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Towards Actionable Collaborative Discourse Analysis: Bridging Advanced Computational Analysis with Practical Implementation

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Abstract: Since the inception of learning analytics, the CSCL community has been applying a range of methods to examine collaborative discourse, such as natural language processing and networked approaches. Despite significant advancements in methods, a critical gap persists in translating these data-driven insights into actionable strategies to inform pedagogical decisions. The proposed hybrid symposium seeks to bridge this gap by engaging learning scientists, CSCL researchers, and educators in discussions that integrate advanced discourse analytics with pedagogical design. Through five diverse presentations, the symposium will explore the integration of advanced discourse analysis techniques, such as networked approaches, multimodal analytics, and clustering analysis, into pedagogically meaningful designs and actionable pedagogical insights for collaborative learning environments. By fostering dialogue on the challenges and opportunities in contextualizing computational insights, this symposium aims to establish actionable approaches for enriching collaborative discourse and advancing the broader CSCL community's theoretical, methodological, and practical understanding.

Introduction

Collaborative discourse plays a central role in computer-supported collaborative learning (CSCL) by facilitating critical thinking, problem-solving, and constructive dialogue. Defined broadly, collaborative discourse involves interaction among individuals engaging in the collective process of knowledge creation, where each contributes to and takes responsibility for advancing shared knowledge (Scardamalia & Bereiter, 2014). This process encompasses a variety of interactional dynamics at both individual and group levels, from generating and exchanging ideas, to challenging others' perspectives and collaboratively refining concepts together (Cress & Kimmerle, 2018). Through these exchanges, discourse fosters not only individual cognitive growth but also the development of essential higher-order skills such as critical thinking, effective communication, and collaboration, which are vital in educational contexts and beyond (Baker & Lund, 1997; Noroozi et al., 2018). Recently, the rapid application of generative artificial intelligence, such as conversational agents, introduces both opportunities and complexities in supporting and analyzing collaborative discourse. While AI-driven tools offer potential for dynamic, real-time discourse that can adapt to individual learners' contributions and scaffoldings, they also demand careful consideration to ensure these technologies foster rich, group-oriented learning experiences rather than isolated interactions.

Over the past decades, advancements in technology have introduced innovative methods for automated discourse analysis, leveraging techniques such as Natural Language Processing (NLP), computer vision, and network science. These computational approaches allow for a more granular and nuanced understanding of discourse, capturing the intricate ways in which students build knowledge collaboratively (Cress & Kimmerle, 2018). As an analytical lens, several frameworks have been proposed to facilitate in-depth examination of discourse, including Computer-Mediated Discourse Analysis (CMDA; Herring, 2004) and the Joint Attention–Interaction–Creation (AIC) Framework (Zhu & Chen, 2023). For example, Zhu and Chen (2023) proposed the AIC framework, which uses NLP and socio-semantic network analysis (SSNA) to capture the contextual dynamics of discourse through the networked lens. Beyond analytical advancement, practical computational tools have been developed to support discourse analysis at scale, such as the Epistemic Network Analysis (ENA) tool

(Shaffer & Ruis, 2017) and the Knowledge Building Discourse Explorer (KBDeX) (Oshima et al., 2012). For instance, Oshima et al. (2012) developed the KBdeX tool, enabling researchers to visualize and analyze how learners' ideas evolve within a collaborative networked environment. These tools have empowered educators and researchers with robust means of capturing, examining, and visualizing discourse patterns, offering significant potential to inform the design of collaborative discourse activities.

Despite these significant advancements in the field, discourse analysis often remains disconnected from pedagogical practices. A notable barrier lies in contextualizing sophisticated analytical findings in ways that directly enhance student engagement in authentic CSCL environments. Several studies have made progress in this intersecting area. For example, Chen, Chang, Ouyang, and Zhou (2018) investigated how a student-facing analytics tool could be adapted and implemented for classroom use to visualize patterns of posting and replying in asynchronous discussions, helping students understand and improve their social engagement. Similarly, Li, Jung, Wise, Sommer, and Axelrod (2021) implemented a student-facing analytic report that displayed metrics indicating quality metrics for meaningful team collaboration in online graduate discussions. While these efforts have demonstrated the potential of automated discourse analysis to inform the design of discourse-rich learning activities, more work is needed to address the actionability of analytical advances in discourse analysis. Particularly, as we continue unveiling the complexity and dynamics of collaborative discourse, it is equally critical to consider how these nuanced insights can drive practical implementations.

