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Extract instructional process from xAPI log data: a case study in Japanese junior high school

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Abstract

This study proposed a method to automatically extract the instructional process from log data, which can be collected daily, to encourage teachers to reflect. We applied the proposed method to log data collected in a classroom and reported how the class proceeded. This is important to obtain feedback on the process of instruction and for teachers to improve their daily teaching. One of the popular methods of extracting instructional processes for teachers' reflection has been video recording. However, it is challenging to use video recording for their reflection in daily classes because of data collection and analysis costs. To resolve this issue, our proposed method utilizes data that can be collected from daily class activities. This study offers a cost-effective and efficient method for teachers to visualize their instructional process and identify areas for improvement, contributing to the overall improvement of education quality.

Keywords: Instructional process, Teaching analytics, xAPI, Multiple data sources

Introduction

Data-driven practice and reflection are required to improve the professional skills of teachers (Mertler, 2013). Thus, we need to support the improvements of data-driven practices in daily teaching (Prieto et al., 2020; Vigentini et al., 2022). Visual analytics, such as dashboards, are one of the crucial techniques in facilitating these data-driven practices in teaching. Dashboards allow teachers to check real-time overviews of the students efficiently (Campen et al., 2023). Presenting student information through dashboards can promote teacher behavior change (Verbert et al., 2014).

However, many dashboards provide only an overview of student performance (e.g., Wise & Jung, 2019). Therefore, there is limited research that feedback its own log data on teachers' performance in class. Few studies have been conducted on dashboards that support teachers' self-evaluation based on teachers' log data (e.g., Bennacer et al., 2021). Current dashboards are limited to only calculating teacher behavior and providing an overview of performance. Additionally, collected data on an instructional process for self-reflection is often collected from videos (e.g., Kleinknecht & Schneider, 2013) and self-reports (Arnold-Berkovits et al., 2019). Hence, these data collection and analyses are expensive and impractical for teachers to utilize daily (Saar et al., 2018).

Based on the above background, we propose a method that automatically extracts and visualizes the teaching process using teachers' log data instead of conventionally used video data. Moreover, we present case studies using the proposed method in a live classroom context. The research questions set in this study are as follows.

Research Questions

RQ1: How can we visualize the instructional process from log data?

RQ2: How does the proposed method support the reflection of teachers' daily teaching?

Literature Review

Data-informed teaching practices for teachers' development

Data-based teaching practices are important for improving the teaching and professional skills of teachers (Luo et al., 2022). Reflection using video data (Kleinknecht & Schneider, 2013) and reflection using paper data (Arnold-Berkovits et al., 2019) have been conducted to improve instruction based on data. While these studies provide the potential for teachers' feedback based on data, there remain research gaps.

One of them is how teachers can integrate these data-driven practices seamlessly into their daily routines. For example, Vanlommel et al. (2017) reported that despite recognizing the effectiveness of data-driven practices, teachers still make intuitive decisions. Further, van den Bosch et al. (2017) show that even though teachers have the skills to understand data, they have difficulty extracting findings about actual teaching. This gap necessitates easily comprehensible approaches for teachers from the classroom (Prieto et al., 2020).

Visual analytics to support teachers

Visual analysis using dashboards is an analysis style that compensates for users' need for data literacy (Verbert et al., 2013). Using visual analytics to understand classroom learning activities is effective in improving teaching (Bennacer et al., 2021; Michaeli et al., 2020; Sciarrone & Temperini, 2020). For example, Sciarrone and Temperini (2020) used data on activities in massive open online courses to develop an informative dashboard that analyzed student dropouts to support teacher reflection. Similarly, other studies provide feedback only on performance outcomes (e.g., Bennacer et al., 2022).

Conversely, visualization focusing on the process is performed in other studies. Chen and Chan's (2022) time series visualized the findings analyzed from video data on how students perform activities in mathematics classes. Further, Prieto et al. (2018) used orchestration graphs to visualize data from multiple devices. Chen (2020) reported that the continuous application of a process-oriented visualization system in teacher education results in improved teaching. This corresponds with other studies that emphasize the importance of feedback from the instructional process to improve day-to-day teaching practices (e.g., Luoto et al., 2022, 2023). Despite the usefulness of such process-focused dashboards being recognized, there are gaps in the literature (Dowell et al., 2021).

Process-focused dashboards, highlighting the concept of time, provide a more detailed view of learning activities (Wise, 2019). For example, Chen et al. (2020) utilized ViSeq to create visualizations that map student learning processes using event timelines and sequences derived from log data. Such process-focused analyses enable teachers to discern and respond to dynamic classroom interactions. However, how to visualize depends on what to visualize or for whom to visualize (Verbert et al., 2020). Hence, there is a need for approaches to visualize process-oriented feedback, which differs from those used for performance outcomes (Sedrakyan et al., 2020). This study builds upon this perspective, proposing a novel method to visualize teaching processes by analyzing teacher log data.

Instructional process

The process of instruction consists of the teacher's activities during class. Recently, methods have been proposed to understand teacher activities during class using log data from information and communications technology (ICT) tools (Hoyos & Velasquez, 2020; Ndukwe & Daniel, 2020). For example, prior research uses log data from the learning management system (LMS) to estimate the results of the type of activities teachers perform during class (Goggins et al., 2016).

However, interpreting the activities from the log data requires special effort, such as interpreting, and it is difficult to perform daily. Therefore, a method is required to extract activities from log data automatically and analyze the teaching process (Saar et al., 2018). Based on this background, we propose a method to visualize the teaching process by expressing the activity based on the type of log data and time difference. Using log data, teachers can reflect on their daily instructional processes.

The importance of teacher reflection using own log data

Reflection based on one's own log data is important for improving teaching skills. Using one's own log data to objectively reflect on oneself objectively promotes behavioral change and growth (Feng et al., 2021). With the emergence of wearable devices, such as Fitbit, data-based reflection has attracted attention, particularly in medical care (Liu et al., 2022). In the field of education, research is being conducted on reflection using data-visualization dashboards (Verbert et al., 2013).

