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Enhancing Moodle Insights: Leveraging Time Tracking Data Beyond Access Counts

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Abstract

Moodle access logs have been widely used in learning analytics and institutional research to analyze educational activities. However, previous research primarily focused on accessing count data, overlooking the potential of leveraging the time-tracking data made possible by the addition of IntelliBoard functionality to Moodle. This study explores novel applications of Moodle's time-tracking data. Specifically, we examined the relationship between access count and learning time data, as well as the analytical possibilities of these datasets, in the context of a faculty development (FD) training course for newly hired instructors. The results suggest that incorporating time-tracking data enables a more detailed analysis of learner behavior, presenting opportunities to inform effective instructional design. This study proposes new methods of utilizing Moodle's time-tracking data to complement the established use of access-count data in learning analytics and institutional research.

Keywords: Moodle, Time tracking data, IntelliBoard, Learning analytics, Teaching analytics, Faculty development

1 Introduction

1.1 Utilizing Learning Management Systems Logs for Educational Improvement

Educational institutions have widely adopted learning management systems (LMSs), such as Moodle, to serve as a vital platform for facilitating online and blended learning environments. The wealth of data generated through learners' interactions with the LMS has driven the field of learning analytics to flourish, providing educators and researchers with valuable insights to support evidence-based decision-making. For example, the LMS log data are used for dropout prevention and other purposes. A previous study proposed a model to predict student dropout in university classes using log data from a LMS [1]. Traditionally, dropout prediction relied on pre-enrollment information or semester grades; however, early intervention is crucial. By employing machine learning on log data, this model continuously identifies at-risk students with high accuracy throughout the course, thereby enabling timely support. Previous research discussed the latest methods for constantly analyzing learner behaviors using data from LMSs and electronic book (eBook) logs [2]. These methods allow for the continuous monitoring and analysis of how students interact with digital learning materials and platforms. By leveraging the rich behavioral data captured in LMS logs, institutions can gain deeper insights into student engagement, learning patterns, and potential challenges. These analytics-driven interventions

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empower educators to provide personalized support and tailor learning experiences to meet each student's unique needs.

1.2 Use of Moodle logs to Improve Education

In a general education subject at a university in Japan, Moodle learning logs were used to analyze students' learning behaviors [3]. This analysis revealed that the number of accesses was high immediately after the quizzes and surveys were posted, peaking on Mondays, which coincided with the assignment deadlines. Additionally, the number of accesses on weekends was lower than that on weekdays. Based on this information, it was suggested that task and quiz settings should consider the characteristics of students' learning behaviors.

Another related study found a correlation between the number of logs in an e-course (i.e., the LMS Moodle) and students' final grades [4]. The results showed that students were most active during test weeks, particularly the day before the tests, exhibiting "last-minute" behavior in completing their obligations close to the deadlines.

Furthermore, another study examined changes in the use of Moodle trends at a medical school during the COVID-19 pandemic [5]. Despite a decrease in overall LMS usage in 2021, compared with that in 2020, certain activities, such as H5P usage, increased. However, the usage of resources such as PDFs and lecture videos remained consistent.
Various studies have sought to understand when and how many students participate in different activities by tracking access counts. However, these studies only aggregated the number of accesses without knowing how much time students spent on each page after accessing it. This is attributed to the specification of Moodle logs, which is unavoidable. Although Moodle can store robust learning logs, its built-in reporting features are limited [6]. However, without knowing the actual time spent on learning, the amount of effort (engagement) invested in learning may not be accurately represented. To appropriately evaluate this, it is necessary to measure the time students spent viewing (and working on) pages.

1.3 Potential of Time Tracking Data Utilization in Moodle

To address the gap in tracking access counts without knowing the actual time spent, the Moodle LMS offers an IntelliBoard plugin [7]. This plugin enables the tracking and recording of learners' time spent on various course components. The time-tracking data can elucidate learners' study habits, pacing, and engagement levels.