This symposium seeks to bridge the gap between computational analysis and practical implementation by exploring how nuanced discourse analysis can be contextualized to inform the design and enactment of pedagogically meaningful collaborative learning experiences. Our goals are threefold: (1) to investigate practical applications of advanced discourse analysis methods within educational contexts; (2) to identify challenges and opportunities in translating computational insights into actionable strategies for educators; and (3) to foster dialogue on future directions for integrating discourse analysis into CSCL environments to support meaningful learner engagement in knowledge construction.

To achieve these goals, this symposium brings together five presentations from scholars across diverse institutions who have been actively exploring the applications of computational discourse analysis in learning contexts. Each presentation offers a unique lens for contextualizing discourse analytics in CSCL practices. These include: uncovering the multi-layered dynamics of idea advancement in knowledge building (Oshima & Oshima); capturing the socio-cognitive and temporal patterns of student participation in social annotation activities (Zhu, Chen, & Jung); analyzing the structural and temporal dimensions of knowledge construction in gamified asynchronous discussions (Moon, McNeill, Edmonds, Banihashem, & Noroozi); leveraging multimodal nonverbal analytics to investigate small group interactions (Dey & Puntambekar); and examining how students interact with generative AI over time in knowledge construction discourse (Jung & Jackson). Key questions that each presentation will respond include:

1. What kinds of computational analysis methods can be effectively translated into pedagogically meaningful designs that foster collaborative learning in practice? How?
2. What are the current challenges and opportunities in applying advanced discourse analytics to the design of collaborative learning activities?
3. In what ways can existing CSCL theories inform the integration of computational discourse analysis into technology-enhanced learning activities?
4. What approaches or principles can be developed to guide future research and design efforts that aim to foster more meaningful collaborative discourse using computational analysis?

Through the five interconnected presentations, followed by a moderated discussion led by the discussant, this symposium aims to contribute to the CSCL community by advancing both methodological approaches and practical implementation that enhance collaborative discourse learning experiences. Participants are invited to engage in reflective discussions, aimed at developing actionable approaches for integrating computational discourse analysis into learning design. Through this dialogue, this symposium aims to strengthen connections between theory, methods, and practice, laying the groundwork for future research that connects computational analysis with pedagogical designs to create impactful collaborative discourses in technology-enhanced settings.

Multi-layered temporal network analysis of discourse

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Multi-layered temporal network analysis of knowledge-building discourse

We propose new analytics for knowledge-building discourse by expanding the Socio-Semantic Network Analysis (SSNA) algorithm within the Knowledge-Building Discourse Explorer (KBDeX: Oshima et al., 2012). The original KBDeX algorithm is based on the premise that we can visualize how learners' ideas are discussed over time through changes in the structure of a vocabulary network. While the algorithm effectively captures how learners construct shared knowledge collaboratively and highlights the differences in group engagement and individual contributions (Oshima et al., 2020), it has not sufficiently addressed the complex dynamics of how learners engage in discourse. In discourse, participants discuss multiple ideas simultaneously, often including topics unrelated to their primary focus. We believe these layers of discourse topics interact, influencing how learners improve their ideas in various ways.

To solve the problem, we expanded the traditional SSNA by referring to previous studies (Poquet et al., 2023; Saqr & Peeters, 2022). First, instead of focusing solely on idea-related words, we included all noun words to encompass the various layers of discourse topics. Second, we analyzed the temporal changes in each word's metrics, particularly its degree-centrality within a vocabulary network, and conducted a hierarchical clustering analysis to identify the discourse topics. Finally, we calculated the total degree-centrality values of the words within each identified discourse topic. To demonstrate the advantages of our new algorithm, we performed a comparative study using both traditional and proposed temporal network analysis on the same datasets.

