Understanding Collaborative Knowledge Building for Diverse Students with LSA

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Abstract. Collaborative knowledge building, a common activity among students in virtual learning communities, has garnered the attention of researchers. Existing studies often analyze the process of collaborative knowledge building within these communities through implicit interaction behaviors, while research focusing on explicit operational behaviors documented in activity logs is relatively scarce. Analysis based on explicit operational behaviors can provide a more comprehensive understanding of the collaborative knowledge building process, which is beneficial for enhancing student's Knowledge building levels. This study selected a course in which 50 students engaged in collaborative knowledge building activities through virtual learning communities. The study employed lag sequence analysis to examine the behavioral data generated by student activities and conducted group analysis for learners at different proficiency levels. The findings indicate that analysis based on explicit operational behaviors effectively identifies significant behavioral sequences and characteristics. The overall behavioral patterns of learners align with Knowledge building theory, and the higher engagement of high performance group learners during the knowledge convergence phase is a primary factor affecting the level of collaborative knowledge building.

Keywords: Knowledge Building; Virtual Learning Community; Learning Behavior Analysis

1 Introduction

As learners' needs for sharing, researching, and discussing during learning grow, virtual learning communities(VLC) are becoming increasingly popular. These communities overcome spatial and temporal barriers to foster collaboration[1], and are often integrated into educational activities, especially collaborative learning[2]. Wikis-based learning communities are a prominent example. However, students still encounter challenges in collaborative learning within these communities, exhibiting unpredictable behavior[3]. Therefore, analyzing student behavior is crucial to understanding and enhancing their knowledge formation process.

Collaborative knowledge building enhances learning in communities[4], but current analysis methods mainly focus on discourse content[5], insufficient for interpreting vast learner behavior and session data in VLC. Mining patterns of student knowledge building behavior is crucial to fully understanding data. Behavioral patterns capture learning dynamics and are invaluable for exploring and predicting collaborative knowledge building.

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2 Literature Review

2.1 Collaborative Knowledge Building

Collaborative Knowledge building is crucial for deep learning. Analyzing student processes aids educators in improving teaching and learning efficiency. Güler[6] found that flexibility, stress management, self-paced learning, and formal dialogue platforms enhance Knowledge building. Lu et al. used socially regulated learning to promote Knowledge building, showing positive impacts. Student behaviors reflect collaborative Knowledge building, linking academic performance and behavior in virtual communities.

Previous research focused on online discourse as the main information exchange channel. However, with big data's impact on educational transformation, learners establish stable network relationships, boosting collaborative learning. Conversation data alone is insufficient; Villegas[7] suggests extracting information from learning management systems to identify valuable insights. Analyzing student behavior patterns can enhance teaching efficiency.

2.2 Behavioral Pattern

Behavioral and session data are vital for understanding online collaborative knowledge building. Lag sequence analysis accurately captures learners' patterns through collaboration and time series[8]. Analyzing Wiki editing data uncovers behavioral characteristics vital for learning activity analysis. Despite progress in implicit interaction research, explicit behavioral data remains underexplored. Traditional, result-focused approaches lack depth, necessitating process-oriented techniques like time series and LSA, plus dynamic community evolution. To fully grasp student's knowledge building in virtual communities, explicit behavioral data analysis is key, enhancing discourse data analysis to depict the process comprehensively.

2.3 This Study

This study explores knowledge building behaviors in VLC, aiming to reveal implicit behavioral patterns through analyzing sequences of these behaviors. Using a specific learning platform, we designed collaborative activities and analyzed student learning behavior data. LSA was employed to investigate behavioral patterns, enabling a dynamic and holistic understanding of collaborative knowledge building processes and characteristics among students. The research questions formulated were as follows:

RQ1: What are the distribution characteristics of student's collaborative knowledge building behaviors in VLC?

RQ2: What differences exist in behavioral patterns between high and low performance groups in VLC?

3 Method

3.1 Curriculum and Participants

This study focused on a collaborative learning activity involving 50 master's students in Educational Technology, aged primarily 22-24. Among them, 43 were female (86%) and 7 were male (14%). All students had prior experience in collaborative learning and were enrolled in the "Fundamentals of Educational Technology Theory" course. Using Moodle and Wiki technology, students divided into 18 groups of 2-3 members engaged in theme-based collaborative inquiry learning. Each group identified an inquiry topic, collaboratively edited on Wiki, and produced encyclopedia pages. The learning process comprised five parts: topic selection, identifying interests, seeking relevant materials, integrating knowledge, and discussing. This aligns with the essence of knowledge building, where community members explore topics of interest and pursue genuine issues.