For example, there is a study wherein students use a dashboard for their reflection on their own log data (e.g., Li et al., 2021). Such research has shown certain success in improving academic performance (e.g., Yang et al., 2024). However, there is a lack of research supporting teachers' use of their own log data for reflection (Bennacer et al., 2021, 2022). Moreover, most of the few studies from teachers' own log data refer to only an overview of instructional performance, not an instructional process (e.g., Su et al., 2021). In fact, van Leeuwen et al. (2019) argue that information on how teachers' instruction process influences students may promote instruction improvement. In other words, to improve teaching, we need not only the results of students' and teachers' performance but also information about the process of instruction. Therefore, we consider how the proposed method can improve daily lessons using log data from the learning evidence analytics framework (LEAF) system by confirming students' log data with the teacher's instruction process. Further, we compare how the students change as a result of the instruction process and consider the type of reflection for teachers to engage.

Method

Learning Evidence Analytics Framework (LEAF)

The data analyzed in this study were obtained from the LEAF system (Figure 1). The LEAF was created to support the daily learning of teachers and students by leveraging big educational data obtained from the system (Ogata et al., 2018). It consists of Moodle, an LMS; BookRoll, an E-book reader (EBR); and LogPalette, an analysis tool (AT). Teachers use the LEAF system to learn daily, and the LEAF system stores students' learning logs.

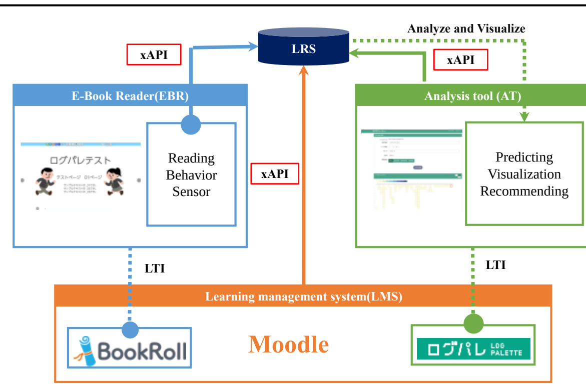


Fig. 1 The architecture of the LEAF platform

The Experience API (xAPI) stored in the learning record store (LRS) is the data obtained from the LEAF system, which has at least the actor, verb, and object attributes. The main advantages of the xAPI are data scalability and flexibility (Manso-Vazquez et al., 2018). Further, it is highly scalable because it can accommodate new third-party educational systems (Serrano-Laguna et al., 2017). We used the xAPI data stored in the LRS throughout the LEAF system.

Data collection and analysis method

RQ1: How can we visualize the instructional process from log data?

To answer RQ1, we conducted an in-depth analysis of xAPI log data from 31 teachers at the participating schools. Of these, 26 were subject teachers, while the remaining five, including the vice-principal, were involved in administrative or supportive tasks. Our focus was on the 26 subject teachers. We collected data for a six-month period, from April 1 to September 30, 2022, aligning with Japan's first semester. The initial dataset comprised 195,161 statements. From this, we extracted 57,116 statements identified as relevant to classroom activities based on the timetable in the Appendix. We then refined the dataset by excluding log entries from the vice-principal and other non-subject teacher roles, as these were not directly related to classroom teaching. This refinement resulted in a final dataset of 53,393 statements from the 26 subject teachers for our analysis (Figure 2).

To address the challenges identified by the raw log data's complexity, which contained extensive and varied entries, our methodology involved a detailed process of data transformation. This transformation process included filtering and categorizing data based on specific teacher actions and classroom activities. As a result, we simplified and focused the dataset for more effective analysis. To be specific, we extracted (1) the systems used, (2) the functions used, and (3) the operations performed using the xAPI data. After

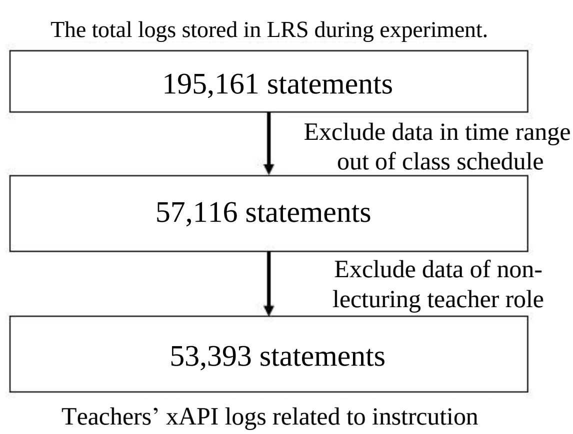


Fig. 2 Filtering criteria of teachers' dataset

processing the data, we grouped the processed data using the system function and defined the teachers' actions. We also developed a color-coding scheme as part of this data transformation to visually distinguish different teaching activities and their durations. Subsequently, we defined the teachers' activity as a band that expressed how long the teachers' action lasted and visualized the teaching process more intuitively. Figure 3 presents an overview of the proposed method. This comprehensive approach not only resolved the complexity of the raw data but also facilitated an intuitive understanding of the instructional process, as visualized in Figure 3. In the Results and Interpretation section, we discuss the details of how we extracted the instructional processes from the teachers' actions.

RQ2: How does the proposed method support the improvement of teachers' daily teaching?

To answer RQ2, we investigated how the techniques proposed in RQ1 can help improve everyday teaching using the xAPI log data from the LEAF system. Meanwhile, we focused on students' responses to teachers' instructional processes. Moreover, students' log data was used to measure their responses. The students' log data refers to the frequency of interactions they had with tools in the LEAF system. These logs provide a benchmark for students' responses to various instructional strategies.