Comparison between the traditional and the new analytics using the same discourse datasets

We utilized discourse datasets from three groups of three or four university students, along with their task requirements, to propose new happiness indices based on their studies of the current index. Using the Knowledge Forum as a platform, the students reported their progress and reflections weekly. As a result, the three groups achieved varying levels of learning performance—high, medium, and low—based on the evaluation criteria. Our comparative analysis revealed several key findings. First, traditional temporal network analysis using KBDeX did not consistently showcase distinct discourse patterns, contributing to the differences in performance levels. In contrast, our new analysis highlighted more nuanced variations in discourse patterns across the three learning performance levels. Based on our multi-layered temporal network analysis results, we identified two essential conditions for achieving high learning performance: (1) the comparison of multiple ideas within learners' judgment of idea promisingness and (2) ongoing engagement to warrant their ideas. These findings suggest two key points: (1) learners can generate more effective ideas when they are encouraged to explore contrasting cases (Schwartz et al., 2011) instead of getting locked into a single promising idea, and (2) the process of improving ideas should be enhanced by supporting learners in collaboratively developing their ideas and diversifying their approaches (Hong, & Sullivan, 2009).

The proposed new approach will provide educators and students with a timely formative assessment of their collaborative discourse on idea improvement. By providing the criteria to evaluate their discourse, such as comparative case analysis and justification of their proposed ideas, students, with support from their teachers, will be able to monitor and revise the direction of their discourse to lead to productive knowledge-building.

Modeling idea creation in collaborative discourse: A networked approach

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In CSCL, ideas generated through collaborative discourse are informative indicators of students' learning and collaboration. Ideas are often stored as texts, such as discussion posts or chat messages, reflecting the product of emergent and interactive socio-cognitive endeavors. Therefore, analyzing ideas requires capturing contextual information in addition to the ideas themselves, which remains challenging given the multidimensional nature of collaborative learning. To address this analytical challenge, we introduce the development of the Joint Attention–Interaction–Creation (AIC) framework and exemplify its application in classrooms through a case study. We further explore the actionable implications of this methodological innovation by detecting students' emerging participation roles using a temporal clustering approach grounded in the AIC framework.

The Joint Attention–Interaction–Creation (AIC) framework

The AIC framework was developed from the networked lens, informed by NLP techniques, and inspired by socio-semantic network analysis (SSNA). Rooted in CSCL literature, AIC captures key learning constructs—joint attention, interaction, and creation—through three networks that represent important dynamics in collaborative discourse. AIC first captures learners' joint attention before an idea is created through a *Joint Attention Network (AN)*. For discourse in text-based digital spaces, joint attention refers to a shared focus on a common reference, for instance, a sentence highlighted from a shared reading, which intrigues the discourse. AN operates collaborators' attentions as a network of "semantic spaces" (Lund & Burgess, 1996) by examining the semantic similarity between each pair of references. With joint attention, learners start sharing ideas and building on each other's contributions through interaction, which is then captured by *Interaction Network (IN).* Informed by Social Network Analysis (SNA), IN tells us important information about the individual student's contribution (e.g., by calculating degree centrality) as well as the class interaction patterns. While IN provides a descriptive report of learners' interactions, *Creation Network (CN)* then captures the production generated from the interaction. One assumption of CN is that learners' ideas can be represented as clusters of keywords in the discourse (Ohsaki & Oshima, 2021). CN represents learners' idea creation through a network of words, which are selected from the discourse based on their influence. To exemplify the AIC framework, we present a case study analyzing collaborative discourse in an undergraduate class. This case demonstrates the application of the framework in investigating both network-level structures and individual node connectivity, capturing individual contributions as well as the community's knowledge advancement.

Advancing the AIC framework through temporal clustering

In CSCL research, participating roles have been recognized as a fundamental aspect of group dynamics, which is essential for collaborative knowledge construction (Ouyang & Chang, 2019). Emerging role detection can help adjust and calibrate the activity design in real-time to provide dynamic models of teaching and learning (Wise et al., 2021). Building on the initial development of the AIC framework and application of linguistic modeling, we applied temporal clustering to identify students' emerging roles in social annotation activities over time. For this clustering analysis, we used the K-means algorithm (Roh, 2017) with a set of features related to cognitive (e.g., Joint attention, Creation, and other linguistic features representing analytical thinking) and social aspects (e.g., Interaction and other linguistic features representing getting attention from others). Preliminary findings revealed three distinct profiles of student engagement in collaborative discourse that show different patterns of cognitive and social aspects of learning over time. Together, this work highlights the potential of leveraging multiple networks and linguistic modeling together to inform class design, facilitation, or evaluation.

