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A Step toward Characterizing Student Collaboration in Online Knowledge Building Environments with Machine Learning

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Abstract: Existing research has substantial progress in uncovering outcomes of collaborative learning in recent years, but more attention can be directed towards the better understanding of collaborative learning processes via quantitative frameworks and methods. Through the use of knowledge building as a collaborative learning pedagogical approach, it is possible for researchers to glean deeper insights into aspects of students' collaboration within authentic learning environments. In this paper, the multimodal approach of data collection and analysis was conducted with a proposed conceptual analytical framework that can characterize constructs of collaborative activities in a knowledge building classroom using machine learning methods. The application in a pilot is discussed along with how this conceptual development can offer a summary of new insights into students' individual and group collaborative trajectories during learning tasks.

Keywords: Computer-supported collaborative learning, student collaboration, knowledge building, multimodal learning analytics, machine learning

1. Introduction

Since the conceptualization of computer-supported collaborative learning (CSCL) in the late 1980s, the field and related studies of collaborative activity among a group of individuals for the purpose of learning and supported by information and communication technologies (Suthers, 2012) have subsequently made significant advancements and inroads into the development of technology-enhanced tools and theories to support the collaborative learning process (Hernández-Sellés et al., 2020). A plethora of frameworks, methods and techniques exists to measure student collaboration in terms of qualitative and quantitative indicators that are found within authentic learning environments (e.g., Martinez et al., 2003; Mercer et al, 2009). Within different forms of collaborative learning and pedagogical approaches, Knowledge Building (Scardamalia & Bereiter, 2003) has emerged as a principle-based approach where collaboration is a means for community knowledge advancement and acquisition, with feasible frameworks and techniques to evaluate the quality of both online and offline face-to-face discourse (e.g., Lee & Tan, 2017).

The measure of student collaboration is however multi-faceted and research studies tend to focus on specific notions of collaborations (e.g., engagement; Halpin et al., 2017) to avoid over-stretching resources. With the advent of virtual learning environments (VLEs) and the affordance of metrics accelerated by digital technology and new norms, recent CSCL research and analyses (Jeong et al, 2019) have been able to produce outcomes of collaborative learning from CSCL research that are more quantifiable and tangible, but this is to the detriment of more emphasis that should be placed on the analysis and understanding of collaborative learning processes. Further, heavy reliance on educators' expertise and experience is still expected in practice (Ben-Peretz, 2001), to observe, analyze, and identify the different extents and levels of student collaboration, and therefore the use of virtual learning environments contributes to an additional digital layer of surveillance and monitoring that educators need to handle as compared to in-person learning. Knowledge building related studies were also of no exception and the critical importance of better understanding the collaboration processes with educational outcomes as by-products has constantly been emphasized but are often times the other way around in most completed studies.

To address these trends, emergent technologies can be tapped to investigate the multidimensions of collaborative activities that influence the quality of collaborative process of learning, but with lesser burdens on the educator and without sacrificing the visibility and degree of understanding about collaborative activities. An emergent and explored way of better understanding the different dimensions of interaction and knowledge growth in a collaborative learning environment is to adopt a multimodal learning analytics (MMLA) approach to investigate a myriad of multimodal data including physiological data (heart rate, skin conductance); physical movement (poses), verbal utterances, tonalities and overlaps of voices (Di Mitri, 2018). This approach is wide-ranging in nature and its use is briefly explained in this paper as the underlying data collection approach.

As part of an eventual goal to obtain a comprehensive prediction of the level of collaboration in an authentic CSCL environment, the design and development of a conceptual multimodal analytical framework is proposed, by conducting the following:

1. First, to categorize different constructs of collaboration into various analytical levels and structures to replicate the possible interactions patterns that exist in a collaborative learning environment (i.e., student-student group; student group—teacher).
2. Next, multimodal data in terms of metrics and what can be measured, will be parsed into the proposed micro, meso, or macro levels for further analysis, and also considering the complexity and scale of the data involved.
3. Finally, the framework will aggregate the measurements of the various modalities and attempt to integrate them into a single indicator to represent the level of collaboration for the measured entity, that is, the group when undergoing group work, and the class during whole-class instruction.

