Kashihara, A. et al. (Eds.) (2024). Proceedings of the 32nd International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

Verbal Interaction Patterns in Online Collaborative Learning Design: Comparison of High Performing and Low Performing Groups

Wenli CHEN[a*], Lishan ZHENG[a], Mei-Yee Mavis HO[a], Hua HU[b] & Qianru LYU[a]
[a]*National Institute of Education, Nanyang Technological University, Singapore*
[b]*Faculty of Education, East China Normal University, China*
*wenli.chen@nie.edu.sg

Abstract: This study explores the differences in students' verbal behavior sequences between high-performing (HP) and low-performing (LP) groups in a computer-supported collaborative learning (CSCL) environment. Employing quantitative content analysis and Lag Sequential Analysis (LSA), this study analyzed the verbal interactions of these two groups. The findings reveal that HP groups frequently engaged in cycles of negotiation, clarity-seeking, and task coordination, leading to effective collaboration and problem-solving. In contrast, LP groups exhibited fragmented problem-solving approaches and frequent off-task behaviors. These insights highlight the importance of structured support and focused task management in enhancing collaborative learning outcomes. These findings suggest that educators should foster learning environments that promote continuous critical evaluation and seamless coordination to improve group performance.

Keywords: Collaborative Learning, Computer-Supported Collaborative Learning, Verbal Interaction, Lag Sequential Analysis, Behavioral Patterns

1. Introduction

Collaborative learning, characterized by joint efforts toward shared goals through continuous communication, is recognized as an effective educational strategy (Wilczenski et al., 2001). In the context of Computer-Supported Collaborative Learning (CSCL), understanding how students interact with each other is critical for optimizing effective learning environments and experiences. Existing studies highlight the importance of both team coordination activities (such as planning and organizing) and task-related interactions (such as commenting and responding to messages) in fostering successful collaborative learning experiences (Vuopala et al., 2016). Moreover, peer interactions within CSCL environments have been shown to enhance students' interest and motivation, encouraging deeper engagement with diverse ideas, and ultimately improving learning outcomes (Molinillo et al., 2018; Moore, 1989).

Verbal communication plays a central role in the collaborative learning process, serving as a key mechanism through which students share knowledge, engage in critical thinking, and solve problems collectively (Dillenbourg, 1999; Mercer, 2000). In CSCL environments, verbal interactions encompass both coordination efforts and task-related discussions, both of which are essential for developing a shared understanding and establishing collaborative learning norms (Ouyang & Xu, 2022). These interactions are vital for grasping the cognitive and social dimensions of learning, which are critical for the development of effective collaborative skills (Johnson & Johnson, 2009; Kwon et al., 2014; Vuorenmaa et al., 2023). Consequently, analyzing students' verbal communication patterns offers valuable insights into their collaborative learning dynamics and the overall effectiveness of their interactions (Roschelle & Teasley, 1995; Stahl, 2006; Wang et al., 2019).

This study aims to delve deeper into these dynamics by employing Quantitative Content Analysis and Lag Sequential Analysis (LSA) to examine the verbal behavior sequences of high-performing (HP) and low-performing (LP) groups (Wu et al., 2016). Identifying sequential patterns in dialogue allows for a nuanced understanding of the strategies employed by students and the impact of these strategies on group performance (Hou et al., 2015）. In this context, understanding the differences between HP and LP groups is crucial for developing tailored interventions that enhance collaborative learning (Malmberg et al., 2015). For instance, strategies such as promoting proactive communication, providing structured task guidance, and fostering continuous engagement and critical evaluation can significantly improve learning outcomes (Kozlowski & Ilgen, 2006; Vygotsky, 1978). By analyzing the behaviors of HP and LP groups, educators can either reinforce strengths in coordination and problem-solving for HP groups or offer additional scaffolding and task management support for LP groups (Bransford et al., 2000; Gillies, 2004). These targeted strategies can lead to a more effective and inclusive collaborative learning environment, addressing the unique needs of each group and ultimately enhancing the overall learning experience (Sawyer, 2004). With the above, this study aims to address the following research question: What are the differences in verbal behavioral sequences between HP and LP groups during collaboration?

2. Methods

2.1. Experimental Design & Data Collection

The experiment was conducted in a university laboratory with ethical approval from the Institutional Review Board. Sixteen participants, aged 21 to 40 and from diverse academic backgrounds, were paired with unfamiliar partners to minimize the effects of prior collaboration. Each dyad participated in a single session, using individual computers to access a shared online interface for collaborative ideation task, where they designed a multifunctional schoolbag based on prompts related to 'customer traits,' 'outlook,' 'function/technology,' and 'materials.' Prior to the task, participants had 2 minutes for individual preparation in separate workspaces, during which they recorded their ideas without verbal communication. Subsequently, dyads collaborated for 5 minutes, discussing and integrating their ideas verbally in a shared collaboration column (Figure 1).