Overall, the AIC framework and the temporal clustering approach aim to provide actionable insights for dynamically adjusting teaching strategies, such as assigning roles to balance participation, scaffolding underrepresented students, and enhancing the overall alignment between discourse activities and learning goals.

Analyzing knowledge construction patterns in gamified asynchronous discourse: Bridging computational analysis and pedagogical practice

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We propose an integrated analytical case to explore knowledge construction patterns in CSCL environments, specifically focusing on gamified asynchronous discussions. Building on foundational work in collaborative discourse (Scardamalia & Bereiter, 2014) and recent advancements in discourse analysis techniques, our research adopts an explanatory mixed-method approach to uncover how students engaged in knowledge co-construction within a gamified learning environment. While automated analytics for discourse analysis have advanced, translating these insights into actionable strategies particularly in gamified online learning contexts remains limited.

Our study accordingly demonstrates how analytic insights derived from gamified discourse environments can be applied to guide instructional design and collaborative learning facilitation. We specifically investigate how nuanced discourse analysis can be contextualized to inform the design and implementation of pedagogically meaningful collaborative learning experiences. To answer our four research questions, this study implements complementary analytical approaches: (a) epistemic network analysis (ENA) (Shaffer & Ruis, 2017) and (b) sequential pattern mining (SPM) with qualitative content analysis. This integration is particularly suited for gamified asynchronous discussions as it captures both the structural and temporal dimensions of knowledge construction. Guided by collaborative knowledge building theory (Scardamalia & Bereiter, 2014), we use ENA to trace how students build and connect ideas over time, reflecting epistemic depth and group knowledge advancement. ENA reveals the interconnected nature of ideas and concepts within discussions, mapping how different knowledge elements are linked in students' discourse. Meanwhile, informed by argumentation and social interaction frameworks in CSCL (e.g., Weinberger & Fischer, 2006), our use of SPM uncovers the temporal progression of these interactions, showing how discussion patterns evolve and how gamification elements influence participation over time. Together, these methods provide a comprehensive view of both what knowledge is being constructed and how this construction unfolds through gamified interactions. Our focus on gamified learning stems from its ability to address low engagement and superficial participation, leveraging motivational elements to foster deeper cognitive and collaborative interactions.

Our study analyzed discussion data from an online forum featuring gamified elements explicitly designed to foster knowledge construction by increasing student engagement and optimizing collaborative workflows. We extracted and analyzed the gamified asynchronous online learning platform ClassCred's data (977 postings and 1,740 responses) based on three key criteria: (1) relevance to course topics and learning objectives, (2) substantive content beyond simple acknowledgments, and (3) participation in meaningful interactions within discussion threads involving at least two participants. ClassCred incorporates gamification elements, such as peer recognition systems, achievement badges, and progress tracking mechanisms, to create a structured setting that supports sustained engagement and deeper knowledge construction. These elements incentivize students to engage in meaningful academic discussions, leading to cognitive demanding tasks (i.e., argumentation and epistemic exploration). Data processing involved meticulous preprocessing steps to ensure accuracy and consistency, focusing on enhancing quality and maintaining the integrity of the gamified interaction patterns. We adopted a coding framework (Weinberger & Fischer, 2006) that classifies discourses across four principal dimensions: Participation, Epistemic Dimension, Argumentative Knowledge Construction, and Social Mode.

Our findings show that specific gamification features explain how deeply students engage with ideas and collaborate. Peer recognition and badge-based rewards encouraged students to provide more thoughtful reasoning and engage in longer, more meaningful discussions. Leaderboard visibility also helped boost participation, especially when used in ways that motivated learners without discouraging lower-performing students. These results highlight how discourse analytics can guide instructional decisions—for example, by identifying which game elements best support deeper learning. Rooted in Herring's (2004) framework analyzing online discourse, we offer practical recommendations as follows: structuring discussions to encourage sustained dialogue, introducing game mechanics at strategic moments, and promoting interaction patterns that support collaborative knowledge-building. Grounded in established collaborative learning research (Noroozi et al., 2018), our study provides practical guidelines for designers and educators aiming to effectively implement gamification elements that enhance knowledge construction; these findings suggest the value of designing gamified platforms with dynamic scaffolds that align motivational structures with epistemic engagement—offering a framework for future CSCL environments.