In this paper, apart from presenting and discussing the design and development of a conceptual analytical framework that is currently being tested in several knowledge building classes, we also report some preliminary findings from a completed pilot case study that used machine learning algorithms and the proposed analytical framework to evaluate and verify the quality of collaboration and collaborative discourse within a knowledge building and CSCL environment. We also seek to answer the following research question: *How are aspects of collaborative learning processes in a knowledge building environment, whether offline (face-to-face) or online, characterized and visualized with the aid of an analytical framework to determine the extent of collaboration in a CSCL environment?*

2. Background and Literature Review

2.1 Knowledge Building and relevant VLE (Knowledge Forum)

Knowledge building is an approach that moves away from traditional instruction-based learning towards the empowerment of students as members of a knowledge building community, allowing them to take charge of their own and the community's knowledge creation processes and the advancement of knowledge (Scardamalia & Bereiter, 2003). Studies on knowledge building have found significant, positive impacts on the development of students' metacognition, collaboration, and epistemic inquiry processes for knowledge acquisition (Yang et al., 2020) and is often supported by the Knowledge Forum, an online discourse platform that facilitates inquiry, discourse, knowledge advancement, and collective cognitive responsibility (Chan & Chan, 2011). On the Knowledge Forum, students engage in online discourse through writing and reading of notes, as well as building-on to notes of other students in class-sized groups or smaller working groups during group work (see Figure 1).

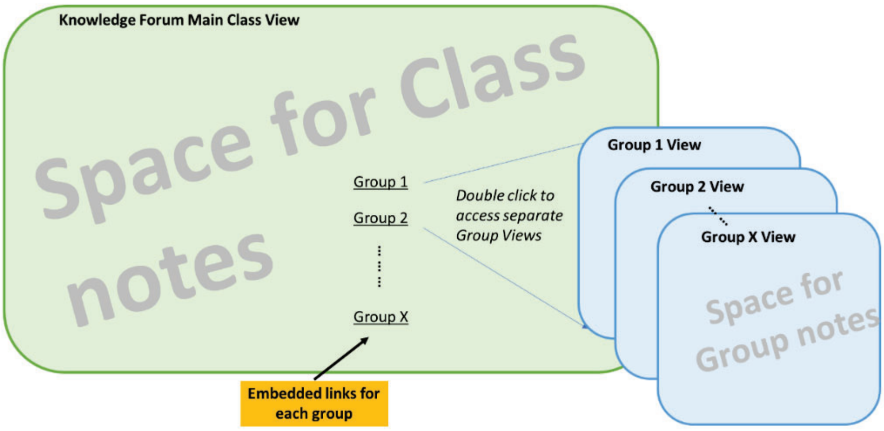

Figure 1. Spatial area on the Knowledge Forum for students to post, share, and build on each other's ideas.

The value in which the knowledge building approach brings to a CSCL environment is the emphasis of valuing student agency and allowing students to figure out gaps, the challenge in addressing the gaps, and the way forward. As such, the analysis of content on the Knowledge Forum is focused on how students displayed agency and how they approach the problem, how they expand the problem, and how they manage collaboration, more than the completion of the task (Zhang et al., 2009) and this can be done in several ways, including the analysis of epistemic emotions (Teo et al., 2022). It is posited that by being able to identify, match, and conceptualize the mentioned processes into clearer, and if possible, more discrete indicators of knowledge building and therefore collaboration, it is possible to then triangulate the quality of face-to-face discourse with online discourse to attempt a better understanding of the nuances of collaboration process in CSCL environments that is less dependent on the final performance and outcomes of assigned tasks.

2.2 Collaboration in a Virtual Knowledge Building Environment

Opinions vary largely when asked to describe a collaborative classroom, considering the multifaceted aspects of a CSCL environment. From the knowledge building perspective, collaboration is seen as the process of students collectively figuring out the incremental steps to improve ideas as well as enacting the steps. Students increasingly take on higher-level responsibilities (e.g., defining gaps mid-way through the inquiry, determining the required experiments and resources, figuring out what additional information might be needed). As more students get involved in the collaborative process, they also begin to value the collective effort, not just tracking of individual progress, and the class accumulates a diversity of ideas, connections across these ideas, with new and novel ideas surfacing that invites further questioning. Students can work in small groups and navigate different class-based or group-based discourse spaces on the Knowledge Forum (see Figure 1), with or without the teacher, who acts as a co-constructor rather than a leader and provider of knowledge. Figure 2 shows snapshots of a class-based or group-based discussion with the respective sharings and ideas reflected on the Knowledge Forum, as possible setups for encouraging and enhancing collaboration in a knowledge building environment.

