover the conceptual initiation and responses related to these eight thematic categories.

[1] https://www.epistemicnetwork.org/

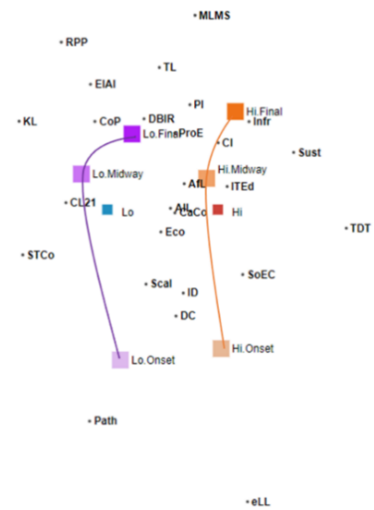


**Figure 1: The means of low-performing (Lo) and high-performing (Hi) groups across three time periods: Onset, Midway, Final.**

# 4 RESULTS

In this section, we first report on how the high and low groups' conceptual foci changed over the three time periods using ENA, and then report on the conceptual activation and responses among both groups of students over the same time periods using ONA.

## 4.1 Comparing the epistemic trajectories of the two performance groups using ENA

Regarding the first research question, we uncovered differences in developmental trajectory between high and low groups through comparing their ENA network configurations across the three time periods: onset, midway and final. Fig. 1 compares the means (*points*) in different periods between the two groups. The movement of the *points* indicates changes in the network configurations in the two groups. Both high and low groups exhibit a similarly shaped trajectory from the onset period to the final period while their means maintain significant difference from each other along the horizontal dimension. Comparatively, the low group's later two *points* are closer to the empirical and theoretical concepts such as CL21 and CoP, whereas the high group's later two *points* closer to more abstract and theoretical concepts such as AfL and Infr.

**Table 3: Eight groups of eLeadership concepts**

| Thematic categories of keywords | Keywords included in the thematic category | Epistemic orientation & nature of thematic category |
|---|---|---|
| 21st Century learning outcomes (CLO21) | digital competence (DC), 21st-century skills (CL21), AI Literacy (AIL) | Empirical (Educational concern) |
| Education system context (ESC) | knowledge ladder (KL), socioeconomic context (SoEC); ITEd policy (ITEd) | Empirical (Educational context) |
| eLearning leadership (eLL) | e-learning leadership (eLL), teacher leadership (TL) | Practical (Implementation constructs) |
| Learning innovation (LI) | curriculum innovation (CI), pedagogical innovation (PI), innovation diffusion (ID) | Practical (Implementation constructs) |
| Ecological scalability (ECOS) | educational ecology (Eco), catalysts of coherence (CaCo), sustainability (Sust); scalability (Scal) | Practical (Implementation constructs) |
| Scalability design theory (SDesT) | architecture for learning (AfL), design-based implementation research (DBIR), infrastructuring (Infr) | Theoretical (Problem conceptualization) |
| Scalability design practice (SDesP) | community of Practice (CoP), teacher design teams (TDT), research practice partnership (RPP) | Theoretical (Strategic conceptualization) |
| Innovation Theory (InnoT) | sociotechnical co-evolution (STCo); pathways of innovation (Path); multilevel multiscale leadership (MLMS) | Theoretical (Strategic conceptualization) |

The movement of these points across different periods indicates that both groups' engagement evolved to connect with more new concepts from the Midway to the Final period. This evolution is shown in Fig. 2, which compares the network models of the two groups during the three periods, with a minimum edge weight of 0.06 for focused analysis. The network displays in column (c) of Fig. 2 present the differences in connections between the two groups using subtraction. Orange lines represent stronger connections in the high group, while purple lines indicate stronger connections in the low group. Network displays in Fig. 2(a) and (b) show the connections in each group at specific periods before subtraction.

The ENA results show that the high group engaged with more diverse concepts earlier than the low group. In the Onset period, both groups discussed the empirical concept of digital competence (DC), but the high group established more connections with a range of key concepts. In the Midway period, both groups engaged with new concepts introduced, but the low group's connections were centralized around the empirical concept CL21, whereas the high group had more diverse cross-connections. In the final period, the low group's connections centered around the practical concept CoP, whereas the high group showed more diverse cross-connections and stronger links among theoretical concepts like Infr, AfL, and Sust.