Research utilizing IntelliBoard time-tracking data within Moodle is scarce. However, some studies have examined the time spent on reviewing resources alone [8]. These studies aimed to compare the minimum time necessary for resource review with the actual time that students invested in this activity. Therefore, they provide valuable insights into how effectively students manage their time during the course. This understanding allows educators to make informed decisions about optimizing student engagement and learning outcomes, potentially fostering improvement in overall course effectiveness and student success. Despite these potential benefits, the exploration of Moodle's time-tracking features remains relatively underdeveloped in the current academic literature, highlighting a promising avenue for future research and innovation in the field of learning analytics and educational technology.

1.4 Aim

This study aims to investigate novel applications of Moodle's access count and time-tracking data, facilitated by IntelliBoard, within the context of an ongoing educational program. Specifically, it seeks to conduct basic analyses using access count data alone, and explore the relationship between access counts and learning time data. By examining the potential uses of these datasets, this study aims to provide insights for more effective instructional design and support for educators. Further, by integrating time-tracking data with the conventional use of access count data in learning analytics, this study contributes to a more comprehensive understanding of learner behavior and experiences within the Moodle LMS.

2 Methods

2.1 Participants and Context

This study was conducted as part of a faculty development (FD) course designed for newly hired university faculty. The FD course was designed to support and enhance the professional development of 11 newly appointed faculty members. The training program, which spans approximately two years from the time new faculty members are hired and focuses on enhancing the target faculty's professional skills in teaching, research, and student support, is delivered in monthly sessions of approximately 90 minutes each. Participation in these sessions and their outcomes will be considered in tenure-track midterm reviews and faculty evaluations.

For this study, data pertaining to activities conducted over a six-month period within the timeframe of the FD course were collected and analyzed. Additionally, informed consent was obtained from participants prior to data acquisition. Table 1 outlines the content and schedule of the FD course, which spanned a 6-month period from October 2023 to March 2024. The training themes for each month included “Theories of Higher Education,” “Information Provided by the Industry-Academia Innovation Center,” “Theories of Course Design,” “Report on Faculty Development Overseas Training and Other Information,” “Theories of Educational Evaluation,” and "Workshop: 'Let's Learn about Coaching (Practical Edition)'”. These were primarily aimed at the initial development of the university faculty members' capabilities.

2.2 Moodle Course for FD program

A corresponding Moodle course was created to support the FD course, and was used to distribute learning materials, submit assignments, and conduct related activities. Unlike the Moodle server, which is typically used for regular classes and training, this course was hosted on a Moodle server dedicated to IntelliBoard.

For each of the aforementioned months, topics were created within the course, and activities were embedded within them. This course was primarily designed to support synchronous training sessions held via Zoom, except in February 2024. It served as a platform for distributing materials, submitting assignments, and facilitating synchronous training sessions, with activities such as discussion boards, quizzes, or surveys excluded.

Table 1: Schedule for the Faculty Development Program for newly hired faculty members

Month	Program
October 2023	Theories of Higher Education • Video viewing on another LMS (Material distribution via Moodle) • Online workshop (90 min on Zoom) • Assignment: Attendance record submission (via Moodle)
November 2023	Information Provided by the Industry-Academia Innovation Center • Online lecture (100 min on Zoom, Materials distribution via Moodle)
December 2023	Theories of Course Design • Video viewing on other LMS (Materials distribution via Moodle) • Online workshop (120 min on Zoom) • Assignment: Attendance record submission (via Moodle)
January 2024	Report on Faculty Development Overseas Training and Other Information • Online lecture (100 min on Zoom, Materials distribution via Moodle) • Lecture video available later (via Moodle)
February 2024 (On-demand)	Theories of Educational Evaluation • Video viewing on other LMS (Materials distribution via Moodle) • Assignment: Video viewing record submission (Moodle)
March 2024	Workshop “Let's Learn about Coaching (Practical Edition)” • Participation for Workshop (Hybrid: In-person or remote via Zoom) • No Moodle usage

2.3 Data Collection

Data on the activities of each participant in the Moodle FD course (such as access information) were collected. To facilitate the visualization of learning outcomes in the Moodle LMS, data was collected using a paid plugin called IntelliBoard. The obtained information included the type of operating system (OS) and browser used by the participants, the frequency and time of access for each activity, and the amount of time spent on access (Time Spent).While simple access frequency can be obtained using standard Moodle features, obtaining information on the OS and browser types, as well as the Time Spent, requires certain modifications (such as plugin installation). Therefore, the unique aspect of this study lies primarily in the collection of Time Spent data.

