Creating and Collecting e-Learning Event Logs to Analyze Learning Behavior of Students through Process Mining

Anake Nammakhunt*, Parham Porouhan, and Wichian Premchaiswadi

***Abstract*—Many traditional educational management models are being switched or shifted into online platforms; thus, assessing behavioral aspects of learners is essential to improving the quality of online teaching and learning processes. Currently, a problem in managing online teaching of courses is that instructors do not have the appropriate tools and techniques to be fully aware of students' behavioral patterns in a data-driven and process-aware approach. This study is divided into three main parts. In the first part, a dataset of online students is transformed and preprocessed. In the second part, the Fuzzy Miner algorithm supported by Fluxicon Disco is applied to the dataset to understand the learning process of the students in terms of the duration and length of the tutorial videos watched online (i.e., fully watched, partially watched, paused, and resumed intervals) and in terms of the frequencies of all activities. In the third part, a comparison between behavioral patterns of high-performance group of students versus their low-performance counterparts attending the same course was conducted, and we used the Dotted Chart Analysis technique supported by ProM to conduct and make the comparisons. The results of the study showed significant differences between the two groups in terms of the duration spent on the tutorial videos and in terms of the sequence and order of the activities performed and executed. The findings of the research can be used by instructors, administrators, and educational managers to improve the course curriculum management process or to boost effective coaching and teaching styles, leading to the optimization of students' learning process by increasing educators' awareness about students' weaknesses and strengths.**

***Index Terms*—Education data mining, education process mining, data analytics, learning behavior, collecting event logs, e-learning system, process discovery, student learning behavior**

I. Introduction

The COVID-19 pandemic has affected the education system globally. In response, educational institutions in Thailand need to urgently adopt online teaching methods to reduce the negative impact on students and the nation [1]. Many educational institutions in Thailand have used e-learning as the primary mechanism for managing online education and have attempted to transform the learning process into a learner-centric approach [2]. The emphasis on self-directed learning [3] enables continuous teaching and learning activities to encourage and support online teaching and provide learners with a means to review lessons, goals, and consistent learning [4]. For online learning, learners must acknowledge what purposes they aim to achieve before deciding what to study. Thus, understanding the learning objective contributes significantly to learners' efforts to learn online.

Consequently, effective online learning will not occur if the learner studies independently without understanding the goals [5]. Additionally, the change in learning methods from classroom learning to online during the COVID-19 outbreak has enabled learners to realize their learning objectives, leading to self-control in learning and self-learning [6]. Furthermore, factors affecting learner satisfaction should be considered in online learning [7]. If learners recognize the benefits and the ease of using an e-system, they will be enabled to learn independently [8]. Moreover, instructors must answer questions quickly and provide timely feedback and suggestions regarding assigned tasks.

By contrast, the instructor's participation, engagement, and interactions enhance learning [9]. Instructor quality is important and directly influences online learning [10]. However, few studies have investigated online learners' learning process by evaluating the e-learning system's event logs to examine behavioral processes. Acknowledging the actual process of learner behavior allows instructors to set conditions to create incentives that motivate learning [11].

Thonburi University is a private university that provides higher education in Thailand. Per government policy, all university faculties have changed their learning methods to teaching via online systems through Microsoft Teams, Zoom, and Google Meet. The professors' teaching videos are uploaded to the university's e-learning system, and then students can review them ad libitum, complete examinations, and submit assignments through the internal e-learning system, which provided the data that we monitored and evaluated in this study.

Before conducting this research, we provided training on using the e-learning system for 103 instructors who provided feedback and recommendations for learner attendance tracking reports: 1) LMS Moodle's Course completion report shows whether the learner has completed a given topic but does not demonstrate the in-depth process of the activity, the learners' time used for activities for each topic, or if re-learning on the same topic occurred [12]. 2) Report Logs and Live Logs that show details of each activity one by one, and there are many activities per course, making it possible to monitor the process of learning behavior of learners that is difficult to understand. Such processes result from the system usage, activities, and the change in many activities according to the learners' behavior, causing the data to be distributed abnormally [13–17]. The most important challenge dealing with such processes is that conducting a statistical approach is not the best way to analyze and investigate such processes [18]. 3) Instructors can access the "Add activity or resource"

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panel page to add additional features and student activities, such as Assignments, Labeling the collected video data, Webpage visited, and URL. The accessed materials and many others as shown in Fig. 1 [19, 20]. Instructors use the YouTube video presentation method with 98% insertion of Module Label activity, Module URL 1%, Module Page 1%, and Module SCORM unavailable.