To apply the visualization method to the case study, we selected three mathematics lessons conducted on April 26, 2022. These lessons were taught by a teacher who has been employed at the school since 2021 and who currently teaches second-year students at a junior high school. In Japan, second-year junior high school students are typically aged between 13–14 years. The participating students attended offline, face-to-face classes, reflecting a typical Japanese educational setting. Each student was equipped with a personal tablet device, which they brought to the classroom. The usage of these tablets was optional, and any interaction with the tablets by both teachers and students was recorded as log data in the LRS. This study specifically analyzed the frequency of log data to understand changes in tablet usage prompted by the teacher's instructions.

The three-lesson case study was selected because Teacher A, of 26 teachers left a record as a text. The text described the intention of the teaching process, which was difficult to estimate from the log data. Figure 4 summarizes the text left by the teacher. According to this text, the three classes had the same instructional goal, knowledge to be acquired, and instructional process.

The class was designed to teach students how to solve graphs and equations using problem exercises. The core knowledge to be acquired was the relationship between solutions and intersection coordinates. First, the teacher taught students basic knowledge using e-books. After acquiring new knowledge, the teacher solidified it through problem

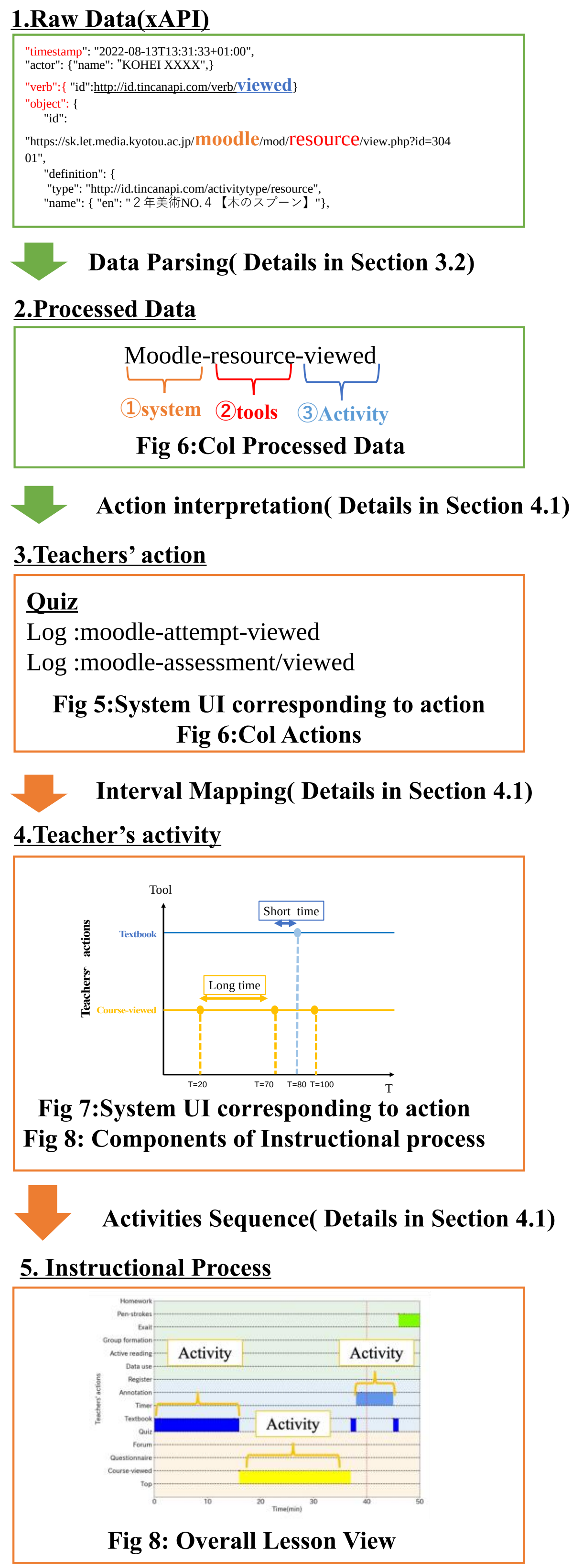


Fig. 3 Overview of the proposed method

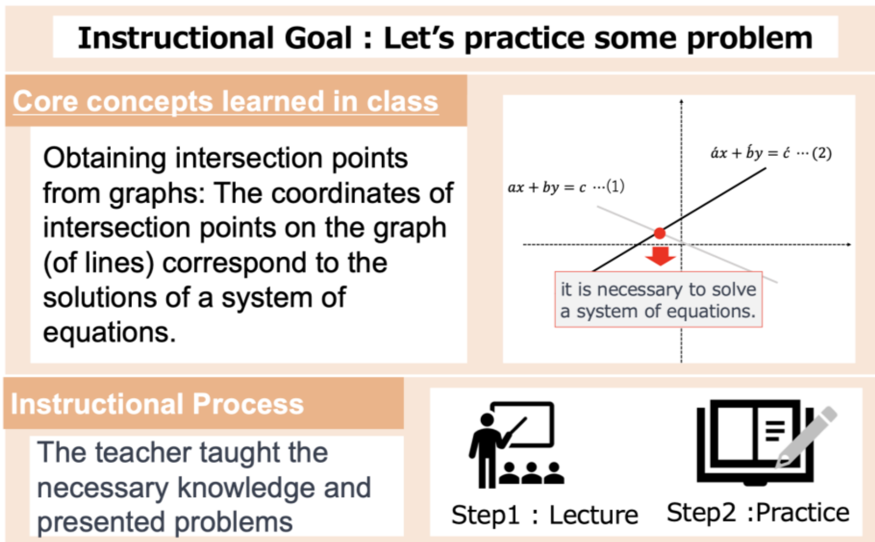


Fig. 4 The instructional goal of the analyzed class

exercises. In other words, the pre-planned teaching process involved knowledge transfer and problem practice. All three classes (classes A, B, and C) followed the same instructional process.