2.3 Tapping on Multimodal Learning Analytics for Characterization

Multimodal Learning Analytics (MMLA) refers to the collection, analysis, utilization, and integration of multimodal data to study, characterize, and inform student learning behaviors (Rodríguez-Triana et al., 2018). Previous work from Di Mitri et al. (2018) has conceptualized a classification framework to conduct extensive literature review on empirical studies in MMLA, using the findings to propose a taxonomy of multimodal data for learning, with additional research also examining the significance and influence of multimodalities in the collaborative process (Rodríguez-Triana et al., 2018).

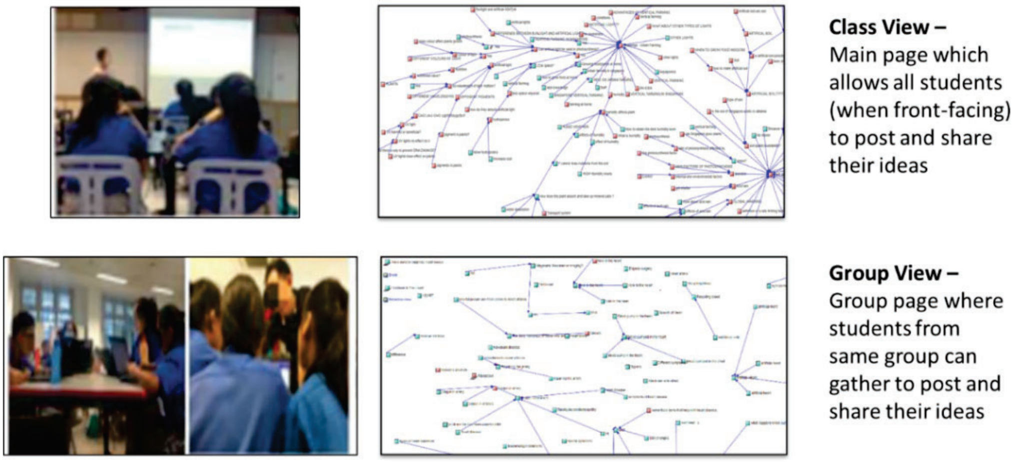

Figure 2. Snapshots of class lesson (top left) and group discussions (bottom left), and screenshots (right) of their created and shared notes on the Knowledge Forum.

In all, findings from these studies were able to identify learning analytics modalities that could be used to support and enrich learner collaboration, including the use of speech, body poses, and facial expressions. As a result, multimodal data can theoretically be used to classify and inform different dimensions of learning, but the major impediment in wide-scale adoption lies in the need to convincingly weave an integrative picture that includes all necessary collaboration process that happened in a CSCL environment, in addition to the complex benchmarking effort required to ensure the validity of multimodal analysis of collaborative processes beyond the product or final artefacts. This study seeks to identify the specifics in the mentioned gaps and also attempts to address several of the difficulties in implementation.

2.4 Proposed Design of Conceptual Analytical Framework

Educators and researchers have long viewed teaching and learning from a variety of perspective, some of which include the sociological perspective (e.g., Jarvis, 2007) that is concerned with structure and functions of the society and educational processes that are situated within; the social psychology perspective that studies interactions between teachers, students, and other stakeholders (e.g., Gehlbach, 2010); Vygotsky and Piaget's postulations that social interaction is fundamental to cognitive development, albeit with different foci on social basis of mind and individual as starting point respectively (Rogoff, 1999); and Engeström's Activity Theory (2000) as a framework for analyzing and redesigning work. Among the many other perspectives that take a manifold of view of knowledge that analyzes interaction levels and learning processes, we consider that within an increasingly volatile and uncertain education landscape, there can be a perspective that builds on evolutionary realism, one which is based on Dopfer's micro-meso-macro architecture (2004) that is motivated by the need to handle emergent and highly complex situations as a population, a structure, and a process of rules. This adopted micro-meso-macro concept for this study is a multilevel classification and analytical framework that was successfully utilized by Lee et al. (2022) to understand and study behaviors of and relations of society on different levels, and to explain interaction patterns within an ecosystem.