While the high group initiated discussions with diverse concepts from the Onset and had more cross connections, their interactions with some low group students also broadened the latter's engagement with more diverse ideas from the Midway period. For example, in a discussion thread about "*Whether AI has promoted equity or widen the gap in education between well-developed regions and less-developed regions*", four students in the high group started discussing the topic from the Onset and then one low group student joined the discussion in the Midway period. In that discussion, high group students already touched on some concepts from the later sessions. Among these students, one individual (10364) mobilized the concept of infrastructure (Infr) to discuss the issues faced by children from low socioeconomic backgrounds.

> "Aye. That's true. I totally agree with you on this one, when there is no access to computers or internet, all the discussion on using AI to help talent children in poor regions will be in vain. I am thinking using technology to help the kids in a region with adequate developed infrastructure and hardware . . .." (Student 10364, Onset).

## 4.2 Comparing the patterns of conceptual activation and responses of the two performance groups using ONA

In this section, we first report on the patterns of conceptual activation and responses of the two performance groups during the entire course, and then a comparison for each of the three time periods as used in the ENA analysis reported above.

*4.2.1 The patterns of conceptual activation and responses throughout the entire course.* Concerning the second research question, we found that there were differences in activation and responses of concepts between low and high groups throughout the entire course period. We found a significant difference between the high group (mean = 0.13, $SD = 0.22$) from the low group (mean = -0.17, $SD = 0.13$; $t = 3.99$, $p = 0.001$, Cohen's $d = 1.57$) along the x axis (MR1). Along the y axis (SVD2), there was no statistically significant difference between the high group and the low group. This aligns with the comparative results in the ENA.

In Fig. 3, networks (a) and (b) display the models of each group before subtraction, showing the configuration of the eight thematic categories (Table 3). Black chevrons indicate the direction of information flow between constructs [40]. For example, in Fig. 3(a),


**Figure 2: The network configurations of (a) low-performing (b) and high-performing groups and (c) their subtraction results across three different time periods: Onset, Midway, Final.**

CLO21 is more frequently used in response to LI, as shown by the chevron pointing toward CLO21. This means the low-performing group tended to use CLO21 to respond to LI rather than the other way around. Fig. 3(c) shows the differences in response patterns between the two groups after subtraction. Red edges represent stronger connections in the high group, while blue edges indicate stronger connections in the low group.

The three ONA result displays in Fig. 3 show differences in response patterns between the two groups. Fig. 3(a) and (b) indicate that both groups engaged heavily in discussions around the empirical constructs in CLO21. The subtraction network in Fig. 3(c) reveals that the low group used the empirical construct CLO21 to respond to the practical constructs ECOS and LI more frequently. In contrast, the high group used the theoretical construct SDesT and the practical construct eLL more to respond to CLO21.

*4.2.2 The patterns of conceptual responses across three time periods.* We further uncovered patterns of conceptual responses by comparing the ONA results for the two performance groups during three periods (see Fig. 4). The means for both groups remained significantly different along the x dimension throughout the phases.

- **Onset period**: Significant difference along the x axis (MR1) between the high group (mean = 0.14, SD = 0.27) and the low group (mean = -0.23, SD = 0.25; t = 3.12, p = 0.007, Cohen's d = 1.38). No significant difference along the y axis (SVD2).
- **Midway period**: Significant difference along the x axis (MR1) between the high group (mean = 0.15, SD = 0.19) and the low group (mean = -0.20, SD = 0.15; t = 5.04, p = 0.000, Cohen's d = 2.05). No significant difference along the y axis (SVD2).