To improve the teaching skills of teachers, it is necessary not only to review their teaching but also to check the reactions of the students (van Leeuwen, 2019). We focused on points where the teacher's instructions were different and investigated the reactions of the students. A teacher's instructional process is not fixed. Teachers adjust according to the class time and the situation of the students. We considered it important to know what types of student reactions were obtained by giving different instructions according to the context. Based on the above, we discuss how the proposed method affects teachers' reflections.

Results and Interpretation

To address the research questions directly, we first focused on effectively visualizing the educational process from log data. Specifically, to answer RQ1, we devised a color palette that aligns with the diverse actions of teachers. This provides a clear and intuitive means to discern the utilization patterns of different systems and tools within the institutional process. To answer RQ2, we also applied it to xAPI log data obtained from real-world classes. We provided case studies on how students' responses and teachers' instructional processes can be useful for daily teachers' reflections.

Proposed method for extracting instructional processes

Figure 5 and Table 1 show specific results of investigating which function of which system the 35 types of data are related to and grouping them based on the function. Each group represented a teachers' actions. First of all, we explain the function of Moodle as LMS (Figure 5(a)). "Top" showed the top screen of Moodle and corresponded with preprocessed data. "Course-viewed" was linked to the material files in Moodle and external tools such as LogPalette and BookRoll. "Quiz" was a log using Moodle's quiz function, "Forum" was a log using Moodle's forum function, and "Questionnaire" was a log using Moodle's questionnaire function. Next, we explain the function of BookRoll as EBR (Figure 5(b)).

Fig. 5 (a) Example of teachers' actions based on the learning system – Moodle(LMS)

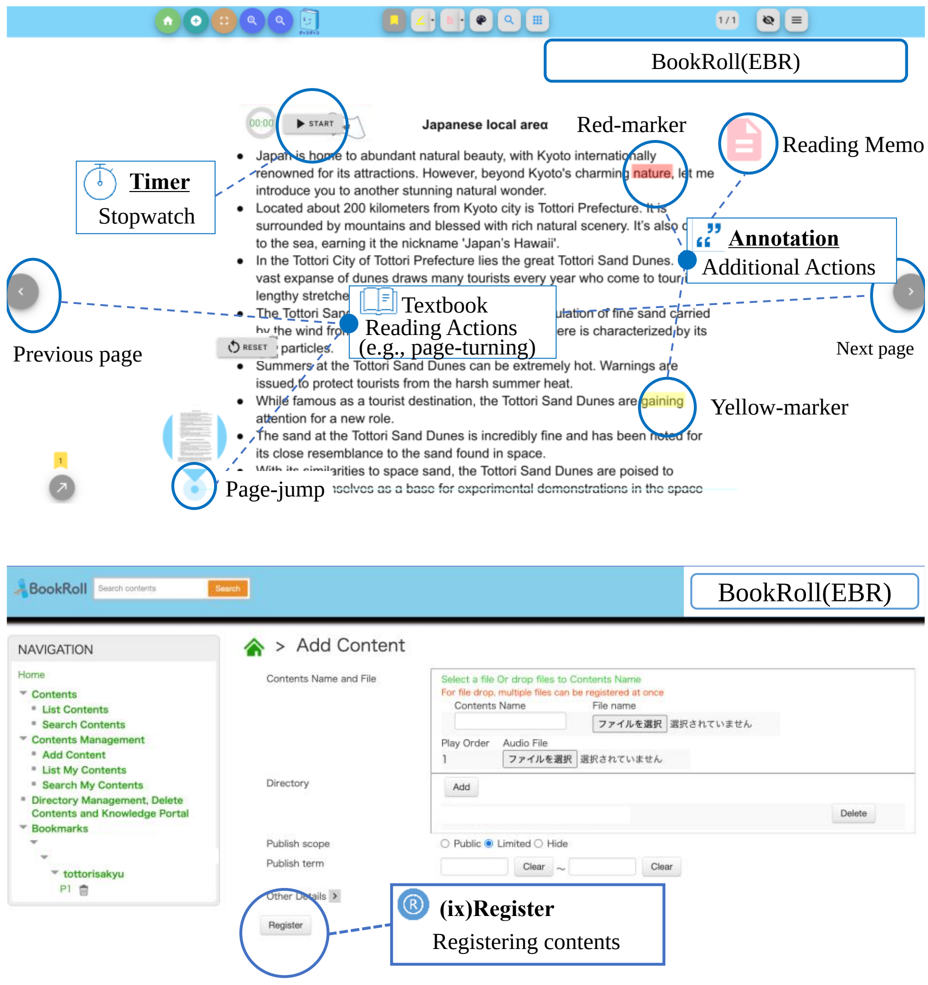


Fig. 5 (b) Example of teachers' actions based on the learning system – BookRoll(EBR)

"Textbook" is a simple reading, such as opening the textbooks and reading pages in BookRoll. "Annotation" was an action that is performed while reading the textbook, such as adding a memo or bookmark. "Timer" was a timer function for measuring reading comprehension time. "Register" was the teachers' action in registering the contents. Finally, we explain the function of LogPalette as AT (Figure 5 (c)). "Data use" was a log related to the teachers' action of searching for learning materials when using LogPalette. "Active reading," "Group formation," "Exait," "Pen-strokes," and "Homework" were the applications in learning analytics tools supporting learning and teaching activity.

We created a color palette based on the teachers' actions to understand the relative usage of different systems and tools. The specific colors are shown in Table 1. We used triadic colors for high contrast to represent each system, selecting tones from the red-yellow, blue, and green spectrum as background colors for the LMS, EBR, and AT, respectively.