3.2 Data Analysis

In the learning activity, students grouped to select topics in educational technology searched for materials, organized information, and created Wiki pages. Wiki activities were logged, and data was cleaned, coded, and analyzed using GSEQ to generate an adjusted residual table. This table was used to create a behavior transition diagram, revealing knowledge building patterns and differences among students with varying performance in VLC.

3.3 Coding Interactive Behavior

Students interacted socially through Wiki, facilitating knowledge building. Cress and Kimmerle[9] proposed a cognitive model for collaborative knowledge building in Wiki systems, emphasizing the interdependence of social and cognitive systems. Their model identifies four stages: internalization, externalization, combination, and mutual stimulation. This framework underlies our understanding of collaborative knowledge building behaviors in Wiki in this study. To form a coding scheme for collaborative editing behaviors, we: (1) accessed student's collaborative learning event records from activity logs, (2) categorized these events based on their descriptions, and (3) referenced established coding frameworks to create a coding scheme tailored to our research.

Li et al.[10] proposed a Wiki collaborative knowledge building analysis model, emphasizing the importance of editing behaviors. Their coding approach aligns with this study, both relying on Cress and Kimmerle's cognitive model as a theoretical framework. Li's coding system, originally for domestic classrooms, was adapted due to data source differences. Li et al. categorize Wiki editing behaviors into three stages: knowledge sharing (PI), knowledge combination (PII), and knowledge convergence (PIII). This study adopted the stage division from the original system and adjusted editing behavior units based on collaborative editing event categorization, creating a new coding scheme. In the sharing stage, learners contribute and refine the content on Wiki, corresponding to "new topic creation" events in this study(Table 1).

The knowledge combination stage involves cognitive interactions with Wiki, leading to Wiki content refinement aligned with topic integration. Behaviors include collaborative updates, agreement, questioning, and reflection. In the convergence stage, learners summarize and synthesize group outcomes, reflecting and transferring knowledge through viewing Wiki and summarizing reflections. A self-narrative stage accounts for prerequisite knowledge. A tailored coding table for this Wiki enables analysis of student behaviors, deepening understanding of collaborative knowledge building.

Table 1. Coding Table for Knowledge Construction Behavior

Stage	Meaning of behavior	Concrete explanation	Coding
Self-narrative	Prior knowledge	Individual learning related to collaborative group tasks to communicate with peers	PN
Knowledge sharing	Add Sharing	Use your existing knowledge to add new Wiki content for peer review	PI
Knowledge link	Supplementary modifications	Refine your own edited Wiki content in agreement with your peers' concepts	PIIa
	Amendment	Questioning peers, or responding to peers' questioning, leading to changes in Wiki content	PIIb
Knowledge convergence	Comprehensive Browsing	Read and learn from your group and other groups' Wiki pages!	PIIIa
	summarize and reflect	Refine, summarize, and conclude the results of the Wiki multi-editorial content	PIIIb

4 Results

4.1 Student Performance Groups

After learning, scores reflecting collaborative Knowledge building were derived from peer and teacher assessments(Table 2). Groups were categorized as high (11) or low (7) performance based on a cutoff score of 88/100. To validate grouping, a difference test was conducted. Homogeneity of variances test failed, leading to non-parametric tests for group differences(Table 3). These tests rejected the null hypothesis, confirming differences between high and low-performance groups, and validating the grouping rules.

Table 2. Variance chi-square test

Variant	Type of test	Levin statistics	df1	df2	Significance
Mark	Based on average values	4.976	1	16	0.040
	Based on median	5.108	1	16	0.038
	Based on the median with adjusted df	5.108	1	11.995	0.043
	Based on post clipping average	4.970	1	16	0.040

Table 3. Summary of hypothesis testing for nonparametric tests

Test	Significance
Wolde-Wolfowitz Trip Inspection	.000
Extreme reaction test	.000
Mann-Whitney rank sum test	.000
Kolmogorov-Sminov test	.001

4.2 Behavioral Pattern Analysis

The encoded data were input into the GSEQ software for analysis, resulting in an adjusted residual matrix, as shown in Table 4 and Table 5.

Table 4. Behavioral residual matrix for high-level groups

Given:	PN	PIa	PIb	PIIa	PIIb	PIIIa	PIIIb
PN	45.24	-9.03	-8.02	-4.74	-12.58	-1.94	45.24
PI	-9.41	-12.69	-11.43	-6.4	28.49	-3.75	-9.41
PIIa	-9.02	53.23	-11.52	-6.14	-23.42	-3.59	-9.02
PIIb	-4.2	-6	-3.64	28.91	-3.01	-0.15	-4.2
PIIIa	-12.39	-21.14	25.34	-0.91	4.31	4.13	-12.39
PIIIb	-0.26	-3.75	-3.25	1.58	2.01	10.28	-0.26