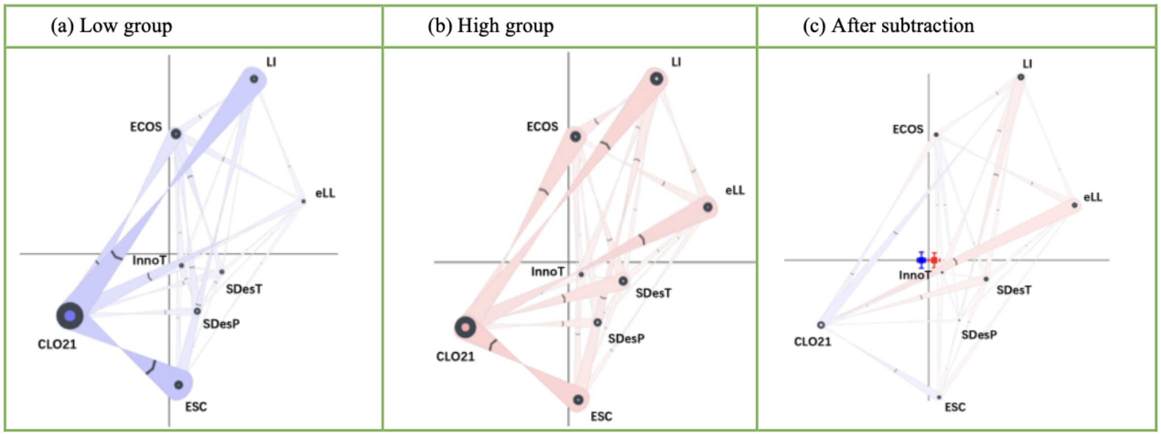


**Figure 3: The patterns of concepts between (a) low-performing (blue edges) and (b) high-performing groups (red edges) and (c) their subtraction results throughout the entire course period.**

- **Final period**: Significant difference along the x axis (MR1) between the high group (mean = -0.13, SD = 0.12) and the low group (mean = 0.17, SD = 0.20; t = -4.23, p = 0.001, Cohen's d = 1.90). No significant difference along the y axis (SVD2).

Regarding the trajectory of conceptual responses, the low group initially used empirical constructs CLO21 and ESC to respond to practical constructs like LI and eLL, indicating a focus on empirical knowledge related to educational concerns. The prominence of CLO21 shows many discussions involved responses within this concept. During the Midway period, the low group engaged intensely with CLO21 and ESC, but also began using the practical construct LI and ECOS for problem conceptualization. By the final period, the low group shifted from intense use of empirical constructs under CLO21 to employing more diverse theoretical constructs like InnoT, SDesP, SDesT, and practical constructs like ECOS.

For the high group, initial responses during the Onset period were similar to the low group, focusing on empirical constructs like CLO21 and ESC. The subtraction results show the high group also used practical constructs like LI and eLL more prominently. During the Midway period, the high group shifted to more diverse constructs, using practical (e.g., ECOS, LI) and theoretical constructs (e.g., SDesP) to respond to CLO21, with other dominant cross-connections. In the Final period, they focused more on non-empirical concepts, using multiple theoretical constructs such as SDesT, SDesP, and InnoT, along with practical constructs like ECOS.

The comparison plots from Onset through Midway to Final between the low and high groups revealed some distinct differences. First, the high group mobilized comparatively more abstract theoretical constructs and earlier and used more diverse constructs to respond to other concepts earlier. For example, in a discussion thread about "What is educational leadership?", two students in the high group and two students in the low group discussed the topic during the Midway period. Student 9887 from the low group utilized the practical construct, eLL, to respond to the last posting involving the practical constructs, eLL and ECOS and theoretical construct, SDesT posted by student 9889 from the high group.

> "School Culture and Climate: **Educational leaders** foster a positive and inclusive school culture that values diversity, promotes collaboration, and ensures a safe and **supportive learning environment** for all students. They act as role models for students and educators, promoting fairness, **equity**, and social justice in education." (Student 9889, high group, Midway).

> "I may express **Teacher Leadership** in the context of early childhood education. In kindergarten, . . . It involves demonstrating expertise, influencing positive change, and making meaningful contributions to the field of early childhood education." (Student 9887, low group, Midway).

## 5 DISCUSSION

This study aimed to compare conceptual engagement patterns between low- and high- performing groups. Both ENA and ONA results showed that students in both groups changed their conceptual connections over time during the eLeadership course, learning to connect new knowledge resources during forum discussions. The integration and reorganization of concepts in these models indicate learning [27]. From a systems perspective on knowledge development [25], the ENA and ONA models illustrated which knowledge resources students activated and how they made connections over time.

