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A Cross-Platform Engagement Analysis for Supporting Knowledge Transformation Through Complex Learning Settings

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Abstract: To promote the transformation of conceptual knowledge into practical knowledge, educators would incorporate real-world situations as a learning setting. Yet, it is uncertain whether learners who actively acquired knowledge in the classroom will also be engaged in applying knowledge in the real world. Educators have scarce clues to understand learners' status and provide adequate support in such learning processes. Utilizing digital tools, especially cross-platform approaches, has the potential to address this issue by collecting and analyzing activity logs of various tools used in each learning setting. Nonetheless, prior studies rarely examined the continuity of engagement across complex learning settings involving the real world. This study aims to fill the gap by analyzing a dataset from a university course in Japan. We investigated the activity logs from a material reader for knowledge acquisition in the classroom and those from a mobile app dedicated to knowledge application in the real world. As a result, we found that engagement in the knowledge acquisition activity was not promising engagement in the knowledge application activity. We then identified four types of engagement across the complex learning settings. Notably, the types that were relatively less engaged in the knowledge application activity showed lower understanding levels, despite a certain engagement in the knowledge acquisition activity. The findings emphasize the importance of scaffolding during activities in the real world. Further, we discuss the potential of cross-platform analytics toward more effective knowledge transformation that leverages complex learning settings.

Keywords: Engagement, cross-platform analytics, learning analytics, knowledge transformation

1. Introduction

One of the educational goals is transforming conceptual knowledge into practical knowledge. In higher education, educators may include hands-on practices in addition to lectures in light of pedagogical strategies such as the experiential learning cycle (Kolb, 1984) and learning by doing (Gibbs, 1988). In particular, real-world situations can be a suitable learning setting for mitigating theory-practice gaps (Morley & Jamil, 2021). However, it is challenging to tailor a smooth transition from knowledge acquisition to applications with adequate understanding levels. In particular, understanding learners' engagement beyond the classroom settings is difficult, whereas educators have essential roles in maintaining learning ecologies across formal and informal circumstances (Peters & Romero, 2019).

Harnessing digital tools can enhance a wide range of learning experiences, including lectures in the classroom, online courses, and even field activities. Moreover, learning analytics have the potential to support learners by tracing their progress in complex learning settings (Moon et al., 2023). It leads to the assumption that analyzing learners' digital activities in various situations allows us to understand learners' progress of knowledge acquisition and application. Further, such technology-enhanced approaches could contribute to smooth knowledge transformation through the classroom and real-world settings. Nonetheless, prior analyses have tended to focus on one-sided analysis (Mangaroska et al., 2021).

This study thus examines engagement across knowledge acquisition in the classroom and knowledge application in real-world settings with the following research questions:

RQ1: How are engagement in knowledge acquisition and understanding levels related to engagement in knowledge application?

RQ2: What kinds of engagement types emerge across complex learning settings?

RQ3: How do understanding levels differ among the engagement types?

2. Related Works

Real-world situations can be a suitable option to promote knowledge transformation with memorable events (Morley & Jamil, 2021). For the implementation, learning designs tend to be complex because of the mixture of preparatory and reflective activities in the classroom that amplify the effectiveness of field experiences (Lee et al., 2020).

Prior studies of ubiquitous learning have proposed mobile apps to support knowledge application in real-world settings by connecting curricular topics covered in the classroom. For instance, language learning in life space (Yang & Song, 2023), cultural heritage learning (Ruiz-Calleja et al., 2023), and science education at a museum (Hsu et al., 2016). However, the solutions relying on a single digital tool may not be scalable. Educators would employ different digital tools suitable for specific learning settings. Thus, there will be a need for other approaches that can continuously support across complex learning settings.

Several studies have proposed cross-platform analytics. Such approaches enable us to collect and analyze learner behaviors derived from different digital tools. A study of programming education gathered data from discrete tools for online lectures and coding practice to analyze the important features of programming performance (Mangaroska et al., 2021). Regarding the knowledge application in real-world situations, a seamless learning environment that accumulates data from modulated tools, including a mobile app, was introduced (Flanagan & Ogata, 2018). It can preserve activity logs from a material reader for classroom learning and also from a mobile app that stores the records of field-based activities. A study employed this environment for situated language learning. Through cross-platform analytics, the researchers demonstrated visual feedback depicting the connections between the vocabulary taught in class and actual instances found in life space (Mouri et al., 2018). Another study detected relevance between the learners' text outputs about real-world activities and the course content in a lecture series (Ishihara et al., 2024). As such, cross-platform analytics can open ways to understand continuous mobility of learning across various contexts and spaces.