Fig. 1. A screenshot showing the dashboard (control panel) of the designed e-learning platform on LMS Moodle for instructors to add an activity or resource and to eventually collect student datasets [19, 20].

Next, we evaluated the learning system process by analyzing the event log data. We found a lack of learning via video, such as clicking on the video Start, Play, Stop, Change video Playback Position, and Close. Recording such behavioral event logs would help clarify learners' learning process or in-depth online learning behavior. Moreover, knowing whether the students are attending that lesson will enable teachers to analyze, develop, and improve the lesson content, improving the production process of teaching video materials.

In this study, we aimed to examine students' access to video materials in the LMS Moodle system to create a system for collecting event logs from the plug-in for LMS Moodle in the critical part of the behavioral analysis of the learning process.

The main contribution of this study and what distinguishes it from other research in this field is that we propose a new approach to obtain appropriate data in a data-driven manner as an input for process mining analysis based on students' behavior while watching online videos during an e-learning experiment. A primary problem of online teaching is that instructors are not fully aware of students' behavioral patterns throughout the course. Most of the instructors' judgments of student performance are based on submitted assignments or examinations. In this study, we offer a data-driven and process-aware approach. This approach enables managers and instructors of e-learning courses to track, trace, monitor, and distinguish the navigation of students by using the online developed platform. In the proposed approach, the instructors can monitor, for example, the duration and lengths of the videos watched, page navigation, duration of active or idle time, and frequency of visiting the materials and resources and can classify student performance into high and low groups. In addition, we reviewed the secondary data and carefully studied the literature. These endeavors showed that only a few studies had investigated students' behavior while watching videos online (using different approaches and techniques). The number of these studies was limited because of technical difficulties regarding the extraction of the video-watching data using plug-ins, which extract the exact duration of watched videos or pauses/stops (and resumes). Therefore, our approach not only assesses students' behavior (i.e., pages visited, and materials accessed or navigated) but also considers the time learners spent performing activities or watching tutorial videos.

We also compared the learning behaviors of two groups of students the LMS Moodle system scored 70% or more or scored less than 70% as a guideline to improve the process of teaching online learning through the e-learning that impacts academic achievement and proper development. Instructors can obtain benefits from the system developed for creating activities that lead to boosted motivation, enhanced learning, improved lesson content, and more effectively and efficiently produced teaching videos to encourage students to learn and generate overall increased interaction with the system. These results and findings (i.e., insights or instructor's awareness) also enable learners to quickly adapt themselves to the online learning or e-learning scenario, making them familiar with the self-learning process and life-long learning (i.e., output based learning) in a sustainable manner.

At the managerial level, the benefits of the proposed approach are realized in the analysis of students' behavior while watching videos on the e-learning platform and in our analytics results. These results can be used by lecturers and instructors to improve course curricula or managerial coaching and monitoring styles in classrooms, improving instructors' teaching styles and optimizing students' learning process. Moreover, using our proposed approach, educational administrators, managers, and instructors can track and distinguish students' behavioral patterns while watching online video tutorials (and other learning materials provided, e.g., PowerPoint slides, the exercises) in the context of high-performance and low-performance group. These results facilitate managers' and educators' awareness of students' weaknesses and strengths to make necessary modifications to increase the quality of the offered learning materials.

II. Objectives of This Study

The main objectives of the study are as follows:

A. To study the process of learners' accessing the e-learning system from the online learning event log.

B. To develop a plug-in for storing event log data into video learning and integrate event log data according to process mining analysis data requirements.

C. To analyze online learning event log data via an e-learning system with process mining technique.

D. To compare online learning behaviors through an e-learning system between learners whose exam score was either 70% or more and less than 70%.