Within the course expectations, students continuously integrated new concepts in their discussions on e-Leadership. Over time, their novice concepts evolved with new knowledge resources. However, low- and high- performing students differed in when and how they activated and used these resources. Existing studies show that novice learners and experts organize their knowledge differently to solve unfamiliar problems [25][26]. This study further highlighted differences in epistemic orientation, showing variations in how and when learners integrated and organized new knowledge resources.

The ENA results showed significant differences in conceptual engagement patterns between low- and high-performing groups.

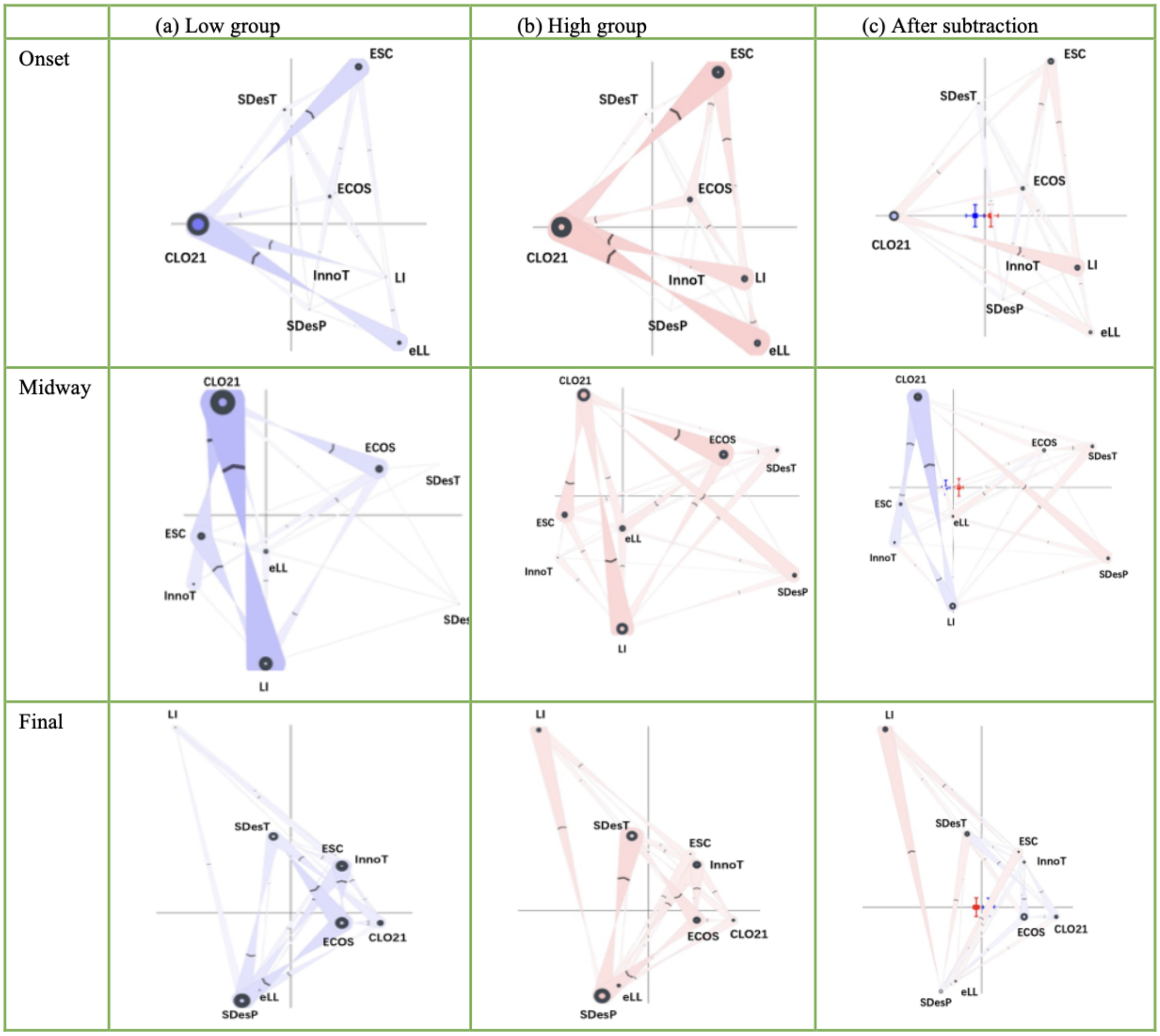


**Figure 4: The patterns of conceptual networks between (a) low-performing (b) and high-performing groups and (c) their subtraction results across three different time periods: Onset, Midway, Final.**

Both groups engaged with new keyword concepts, but their development over time differed (Fig. 1). The high group tended to include theoretical and abstract concepts, while the low group focused more on practical and empirical concepts. The high group also activated new keyword concepts and integrated theoretical with empirical and practical concepts earlier than the low group (Fig. 2).