Yet, none of these studies fully explored the associations of learners' engagement in complex learning settings. Real-world experiences cannot be replayed. Therefore, letting learners be less engaged may result in limited achievement. In the domain of technology-enhanced teaching and learning, studies advocate that activity logs in digital tools proximate engagement (Ahmadi et al., 2023; Motz et al., 2019). Such logs derived from multiple digital tools provide educators with clues to improve learning designs equipped with them (Horikoshi et al., 2025). Thus, it is valuable to investigate learners' distributed engagement through cross-platform analytics.

3. Method

3.1 Context of Data Collection

We collected a dataset from a university course in Japan. The subject of the course was human interface, and the main language was Japanese. This weekly course started in October 2024 and ended in January 2025. Five teachers took turns lecturing, and 39 students registered for the course. From the first to the fourth week, the students tackled a weekly assignment that required them to find and analyze actual human interfaces in life space. Then, they wrote an analysis report about the interfaces they found by referring to the previous course content. In the subsequent class, they took five multiple-choice quizzes as an understanding check activity, of which scores ranged from zero to 10. After that, they discussed each one's analysis among peers then moved on to the next lecture to acquire new knowledge of course content (Figure 1 a).

The students' engagement in each activity and achievement can be framed in the revised Bloom's taxonomy (Krathwohl, 2002). It helps us categorize various learning activities into the six levels of learning achievement, from simple to complex: remember, understand, apply, analyze, evaluate, and create. Engagement in the lectures, which expected the acquisition of basic knowledge of human interface, corresponds to the achievement of remembering in the taxonomy. Scores of the quizzes represent the achievement of understanding. Engagement in real-world tasks that expected knowledge application corresponds to the achievement of applying. The quality of the analysis reports can indicate the achievement of analyzing. Engagement in peer discussions that expected mutual evaluations of each one's analysis report can be regarded as the achievement of evaluating.

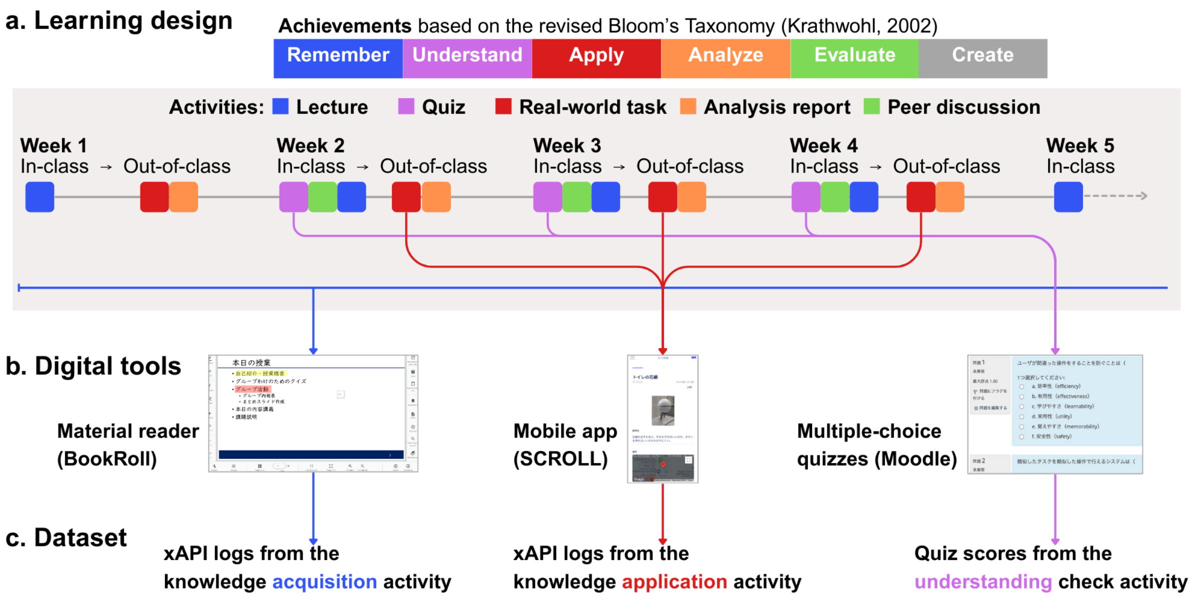

Figure 1. Overview of learning design, tools, and dataset.