III. Literature Review

E-learning is a learning method that requires knowledge of the role of self-learning to enhance readiness for online learning [21]. Additionally, the role of facilitating and the instructors' ability to teach the learners affect the level of learners' satisfaction [9], [22]. During the COVID-19 pandemic, instructors had to adapt teaching styles, teaching techniques, and teaching processes to sharpen skills and enhance learners' knowledge in this new environment. Thus, instructor quality determines learners' satisfaction. In addition, instructors should consider the core expectations of most learners, that is, before entering university, learners expect to obtain a job after graduation [23]. Therefore, the design of an online course requires explicitly stating the necessary details, such as course content, educational objectives, course structure, and corresponding results. The awareness of e-learning's benefits for learners will help learners use the system and improve themselves effectively. Furthermore, instructors are required to answer questions quickly and provide feedback on assignments to learners at appropriate intervals to help online learners engage and interact with instructors. The instructors' advice is essential to the learners' learning to achieve the purpose [24].

LMS Moodle is an example of integrated learning technology and is a tool for online teaching management through the internet [25, 26]. Event Logs of clicking behavior in learning activities obtained through the e-learning system are stored in the database in a structured data format and as continuous data with large amounts of data, called big data. Data management is required to gain the benefit of information, including storage space and the consideration of the speed of data processing for analysis and decision-making. For instance, designing a data storage table is conducted in the denormalized model. By contrast, data partitioning is suitable for attributes with low cardinality, which normally requires to be adhered to specific attributes as filters in queries, such as country, province, department, or school year, to avoid over-partitioning [27]. LMS Moodle Event Logs can be applied to process mining techniques to discover learners' learning behaviors through the system [28], [29].

Process mining is a business process discovery technique to visualize the actual process in a Process Map of the activity generated by event log data [30]. It is also a tool for identifying and discovering how individuals and/or entities have performed and executed activities in terms of an orchestrated and repeatable pattern of workflows and for conducting Delta analysis to find differences between the datasets in each possible situation. Such identifications and discoveries enable testing the consistency of the process model by conducting comparisons with the original model or with theoretical processes [31] to study possible processes in the development of operational processes or operational planning to achieve goals that can be applied to multiple sectors (e.g., the business, education, and government sectors) [28].

Therefore, process mining aims to obtain information about the event log process to study the processes that occur regarding the individuals or entities involved in each event or activity. Every activity has a timestamp recorded each time to explore the good characteristics of a possible event-driven process chain [30]. Hence, the researcher applied the process mining technique to find the learning process of online learners through an e-learning system. The process mining technique discovers the learning process of learners through video media from complex event log data to eliminate unrelated models by presenting specific aspects and areas that show relevant or distinctive behavior. This finding makes the discovered model comprehensive and beneficial to education stakeholders [31].

In Silva *et al.*'s work [32], two process mining techniques, namely, as "fuzzy miner" and "dotted chart analysis," were used to simulate and discover students' behavior while watching videos in an online learning environment. Moreover, in Silva *et al.*'s work [32], a time comparison and investigation of students spending time on the provided video materials was also discussed and presented. In Silva *et al.*'s work [32], the researchers used and applied the fuzzy miner process mining technique as an algorithm with two metrics that can support process simplification, including significance and correlation. The significance level was determined by the frequency of frequently discovered events or its correlation to another more frequent activity considered more significant. Thus, the highly significant behavior remains in the simplified model. Additionally, the correlation assesses less significant behaviors with a higher correlation that will remain in the model but are hidden in the cluster within the simplified model and removed less significant and low correlation behaviors from the simplified model [32].

The fuzzy mining algorithm is used for accuracy and model simplifying and focuses on frequent activities and processes to demonstrate the behavior explicitly and comprehensively [28, 33]. Thus, fuzzy miner is an ideal algorithm for discovering the learning process of online learners whose behaviors are mostly unstructured. Using the fuzzy miner algorithm in Fluxicon Disco, many highly complex activities with complicated structures can be easily simplified by filtering (and getting rid of) less important Activities and Relationships in terms of frequency of occurrence. Accordingly, the more the total frequency of an activity or a relationship (between two activities), the more important it is.