The ONA results showed that high-performing students were more proactive in activating diverse knowledge resources to address educational concerns (e.g., CLO21, Fig. 3(c)). Midway through the course, while the low-performing group was still focused on CLO21 (Fig. 4(a)), the high group had already incorporated diverse concepts into their discussions. The high group used abstract theoretical constructs to respond to other concepts from the midway point. By the end of the course, the low group also began employing abstract theoretical constructs to address empirical constructs (Fig. 4(a)).

These results have two implications for professional education. First, encouraging students to experiment with new concepts in low-stakes formative assessments can foster professional dialogues. The forum discussions in the e-Leadership course, designed as low-stakes tasks, allowed students to test their ideas in a supportive environment. Leveraging the course's flipped design, high-performing students were more likely to incorporate new concepts from their readings into forum discussions before engaging in deeper class interactions. This proactive behavior may have enhanced their subsequent learning and performance.

Second, the low-performing group benefited from activating diverse knowledge resources through forum interactions with the high-performing group. The ONA subtraction networks showed the largest differences in response patterns during the midway period. By the final periods, these differences reduced, indicating that while the low group was less proactive in experimenting with new concepts, they still incorporated practical and theoretical constructs in their posts. This open exploration in forums encourages the integration of new knowledge resources. Students likely did not have a naive but coherent theory of technology-enhanced learning and educational change scalability. Instead, keywords served as "Knowledge in Pieces" [22]. Participation in forum discussions facilitated conceptual reorganization, leading to a more coherent understanding of key course concepts.

This study highlights the potential of developing ENA and ONA trajectory analysis as formative learning analytics. The reported ENA and ONA analyses were post-course investigations using temporal conceptual configurations at three different periods, not continuous developmental trajectories. Future development of continuous conceptual trajectories based on ENA and ONA could provide valuable tools for teachers to track the knowledge resources students organize, mobilize, and respond to, informing the continuous refinement of learning and feedback design.

An important limitation of this study is that we only investigated epistemic differences between performance groups. We do not know what factors, such as disciplinary background or professional experience, might contribute to differences in individual assignment scores. Further research could identify barriers that prevent low-performing students from activating new knowledge resources. Design-based research with varied course and forum designs may reveal effective interventions to promote proactive activation of new knowledge resources.

# 6 CONCLUSION

This study reveals epistemic differences among adult learners in their conceptual engagement patterns in the humanities. Building on existing research on novice learners and experts (e.g., Nash & Shaffer, 2013) [34], it uncovers disparities between low- and high-performing learners. These disparities highlight a range of epistemic orientations, with some students favoring empirical or practical constructs, while others gravitate towards theoretical ones.

The study demonstrates the potential of Epistemic Network Analysis (ENA) and Ordered Network Analysis (ONA) as tools for generating learning analytics for low-stakes formative assessments, helping to understand differences in learners' conceptual development. Additionally, the findings highlight the benefits of designing learning environments that encourage exploration of new ideas and facilitate the articulation and negotiation of newly acquired knowledge.

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# References

[1] Gaoyin Qian and Donna E. Alvermann. 2000. Relationship between epistemological beliefs and conceptual change learning. *Reading & Writing Quarterly* 16, 1 (January 2000), 59–74. https://doi.org/10.1080/105735600278060

[2] Jason A. Chen and Frank Pajares. 2010. Implicit Theories of Ability of Grade 6 Science Students: Relation to Epistemological Beliefs and Academic Motivation and Achievement in Science. *Contemporary Educational Psychology* 35, 1 (January 2010), 75–87. https://doi.org/10.1016/J.CEDPSYCH.2009.10.003

[3] Krista R. Muis, Gregory Trevors, and Marianne Chevrier. 2016. Epistemic climate for epistemic change. In *Handbook of epistemic cognition*, Jeffrey A. Greene, William A. Sandoval, and Ivar Bråten (eds.), New York, Routledge, 331-359