3.2 Digital Tools

To investigate the students' engagement in complex learning settings, we employed a seamless learning platform (Flanagan & Ogata, 2018), which enables to implement technological assistance in a wide range of learning contexts. It can flexibly accommodate modular digital learning tools, for instance, a learning management system called Moodle, a material reader for classroom learning called BookRoll, and a mobile app for field-based activities called SCROLL (Figure 1 b). After logging in to Moodle, users can access such tools without additional login. During the course, Moodle functioned as a hub for accessing BookRoll, SCROLL, assignment submission pages, and quiz pages. Whenever the students use BookRoll or SCROLL, activity logs are accumulated in a database.

The material reader called BookRoll was used throughout the course period as a viewer of the lecture materials tailored by the course teachers. Operations on the material reader, such as browsing pages and leaving memos, represent the behaviors of knowledge acquisition from lectures. At the end of each class, the students were encouraged to leave memos and/or highlights on BookRoll. It expected students to make lasting impressions of some course content in the lecture prior to a real-world task.

The mobile app called SCROLL, accessible from smartphones and any other connected devices, was introduced for real-world tasks. The students used the app to record photos of actual interfaces and notes about their situational findings. Such a saving behavior substantiated knowledge application because the students were supposed to relate certain course content when they recorded interfaces. Afterward, they reviewed their records on the app as a process of writing an analysis report. Additionally, they could browse peers' records on the app. During the out-of-class periods, there was no reminder nor encouragement for the use of the app.

The structure of log data from the tools above is aligned with the Experience Application Programming Interface (xAPI), a standardized format for e-learning activities. Depending on the operation, xAPI conveys context information about a specific operation, an actor of the operation, and an object of the operation. Such a predefined data structure eases interpreting user operations into learning behaviors. Standardized data is also beneficial for integrating activity logs from different tools, so that the data can be analyzed seamlessly, considering in-class and out-of-class contexts.

3.3 Dataset

We were allowed to access data from the first to the fifth week in the course. The activity logs of the digital tools and the average quiz scores were gathered from 26 students who granted the research use of their data. The frequency of the activity logs from the material reader was considered engagement in the knowledge acquisition activities. Average quiz scores represented the understanding levels of the acquired knowledge of previous lectures. The frequency of the activity logs from the mobile app was regarded as engagement in the knowledge application activities (Figure 1 c).

We categorized the activity logs per tool. On the material reader side, the operations related to browsing a page, searching in lecture material, and clicking a link in a page to access an external information were classified in the *View* category. The operations of outputting highlights, memos, the "favorite" emotions, and bookmarks on a lecture material page were considered the *Save* category. The category also included the operations of editing of memos.

On the mobile app side, the operation of creating a new record was regarded as the *Save* category. The operation of browsing one's own records was considered the *View Own* category. In addition, visiting peers' records was classified as the *View Other* category. Although there were other operations, such as adding "like" emotions and leaving comments on recorded items, these were not taken into account since the instructions did not expect such behaviors. A summary of the dataset is shown in Table 1.

Table 1. *Dataset (n=26)*

Data source	Category	Total	M	SD
Logs from material reader for knowledge acquisition	Save	224	8.62	10.32
	View	35,507	1,365.65	639.64
Logs from mobile app for knowledge application	Save	84	3.23	1.53
	View Own	152	5.85	5.65
	View Other	473	18.19	31.21
Quiz scores (0-10) for understanding check	Average score	26	8.10	1.33

M: Mean, SD: Standard deviation

3.4 Data Analysis

To answer RQ1 concerning the associations of engagement in the knowledge acquisition with other factors, we measured the correlations between the activity logs and the average quiz scores. we standardized each category's logs and then examined its normality of distribution using the Shapiro-Wilk test. Since the logs did not follow the normal distribution, we measured Spearman's rank correlation.