2.4 Time Tracking Methods in IntelliBoard

Here, we provide an overview of the IntelliBoard’s time-tracking methods used to collect Time Spent data. In IntelliBoard, authorized users with administrative privileges can activate time tracking features. This setup can be performed using the plugin settings. Once time tracking is activated, IntelliBoard utilizes a JavaScript file to ping the user every 30 seconds. A waiting period of 60 seconds follows to confirm engagement, during which user activities such as mouse clicks, mouse movements, or keystrokes, may occur. While adjustments to the pinging intervals and waiting periods are possible, for this study, we collected data using the default settings without any modifications.

2.5 Data Analysis

We analyzed the data obtained from Moodle as follows: we cross-tabulated the information on each of the operating systems (OSs) and browsers used for access. Additionally, regarding information on access numbers, we used IntelliBoard to automatically aggregate the values for each day of the week and time period (morning (6am - 12noon), afternoon (12noon- 5pm), evening (5pm–12 midnight), and off Hours (12 midnight–6am)). We further presented these aggregated values.

Regarding the data on Time Spent, we initially aggregated the total time spent by all participants on all activities (Total Time Spent), along with the total number of accesses (Total Visits). Further, for each participant, we analyzed the aggregation of Total Time Spent and Total Visits by performing a regression analysis. Furthermore, we aggregated the actual time spent performing each activity (i.e., the time each activity page was open). We aggregated the time spent on each activity by each participant as Activity Time Spent. We also analyzed the relationship between Activity Time Spent and Total Time Spent.

3 Results

3.1 Data on Operating Systems and Browser Usage

Table 2 presents the aggregated results of the data regarding the usage status of Browsers and OSs. Regarding the aggregation of OSs, Windows accounted for 57.5%, whereas Mac OSs accounted for 42.5%. Considering the browser usage status for each OS, it was noted that among Windows users, the majority used Chrome, accounting for 44.2% of the total. Regarding Mac OS users, those using Firefox accounted for a significant proportion, that is, 24.2 %, followed by Chrome users, who accounted for 11.7% of the total.

Table 2: Browsers and Operating Systems Used

	Operating System	
	Windows	Mac OS
Browser		
• Chrome	44.2%	11.7%
• Firefox	8.3%	24.2%
• Safari	0.0%	6.7%
• Microsoft Edge	5.0%	0.0%

3.2 Visits by Day and Time

Figure 1 depicts a summary of visits to the Moodle course by day and time. Monday had the most frequent visits, followed by Wednesday. Saturday had the lowest number of visits. Regarding the time of day, the most popular period was afternoon (12pm–5pm), followed by evening (5 pm–12am).