Exploring multimodalities of interactions during collaboration

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Collaborative learning environments aim to have students co-construct knowledge and learn together as a group (Barron, 2003; Dillenbourg, 1999; Roschelle & Teasley, 2005). Having rich discussions is essential for developing shared understanding and knowledge building, and thus, collaborative learning research often focuses on the analysis of verbal interactions. Lower verbal participation is often associated with inattentiveness (Frymier, 2005) and limited learning. However, less vocal or 'silent' students may have as much engagement and comparable learning gains as more vocal students (Obenland et al., 2012; O'Connor et al., 2017). Studies demonstrate a positive association between nonverbal behaviors and social-behavioral engagement (Frymier & Houser, 2016), suggesting that greater engagement in shared activities may be indicative of a more productive collaboration, which in turn, can support building conceptual understanding and learning (Blumenfeld et al. 2006; Järvelä et al., 2016). Thus, examining students' nonverbal interactions in conjunction with their verbal participation, i.e., multimodal analysis, can provide a more holistic understanding of a student's overall participation, and by extension, their collaboration and engagement.

Multimodal analytical studies include examining a wide range of metrics to understand and/or model collaboration, such as verbal, physiological, gaze, eye, head, or body motion, facial expressions, posture, writing, and other task-related activities, engagement, and affect (Cukurova et al., 2018; Järvelä et al., 2016; Schneider &

Pea, 2017; Worsley & Blikstein, 2015). For example, Schneider and colleagues examine joint gaze (Schneider and Pea, 2017) or gaze and gesture (Schneider et al., 2021a) to determine collaboration quality and learning. While researchers acknowledge the value of using multiple modalities to understand collaboration, capturing these complex interactions can be challenging (Jeong et al., 2014), and most multimodal studies, including those mentioned above, limit their focus to just one or two modalities (Schneider et al., 2021b).

We developed the NICE framework–Nonverbal Interactions in Collaborative-Learning Environments–a coding scheme that captures multiple nonverbal modalities during small group interactions (Dey & Puntambekar, 2023). The NICE framework comprises three categories of nonverbal behaviors observed in collaborative groups: (1) *Eye gaze*, which is indicative of attention (Barron, 2003; Schneider & Pea, 2017; (2) *Gesture and use of tool,* which may indicate engagement and participation, and reveal how students share resources during collaboration; and (3) *Body-based behaviors,* such as leaning and head nods which may be indicative of attention and collaboration with the group (Barron, 2003). Using the transcript as an anchor, we coded the multiple nonverbal modalities of each student, irrespective of whether they are speaking or not. Using a binary coding approach, a behavior was coded as present (1) if observed or absent if not (0). The framework provides a more comprehensive and nuanced view of how students participate in and contribute to their groups. The analytics derived from this coding can then be utilized to identify patterns in individual and group participation and engagement.

In this presentation, we will present a case study of the application of the NICE framework to two middle school groups working on a biology unit. We will discuss what the analysis tells us about the multiple modalities of individual participation and engagement, how this contributes to the group processes, and how these interactions play out over time. We discuss our analytic method and its potential actionable insights to inform support for the collaboration. We hope to engage participation during the symposium, on opportunities to use these understandings to develop more meaningful pedagogical decisions for supporting student collaboration, and potential challenges that lie along the way.