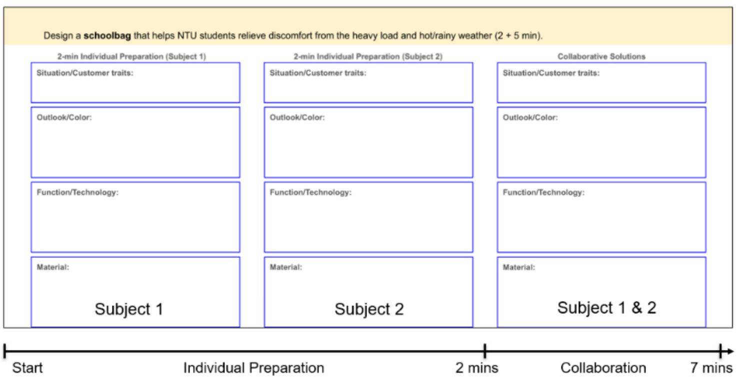

Figure 1. Online task interface used in the study. The first two columns are the individual working spaces while the last column served as the dyads' shared workspace (left to right).

Audio recordings were collected throughout the sessions to analyze verbal discourse behaviors. Since spoken communication was disallowed during individual preparation, only the last 5 minutes of each recording were analyzed. The recordings were transcribed using Whisper, an automatic speech recognition tool, and reviewed by two researchers for accuracy. To assess dyadic collaborative performance, scoring rubrics adapted from previous peer assessment research (Chang et al., 2020; Chang et al., 2021) were used. The rubrics evaluated responses in the collaborative ideation space across four dimensions: 'Completeness,' 'Elaboration,' 'Functionality,' and 'Innovation,' with each dimension scored from one to three. Two raters independently graded the responses, and discrepancies were resolved through discussion. The total scores were then calculated, and dyads were categorized into high-performing (top half, n = 8) and low-performing (bottom half, n = 8) groups based on their performance.

2.1.2 Coding Scheme

Various coding schemes have been developed to analyze interaction patterns in collaborative verbal communication (Chung et al., 2013). Gunawardena et al.'s (1997) Interaction Analysis Model (IAM) explores knowledge construction in computer-mediated settings, categorizing interactions into five stages from information sharing to knowledge affirmation. Building on this, Wang et al. (2020) developed a verb-centric coding scheme for synchronous online learning, focusing on academic relevance, social connectivity, and off-topic behaviors. This study adapted Wang's framework to further emphasize task completion and interaction dynamics, capturing nuanced student interactions and collaborative behaviors. Details of the coding framework are in Appendix Table 1.

In analyzing dialogues within collaborative learning, participants typically follow a turn-taking communication model. Researchers used a predefined coding framework (Table 1) to encode each turn within the dialogue, identifying interaction behavior patterns. The unit of analysis was the individual turn, coded according to predefined categories. To ensure reliability, Cohen's Kappa was calculated across all groups, resulting in an average value of 0.894, indicating substantial agreement between the two coders (Landis & Koch, 1977).

3. Discussion & Conclusion

To ascertain whether these sequences relationships hold statistical significance, in this study, we utilized the software GSEQ 5.1 to conduct Lag Sequential Analysis (LSA) that primarily employed to examine the probability and statistical significance of one behavior occurring immediately after another (Bakeman & Gottman, 1997). In LSA, As shown in Appendix, the columns in the contingency table represent the given behaviors (which occur first), and the rows represent the target behaviors (which occur subsequently). The adjusted residual results (Z-scores) of each behavioral transition determined whether the subsequent behaviors were significant (Z-scores > 1.96, Bakeman & Gottman, 1997). The results reveal that the number of significant sequences in the HP and LP groups was 9 and 8, respectively. We then depicted the behavior transition diagrams for all sequences that reached statistical significance. Numerical values represent the Z-scores of the sequences while arrows indicate the direction of the transition. Statistically significant sequences are represented in a behavioral transition diagram (Figure 2) to provide a comprehensive view of the findings.

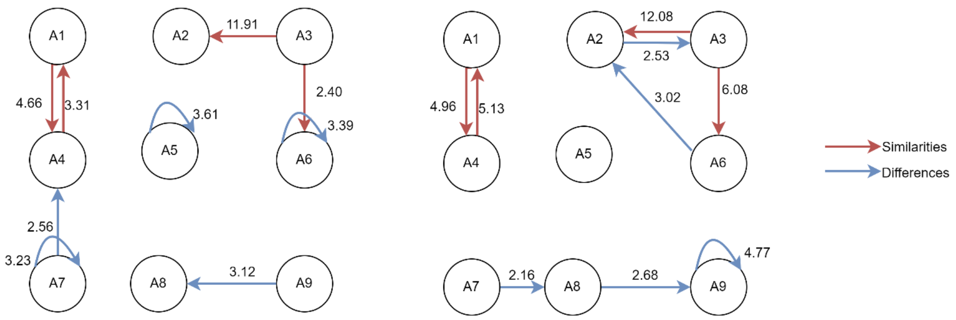

Figure 2. Behavior transition diagram of sequences in the HP group(left) and LP group(right).