In this concept, the micro is the individual, the meso are parts of the society (e.g., groups, organizations), and the macro represents the society as a whole, encompassing political, economic, social, and other factors that affects all its members. Through this framework, behavioral patterns and interactions within and between the different levels can be examined and analyzed in greater detail. Within this study, knowledge building, as an approach and pedagogy, handles theories, ideas, and practices in a structure with agents (knowledge builders in this study) and the multilevel structure of this framework can be adopted to understand ways in which different modalities can be classified to facilitate the identification of different patterns of collaborative activity within and across different interacting members in authentic CSCL environments.

3. Design and Development of Analytical Framework

3.1 Conceptualization of Analytical Framework

The analytical framework examines the various constructs of students' collaboration in a knowledge building environment, including elements from both in-person and virtual learning environment. The stages of data organization, classification, analysis, and visualization are:

(i) *Collection of data from different modalities* **–** Students' collaborative activities in both offline (face-to-face) and online (Knowledge Forum) environments are captured using a range of sensing modalities, including video cameras, audio recorders, physiological sensors, server data logs, and surveys. Features are then generated from the visual, verbal, physiological, textual, and emotional data.

(ii) *Sense-making* – The micro-meso-macro concept as explained in section 2.4 is adopted to make sense of the different data modalities and to subsequently inform the interactions at the following levels and pairings.
- Micro level – Individual students interacting with artefacts and information.
- Meso level – Student collaboration in a group is seen as the meso-structure where interactions take place within a group of students.
- Macro level – Interactions within or between student groups and teacher.
- Micro-meso pair – Students' collaboration in a group shaped by individual students' speech, actions, and behaviors as the microstructure.
- Meso-macro pair – Student engagement between groups (meso-structure) can be shaped by their interactions or the teacher, who represents part of the macro-structure.

(iii) *Relating constructs of students' collaboration with the micro-meso-macro levels* of interactions – Table 1 shows how different analyses are categorized at either of the two levels of interactions and also based on the constructs of collaboration.

Table 1. *How different analyses are categorized at two levels of interactions and based on constructs of collaboration*

<table>
<tr><th></th><th colspan="4">Constructs of collaboration</th></tr>
<tr><th></th><th>Affective component</th><th>Social component</th><th>Shared epistemic component</th><th>Pedagogical & environmental component</th></tr>
<tr><td>Level 2: Student group-teacher (meso-macro)

Note: Teacher-independent collaboration may occur at this level</td><td>Analyze students' emotions in response to teachers' instructions</td><td>Conduct network analysis to obtain collaborative measures and indices</td><td>Analyze teachers' assistance to students in discussing their thoughts</td><td>Analyze received instructions, students' interactions with devices and learning artifacts in the physical space</td></tr>
<tr><td>Level 1: Student-student group (micro-meso)</td><td>Analyze students' expressions towards challenges or collaboration within groups</td><td>Analyze communications and actions at both individual and community level</td><td>Analyze implicit and explicit knowledge artefacts that shape the collaboration</td><td>Analyze students' interactions with each other, with the devices, and on the virtual discourse space</td></tr>
</table>

It is to be noted that at level 1, collaborative activities strictly occur without teachers and is only between students, while it is possible for students in level 2 to continue collaborating with each other with the teacher as an observer (not an active co-constructor). The analyses within each level also remain interrelated and may possibly influence other analysis within their own levels and across both levels. The interactions are also not restricted to a certain area of effect or influence, with each analysis potentially able to influence and affect the quality of students' collaborative learning processes, such as how the analysis of students' emotions in response to teacher's instructions may still affect students' collaboration within groups.

(iv) *Designing visualization and feedback mechanisms to transfer the sense-making process to students* – Table 2 shows how various metrics can be conceptualized across the modalities and micro-meso-macro levels.