Disco is a process mining technology that runs based on fuzzy miner algorithm [34–39] and can automate process discovery, create appealing process diagrams, intelligently automate the processing of raw data, and filter processes from activities or the process path fast regardless of the large or complicated process. It can also display the discovered processes with a bird-eye view and detailed statistical data that can delve into detailed information on individual activities, resources, and data that can be imported into complex CSV and MS Excel files. In addition, Disco quickly sorts and exports data in MXML and XES that can be processed through ProM [40]. ProM is an extensible framework that supports various process mining techniques as plug-ins. It is available for download under an Open-Source GNU Public License at https://www.promtools.org/ [41, 42].

IV. Research Method

A. Population

The purposive sampling method was used on a sample of online learners who used the e-learning system of Thonburi University for a course (202111 Applied Business Programing) in the first semester (126 students) of the 2021 academic year, from May 28 to October 31, 2021, and in the second semester (121 students) of the 2021 academic year, from November 4, 2021, to April 10, 2022. Thus, the final sample was 247 students [34–39].

In other words, in Section V (Results) of Parts C and D of the study, we have focused on behavioral activity of groups of students (i.e., high-performance group versus low-performance group), as well as the duration of the students' study time, throughout the designed and developed e-learning experiment using the novel plug-in video-based approach for capturing and monitoring the behavior of the students while watching videos online.

We selected the aforementioned course to investigate students' behavior throughout the online learning experiment because our team members were the organizers of and instructors for the course. Thus, it was easy to conduct the experiment and directly collect students' data from an authentic educational environment. Another reason why we selected this course for our investigation was the crucial importance of this core course and, thus, its effect on the overall performance of the students regarding graduation from the program.

Accordingly, based on the objectives of this study, the methodology section answers four questions:

A. What are the main elements that affect the study process of learners' accessing e-learning?

B. How can we develop and propose a new plug-in for storing event log data of students' video learning process such that it is compatible with the process mining format and structure for further analysis and investigation?

C. How can we analyze the event log data of students' video learning process via an e-learning system by using process mining techniques, such as fuzzy miner algorithm and dotted chart analysis [34–39].

D. How can we compare and distinguish students' online video-watching and learning behaviors (and patterns) in terms of high-performance students (who obtained a total score of 70% or more) versus low-performance students (who scored less than 70%) in the conducted and developed online exam?

B. Research Tools

Research tools used in this study were experimental tools and data collecting or statistical tools. The experimental tools comprised LMS Moodle, as a tool of the Learning Management System to manage online teaching through the internet network; MySQL, as a tool of the Database Management System; and Plug-in GAct, as a tool for automatic storage of the video viewing event logs. The data collecting or statistical tools are a trigger generation method to transfer real-time attendance event log data to the logstore_video table and the AllEventLogs table by embedding the trigger in the e-learning database system, and the Disco tool, to find a learning process to analyze learners' behavior while entering through the system with the fuzzy mining algorithm. The sample was divided into two groups group 1, with a score of 70% or above, and group 2, with a score of less than 70% to analyze variations in activity frequency with Dotted Charts using ProM tools.

As shown in Section V, the results chapter of this study, Part A deals with students who have enrolled online for all the courses offered using the e-learning platform in semester 1/2020 (7,291 students). Part B shows the approach used in this study for developing a plug-in to capture and monitor the amount of time each student spent on each tutorial learning video material.

Part C shows the activity and behavior of the sample for the developed LMS e-learning system rather than including the activities for all LMS users, namely, the 247 students enrolled in the course. To achieve our objectives, we used the process mining fuzzy mining technique supported by the Fluxicon Disco platform/software to illustrate and simulate the overall workflow of the activities performed by the students.

Part D shows the comparison between behavioral patterns of high-performance group of students and low-performance group of students for 247 students enrolled in the e-learning course. We used the process mining dotted chart analysis technique.

To measure the significant differences between the two groups (i.e., above 70% and below 70 %), two process mining techniques (i.e., fuzzy miner and dotted chart analysis) were applied to the collected dataset. Using these two process mining techniques, we distinguished significant and insightful process differences in the layout (and sequence of performed activities), the type of the executed activities, and the time spent on each task, which were obtained from our raw data. Another reason why a cutoff of 70%, instead of, for example, 90%, was used because we wanted to increase the number of students in the two groups [34–39].

