

A Three-level Computer-Mediated Discourse Analysis to Collaborative Interactions in a Game-based CSCL Environment

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Abstract: This study applies CMDA to analyze communication in a game-based CSCL setting. Examining two groups with differing outcomes, we explored participation, speech acts, and topic development. Findings show interaction density and balanced contributions impact performance, while communicative acts like “Inquire” and “Elaborate” shape collaboration. Topic coherence influences group effectiveness. Visualizations illustrate these dynamics. Despite limitations, CMDA provides insights into CSCL processes and informs adaptive support for collaborative learning.

Introduction

CSCL uses technology to facilitate collaborative problem-solving on ill-structured problems (Jeong et al., 2019), with learners primarily engaging through text-based chats for information exchange, role coordination, and resource sharing (Zheng et al., 2019). While CSCL can promote higher-order thinking and knowledge co-construction, successful collaboration is not guaranteed (Stahl, 2017). This raises the question: why do some groups succeed while others fail? (Stahl, 2006; Stahl, 2017). From a sociocultural perspective, collaboration depends on how interactions unfold over time, and interactions can also shape learning processes and outcomes (Scott & Palincsar, 2013). Within CSCLs, chat data offers insights into collaborative processes (Graesser et al., 2018). Computer-Mediated Discourse Analysis (CMDA) applies linguistic methods to study these interactions (Herring, 2004), revealing patterns linked to successful collaboration (Herring, 2004). As such, this study uses CMDA to examine group interactions and inform instructional design and adaptive interventions. Specifically, we explore three research questions: (1) How do groups participate in collaborative conversation? (2) How do groups use interactional moves to complete tasks? (3) How do groups manage interactional cohesion and co-construct understanding?

Methods

Context and analytical procedures

The learning context is *EcoJourneys*, a game-based CSCL, teaches aquatic ecosystems and fosters collaborative inquiry. Students work in small groups to diagnose an ill-defined problem: the cause of illness in local tilapia. A pre- and post-test (max 36 points) assessed learning gains among 52 middle schoolers from two science classes in the southern U.S. Two groups with similar pre-test scores but differing post-test outcomes were selected. Group A improved by 18.6%, while Group B declined by 5.9%. Collaborative interactions during Deduce and TIDE were analyzed using CMDA. CMDA methods included participation analysis, speech act analysis, and dynamic topic development. Participation analysis examined chat frequency, average message length, and contribution inequality via the Gini index. Speech act analysis applied an adapted CMC taxonomy (Herring et al., 2005) with 16 speech act categories, capturing both informative and social discourse. Dynamic topic development, using Herring’s (2003) techniques and VisualDTA (Herring & Kurtz, 2006), traced topic shifts and coherence in chat data. Messages were coded as on-topic (T), parallel shifts (P, with semantic distance 1-3), or breaks (B, unrelated shifts).

Results

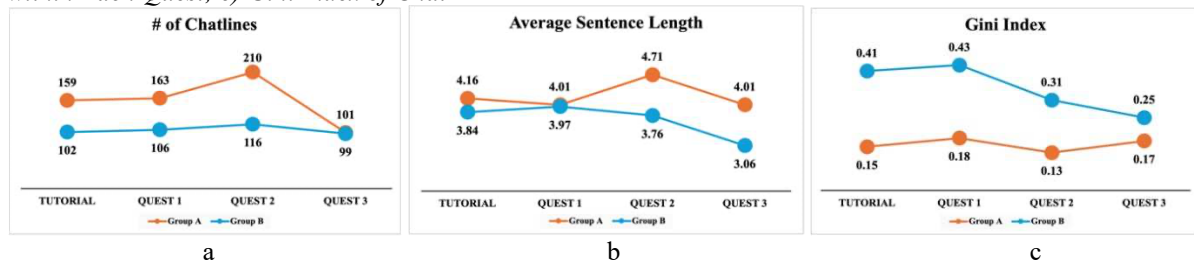
Participation matrix within each group

Group A consistently generated more chatlines than Group B, especially in Quest Two, where they contributed over twice as many (see figure 1). Both groups saw a decline in chatlines by Quest Three, likely due to fatigue. Group A also produced longer messages, suggesting more detailed communication, while Group B’s responses were shorter and declined further in the final quest. For example, Nancy in Group A justified her choice with

reasoning, referencing key terms and evidence, whereas Group B engaged in brief assertion-counter-assertion cycles with little explanation. The Gini index showed Group A's contributions were evenly distributed, while Group B had uneven participation, especially early on, indicating dominance by certain members.