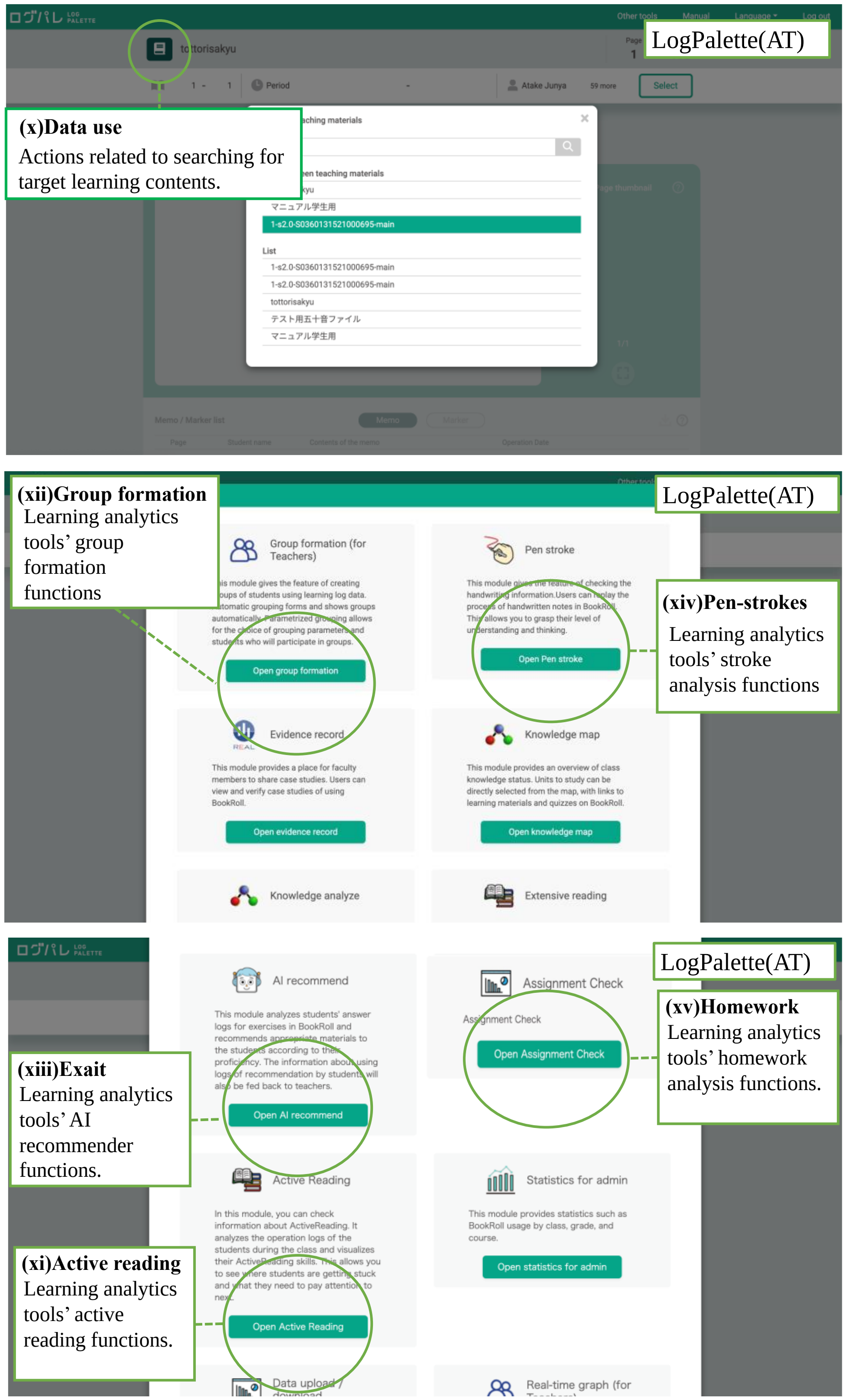


Fig. 5 (c) Example of teachers' actions based on the learning system – LogPalette(AT)

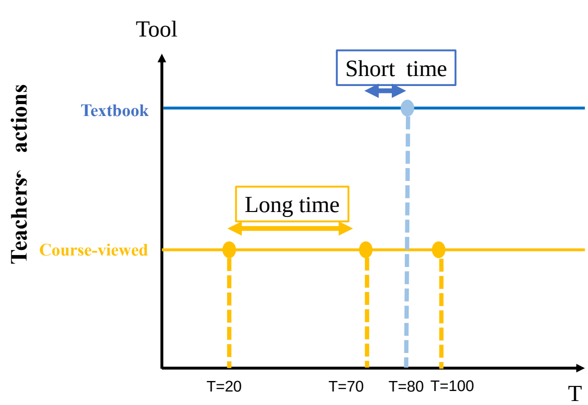
Table 1 Actions, Explanation, Processed Data, and Colors in teachers' activities during the period