Regarding RQ2, which addresses the engagement types across the classroom and real-world settings, we performed an unsupervised clustering based on the activity logs of the knowledge acquisition and application activities. To identify the best clustering result, we conducted the following procedure: dimensional reduction for standardized activity logs, clustering, and silhouette analysis. For dimensional reduction, we used t-distributed Stochastic Neighbor Embedding (t-SNE), which is effective for non-linearly distributed data (Dhalmahapatra et al., 2019). We then conducted k-means clustering with an optimal number of clusters determined by the elbow method. The quality of the clustering results was assessed based on silhouette analysis. As shown in Figure 2, we identified the optimal clustering condition: dimensionality reduction using t-SNE with a perplexity of 2 and k-means clustering with the number of clusters set to 4. The four clusters were compared through box plots to interpret their characteristics of engagement.

For RQ 3, we tested whether there is any statistical difference in the understanding levels of course content among the clusters. As the sample size in each cluster was not sufficient for parametric measures, we performed the Kruskal-Wallis test, a nonparametric measure diagnosing statistical differences among two or more groups. For the post-hoc test that identifies specific pairs holding the differences, we used the Dunn-Bonferroni test.

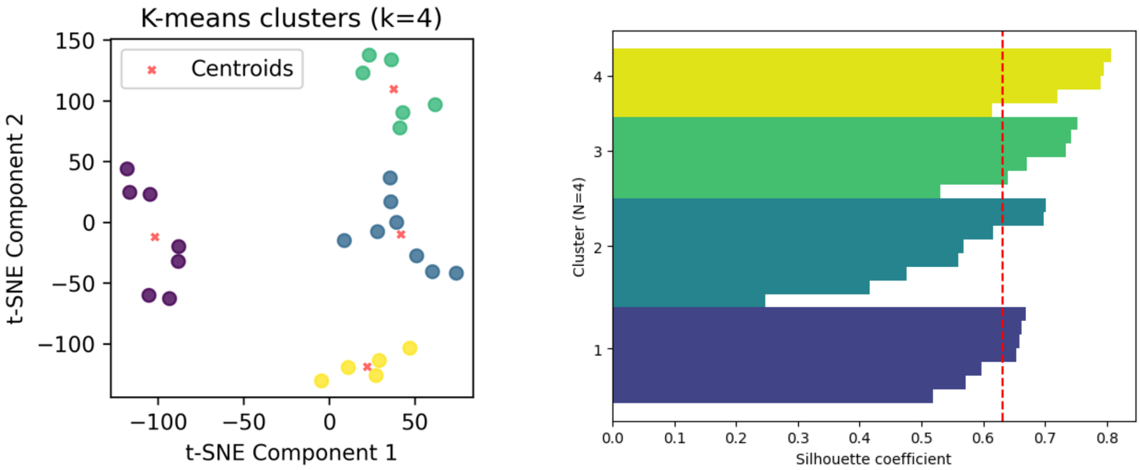

Figure 2. Optimal k-means clustering and its silhouette coefficients

4. Results

4.1 Correlations of Engagement for RQ1

The results of Spearman's rank correlation indicated several statistically significant positive correlations among engagement in the knowledge acquisition activity, average quiz scores as understanding levels of acquired knowledge, and engagement in the knowledge application activity (Table 2). For the association between the knowledge acquisition and application activities, there was a moderate level of statistically significant positive correlation: *View* of the material reader in the knowledge acquisition activity and *View Own* of the mobile app in the knowledge application activity ($\rho(24) = .47$, $p = .015$).

Regarding the associations with understanding levels, the average quiz scores showed moderate levels of statistically significant positive correlations with all categories under the knowledge application activity: *Save* ($\rho(24) = .46$, $p = .02$), *View Own* ($\rho(24) = .61$, $p = .001$), and *View Other* ($\rho(24) = .54$, $p = .004$). In contrast, there was no significant correlations between the categories under the knowledge acquisition activity. The rest of the statistically significant positive correlations were found within the knowledge application activity: *Save* and *View Own* ($\rho(24) = .42$, $p = .035$) and *View Own* and *View Other* ($\rho(24) = .64$, $p < .001$).