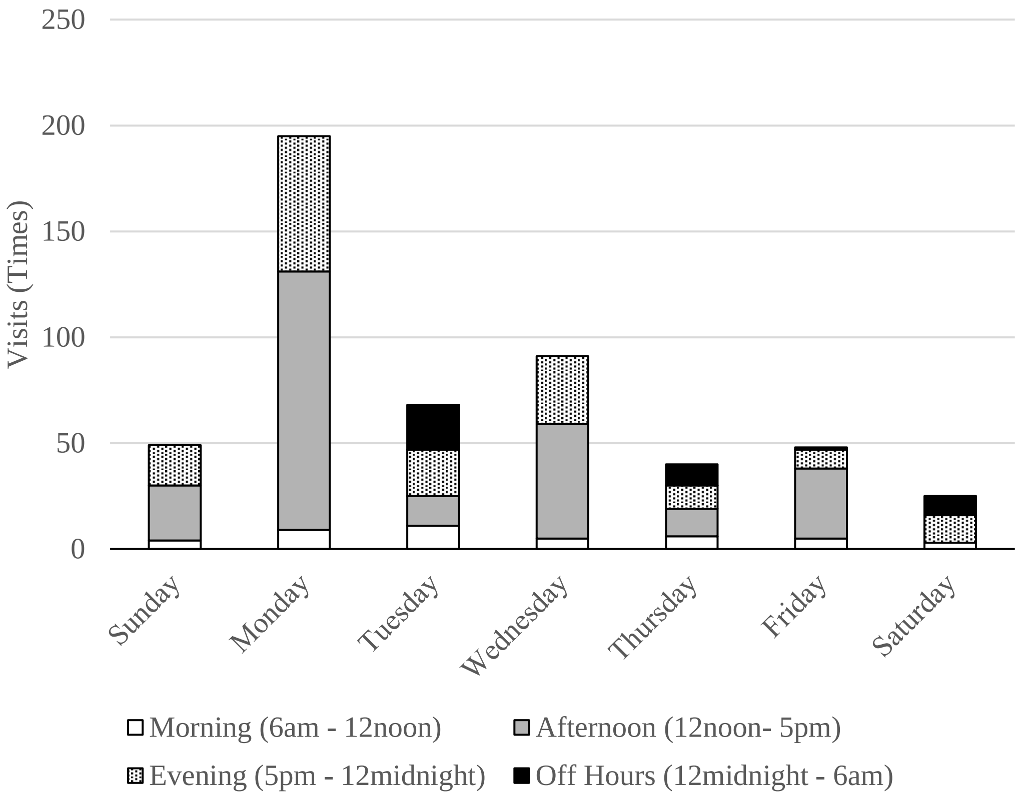

Figure 1: Summary of Visits by Day and Time

3.3 Total Visits and Time Spent

Table 3 illustrates the Total Visits and Time Spent on the course used for this study. The total course utilization for the 11 participants amounted to 407 visits, with a Time Spent duration of 5 hours, 3 minutes, and 30 seconds.

Table 3: Summary of Total Visits and Time Spent

Participants	Visits	Time Spent
11	407	5:03:30

3.4 Relationship between Total Visits and Total Time Spent

Figure 2 presents a scatter plot illustrating the relationship between the number of visits and the total time spent on the Moodle course for each participant. When drawing a regression line for the relationship between the parties, the coefficient of determination R^2 was 0.304.