Sustained knowledge construction with AI: Temporal dynamics in AI-assisted chatbot discourse

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The integration of AI chatbots into educational settings offers promising opportunities to enhance collaborative knowledge construction (Nguyen, 2022). However, despite growing interest in AI-assisted chatbots as learning tools, their effectiveness in facilitating sustained knowledge construction remains underexplored. Chatbot use is often limited to one-off activities, analyzed in isolation rather than as an integral part of a course, which limits our understanding of the temporal dynamics of student discourse with chatbots over time (Labadze, Grigolia, & Machaidze, 2023). This study addresses this gap by examining nuanced patterns and temporal dynamics of knowledge construction facilitated by AI chatbots in an online graduate course in the field of Learning Technologies. Over four weeks, 20 students engaged in weekly learning activities designed to integrate chatbots as collaborative partners. Each chatbot, powered by GPT-3.5, was customized weekly to align with course topics, helping students navigate complex concepts in learning technologies. By embedding chatbots into sustained course activities, the study aimed to analyze how students' discourse with chatbots evolved over time.

To investigate (1) the patterns of knowledge construction that emerge in these interactions and (2) how these patterns evolve over time, this study employed a multi-phase analytical approach. The methods included computational content analysis, ordered network analysis, and sequential transition modeling. Content analysis on individual discourse messages made by students was conducted, drawing on Onrubia and Engel's (2009) four-phase model of knowledge construction, with a fifth phase added to capture minimal participation (Phase 0: Minimal Participation). A total of 1,266 student-chatbot messages were analyzed, categorizing each message into five phases: Phase 0 "Minimal Participation", Phase 1 "Initiation", Phase 2 "Exploration", Phase 3 "Negotiation", and Phase 4 "Co-construction". Then, the sequence of their achieving phases and transitions across these phases were analyzed to identify patterns of self-loops and cross-phase transitions, focusing on foundational phases (Phase 1), exploratory phases (Phases 2 and 3), and advanced phases (Phase 4).

The findings reveal significant variations in both the volume of messages and the depth of knowledge construction across students. On average, students primarily engaged in foundational phases (mean: 1.43, SD: 0.33), but progression and engagement levels differed significantly. Early weeks were characterized by high self-transition rates in foundational phases (Phases 0 and 1), indicating initial exploration. In later weeks, students demonstrated increased fluidity, transitioning to higher phases through specific pathways (e.g., Phase 1 → Phase 3 → Phase 4), signaling progression toward deeper reflection and synthesis. These findings demonstrate the potential of AI-empowered discourse to scaffold learning through iterative refinement and sustained engagement over time; however, the findings also highlight challenges. Many students remain in foundational phases, underscoring the need for interventions carefully designed to encourage transitions into higher phases and prevent stagnation.

Based on these findings from temporal discourse analysis, we propose actionable strategies to enhance chatbot-facilitated learning, which could encompass adaptive scaffolding (to design prompts to encourage progressive transitions, such as connecting new ideas to prior knowledge during initiation, posing open-ended questions to promote higher-level thinking, and offering reflective prompts to break repetitive self-loops), dynamic feedback mechanisms (to embed chatbots with real-time, phase-specific feedback to guide students through iterative refinement processes), and integration into course design (to embed chatbots into sustained, scaffolded learning activities, ensuring alignment with course objectives and fostering cumulative learning across weeks). Together, this study contributes to the actionable use of AI-empowered discourse by translating computational insights into learning support to promote meaningful, sustained knowledge construction.

Significance of the symposium

This symposium highlights the critical need to bridge advanced computational discourse analysis with practical implementation in authentic educational settings. Bringing together junior and senior researchers in CSCL, learning analytics, and educational technology, it explores how sophisticated discourse analysis can enhance collaborative learning when effectively integrated into pedagogical practices. The presented studies employ diverse analytical methods, including SSNA, temporal network analysis, ENA, SPM, clustering analysis, and multimodal analytics, to analyze both textual data and nonverbal behaviors such as eye gaze, gestures, and body-based actions. These studies leverage discourse analysis to inform pedagogical decisions and support learning by capturing collaborative learning dynamics across different contexts, including knowledge-building discourse on Knowledge Forum (J. Oshima & R. Oshima), a social annotation platform (Zhu et al.), gamified asynchronous online discussions (Moon et al.), in-person small group interactions (Dey & Puntambekar), and student-AI chatbot interactions (Jung & Jackson). Collectively, the symposium not only showcases methodological advancements but also highlights innovative ways to contextualize leveraging advanced computational techniques to inform the design and support to enrich collaborative learning experiences. By facilitating dialogue among the participants, this symposium aims to build a shared understanding of how nuanced discourse analytics can support educational practices, fostering more impactful, collaborative learning experiences. Through this collaborative exchange, the symposium will contribute to the broader CSCL and learning sciences community by translating complex discourse analytics into meaningful educational practice, strengthening the role of discourse analysis as a tool for meaningful educational design.