Table 2. *Conceptualized list of metrics across the modalities and micro-meso-macro levels*

Levels (referring to) **Modalities**	**Micro** (Students working on their own, conducting individual reflections, with focus on quality of individual notes on Knowledge Forum)	**Meso** (Individual students interacting with their groups, building on notes within their groups, with possible teacher interactions)	**Macro** (Student interacting across groups and co-constructing with their teacher in whole-class discussions using class-based view on Knowledge Forum)
Face-to-face discourse (verbal)	—	Semantic patterns of speech within group	Semantic patterns of speech across group
Online discourse (on Knowledge Forum)	Complexity of individual ideas and contribution across all views	Types of scaffold used within the group's Knowledge Forum view	Types of scaffold used within the class's Knowledge Forum view
Knowledge Forum activity	Number of created and modified notes, and scaffolds used	Number of build-on notes and read notes within the group's Knowledge Forum view	Number of build-on notes and read notes within the class's Knowledge Forum view
Motoric actions	—	Hand gestures, body movements, and head poses during group discussions	Body movements when interacting and discussing between groups
Electrodermal activity	Individual skin conductance level	Skin conductance when interacting within group	Skin conductance when interacting between groups
Emotions	Epistemic and non-epistemic (universal, basic) emotions	—	—
Teachers' actions	—	—	Teachers' pedagogy (context), speech, and actions

3.2 Pulling Modalities Together to Characterize and Measure Student Collaboration

Several machine learning algorithms were found to be appropriate and feasible for making sense of the different modalities. Through this study, a pilot was conducted and implemented to conduct sense-making and interpretation processes of discourse (online and face-to-face), physiological data, and epistemic emotions. To decide on an appropriate choice of methods for the pilot, prior tests (Hartmann et al., 2019) helped to shortlist text classification methods for unstructured textual discourse, of which linear regression (LR), neural network (NN), support vector machine (SVM), and Naïve Bayes (NB) made the cut for further testing in this study. We have also taken into consideration that this shortlist of methods were widely surveyed and used in sentiment detection and classification of content categories (Hartmann et al., 2019). Convolutional neural networks (CNN) were then used to analyze student expressions, together with digital signal processing of data from physiological sensors, to determine students' epistemic emotions (Lee et al., 2023).

With the above-mentioned methods, the pilot study will be able to identify specific or combination of modalities that contribute to collaborative learning and also the extent of collaborative knowledge building activity within a CSCL environment. In short, the constructs of students' collaboration are characterized through the combined use of the analytical framework with multimodal data and various machine learning methods, so that student collaboration during knowledge building activities can be measured and characterized to levels of knowledge building.

4. Pilot Case Study

4.1 Settings, Participants, Equipment

To obtain data for framework development and machine learning, multimodal data was collected from a Primary 5 (Grade 5) class in a Singapore school, where 20 students attended a 2.5-hour Social Studies lesson "Man and His Environment" that was crafted as a debate on the pros and cons of staying or leaving an assigned area in Southeast Asia, ranging from the Mekong river, Anak Krakatoa (Indonesian volcano), or the Sarawak rainforests. Students were encouraged to debate the present problems and potential benefits of the geographical area they were assigned to and to craft a possible solution for their predicament. Over 50 hours of individual video and audio data were collected with students' consent, in line with local ethics review and adherence to regulations for data and privacy protection. This is in addition to online Knowledge Forum data that records students' actions, activities and learning artifacts.

During the lesson, the following array of sensors were deployed: H6 audio recorder for recording verbal discourse, XiaoMi360 camera for capturing student movements and poses around a table during collaboration, GoPro camera to provide a third-person view of collaborative activities between groups, Empatica E4 wristband for students who gave additional consent, and pen-and-paper emotion surveys. Altogether, online Knowledge Forum data, verbal, physiological, and emotional data were collected and transcribed, and prepared as inputs for processing in the analytical framework with machine learning methods.

4.2 Data Analysis and Findings

While working with Knowledge Forum notes and verbal data, these were broken down into discourse turns before analysis for content of speech and the type of verbal moves made by the student. The Knowledge Forum data was analyzed for content and student trace activity on the platform (e.g., number of notes read, posted, build-on) were also tracked and consolidated. Other collaborative indexes of the student's contribution on the Knowledge Forum were also extracted using the Knowledge Building Discourse Explorer (KBDeX, Oshima et al, 2012) and networks were analyzed to uncover structures of knowledge building.