As shown in Figure 2, high-performance (HP) groups demonstrate effective collaboration through several key behavioral paths. Self-loops in A5 (negotiation), A6 (discover uncertainty), and A7 (lead task coordination) indicate continuous engagement in critical evaluation, clarity, and coordination. For instance, members repeatedly refine proposed solutions (A5), address ambiguities (A6), and maintain focus through persistent coordination efforts (A7). The transition from A7 to A4, where task coordination leads to agreement, highlights how coordination results in consensus and cohesive action. Even when off-task behavior occurs (A9), HP groups typically return to task relevance (A8), maintaining overall productivity. In contrast, low-performance (LP) groups exhibit behavioral sequences that reflect challenges in staying on track and managing discussions (Molinillo et al., 2018). The transition from A6 to A2 to A3 shows a fragmented approach to problem-solving, where identified uncertainties (A6) lead to ineffective requests for help (A2) and unproductive responses (A3). Additionally, the sequence from A7 to A8 to A9 indicates a breakdown in focus, where task coordination (A7) devolves into irrelevant content (A9), highlighting persistent distraction and lack of task commitment.

The findings have significant implications for educators and instructional designers. For HP groups, reinforcing their strengths in coordination and critical evaluation can be achieved by providing complex, open-ended tasks that challenge their leadership and problem-solving skills (Johnson & Johnson, 1999). For LP groups, targeted strategies are needed to address challenges such as fragmented problem-solving and distractions. Assigning specific roles and responsibilities, along with implementing monitoring tools and regular feedback, can help LP groups maintain focus and improve task management (Barron, 2003; Chen et al., 2018). These interventions can foster proactive communication, clear task guidance, and environments that support continuous engagement and critical evaluation (Volet et al., 2017; Järvelä et al., 2019).

4. Limitations and Future Work

This study primarily examines verbal data from collaborative learning design session, which provides valuable insights into the communication patterns and behavioral dynamics of HP and LP groups. However, this focus on verbal interaction alone may not capture the full complexity of collaborative processes in computer-supported collaborative learning (CSCL) environments. Future research should incorporate additional modes of interaction, including online interactions and non-verbal communication, to gain a holistic understanding of the CSCL process. By examining multiple modalities of interactions, future studies can provide a more comprehensive picture of how collaborative learning unfolds in various contexts.

Acknowledgements

This study was funded by National Institute of Education (NIE), Nanyang Technological University (NTU), Singapore (RS 1/22 CWL) and administered by NIE, NTU. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of NIE, NTU. The study was approved by the NTU IRB (IRB approval number: IRB-2022-210).

References

Bakeman, R., & Gottman, J. M. (1997). *Observing interaction: An introduction to sequential analysis*. Cambridge university press.

Barron, B. (2003). When Smart Groups Fail. *Journal of the Learning Sciences*, 12(3), 307–359. https://doi.org/10.1207/S15327809JLS1203_1

Bransford, J. D., Brown, A. L., & Cocking, R. R. (2000). *How people learn* (Vol. 11). Washington, DC: National academy press.