[4] Omid Noroozi. 2022. The role of students' epistemic beliefs for their argumentation performance in higher education. *Innovations In Education And Teaching International* 60, 4 (June 2022), 501–512. https://doi.org/10.1080/14703297.2022.2092188

[5] Stephanie Pieschl, Elmar Stahl, and Rainer Bromme. 2008. Epistemological beliefs and self-regulated learning with hypertext. *Metacognition and Learning* 3, 1 (April 2008), 17–37. https://doi.org/10.1007/S11409-007-9008-7

[6] Marlene Schommer-Aikins, Orpha K. Duell, and Rosetta Hutter. 2005. Epistemological Beliefs, Mathematical Problem-Solving Beliefs, and Academic Performance of Middle School Students. *Elementary School Journal* 105, 3 (January 2005), 289–304. https://doi.org/10.1086/428745

[7] T. Mikael Winberg, Anders Hofverberg, and Maria Lindfors. 2019. Relationships between epistemic beliefs and achievement goals: developmental trends over grades 5–11. *European Journal of Psychology of Education* 34, 2 (April 2019), 295–315. https://doi.org/10.1007/S10212-018-0391-Z

[8] Barbara K. Hofer and Paul R. Pintrich. 2002. Personal epistemology: The psychology of beliefs about knowledge and knowing. Lawrence Erlbaum Associates Publishers, Mahwah, NJ, US

[9] Patricia M. King and Karen Strohm Kitchener. 2004. Reflective Judgment: Theory and Research on the Development of Epistemic Assumptions Through Adulthood. *Educational Psychologist* 39, 1 (March 2004), 5–18. https://doi.org/10.1207/S15326985EP3901_2

[10] Gregory J. Kelly and Peter Licona. 2018. Epistemic practices and science education. In *History, Philosophy and Science Teaching: New Perspectives,* Michael P. Clough (eds.). Springer International Publishing, Cham, 139-165

[11] Miguel Landa-Blanco and Antonio Cortés-Ramos. 2021. Psychology students' attitudes towards research: the role of critical thinking, epistemic orientation, and satisfaction with research courses. *Heliyon* (November 2021). https://doi.org/10.1016/J.HELIYON.2021.E08504

[12] Emanuel Missias Silva Palma, Sônia Maria Guedes Gondim, and Carolina Villa Nova Aguiar. 2018. Epistemic Orientation Short Scale: Development and Validity Evidence in a Sample of Psychotherapists. *Paidéia (Ribeirão Preto)* 28, (October 2018). https://doi.org/10.1590/1982-4327E2817

[13] William K. Wilkinson and Christopher Migotsky. 1994. A Factor Analytic Study of Epistemological Style Inventories. *The Journal of Psychology* 128, 5 (September 1994), 499–516. https://doi.org/10.1080/00223980.1994.9914909

[14] Yejun Bae, Brian Hand, and Gavin W. Fulmer. 2022. A generative professional development program for the development of science teacher epistemic orientations and teaching practices. *Instructional Science* 50, 1 (January 2022), 143–167. https://doi.org/10.1007/s11251-021-09569-y

[15] Catherine Lammert, Ruchika Sharma, and Brian Hand. 2023. Beyond pedagogy: the role of epistemic orientation and knowledge generation environments in early childhood science teaching. *International journal of science education* 45, (January 2023), 431–450. https://doi.org/10.1080/09500693.2022.2164474

[16] Jee Kyung Suh, Jihyun Hwang, Soo-Youn Park, and Brian Hand. 2022. Epistemic orientation toward teaching science for knowledge generation: Conceptualization and validation of the construct. *Journal of Research in Science Teaching* 59, 9 (March 2022), 1651–1691. https://doi.org/10.1002/tea.21769

[17] Dagmar Zeithamova, Michael Mack, Kurt Braunlich, Tyler Davis, Carol A. Seger, Carol A. Seger, Marlieke T. R. van Kesteren, Andreas Wutz, and Andreas Wutz. 2019. Brain Mechanisms of Concept Learning. *The Journal of Neuroscience* 39, 42 (October 2019), 8259–8266. https://doi.org/10.1523/JNEUROSCI.1166-19.2019