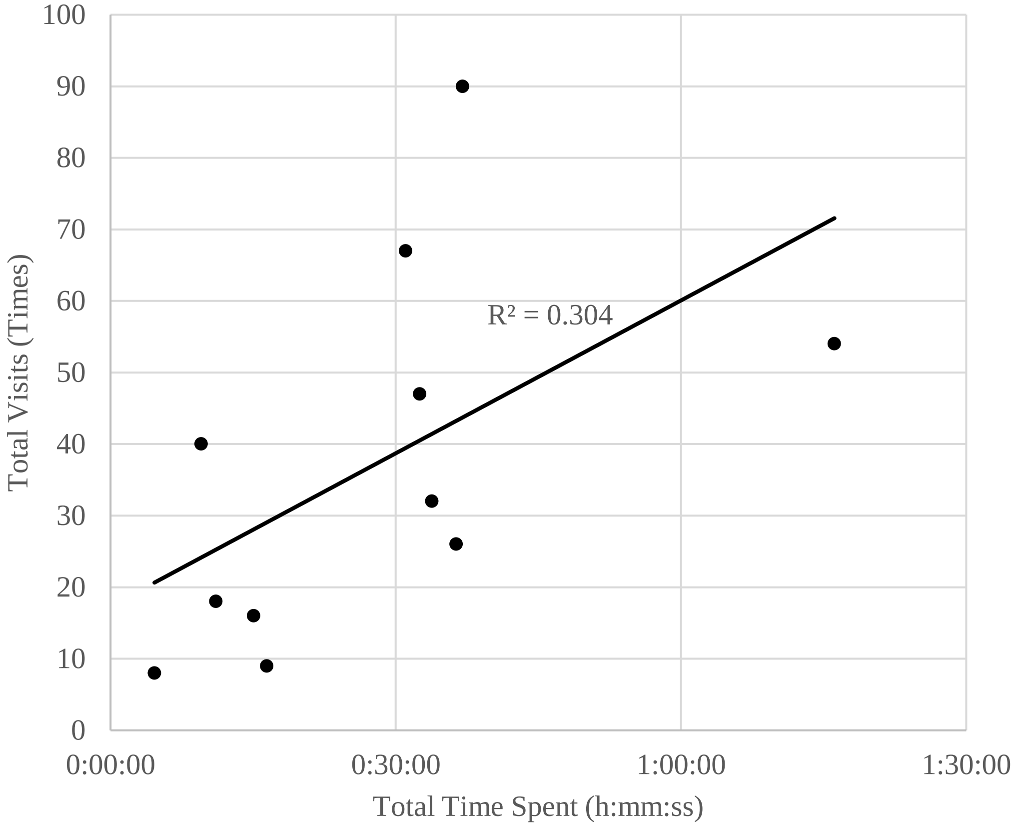

Figure 2: Scatter plot of Total Visits and Total Time Spent for each learner

3.5 Time Spent for each Activity

Table 4 shows the Time Spent on each activity, along with the number of visits for each activity. The number of activities in the Moodle course used in this study was three assignments, 14 files, and one page, with the highest number of visits recorded for files at 77. However, Time Spent was the shortest for files (1 min 51 s) and the longest for pages (41 min 20 s).

Table 4: Visits and Time Spent by Type of Activity

Types of Activity	Number of Activities	Visits	Time Spent
Assignment	3	23	0:22:16
File	14	77	0:01:51
Page	1	3	0:41:20

Lastly, figure 3 presents the results of the Activity Time Spent for each participant, along with the relationship to the Total Time Spent. There was one participant whose Total Time Spent was approximately 1 hour and 16 minutes, while the Activity Time Spent was approximately 40 minutes, appearing as an outlier (the triangular plot in Figure 3). However, for the other participants, the Total Time Spent was within 38 minutes, and the Activity Time Spent was within 9 minutes. When the regression line was plotted excluding the outliers, the coefficient of determination R^2 was 0.446.