The integrated set of textual data and features (selected K best for training: K=4000 for verbal, K=3000 for Knowledge Forum) was then readily used to create a machine learning model for prediction purposes. To mitigate overfitting since no new data was collected or generated, convolutional neural network was chosen for fixed input and output sizes, with regularization applied to the model to improve generalizability. Large language models (e.g., BERT) were attempted but unfeasible for smaller setups. Model training was conducted using verbal and online discourse labels, coded by two knowledge building experts based on the knowledge building levels. The levels are casual talk (CT, for verbal data) or non-content (NC, for Knowledge Forum data); question level 1 (Q1) for simple fact-seeking questions; explanation level 1 (E1) for simple explanations without elaborations; question level 2 (Q2) for expanded explanation-seeking questions; and explanation level 2 (E2) for explanations with elaborations, evidence, and justifications. These levels are encoded from 0 to 4 accordingly. In this model of five dropout layers (to avoid over-fitting) and one gaussian noise layer (to add randomness for robustness), the training accuracy is 0.789 with a test accuracy of 0.601.

Visual data (video) consisting of motoric actions taps on the OpenPose library to analyze various skeletal movements of students and teacher when he appears in frame. For video data that capture more details of students' expressions, convolutional neural networks (CNNs) were implemented to identify one of the following nine epistemic emotions: Activeness, anxiety, boredom, confusion, curiosity, enjoyment, frustration, interest, and surprise (Lee et al., in press). Physiological markers including electrodermal activity and heart rate data were analyzed using peak-detection using the E4 software. Seven self-reporting surveys were administered between tasks throughout the lesson and the responses related to epistemic emotions were also analyzed using IBM Statistical Package for Social Sciences (SPSS) software for descriptive analysis and triangulation.

From the case study, we were able to preliminarily characterize several aspects of student collaboration using the analytical framework, which were triangulated with the teacher's instructions, and actions. For example, these characterizations include how greater student movements relates with an increase in student responses, while an increase in student communications signify better quality of contributions in speech and on the Knowledge Forum. Knowledge building contributions on the Knowledge Forum were also found to be expanded and better quality (Q2 and E2) than communicated verbally. From the analysts' point of view, several of such instances throughout the 2.5-hour lesson were identified where these constructs of student collaborations were prominent. However, limited data for training and testing may also mean that the same aspects of student collaboration are challenging to reproduce in different contexts and by other students. Nonetheless, the current findings are supportive of the framework's application in examining interaction patterns within a collaborative knowledge building environment.

4.3 Aggregation and Visualization of Findings

Using the above findings, it was also essential to aggregate measurements and provide a visual interface with simplified information on an interactive dashboard (see Figure 3). This dashboard with video playback and seeking functionality also provides an approximate measure called the "Fusion score" that incorporates measures obtained from the different modalities with adjustable weightages so that the end-user, be it a teacher or analyst, can understand the extent of collaboration for a group or class. With a score of 0 to 1, the prototype's fusion score is aligned to three major stages of the knowledge building process, starting with idea sharing activities that exhibit scores closer to 0, while idea improvement activities will score higher, followed by activities with rise above that will score closer to 1.

4.4 Limitations

Among several limitations, we address two significant limitations that have been briefly mentioned thus far and are currently being worked on. The first pertains to the limited datasets that can be used for training models, testing, and refining of the analytical framework. A larger dataset of five lessons, considered a large trove of data considering the multimodality nature, is currently considered for subsequent use, as such an inclusion will be beneficial in testing the validity and reliability of the larger system. The other limitation refers to the methodical and practical challenges that can affect the sustainability and scalability of this MMLA study, which are also highlighted by Yan et al (2022), with recommendations to ensure that MMLA innovations that used discontinued technologies are constantly upgraded and caution is taken in ensuring minimal systemic bias while using MMLA innovations.