Table 5. Behavioral residual matrix for low-level groups

Given:	PN	PIa	PIb	PIIa	PIIb	PIIIa	PIIIb
PN	31.5	-7.5	-6.04	-2.9	-8.97	-1.59	31.5
PI	-7.45	-9.59	-8.8	-4.21	22.1	-2.76	-7.45
PIIa	-7.17	37.28	-8.71	-3.95	-16.14	-2.59	-7.17
PIIb	-1.73	-4.18	-0.67	13.6	-0.45	-0.25	-1.73
PIIIa	-9	-13.73	18.59	2.48	1.1	2.29	-9
PIIIb	-0.54	-2.35	-1.22	1.49	-0.48	11.18	-0.54

The adjusted residual matrix displays the residual parameters, also known as Z-values, obtained based on the frequency of behavioral transitions. Z-values can be used to determine whether a sequence of behaviors, including a specific behavior and its accompanying behaviors, is significant. If the Z-value is greater than 1.96, it indicates that the behavior sequence is statistically significant. Based on the analysis of significant behavior sequences from Table 4 and Table 5, behavior sequence transition diagrams were created to illustrate the patterns of learners' collaborative Knowledge building behaviors. The behavior sequence transition diagrams for the two groups of learners are shown in Figure 1 and Figure 2.

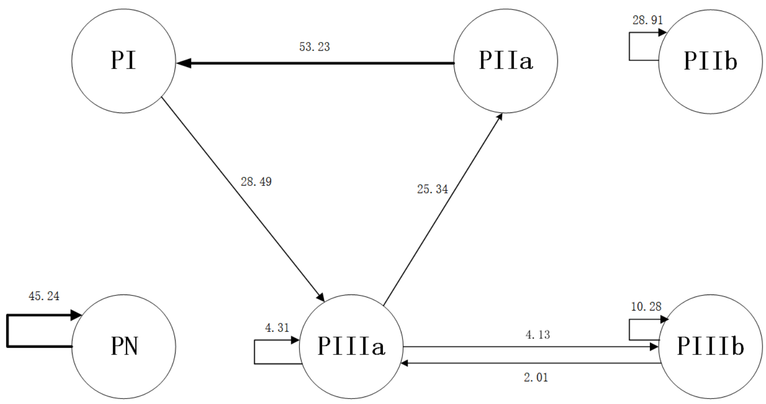

Fig. 1. Behavioral sequence of high-performance students

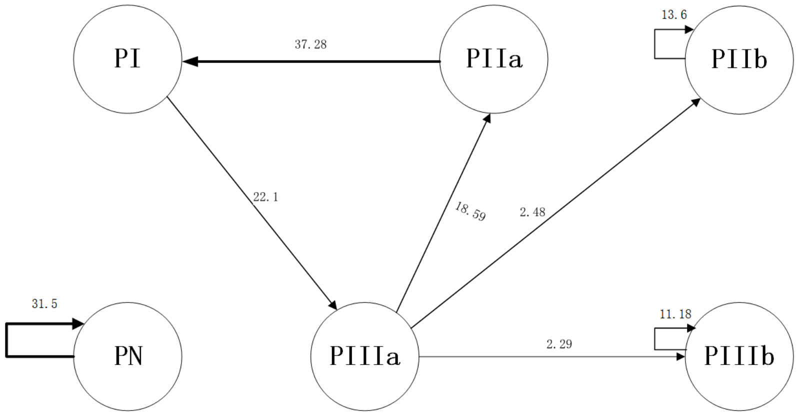

Fig. 2. Behavioral sequence of low-performance students

The high-performance group exhibited nine significant behavior transition sequences: PN→PN, PI→PIIIa, PIIa→PI, PIIb→PIIb, PIIIa→PIIa, PIIIa→PIIIa, PIIIa→PIIIb, PIIIb→PIIIa, and PIIIb→PIIIb.

The low-performance group exhibited eight significant behavior transition sequences: PN→PN, PI→PIIIa, PIIa→PI, PIIb→PIIb, PIIIa→PIIa, PIIIa→PIIb, PIIIa→PIIIb, and PIIIb→PIIIb.

4.3 Typical Behavior Sequence

Comparing the behavior transition diagrams, we observe shared sequences like PN→PN and PIIb→PIIb among both groups, reflecting learners' tendency to repeatedly engage in behaviors like acquiring knowledge and refining modifications. Sequences like PI→PIIIa form a cyclic pattern, indicating learners' browsing, sharing, and modifying knowledge. The sequence PIIIb→PIIIb suggests learners summarize new knowledge through comments. Unique to the high-performance group are sequences like PIIIa→PIIIa, indicating a focus on reviewing encyclopedia pages. Conversely, the low-performance group is prone to cognitive conflicts and revisions, as indicated by the sequence PIIIa→PIIb.