System	Actions (UI element)	Explanations and Examples	Processed Data
LMS	Top (Fig 5a-i)	Actions in LMS's top pages.	(1) Lms (2) Moodle-course-registered
LMS	Course-viewed (Fig 5a-ii)	Browsing the contents on a course page.	(3) Moodle-course-viewed (4) Moodle-link-viewed (5) Moodle-module-completed (6) Moodle-module-viewed (7) Moodle-resource-viewed
LMS	Questionnaire (Fig 5a-iiii)	LMS's questionnaire functions.	(8) Moodle-survey-viewed
LMS	Forum (Fig 5a-iv)	LMS's Forum functions.	(9) Moodle-assessment-viewed (10) Moodle-attempt-viewed
LMS	Quiz (Fig 5a-v)	LMS's Quiz functions.	(11) Moodle-forum-topic-viewed (12) Moodle-discussion-viewed (13) Moodle-discussion-create (14) Moodle-discussion-replied
EBR	Textbook (Fig 5b-vi)	Actions related to reading contents.	(15) BookRoll-bookRoll-closed (16) BookRoll-bookRoll-exited (17) BookRoll-bookRoll-launched (18) BookRoll-bookRoll-opened (19) BookRoll-bookRoll-read (20) BookRoll-bookRoll-searched
EBR	Timer (Fig 5b-vii)	Actions related to measuring reading time.	(21) BookRoll-bookRoll-stopped (22) BookRoll-bookRoll-paused
EBR	Annotation (Fig 5b-viii)	Additional actions related to reading activities.	(23) BookRoll-bookRoll-highlighted (24) BookRoll-bookRoll-noted (25) BookRoll-bookRoll-bookmarked
EBR	Register (Fig 5b-ix)	Registering contents.	(26) BookRoll-bookRoll-imported
AT	Data use (Fig 5c-x)	Actions related to searching for target learning contents.	(27) Analysis-#-viewed (28) Analysis-context-selector-monitored
AT	Active reading (Fig 5c-xi)	Learning analytics tools' active reading functions.	(29) Analysis-ActiveReading-monitored (30) Analysis-active-reading-launched
AT	Group formation (Fig 5c-xii)	Learning analytics tools' group formation functions.	(31) Analysis-TeacherEvaluation-Teacher-Evaluation (32) Analysis-group-formation-launched
AT	Exait (Fig 5c-xiii)	Learning analytics tools' AI recommender functions.	(33) Analysis-exait-launched
AT	Pen-strokes (Fig 5c-xiv)	Learning analytics tools' stroke analysis functions.	(34) Analysis-stroke-analyze-launched
AT	Homework (Fig 5c-xv)	Learning analytics tools' homework analysis functions.	(35) Analysis-vacation_assignment_checks-reflected

Additionally, specific colors for each action within these systems were detailed in the Colors column of Table 1, providing a distinct visual distinction for each type of activity. When visualizing something, dashboards should choose colors that place as little cognitive load on the users as possible (Ramaswami et al., 2023). Therefore, set colors related to the system colors that teachers are familiar with daily. Figure 5, displayed on the interface, is a Demo to explain actions.

Teachers' actions can be described as point-process data. Therefore, we aggregated the data every minute and converted them into time-series. Teachers' actions can be described as point-process data. Therefore, we aggregated the data every minute and converted them into time-series data. When multiple teachers' actions were observed in a minute, we assigned actions based on the amount of information. Further, we calculated and expressed the intervals at which the log data occurred. Specifically, we used the width to represent the time difference between activities, as shown in Figure 6. In other words, if the activity occurring during the observation period [0,t] is T(n), the time difference, T(n + 1) – T(n), from the next activity is filled with colors. We extracted the teachers' activities from the period and their actions.

Finally, the instructional process is illustrated in Figure 7. The x-axis represents the time spent, in minutes, from the start to the end of the lesson. The y-axis represents the teachers' actions displayed during the lesson. Using this method, we could automatically express the instructional process from the log data. We visualized the duration of each activity. Activities (1) read "Textbook," (2) browse Moodle "Course-viewed," (4) use "Annotation," and (6) use "Pen-stokes" app continued for at least 5 minutes. Conversely, the duration of activities (3) read "Textbook" and (5) read "Textbook" was short. In other words, it was possible to visually determine which activities required time.



A teacher's Processed data

Time(T)	Processed data
20	Course-viewed
70	Course-viewed
80	Textbook
100	Course-viewed

Fig. 6 Extracting time-interval between teachers' processed data

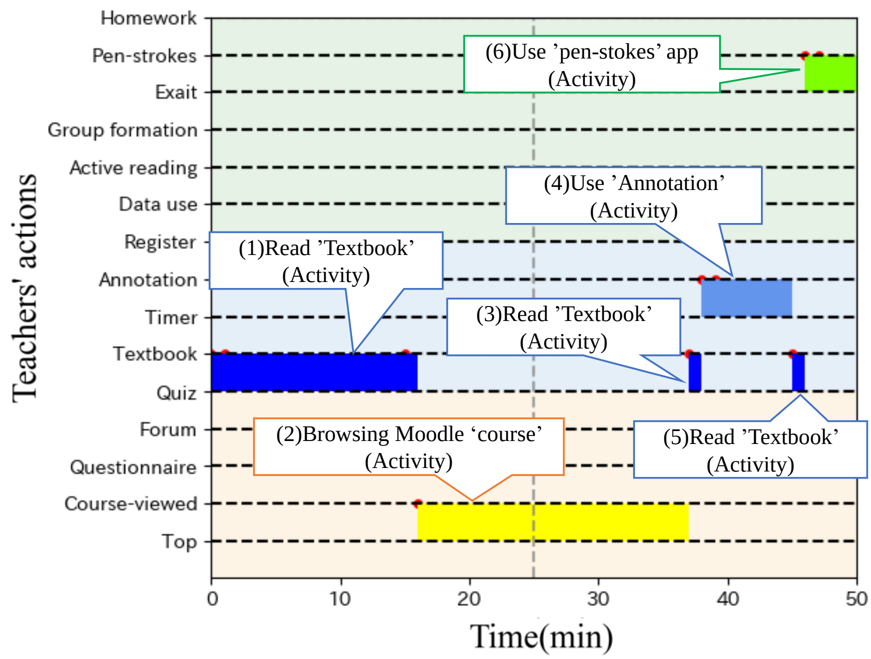


Fig. 7 Proposed visualization for instructional process during the lecture

Applying the proposed method to classroom data

The left panel of Figure 8 shows the teacher's instructional process visualized using the proposed method. In class A, the E-book reader "Textbook" was first used, followed by "Course-viewed," "Annotation," and "Pen-stokes" app. In class B, the E-book reader "Textbook" was first used, followed by "Annotation" and "Pen-strokes." In class C, "Course-viewed" was used first, followed by "Textbook," "Pen-stokes," and "Course-viewed."

From the above, the tools used were almost the same; however, approximately 40 minutes after the start of the class, we found differences for each class. The teacher used the "Annotation" in classes A and B but not in class C. These results indicated that the teachers adjusted their teaching methods according to the class, even if the goals were the same.