Table 2. *Spearman's Rank Correlations Among Categories (n=26)*

Data source	Category	1	2	3	4	5	6
Logs from material reader for knowledge acquisition	1. Save	-					
	2. View		-				
Logs from mobile app for knowledge application	3. Save			-			
	4. View Own		.47*	.42*	-		
	5. View Other				.64**	-	
Quiz scores for understanding check	6. Average score			.46*	.61**	.54**	-

*p < .05, **p < .01

4.2 Types of Engagement for RQ2

The clustering addressed RQ2 that focuses on engagement types across the classroom and real-world learning settings. The results identified four clusters. The box plots depicted each cluster's characteristics (Figure 3). The students in Cluster 1 showed remarkable active usage of mobile app in the knowledge application activity, whereas their *Save* behaviors on the material reader in the knowledge acquisition activity was under average. For those in Cluster 2, all their engagement was under average. Cluster 3 holds students who notably showed the *Save* behaviors on the material reader in the knowledge acquisition activity, whereas other behaviors were near average. Students in Cluster 4 showed active *View* behaviors on the material reader in the knowledge acquisition activity, while their knowledge application activity using the mobile app was under average. The results indicate that the students' engagement differed depending on the learning setting and the operational behavior.

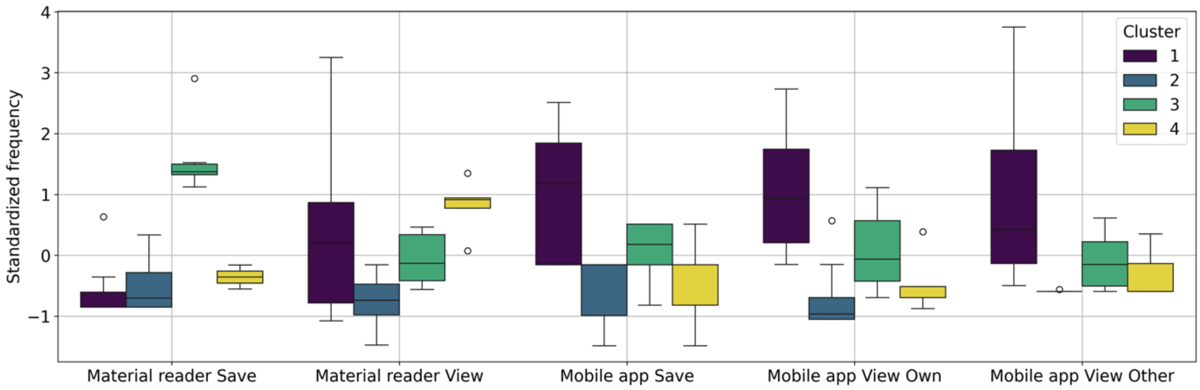

Figure 3. Standardized frequency of activity logs per cluster.

4.3 Difference in Understanding Level Among Clusters for RQ3

For RQ3, the statistical tests revealed the difference among the clusters regarding average quiz scores. The descriptive statistics of average quiz scores per cluster are shown in Table 3. A Kruskal-Wallis test indicated a statistically significant difference among the four clusters ($H(3) = 8.99$, $p = .03$). Then the post hoc Dunn-Bonferroni test identified one significant statistical difference between Clusters 1 and 2 (adjusted $p = .04$), as shown in Figure 4.

The descriptive statistics indicate that Cluster 1, highly engaged in the knowledge application activity, marked the highest average quiz scores. Cluster 3, near average overall but actively saved during the knowledge acquisition activity, followed Cluster 1. Cluster 4, less engaged in most activities except frequent viewing during the knowledge acquisition activity, resulted in third place. Cluster 2, relatively low engagement in all activities, marked the lowest scores.