[18] Regina F. Frey, Michael J. Cahill, and Mark A. McDaniel. 2017. Students' Concept-Building Approaches: A Novel Predictor of Success in Chemistry Courses. *Journal of Chemical Education* 94, 9 (May 2017), 1185–1194. https://doi.org/10.1021/ACS.JCHEMED.7B00059

[19] Regina F. Frey, Mark A. McDaniel, Diane M. Bunce, Michael J. Cahill, and Martin D Perry. 2020. Using Students' Concept-building Tendencies to Better Characterize Average-Performing Student Learning and Problem-Solving Approaches in General Chemistry. *CBE- Life Sciences Education* 19, 3 (September 2020). https://doi.org/10.1187/CBE.19-11-0240

[20] Peter Smagorinsky. 2013.The development of social and practical concepts in learning to teach: A synthesis and extension of Vygotsky's conception. Learning. *Culture and Social Interaction* 4, 2(December 2013). https://doi.org/10.1016/j.lcsi.2013.07.003

[21] Joseph R. Royce. 1975. Epistemic Styles, Individuality, and World-View. In *Perspectives in Information Science*, Anthony Debons and William J. Cameron. (eds.),. Springer Netherlands, Dordrecht, 259-295. https://doi.org/10.1007/978-94-011-7759-7

[22] Andrea A. Disessa. 2014. A history of conceptual change research. In *The Cambridge Handbook of the Learning Sciences,* R. Keith Sawyer (eds.), Cambridge University Press , 88–108. https://doi.org/10.1017/cbo9781139519526.007

[23] Henry M. Wellman and Susan A. Gelman. 1992. Cognitive development: Foundational theories of core domains. *Annual Review of Psychology* 43, 1 (January 1992), 337–375. https://doi.org/10.1146/ANNUREV.PS.43.020192.002005

[24] Jean Bédard and Michelene T.H. Chi. 1992. Expertise. *Current Directions in Psychological Science 4*, 1 (August 1992), 135-139. https://doi.org/10.1111/1467-8721.ep10769799

[25] Andrea A. Disessa. 1996. What do "just plain folk" know about physics? In *The Handbook of Education and Human Development: New Models of Learning, Teaching, and Schooling,* D. R. Olson and N. Torrance (eds.). Oxford, UK: Blackwell Publishers, Ltd., 709-730

[26] Joseph F. Wagner. 2006. Transfer in pieces. *Cognition and Instruction 24*, 1 (March 2006), 1–71. https://doi.org/10.1207/S1532690XCI2401_1

[27] Andrea A. Disessa. 2018. A Friendly Introduction to "Knowledge in Pieces": Modeling Types of Knowledge and Their Roles in Learning. In *Invited Lectures from the 13th International Congress on Mathematical Education. ICME-13 Monographs,* Kaiser, G., Forgasz, H., Graven, M., Kuzniak, A., Simmt, E., and Xu, B. (eds). Springer, Cham, 65–84.

[28] Andrea A. diSessa. 1993. Toward an Epistemology of Physics. *Cognition and Instruction* 10, 2 (April 1993), 105–225. https://doi.org/10.1207/S1532690XCI1002

[29] Andrea A. diSessa, Bruce L. Sherin, and Mariana Levin. 2016. Knowledge Analysis: An Introduction. In *Knowledge and Interaction*, Andrea A. diSessa, Mariana Levin, Nathaniel J.S. Brown (eds.), Routledge, New York, 30-71

[30] Levin Mariana, Swanson Hillary, Disessa Andrea A, Leitch Michael, Orrill Chandra, and Sherin, Bruce. 2024. Novel Technologies and Epistemic Considerations in Studying Knowledge-in-Use and in-Transition. In *Proceedings of the 18th International Conference of the Learning Sciences-ICLS 2024*, 1965-1972

[31] Andrea A. diSessa. 1988. Knowledge in pieces. In *Constructivism in the computer age*, G. Forman and P. B. Pufall (eds.), Lawrence Erlbaum Associates, Inc., 49–70. https://doi.org/10.1159/000342945

[32] David Williamson Shaffer. 2006. Epistemic frames for epistemic games. *Computers & Education* 46, 3(April 2006), 223-234. https://doi.org/10.1016/j.compedu.2005.11.003