Chang, D., Hwang, G. J., Chang, S. C., & Wang, S. Y. (2021). Promoting students' cross-disciplinary performance and higher order thinking: A peer assessment-facilitated STEM approach in a mathematics course. *Educational Technology Research and Development*, 69, 3281-3306.
Chang, S. C., Hsu, T. C., & Jong, M. S. Y. (2020). Integration of the peer assessment approach with a virtual reality design system for learning earth science. *Computers & Education*, 146, 103758.
Chen, X., Breslow, L., & DeBoer, J. (2018). Analyzing productive learning behaviors for students using immediate corrective feedback in a blended learning environment. *Computers & Education*, 117, 59-74.
Chung, C. W., Lee, C. C., & Liu, C. C. (2013). Investigating face ‐ to ‐ face peer interaction patterns in a collaborative W eb discovery task: the benefits of a shared display. *Journal of Computer Assisted Learning*, 29(2), 188-206.
Dillenbourg, P. (1999). What do you mean by collaborative learning?. *Collaborative-learning: Cognitive and Computational Approaches*., 1-19.
Gillies, R. M. (2004). The effects of cooperative learning on junior high school students during small group learning. *Learning and instruction*, 14(2), 197-213.
Gunawardena, C. N., Lowe, C. A., & Anderson, T. (1997). Analysis of a global online debate and the development of an interaction analysis model for examining social construction of knowledge in computer conferencing. *Journal of educational computing research*, 17(4), 397-431.
Hou, H.-T., Wang, S.-M., Lin, P.-C., & Chang, K.-E. (2015). Exploring the learner's knowledge construction and cognitive patterns of different asynchronous platforms: Comparison of an online discussion forum and Facebook. *Innovations in Education and Teaching International*, 52(6), 610–620. https://doi.org/10.1080/14703297.2013.847381
Järvelä, S., Järvenoja, H., & Malmberg, J. (2019). Capturing the dynamic and cyclical nature of regulation: Methodological Progress in understanding socially shared regulation in learning. *International journal of computer-supported collaborative learning*, 14, 425-441.
Johnson, D. W., & Johnson, R. T. (1999). Making cooperative learning work. *Theory into practice*, 38(2), 67-73.
Johnson, D. W., & Johnson, R. T. (2009). An educational psychology success story: Social interdependence theory and cooperative learning. *Educational researcher*, 38(5), 365-379.
Kozlowski, S. W., & Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. *Psychological science in the public interest*, 7(3), 77-124.
Kwon, K., Liu, Y. H., & Johnson, L. P. (2014). Group regulation and social-emotional interactions observed in computer supported collaborative learning: Comparison between good vs. poor collaborators. *Computers & Education*, 78, 185-200.
Landis, J. R., & Koch, G. G. (1977). An application of hierarchical kappa-type statistics in the assessment of majority agreement among multiple observers. *Biometrics*, 363-374.
Malmberg, J., Järvelä, S., Järvenoja, H., & Panadero, E. (2015). Promoting socially shared regulation of learning in CSCL: Progress of socially shared regulation among high-and low-performing groups. *Computers in Human Behavior*, 52, 562-572.
Mercer, N. (2004). Sociocultural discourse analysis. *Journal of applied linguistics*, 1(2), 137-168.
Molinillo, S., Aguilar-Illescas, R., Anaya-Sánchez, R., & Vallespín-Arán, M. (2018). Exploring the impacts of interactions, social presence and emotional engagement on active collaborative learning in a social web-based environment. *Computers & Education*, 123, 41–52. https://doi.org/10.1016/j.compedu.2018.04.012
Moore, M. G. (1989). Three types of interaction.
Ouyang, F., & Xu, W. (2022). The effects of three instructor participatory roles on a small group's collaborative concept mapping. *Journal of Educational Computing Research*, 60(4), 930–959.
Roschelle, J., & Teasley, S. D. (1995). The construction of shared knowledge in collaborative problem solving. *Computer supported collaborative learning* (pp. 69-97). Springer Berlin Heidelberg.
Sawyer, R. K. (2004). Creative teaching: Collaborative discussion as disciplined improvisation. *Educational researcher*, 33(2), 12-20.
Stahl, G. (2006). *Group cognition: Computer support for building collaborative knowledge (acting with technology)*. The MIT Press.
Volet, S., Vauras, M., & Salonen, P. (2009). Self-and social regulation in learning contexts: An integrative perspective. *Educational psychologist*, 44(4), 215-226.
Vuopala, E., Hyvönen, P., & Järvelä, S. (2016). Interaction forms in successful collaborative learning in virtual learning environments. *Active Learning in Higher Education*, 17(1), 25-38. 47.
Vuorenmaa, E., Järvelä, S., Dindar, M., & Järvenoja, H. (2023). Sequential patterns in social interaction states for regulation in collaborative learning. *Small Group Research*, 54(4), 512-550.
Vygotsky, L. S., & Cole, M. (1978). *Mind in society: Development of higher psychological processes*. Harvard university press.

Wang, C., Fang, T., & Gu, Y. (2020). Learning performance and behavioral patterns of online collaborative learning: Impact of cognitive load and affordances of different multimedia. *Computers & Education*, 143, 103683. https://doi.org/10.1016/j.compedu.2019.103683

Wang, S., Wu, C., & Hou, H. T. (2019). Integrating Board Game Elements, Collaborative Discussion, and Mobile Technology to a Gamification Instructional Activity-A Case of High School Chemical Course. *International Journal of Learning Technologies and Learning Environments*, 2(2), 11-20.

Wilczenski, F. L., Bontrager, T., Ventrone, P., & Correia, M. (2001). Observing collaborative problem‐solving processes and outcomes. *Psychology in the Schools*, 38(3), 269-281.

Wu, S. Y., Chen, S. Y., & Hou, H. T. (2016). Exploring the interactive patterns of concept map-based online discussion: A sequential analysis of users' operations, cognitive processing, and knowledge construction. *Interactive Learning Environments*, 24(8), 1778-1794.