Table 3. *Descriptive Statistics of Average Quiz Scores per Cluster*

Cluster	Number of students	M	SD	Median
Cluster 1 (Application-engaged)	7	9.14	0.47	9.33
Cluster 2 (Less-engaged-overall)	8	7.17	1.51	6.83
Cluster 3 (Acquisition-save-engaged)	6	8.56	0.89	8.83
Cluster 4 (Acquisition-view-engaged)	5	7.60	1.23	7.33

M: Mean, SD: Standard deviation

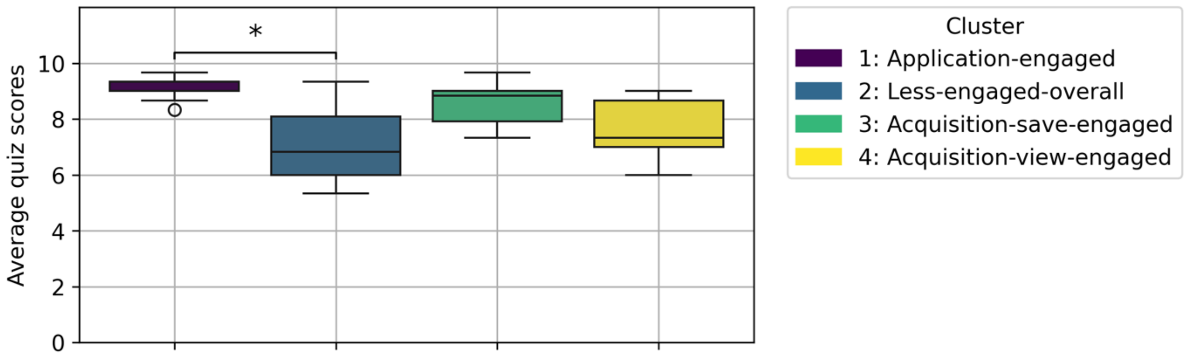

Figure 4. Average quiz scores per cluster.

5. Discussion

5.1 Key Findings

The correlation analysis for RQ1 suggests that engagement in the knowledge acquisition activity in the classroom setting was not promising engagement in the knowledge application activity in real-world setting. We observed only the category of *View* under the knowledge acquisition activity showed a significant positive correlation with the category of *View Own* under the knowledge application activity. Engagement in the knowledge acquisition did not show any correlation with the performance of quizzes in the classroom setting. In contrast, the students engaged in the knowledge application activity tended to build better understandings, even though their engagement in the knowledge acquisition activity was not always high. These findings suggest that engagement in the knowledge acquisition activity has limited associations with higher-order achievement. Rather, the results emphasize the importance of engagement in knowledge application in different situations, which reinforces understanding of knowledge with multiple aspects (Spiro et al. 2013).

Regarding RQ2 and RQ3, we identified four engagement types across the classroom and real-world learning settings. Cluster 1, highly engaged in the knowledge application activity, achieved the best average quiz scores. Although their engagement in the category of *Save* in the knowledge acquisition activity was below average, it might be not essential for developing profound understanding. Their average quiz scores tended to be better than Claster 3 that showed the highest engagement in the category of *Save* in the knowledge acquisition activity. Clusters 2 and 4 showed relatively lower engagement among the clusters. Also, their understanding levels were lower than Clusters 1 and 3. In particular, the difference in the scores between Clusters 1 and 2 was statistically significant. Although no cluster fell into the at-risk level of understanding, the students in Clusters 2 and 4 might need an enhancement for more active knowledge applications, which could lead to deeper understandings of course content.

Notably, the variance of the average quiz scores tended to be narrower when engagement in the knowledge application activity was high. The standard deviation of Cluster 1 was 0.47. That of Cluster 3 was 0.89. Clusters 4 and 2 followed them with their scores of 1.23 and 1.51, respectively. The tendency implies that it was quite promising that the students engaged in the knowledge application activity achieved higher understanding levels.

5.2 Implications

Our cross-platform engagement analysis revealed that engagement can vary depending on the context (knowledge acquisition in the classroom or application in the real world) and the behavior (*View* or *Save*). That means, high engagement in a learning context does not promise continuous engagement in another context. Additionally, the results indicated that the students in the clusters with lower engagement in the knowledge application activity showed relatively lower understanding levels. These findings advocate the need for learning analytics that support wider learning experiences (Ferguson et al., 2019).

Cross-platform analytics could satisfy the need. One potential is to ease the difficulty of evaluating learner achievement while keeping contextual and spatial mobility. In this study, for instance, the students' engagement and understanding levels can be mapped to the revised Bloom's taxonomy by cluster. As shown in Figure 5, the students in Cluster 1 can be assessed as a well-accomplished group in terms of active knowledge application with high understanding levels. In contrast, the students in Cluster 2 may be subject to scaffolding due to lower engagement and understanding levels.