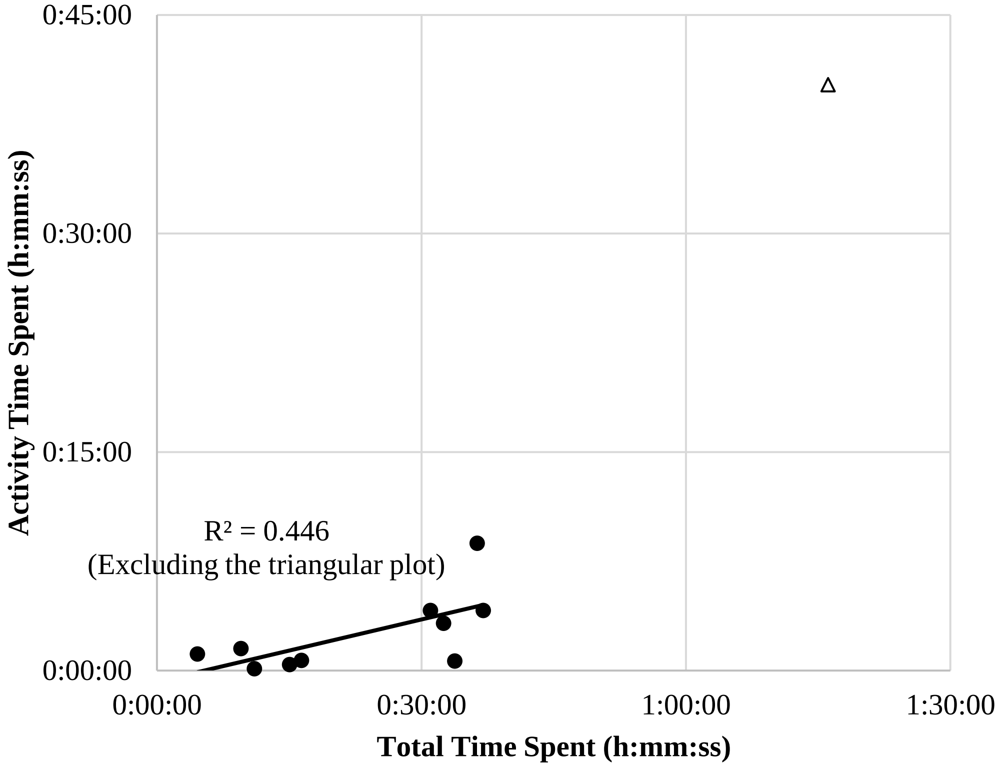

Figure 3: Scatter plot of Total and Activity Time Spent for each learner

4 Discussion

4.1 OS and Browser Data and its Utilization

Information concerning OSs and browser usage, which is typically unavailable through standard Moodle features, can be acquired using IntelliBoard. In the Moodle environment used in this study, Windows accounted for 57.5% of the total, whereas Mac OSs accounted for 42.5%. As of March 2024, the market share of OSs in Japan was distributed as follows [9]: Windows held the largest share at 44.71%, followed by iOS at 24.89%, and Android at 13.2%. The Unknown category accounted for 8.29%, whereas macOS (formerly OSX) accounted for 7.71%. Linux accounted for 0.66%, whereas the other operating systems accounted for 0.54%. This study did not consider access to iOS or Android devices. In other words, only PCs were used, and tablets and smartphones were not. Upon examining browser usage within each operating system, it was observed that Chrome was predominantly used by Windows users, accounting for 44.2% of the total. Conversely, among MAC OS users, Firefox emerged as a significant choice, accounting for 24.2%, followed by Chrome, which accounted for 11.7%. Presumably, because many individuals conducting research, such as university faculty, were involved in the training, there might be a higher prevalence of MAC usage compared with the general user population. Additionally, the relatively low usage of default OS browsers such as Safari or Edge could be attributed to the professional context, possibly indicating a preference for other browsers among educators. This information on OSs and browsers could be crucial for distributing course materials and facilitating video viewing during lectures. For instance, certain videos may not be compatible with specific OSs or browsers, and certain documents (e.g., PDFs) may not open properly on certain OSs. Hence, leveraging this information in future could help optimize the accessibility and usability of course materials and resources.

4.2 Utilization of Data on Visits by Day and Time

According to our data, the day with the most frequent visits in the Moodle course was Monday, followed by Wednesday. The fewest visits occurred on Saturdays. Regarding the time of day, the most popular period was the afternoon (12 pm–5 pm), followed by the evening (5 pm–12 am). These patterns were presumed to be related to the participants being university faculty members and the deadlines for assignments. These findings are consistent with those of previous research [3] concerning the influence of assignment deadlines. Among the months with assignment deadlines (October, December, and February), both October and December had deadlines falling on Mondays. Additionally, usage in the morning (6 am-12 pm) was generally low, which is attributable to it being primarily dedicated to work hours. If the users were students, there might have been some usage during the morning for classes; hence, analyzing usage by time slots could be meaningful for evaluating the characteristics of the participants. Based on such data, setting tasks that consider timeslots and days of the week could potentially alleviate learners' burden and prevent submission oversights.

4.3 The Effectiveness of Time Spent Data

This section examines how to effectively utilize the Time Spent data, which is the primary characteristic aspect of the data in this study, through comparisons with the access count (Visits) data. Figure 2 presents a scatter plot illustrating the relationship between the number of visits and the total time spent in the Moodle course for each participant. When drawing a regression line for the relationship between the parties, the coefficient of determination R^2 was 0.304. It is understandable that, as the number of visits increases, the time spent also relatively increases; this trend is evident from the coefficient of determination. However, by examining the distribution of the plots, it is clear that even with similar numbers of visits, there is a wide range of time spent, and vice versa. In other words, previous studies have often examined learners' levels of engagement based on access counts and provided examples of learning improvements. However, because the number of visits and actual learning time can vary considerably, the time spent may provide a more accurate representation of the learners' situation. Specifically, in cases where the access count is high but the actual learning time is short, an analysis based solely on the access count may result in an inaccurate assessment of learners' engagement, potentially overlooking students who need more support to improve their learning. Conversely, it is also possible that students with low access counts are still able to learn effectively. Therefore, using the time spent on the data, it may be possible to better evaluate the qualitative aspects of learners' learning processes.