Figure 1

Results of Participation Analysis by Groups: a) Number of Chatlines; b) Average Number of Words by Group within Each Quest; c) Gini Index of Chat



Computer-mediated communication acts distribution

We applied 16 speech act codes to chat data from both groups. Group A had 623 utterances, while Group B had 423. Group A showed higher inquiry (11.1% vs. 7.7%), often probing reasoning rather than just task instructions. They also had more elaboration (6.9%) and coordination (9.7%), fostering collaboration. In contrast, Group B used more direct acts (21.2%), often issuing commands rather than engaging peers (e.g., “just write as I say and hit submit”). Group B also had fewer invites (0.5%) and more off-task interactions (25.8%), likely hindering discussion. Group A's higher inform acts (14.7% vs. 6.9%) facilitated knowledge sharing, while similar claim, react, and comment rates suggest expected collaborative engagement.

Dynamic topic development

Table 1 highlights differences in coherence and topical development between groups. Group A remained mostly on-topic (80.3%), with 13.6% parallel shifts and 6.8% topic breaks, maintaining a low semantic distance (0.36). In contrast, Group B had fewer on-topic utterances (68%), minimal parallel shifts (2.1%), and a high rate of topic breaks (29.9%), resulting in a greater semantic distance (1.6) and weaker coherence. In particular, Group A's discussion evolved through structured exchanges with brief topic drift, while Group B's conversation was fragmented by off-topic sub-threads, disrupting collaborative problem-solving.

Table 1

Metrics of Dynamic Topic Development Coding

Groups	On-topic	Parallel Shifts	Breaks	Number of utterances	Avg. semantic distance (all)
Group A	80.3%	13.6%	6.8%	623	0.36
Group B	68%	2.1%	29.9%	423	1.6

Discussion and conclusion

This study applied three levels of CMDA to analyze chat data from two groups with differing collaborative learning outcomes. Beyond highlighting key differences between Group A and Group B, the findings demonstrate CMDA's value in examining communication patterns. At the macro level, participation analysis reveals interaction density's role in group performance. Speech act analysis identifies how speech acts like “Inquiries” and “Direct” shape group dynamics, suggesting that future research could explore act sequences linked to better learning outcomes. Dynamic topic development analysis measures coherence, with parallel shifts signaling idea-building and semantic distance reflecting conversational continuity. The structured, problem-driven nature of the learning context likely influenced these dynamics, emphasizing the importance of refocusing after brief topic drifts. Visualizations further illustrate collaborative processes, helping pinpoint productive exchanges and breakdowns. These insights can inform adaptive support in game-based CSCL environments. However, the study's small sample size limits generalizability, and its problem-driven focus may not apply to other learning activities. Despite these limitations, this research advances CSCL by integrating CMDA methods, offering a deeper understanding of communication patterns' impact on group performance and learning outcomes.

References

- Graesser, A. C., Fiore, S. M., Greiff, S., Andrews-Todd, J., Foltz, P. W., & Hesse, F. W. (2018). Advancing the science of collaborative problem solving. *Psychological science in the public interest*, 19(2), 59-92.
- Herring, S. C. (2003). Dynamic topic analysis of synchronous chat. In *New research for new media: Innovative research methodologies symposium working papers and readings* (pp. 47-66). University of Minnesota School of Journalism and Mass Communication.
- Herring, S. C. (2004). Computer-mediated discourse analysis: An approach to researching online behavior. *Designing for virtual communities in the service of learning*, 338, 376.
- Herring, S. C., & Kurtz, A. J. (2006). Visualizing dynamic topic analysis. In *Proceedings of CHI'06* (pp. 1-6). ACM Press.
- Herring, S. C., Das, A., & Penumarthy, S. (2005). CMC act taxonomy. <http://ella.slis.indiana.edu/~herring/cmc.acts.html>
- Jeong, H., Hmelo-Silver, C. E., & 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, 100284.
- Scott, S., & Palincsar, A. (2013). *Sociocultural theory*.
- Stahl, G. (2006). *Group cognition: Computer support for building collaborative knowledge (acting with technology)*. The MIT Press.
- Stahl, G. (2017). Group practices: A new way of viewing CSCL. *International Journal of Computer-Supported Collaborative Learning*, 12, 113-126.
- Zheng, J., Xing, W., & Zhu, G. (2019). Examining sequential patterns of self-and socially shared regulation of STEM learning in a CSCL environment. *Computers & Education*, 136, 34-48.

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