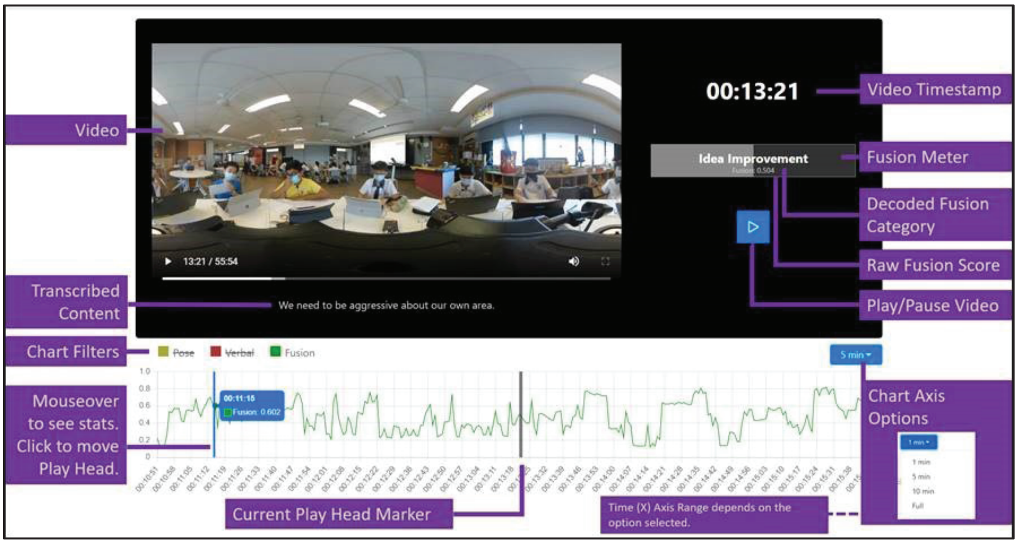

Figure 3. Interactive dashboard with video playback and seeking functionality, and indicators that provide insights about extent of collaboration in a knowledge building lesson.

5. Conclusion

CSCL is a well-established field with many technological and theoretical advancements over the past few decades, contributing to concerted efforts directed towards the better understanding of collaborative learning processes. Through the use of knowledge building as a collaborative learning pedagogical approach, a concentrated focus on the learning processes allows researchers to glean deeper insights into aspects of students' collaboration in authentic learning environments. The use of MMLA and the proposed analytical framework brings together multiple modalities to inform learning behaviors and to characterize student collaboration with the aid of machine learning methods. Preliminary findings from a pilot case study has shown that several constructs of student collaboration can be characterized and the limitations in current form can be duly addressed with sufficient research and time.

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References

Ben-Peretz, M. (2001). The impossible role of teacher educators in a changing world. *Journal of teacher education, 52*(1), 48-56.

Chan, C. K. K., & Chan, Y.-Y. (2011). Students' views of collaboration and online participation in Knowledge Forum. *Computers & Education, 57*(1), 1445-1457. https://doi.org/10.1016/j.compedu.2010.09.003

Di Mitri, D., Schneider, J., Specht, M., & Drachsler, H. (2018). From signals to knowledge. A conceptual model for multimodal learning analytics. *Journal of Computer Assisted Learning, 34*(4), 338–349. https://doi.org/10.1111/jcal.12288

Dopfer, K., Foster, J., & Potts, J. (2004). Micro-meso-macro. *Journal of evolutionary economics, 14*, 263-279. https://doi.org/10.1007/s00191-004-0193-0

Engestrom, Y. (2000). Activity theory as a framework for analyzing and redesigning work. *Ergonomics, 43*(7), 960-974.

Gehlbach, H. (2010). The social side of school: Why teachers need social psychology. *Educational psychology review, 22*, 349-362. https://doi.org/10.1007/s10648-010-9138-3