4.4 Utilization of Time Spent for Each Activity

The data show a significant difference in the time spent on different activities. Regarding the Files, the highest number of visits was recorded at 77. However, the Time Spent was the shortest for files (1 minute 51 seconds), and the longest for pages (41 minutes 20 seconds). This disparity in time spent is attributable to the nature of different activities. When a learner clicks on a file, they are often redirected to a different page (linked content), and the time spent on the original file page is very short. The time spent viewing the file content was not captured by this dataset. There is a need for more tools to evaluate this, which can be considered as a future improvement. Similar to previous research, if it becomes possible to acquire data on the viewing of materials in the form of e-books [2] and also obtain data on the time spent using them, this could complement the use of an intelligent board. There was only one page containing the recorded training video. The time spent watching this video was directly captured in the Time Spent data, resulting in a much longer duration compared with other activities. For video viewing, it may also be possible to use other tools to measure the time spent. In summary, the time spent on each activity had distinct characteristics. Considering student learning time, especially for university courses, these measurements can be useful in determining appropriate task loads (not too much or too little) to ensure optimal learning.

Considering the relationship between the Total Time Spent and the Activity Time Spent by each learner, it is clear that the Activity Time Spent was significantly less than the Total Time Spent. This suggests that a substantial amount of time is spent on activities other than actual course activities, such as browsing course pages. This may be related to the fact that the course in this case had extensive explanations on the course pages. However, the results indicate that there could be opportunities to encourage learners to spend more time on actual learning activities. Thus, the data on where time is spent and whether it is being used effectively can provide valuable insights for improving the learning experience.

4.5 Limitations of the Study and Future Research Directions

One of the key limitations of this study is the small sample size, with only 11 participants in the course. Consequently, it is unclear how the findings would apply to cases involving larger numbers of participants. Additionally, the Moodle course content (activities) used in this study did not include certain time-intensive activities, such as quizzes or forums. Consequently, the analysis did not capture the usage patterns or time spent on these types of activities. To address these limitations, future research should explore the utilization of Time Spent data in cases with a greater number of participants, as well as courses that incorporate a wider range of learning activities. This would provide a more comprehensive understanding of how Time Spent data can be effectively leveraged to gain insights into learner behavior and engagement.

The participants in this study included university faculty members required to complete a training course. This means that the analysis could not examine the behavior of learners who may have dropped out or faced difficulties during the learning process. In a university course setting, however, Time Spent data could potentially be used to identify and support struggling students, which would be an important area for future investigation.

Lastly, this study analyzes a single course. Expanding research to include multiple courses would allow for a comparative analysis of how the utilization of Time Spent data varies across learning environments. This could provide valuable insights into course-specific usage patterns, and help develop a deeper understanding of learner behavior and its influencing factors.

In summary, although this study offers important insights into the potential of Time Spent data in learning analytics, future research should address these limitations by exploring larger-scale studies, a broader range of learning activities, the application of Time Spent data to support struggling learners, and comparative analysis across multiple courses.

5 Conclusion

This study investigates the use of Moodle's time-tracking data, along with access count data, to understand the learning behaviors of newly hired instructors in a faculty development training course. Integrating these data types provided a comprehensive view of learner engagement. The analysis revealed nuanced patterns: some had high access counts but low engagement times, whereas others showed the opposite. The time-based analysis also highlighted how instructors allocated their time across course components. Practical applications include timely interventions, tailor-made instructional designs, and support for self-regulated learning. Leveraging Moodle's data can enhance faculty development programs and contribute to evidence-based decision making in education. Further research is required to explore broader applications and translate insights into actionable strategies to support learners and improve teaching practices.

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