References

Baker, M., & Lund, K. (1997). Promoting reflective interactions in a CSCL environment. *Journal of Computer Assisted Learning, 13*(3), 175-193.

Barron, B. (2003). When smart groups fail. *Journal of the Learning Sciences*, *12*(3), 307-359.

Blumenfeld, P. C., Kempler, T. M., & Krajcik, J. S. (2004). Motivation and cognitive engagement in learning environments. In R. K. Sawyer (Ed.), *The Cambridge Handbook of the Learning Sciences* (pp. 475–488). New York, NY: Cambridge University Press.

Chen, B., Chang, Y. H., Ouyang, F., & Zhou, W. (2018). Fostering student engagement in online discussion through social learning analytics. *The Internet and Higher Education, 37*, 21-30.

Cress, U., & Kimmerle, J. (2018). Collective knowledge construction. In F. Fischer, C. E. Hmelo-Silver, S. R. Goldman, & P. Reimann (Eds.), In *International handbook of the learning sciences* (pp. 137-146). Routledge.

Cukurova, M., Luckin, R., Millán, E., & Mavrikis, M. (2018). The NISPI framework: Analysing collaborative problem-solving from students' physical interactions. *Computers & Education, 116*, 93-109.

Dey, I., & Puntambekar, S.: Examining nonverbal interactions to better understand collaborative learning. In *Proceedings of the 16th International Conference on Computer-Supported Collaborative Learning* (pp. 273–276). International Society of the Learning Sciences (2023).

Dillenbourg, P. (1999). What do you mean by "collaborative learning"? In P. Dillenbourg (Ed). *Collaborative-learning: Cognitive and Computational Approaches* (pp.1-19). Oxford: Elsevier.

Frymier, A. B. (2005). Students' classroom communication effectiveness. *Communication Quarterly, 53*, 197–212.