5 Discussion

This study examined student behavior in VLC, revealing distinct collaborative Knowledge building patterns. This study also developed a coding framework, considering the use of explicit operational behaviors in activity logs. Compared to previous papers that focusing on human interaction, the logs data offers a more precise depiction of learners' usage patterns in VLC, and facilitates convenient data capture.

The high and low performance groups displayed different behaviors, with peak engagement during knowledge convergence. Performance is driven by the learner's behavior[11]. These patterns demonstrate the interconnectedness of knowledge building stages. Learners repeated sequences, seeking prerequisite knowledge, resolving conflicts, and awaiting others' work for summary and reflection. Comparing the behavioral patterns, the high-performance group's sequences indicate deeper engagement in knowledge convergence, crucial for refining and integrating ideas. In contrast, the low-performance group's limited engagement in this stage could explain their lower collaborative Knowledge building levels. While the exclusive sequence PIIIa→PIIb in the low-performance group doesn't necessarily hinder Knowledge building, it reflects challenges in discussing and resolving viewpoint conflicts. Overall, sustained engagement in knowledge convergence is key to effective collaborative learning.

6 Conclusion

This study analyzed interaction data from 50 students in VLC, using LSA and a collaborative Knowledge building coding framework. Analyzing behavioral data proved feasible and effective in understanding learners' behavior sequences. It may aid educators and researchers in explaining student’s Knowledge building process from a behavioral perspective. However, caveats are noteworthy. Firstly, the study primarily interprets Knowledge building through behavioral meanings, future studies could explore additional factors like learning strategies. Secondly, data was sourced from platform logs, but external factors may influence learners' behaviors. Lastly, the coding scheme was developed by a limited number of developers, enhancing reliability with methods like the Delphi technique could be beneficial.

References

[1] Crites, G. E., Berry, A., Hall, E., Kay, D., Khalil, M. K., & Hurtubise, L. (2020). Applying multiple frameworks to establish effective virtual collaborative teams in academia: a review and recommendations. Medical Education Online, 25(1), 1742968 DOI: 10.1080/10872981.2020.1742968

[2] Hasani, L. M., Santoso, H. B., & Junus, K. (2022). Designing Asynchronous Online Discussion Forum Interface and Interaction Based on the Community of Inquiry Framework. International Review of Research in Open and Distributed Learning, 23(2), 191-213. DOI: 10.19173/irrodl.v23i2.6016

[3]Serradell L. E., Lara N. P., & Martínez M. S. (2023). The Pareto Principle in virtual communities of learning. Computers in Human Behavior, 138, 107444. DOI: 10.1016/j.chb.2022.107444

[4] Tobarra, L., Robles G, A., Ros, S., Hernández, R., & Caminero, A. C. (2014). Analyzing the students’ behavior and relevant topics in virtual learning communities. Computers in Human Behavior, 31, 659-669. DOI: 10.1016/j.chb.2013.10.001

[5] Lu, J., Chen, X., Wang, X., Zhong, R., & Wang, H. (2022). Research on the Influence of Socially Regulated Learning on Online Collaborative Knowledge Building in the Post COVID-19 Period. Sustainability, 14(22), 15345. DOI: 10.3390/su142215345

[6] Güler, K. (2022). Structuring knowledge-building in online design education. International Journal of Technology and Design Education, 1-32. DOI: 10.1007/s10798-022-09756-z

[7] Villegas C, W., & Luján M, S. (2017, March). Analysis of data mining techniques applied to LMS for personalized education. In 2017 IEEE World Engineering Education Conference (EDUNINE) (pp. 85-89). IEEE. DOI: 10.1109/EDUNINE.2017.7918188

[8] Ma, Zhiqiang, Wang, Yichi, Yue, Yunzhu, & Du, Hongyu. (2019). Research on Online Learning Behavior Pattern from the Perspective of Learning Analysis. Modern Distance Education (6), 35-44. DOI: 10.13927/j.cnki.yuan.2019.0061.

[9] Cress, U., & Kimmerle, J. (2008). A Systemic and Cognitive View on Collaborative Knowledge Building with Wikis. International Journal of Computer-Supported Collaborative Learning, 3, 105-122. DOI: 10.1007/s11412-007-9035-z
[10] Li, Shuang, Tang, Qi, & Wang, Cixiao. (2014). Model Reflection and Case Study of Distance Collaborative Knowledge Building Analysis in Wiki Environment. Modern Distance Education (3), 55-61. DOI: 10.13927/j.cnki.yuan.2014.0034.
[11] Lan, A. S., Brinton, C. G., Yang, T. Y., & Chiang, M. (2017). Behavior-Based Latent Variable Model for Learner Engagement. International Educational Data Mining Society.