[33] David Williamson Shaffer. 2010. The Bicycle Helmets of "Amsterdam": Computer games and the problem of transfer. E*pistemic Games Group Working Paper.* Madison: University of Wisconsin-Madison,

[34] Padraig Nash and David Williamson Shaffer. 2013. Epistemic Trajectories: Mentoring in a Game Design Practicum. *Instructional Science* 41, 4 (July 2013), 745–771. https://doi.org/10.1007/S11251-012-9255-0

[35] David Williamson Shaffer, Wesley Collier, and A. R. Ruis. 2016. A Tutorial on Epistemic Network Analysis: Analyzing the Structure of Connections in Cognitive, Social, and Interaction Data. *Journal of learning Analytics* 3, 3 (December 2016), 9–45. https://doi.org/10.18608/JLA.2016.33.3

[36] Amanda Barany and Aroutis Foster. 2020.Mapping Identity Exploration of Science Careers using Epistemic Networks. In *Society for Information Technology & Teacher Education International Conference.* Association for the Advancement of Computing in Education (AACE), 1610-1619

[37] Zhongwen Sun, Rumeng Xu, L. Deng, Fangzhou Jin, Zicong Song, and Chin Lin. 2022. Beyond coding and counting: Exploring teachers' practical knowledge online through epistemic network analysis. *Computers & Education* 192, (October 2022), 104647. https://doi.org/10.1016/j.compedu.2022.104647

[38] Gina Navoa Svarovsky. 2011. Exploring complex engineering learning over time with epistemic network analysis. J*ournal of Pre-College Engineering Education Research (J-PEER)* 2, 1(October 2011). 19- 30. https://doi.org/10.5703/1288284314638

[39] Bian Wu, Yiling Hu, and Minhong Wang. 2019. Scaffolding design thinking in online STEM preservice teacher training. *British Journal of Educational Technology* 50, 5 (September 2019), 2271–2287. https://doi.org/10.1111/BJET.12873

[40] Yuanru Tan, Andrew R Ruis, Cody Marquart, Zhiqiang Cai, Mariah A Knowles, and David Williamson Shaffer. 2022. Ordered network analysis. In *Advances in Quantitative Ethnography. ICQE 2022. Communications in Computer and Information Science,* Damşa, C. and Barany, A. (eds). Springer, Cham, 101–116. https://doi.org/10.1007/978-3-031-31726-2_8

[41] Linxuan Zhao, Yuanru Tan, Dragan Gašević, David Williamson Shaffer, Lixiang Yan, Riordan Alfredo, Xinyu Li, and Roberto Martinez-Maldonado. 2023. Analysing Verbal Communication in Embodied Team Learning Using Multimodal Data and Ordered Network Analysis. In *the Artificial Intelligence in Education, AIED 2023. Lecture Notes in Computer Science.* Springer, Cham. https://doi.org/10.1007/978-3-031-36272-9_20

[42] Pakon Ko, Nancy Law, and Cong Liu. 2024. Exploring Students' Changing Conceptions About eLearning Leadership. In *Advances in Quantitative Ethnography. ICQE 2024. Communications in Computer and Information Science*, Kim, Y.J., Swiecki, Z. (eds). Springer, Cham, 202-216.

[43] Centre for Information Technology in Education, University of Hong Kong. (n.d.) *Mission-focused inquiry learning (MFIL) Pedagogical Approach Patterns.* https://lds-info.cite.hku.hk/product/mission-focused-inquiry-learning-mfil/

[44] Forehand Mary. 2010. Bloom's taxonomy. *Emerging perspectives on learning, teaching, and technology* 41.4(2010), 47-56.

[45] David Shaffer and Andrew Ruis. 2017. *Epistemic Network Analysis: A Worked Example of Theory-Based Learning Analytics.* 175–187.

[46] Marcia Moraes, Sadaf Ghaffari, Yanye Luther, and James Folkestad. 2023. Combining Automatic Coding and Instructor Input to Generate ENA Visualizations for Asynchronous Online Discussion. In *Advances in Quantitative Ethnography. ICQE 2023. Communications in Computer and Information Science*, Arastoopour Irgens, G., Knight, S. (eds). Springer, Cham, 381-394.