Halpin, P. F., von Davier, A. A., Hao, J., & Liu, L. (2017). Measuring student engagement during collaboration. *Journal of Educational Measurement, 54*(1), 70-84.
Hartmann, J., Huppertz, J., Schamp, C., & Heitmann, M. (2019). Comparing automated text classification methods. *International Journal of Research in Marketing, 36*(1), 20-38. https://doi.org/10.1016/j.ijresmar.2018.09.009
Hernández-Sellés, N., Muñoz-Carril, P., & González-Sanmamed, M. (2020). Interaction in computer supported collaborative learning: an analysis of the implementation phase. *International Journal of Educational Technology in Higher Education, 17*(1), 1–13. https://doi.org/10.1186/s41239-020-00202-5
Jarvis, P. (2007). *Globalization, lifelong learning and the learning society: Sociological perspectives*. Routledge.
Jeong, H., Hmelo-Silver, C., & Jo, K. (2019). Ten years of Computer-Supported Collaborative Learning: A meta-analysis of CSCL in STEM education during 2005–2014. *Educational Research Review, 28*, 1-17. https://doi.org/10.1016/j.edurev.2019.100284
Lee, A. V. Y., & Tan, S. C. (2017). Promising ideas for collective advancement of communal knowledge using temporal analytics and cluster analysis. *Journal of Learning Analytics, 4*(3), 76-101. http://dx.doi.org/10.18608/jla.2017.43.5
Lee, A. V. Y., Teo, C. L., & Tan, S. C. (2022). Rethinking teaching and learning with preschoolers: Professional development using knowledge building and a 3M analytical framework. *International Journal of Educational Research Open, 3*, 100147.
Lee, A. V. Y., Teo, C. L., Yuan, G., Ong, A., Lim, R. E. C., Bounyong, S., Juliano, F., & Zhao, A. M. (2023, in press). *Towards recognition of students' epistemic emotions in a student knowledge building design studio.* In *Proceedings of the ISLS Annual Meeting 2023*. Montreal, Canada: International Society of the Learning Sciences.
Martınez, A., Dimitriadis, Y., Rubia, B., Gómez, E., & De la Fuente, P. (2003). Combining qualitative evaluation and social network analysis for the study of classroom social interactions. *Computers & education, 41*(4), 353-368. https://doi.org/10.1016/j.compedu.2003.06.001
Mercer, N., Littleton, K., & Wegerif, R. (2009). Methods for studying the processes of interaction and collaborative activity in computer-based educational activities. In K. Kumpulainen, C. E. Hmelo-Silver, & M. César (Eds.), *Investigating classroom interaction* (pp. 27-42). Brill. https://doi.org/10.1163/9789087907624_004
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. https://doi.org/10.1007/s11423-012-9265-2
Rodríguez-Triana, M. J., Prieto, L. P., Martínez-Monés, A., Asensio-Pérez, J. I., & Dimitriadis, Y. (2018, March). The teacher in the loop: Customizing multimodal learning analytics for blended learning. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge (LAK '18)* (pp. 417-426). New York, NY: Association for Computing Machinery. https://doi.org/10.1145/3170358.3170364
Rogoff, B. (1999). Cognitive development through social interaction: Vygotsky and Piaget. In P. Murphy (Ed.), *Learners, learning and assessment* (pp. 69-82). Paul Chapman Publishing.
Scardamalia, M., & Bereiter, C. (2003). Knowledge building environments: Extending the limits of the possible in education and knowledge work. In A. DiStefano, K.E. Rudestam, & R. Silverman (Eds.), *Encyclopedia of distributed learning*. Thousand Oaks, CA: Sage Publications.
Suthers, D. D. (2012). Computer-supported collaborative learning. In N. M. Seel (Ed.), *Encyclopedia of the Sciences of Learning*. New York, NY: Springer.
Teo, C. L., Ong, A., & Lee, V. Y. A. (2022). Exploring students' epistemic emotions in knowledge building using multimodal data. In A. Weinberger, W. Chen, D. Hernandez-Leo, & B. Chen. (Eds.), *Proceedings of the 15th Computer-Supported Collaborative Learning: CSCL 2022* (pp. 266-273). Hiroshima, Japan: International Society of the Learning Sciences.
Yan, L., Zhao, L., Gasevic, D., & Martinez-Maldonado, R. (2022, March). Scalability, sustainability, and ethicality of multimodal learning analytics [Online]. In *Proceedings of the 12th International Conference on Learning Analytics and Knowledge (LAK '22)* (pp. 13-23).
Yang, Y., van Aalst, J., & Chan, C. K. (2020). Dynamics of reflective assessment and knowledge building for academically low-achieving students. *American Educational Research Journal, 57*(3), 1241-1289.
Zhang, J., Scardamalia, M., Reeve, R., & Messina, R. (2009). Designs for collective cognitive responsibility in knowledge-building communities. *Journal of the Learning Sciences, 18*(1), 7–44. https://doi.org/10.1080/1050840080258167