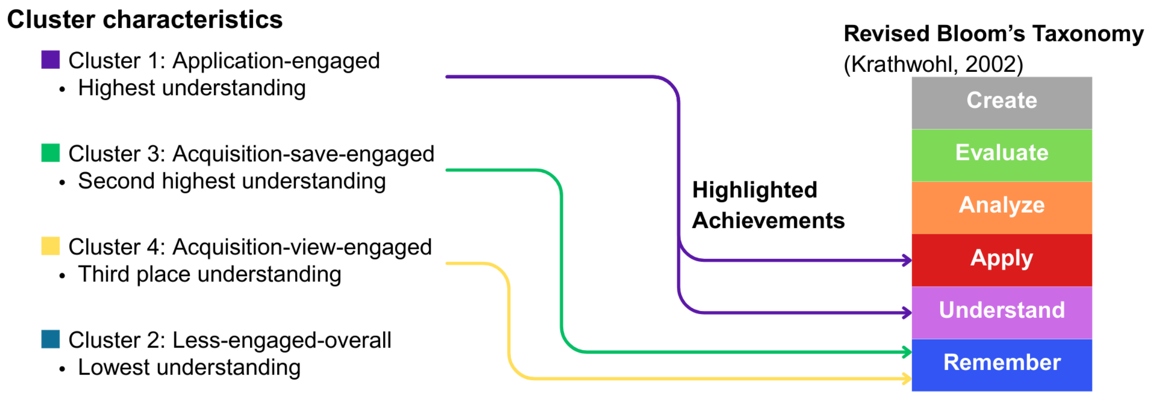

Figure 5. Mapping of highlighted achievements of clusters to the revised Bloom's taxonomy.

Given such inconsistent learner engagement, ensuring learners' continuous engagement is vital. This entails the need for further research. In this study, the material reader BookRoll and the mobile app SCROLL enabled the students to interact with learning resources in the classroom and also their findings in the real world. However, there was a lack of timely feedback. Feedback based on cross-platform analytics could enhance contextual and temporal reflection. For educators, visualizing the transition of learner engagement in tool usage will be helpful in terms of reviewing and improving activity designs (Horikoshi et al., 2025). For learners, feedback based on one's own engagement trajectories can be used for self-monitoring. Frequent self-monitoring is a key to establishing self-regulated learning and higher learning performances (Yang & Song, 2023). In light of such potential, future studies of cross-platform analytics should consider feedback systems to sustain the continuity of engagement across heterogeneous learning settings.

5.3 Limitations

Despite the findings and the potential of cross-platform analytics, this study holds limitations. Our analysis focused on viewing and saving activity logs as the basic engagement underlying the two digital tools. It might overlook other essential logs related to engagement. In addition, the dataset was collected from a limited part of a course. Other activities, such as analysis report assignments and peer discussions, were not considered. Analyzing the content of such outcomes may offer clues to infer the students' higher-order achievement, i.e., analyzing, evaluating, and creating in the revised Bloom's taxonomy.

Also, our analysis did not consider the temporal and social perspectives. The data was collected from a weekly course, and there were interactions among peers. Further analysis should address the students' temporal changes of engagement and the effects of social interactions.

Another main limitation is the lack of generalizability of the findings. We performed the non-parametric statistical tests because of the small sample size of which data was not normally distributed. Also, the degree of each student's prior knowledge and motivation of the course content may influence the behaviors. Such factors should be controlled in future analyses. For more rigorous discussions, additional case studies using larger datasets are needed.

6. Conclusion

This study demonstrated cross-platform analytics to address the difficulty of understanding learners' engagement across knowledge acquisition in the classroom and application in the real world. The results revealed that engagement appeared inconsistently. Moreover, the student groups that had less engagement in the knowledge application activity showed lower understanding levels. The trackability of cross-platform analytics can support educators and learners in leveraging contextual, spatial, and temporal mobility. Despite current limitations, further studies could exploit its potential for a more effective knowledge transformation through complex learning settings.

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