Frymier, A. B., & Houser, M. L. (2016). The role of oral participation in student engagement. *Communication Education, 65*(1), 83-104.
Herring, S. C. (2004). Computer-Mediated Discourse Analysis: An Approach to Researching Online Behavior. In S. A. Barab, R. Kling, & J. H. Gray (Eds.), *Designing for virtual communities in the service of learning* (pp. 338–376). Cambridge University Press. https://doi.org/10.1017/CBO9780511805080.016
Hong, H. Y., & Sullivan, F. R. (2009). Towards an idea-centered, principle-based design approach to support learning as knowledge creation. *Educational Technology Research and Development*, *57*, 613–627.
Järvelä, S., Järvenoja, H., Malmberg, J., Isohätälä, J., & Sobocinski, M. (2016). How do types of interaction and phases of self-regulated learning set a stage for collaborative engagement?. *Learning and Instruction*, *43*, 39-51.
Jeong, H., Hmelo-Silver, C. E., & Yu, Y. (2014). An examination of CSCL methodological practices and the influence of theoretical frameworks 2005–2009. *International Journal of Computer-Supported Collaborative Learning, 9*, 305-334.
Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: systematic literature review. *International Journal of Educational Technology in Higher Education, 20*(1), 56.
Li, Q., Jung, Y., Wise, A. F., Sommer, S., & Axelrod, V. G. (2021). Designing analytics to support team learning. *Perspectives on Digitally-Mediated Team Learning*, 147-165.
Lund, K., & Burgess, C. (1996). Producing high-dimensional semantic spaces from lexical co-occurrence. *Behavior Research Methods, Instruments, & Computers, 28*(2), 203-208.
Matsuzawa, Y., Oshima, J., Oshima, R., Niihara, Y., & Sakai, S. (2011). KBDeX: A platform for exploring discourse in collaborative learning. *Procedia-Social and Behavioral Sciences, 26*, 198-207.
Nguyen, H. (2022). Let's teach Kibot: Discovering discussion patterns between student groups and two conversational agent designs. *British Journal of Educational Technology, 53*(6), 1864-1884.
Noroozi, O., Kirschner, P. A., Biemans, H. J., & Mulder, M. (2018). Promoting argumentation competence: Extending from first-to second-order scaffolding through adaptive fading. *Educational Psychology Review, 30*(1), 153-176.
O'Connor, C., Michaels, S., Chapin, S., & Harbaugh, A. G. (2017). The silent and the vocal: Participation and learning in whole-class discussion. *Learning and Instruction, 48*, 5–13.
Obenland, C. A., Munson, A. H., & Hutchinson, J. S. (2012). Silent students' participation in a large active learning science classroom. *Journal of College Science Teaching, 42*(2), 90–98.
Ohsaki, A., & Oshima, J. (2021). Socio-semantic network analysis of knowledge-creation discourse on a real-time scale. *International Conference on Quantitative Ethnography* (pp. 170-184).
Oshima, J., Oshima, R., & Matsuzawa, Y. (2012). Knowledge Building Discourse Explorer: A social network analysis application for knowledge building discourse. *Educational Technology Research and Development*, *60*(5), 903–921.
Oshima, J., Oshima, R., & Saruwatari, S. (2020). Analysis of students' ideas and conceptual artifacts in knowledge-building discourse. *British Journal of Educational Technology*, *51*(4), 1308–1321.
Poquet, O., Trenholm, S., & Santolini, M. (2023). Forum posts, communication patterns, and relational structures: A multi-level view of discussions in online courses. *Educational Technology Research and Development*, 1–24.
Roschelle, J., & Teasley, S. (1995). The construction of shared knowledge in collaborative problem solving. In C. O'Malley (Ed.), *Computer-supported collaborative learning* (pp. 69–197). Springer.
Saqr, M., & Peeters, W. (2022). Temporal networks in collaborative learning: A case study. *British Journal of Educational Technology*, *53*(5), 1283–1303.
Scardamalia, M., & Bereiter, C. (2014). Knowledge building and knowledge creation: Theory, pedagogy, and technology. In R. K. Sawyer (Ed.), *The Cambridge Handbook of the Learning Sciences* (pp. 397-417). Cambridge University Press.
Schneider, B., & Pea, R. (2017). Real-time mutual gaze perception enhances collaborative learning and collaboration quality. *Educational Media and Technology Yearbook, 40*, 99-125.
Schneider, B., Worsley, M., & Martinez-Maldonado, R. (2021a). Gesture and gaze: Multimodal data in dyadic interactions. *International Handbook of Computer-Supported Collaborative Learning*, 625-641.
Schneider, B., Sung, G., Chng, E., & Yang, S. (2021b). How can high-frequency sensors capture collaboration? A review of the empirical links between multimodal metrics and collaborative constructs. *Sensors, 21*(24), 8185.
Schwartz, D. L., Chase, C. C., Oppezzo, M. A., & Chin, D. B. (2011). Practicing versus inventing with contrasting cases: The effects of telling first on learning and transfer. *Journal of Educational Psychology*, *103*(4), 759–775.

Shaffer, D., & Ruis, A. (2017). Epistemic network analysis: A worked example of theory-based learning analytics. *Handbook of Learning Analytics*.

Weinberger, A., & Fischer, F. (2006). A framework to analyze argumentative knowledge construction in computer-supported collaborative learning. *Computers & Education*, *46*(1), 71-95.

Wise, A. F., Knight, S., & Shum, S. B. (2021). Collaborative learning analytics. *International handbook of computer-supported collaborative learning* (pp. 425-443). Springer.

Worsley, M., & Blikstein, P. (2015). Leveraging multimodal learning analytics to differentiate student learning strategies. *In Proceedings of the fifth International Conference on Learning Analytics and Knowledge,* ACM, pp. 360-367.

Zhu, X., & Chen, B. (2023). Understanding Idea Creation in Collaborative Discourse through Networks: The Joint Attention-Interaction-Creation (AIC) Framework. In *Proceedings of the 16th International Conference on Computer-Supported Collaborative Learning* (pp. 155-162). International Society of the Learning Sciences.