We examined the number of student learning logs per lesson for comparison at 40 minutes when the teacher's activity changed. In our study, the independent variable was the type of teacher's action, including "Textbook" reading, "Course-viewed," "Annotation," and use of the "Pen-strokes" app, as detailed in Table 2. The dependent variable was the students' engagement with the instructional content, measured by the frequency of their learning logs, which were collected before and after the observed change in teacher activity. We analyzed these logs to assess the impact of different teaching actions on student engagement.

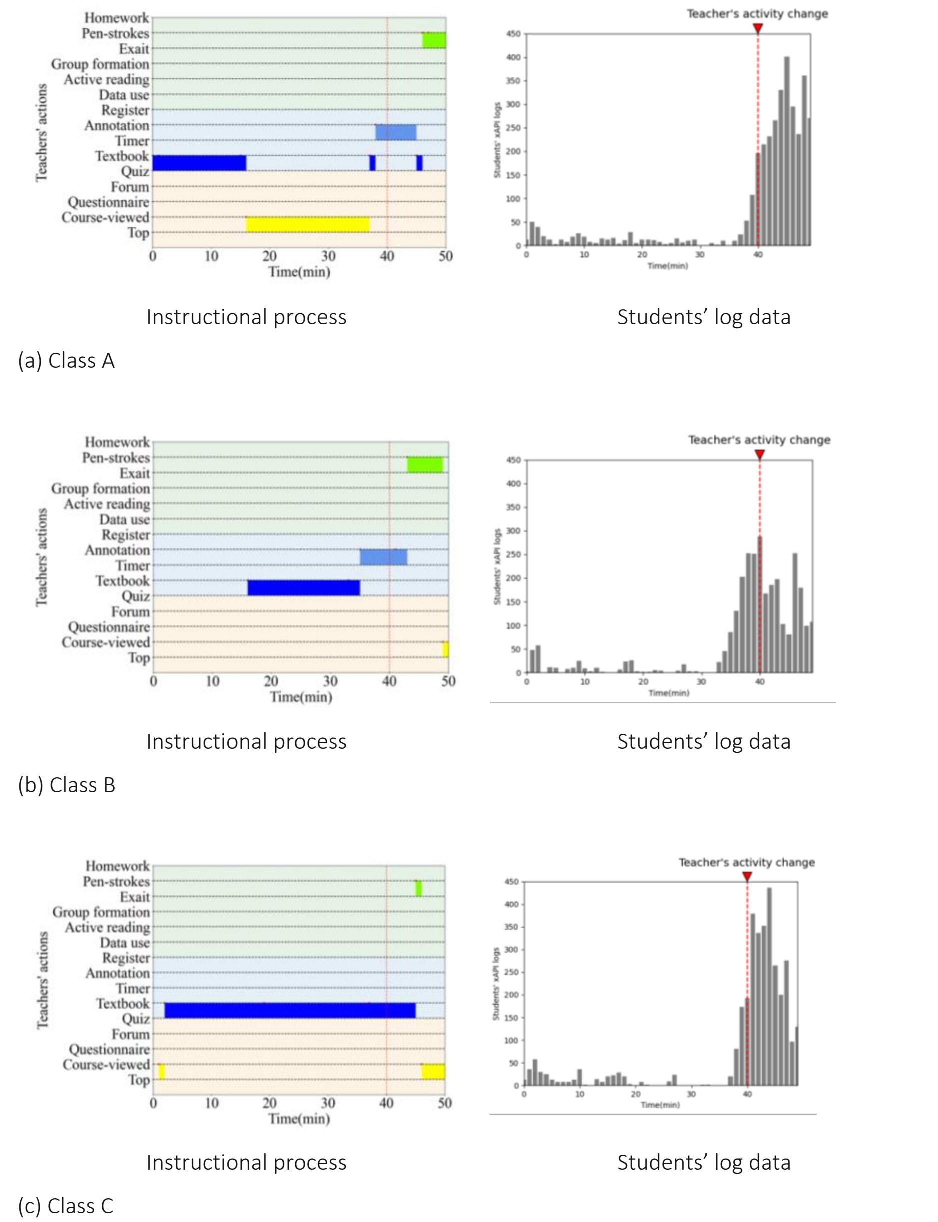


Fig. 8 Visualization of the teacher's instructional process

A histogram was generated to show the changes in the number of logs of students in classes A, B, and C every 1 minute. The results indicated that students' access to all classes increased between the 30th and 40th minute. Welch's t-test examined the number of student logs between the 30th and 39th minute (before) and between the 40th and 49th minute (after). The results showed statistically significant differences in all classes, indicating that teachers adjusted tool usage according to class to achieve similar results in each class.

Table 2 presents the students' logs during the analyzed class, showing the mean and standard deviation of the number of logs before and after the teacher's activity change.

Table 2 Students' logs between before and after the teacher's activity changed

	Before (30 min–39 min)		After (40 min–49 min)		
Class	n	Mean (SD)	n	Mean (SD)	t
Class A	31	2.06 (1.09)	36	5.25 (3.33)	5.40 **
Class B	35	3.62 (2.11)	34	4.85 (2.82)	2.03 *
Class C	27	2.07 (1.07)	32	5.53 (3.29)	5.59 **

Welch's t-test results were displayed, indicating significant differences in all classes (Class A: $t(65) = 5.40$, $p < 0.01$; Class B: $t(67) = 2.03$, $p < 0.05$; Class C: $t(57) = 5.59$, $p < 0.01$). These findings suggest that there were differences in the instructional processes of the teachers but not in the students' reactions. Overall, this study provides evidence that teachers can adjust tool usage to achieve similar results across different classes. These findings have implications for the design and implementation of technology-enhanced learning environments.

Discussion

Our results show that teachers adjust their teaching processes from class to class to obtain the same responses from students. We suggest the role of our method in enhancing teacher's reflection on their daily teaching practices. Thus, we argue that by using the proposed method, teachers can reflect on their own teaching process (e.g., Saar et al., 2018).

Key findings

RQ1: How can we visualize the instructional process from log data?

In conclusion, using this method, we visualized the instructional process from the log data (Figure 7). Additionally, it was suggested that teachers adjust the instructional process according to the class to obtain the same responses from the students (Figure 8). Based on these results, we claim that teachers can reflect on their instructional processes using the proposed method.

RQ2: How does the proposed method support the reflection of teachers' daily teaching?

Additionally, it was suggested that the teacher's instruction changed according to the class, even if the content and subject were the same (Table 2). This result is consistent with previous research showing that teachers change their teaching according to children's behaviors (Nurmi & Kiuru, 2015). In general, teaching is influenced by teachers' beliefs (Uibu et al., 2011) and experiences from practice (Gube, 2024). Based on previous studies, these results indicated that teachers use the knowledge gained from practice to optimize their daily instruction to achieve the same lesson outcomes. This result suggested that our method may support teachers to know they adjusted their teaching strategies according to the class if we provide the visualization of their instructional processes with our method.

Contributions and implication of teachers' reflection

To improve the quality of education, teachers must interpret information from their daily classroom practices (Ndukwe & Daniel, 2020). However, previous studies have used video data (Preiss, 2009). Recording daily lessons was time-consuming because of data collection costs. In the proposed method, we used only daily log data from ICT tools. Therefore, since there is little cost to collect, we believe that teachers could use it for daily reflection on their instructional processes.

Additionally, it has been reported that teachers' reflection based on data has little to do with characteristic information such as the age and gender of teachers (van Leeuwen et al., 2021). In other words, teaching ability will improve by looking back through practice and encouraging behavioral change. To further enhance this, our method can be applied to a user-friendly dashboard that presents teachers' instructional processes and students' reactions in a comprehensive manner. Dashboards can be used for daily reflection (Verber et al., 2013). Feedback from dashboards can increase process feedback and prompt, effective interventions compared to human feedback (Campen et al., 2023). The quality of teachers' reflections and instruction will be improved using the dashboard that presents the teachers' instructional processes and the students' reactions every day.

This study contributes to the field of education by providing a cost-effective and efficient method for teachers to reflect on their instructional processes using log data. By visualizing their instructional processes, teachers can identify areas for improvement and adjust their teaching strategies according to the class, leading to consistent learning outcomes. Furthermore, this study highlights the importance of data-driven decision-making in education. If teachers use log data to gain insight into their daily classroom practices, they can make daily data-driven decisions. Data based on one's experience does not need to consider the domain background; therefore, the load of data analysis is small. The proposed method can improve the quality of teaching and student learning outcomes. Our approach emphasizes the importance of data-driven decision-making in education, underscoring its utility in facilitating continuous improvement in teaching methodologies and student learning experiences.

Ethical considerations of using log data

An essential aspect of using log data, such as that from the LEAF system, is ensuring ethical handling and interpretation. The LEAF system captures a wide array of data, including teachers' and students' interactions with various educational tools. This data, while invaluable for educational insights, also raises privacy and ethical use concerns. We ensured that all data used in this study adhered to strict confidentiality and privacy guidelines, with necessary permissions obtained from relevant authorities.

Moreover, the nature of the data demands careful consideration. While the data offers a window into the instructional process, it also represents individual behaviors and preferences. Thus, we approached the analysis with a focus on broader patterns and trends rather than individual profiling.

Limitations and future works

This study has limitations. The teacher's guidance process was extracted in this study as a log from the rule base. Contexts such as the teacher's role, materials and tools, and student relationships were not considered. It has been reported that teachers' instruction varies according to the material and subject context (Lin et al., 2020). As a prospect, it is necessary to extract teaching processes in other teaching materials, subjects, and classes using the same method and show the limits of its application.

Notably, the classification of actions based on logs is based on system-based rules. The interpretation of actions and activities from event logs, such as point processes, has already been discussed (Romero et al., 2014). The interpretation of log data can lead to different conclusions depending on the analyst's interpretation. Therefore, reasonable methods should be considered when interpreting activities from log data.

Conclusion

In this study, we proposed a method for visualizing the instructional process using log data. Thereafter, we introduced case studies using actual log data. The results show that we can visualize teacher activities and extract instructional processes from log data. Further, visualizing daily lessons using ICT tools is possible, and teachers can use them for daily lesson practices using this proposed method. Moreover, the use of ICT tools for visualizing daily lessons not only simplifies the process but also enables teachers to apply these insights for improved daily lesson practices. This study contributes to the educational field by providing a practical and cost-effective approach to data-driven educational practice. A limitation of this study is that the instructional process was extracted based on system-based rules without considering situational factors such as the teacher's role, teaching materials, tools, and relationships with students. Future research should apply this method in various classroom settings to understand the limitations of this method.

Appendix: Schedule

Slot	Start	Finish
1	8:50	9:40
2	9:50	10:40
3	10:50	11:40
4	11:50	12:40
5	13:20	14:10
6	14:20	15:10
7	15:20	16:10

Abbreviations

ICT: information and communications technology; xAPI: Experience API; LMS: Learning management system; EBR: E-book reader; AT: analysis tool; LRS: learning record store; LEAF: Learning Evidence Analytics Framework.

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Authors' contributions

KN designed the overall research, analyzed data, and drafted the manuscript. IH made significant contributions to the research question, supervised all aspects of the research and manuscript, and provided guidance throughout the process. RM reviewed the research design, contributing to the overall planning and flow of this paper. HO, as the PI of the Let research unit, oversaw all the research conducted with the LEAF platform, including this study, and reviewed the research design and manuscript. He also provided supervision for this research paper.

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Declarations

Competing interests

The authors declare that they have no competing interests.

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