V. Results

A. The Study of Learners' Accessing Process in the e-Learning System from Online Learning Event Logs

We studied the overall system operation process using the e-learning online learning behavior event log from LMS Moodle's el_logstore_standard table. There were 7,291 students in semester 1 of the 2020 academic year, from June 13 to October 31, 2020, and we generated queries to retrieve event logs from the online learning process through the e-learning system shown in Fig. 2.

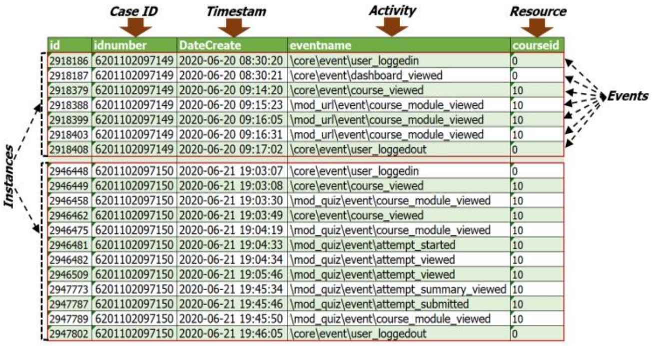
Fig. 2 consists of five columns: 1) "id" column that stores the sequence of events of the activities arising from the automated system access; 2) "idnumber" column stores the student ID information that uniquely identifies the learners who have entered the system. We defined the Case ID of the sub-activities arising from the behavior of each learner;3) "DateCreate" column that stores the Year-Month-Day and Time of the learner's learning process activities in LMS Moodle; 4) "eventname" column that stores the learner's learning behavior in each activity; and 5) "courseid" column that stores the course code when the event log data is retrieved for process discovery with process mining techniques.

Next, to view the activity that shows all 40 learning behaviors, we set the abbreviation of the activity as shown in Table I and performed a search on the learning processes. The Disco tool found that many activities and events made the Process Map diagram large. Thus, we divided the Process Map into three processes to visualize the processes discovered from the event log data: 1) viewing video media via Module URL and Module Page; 2) entering and submitting exercises in both forms of text and file uploading; and 3) entering the exam to study the process of the system from Process Map, including methods and the LMS Moodle event log data store shown in Figs. 2-5.

TABLE I: ACTIVITY LIST TO FIND THE LEARNING PROCESS

Initials	Activity event classes
C1	\core\event\user_loggedin
C2	\core event\dashboard_viewed
C3	\core event\user_profile_viewed
C4	\core\event\user_updated
C5	\core event course_viewed
C6	\mod_url\event\course_module_viewed
C6.1	\mod_url\event\Start Video
C6.2	\mod_url\event\Play Video
C6.3	\mod_url\event\ Pause Video
C6.4	\mod_url\event\ Seeking Video
C6.5	\mod_url\event\End Video
C7	\mod_page\event\course_module_viewed
C8	\core\event\user_loggedou
A1	\mod_assign event\submission_status_viewed
A1.1	\mod_assign\event\submitted\assign_id 3378
A1.2	\mod_assign\event\Modified\assign_id 3378
A1.3	\mod_assign\event\new\assign_id 3378
A1.4	\mod_assign\event\complete\assign_id 3378
A2	\mod_assign\event\course_module_viewed
A3	\mod_assign\event submission_form_viewed
A4	\mod_assign\event\assessable_submitted
A5	\mod_assign\event\submission_status_updated
AF1	\assignsubmission_file\event\assessable_uploaded
AF2	\assignsubmission_file\event\submission_created
AF3	\assignsubmission_file\event\submission_updated
AT1	\assignsubmission_onlinetext event\assessable_uploaded
AT2	\assignsubmission_onlinetext\event\submission_created
AT3	\assignsubmission_onlinetext event\submission_updated
Q1	\mod_quiz\event\course_module_viewed
Q2	\mod_quiz event attempt_started
Q3	\mod_quiz\event attempt_viewed
Q3.1	\mod_quiz\event\todo\quizid 980_3988144
Q3.2	\mod_quiz\event\complete\quizid 980_3988144
Q3.3	\mod_quiz\event\gradedright\quizid 980_3988144
Q3.4	\mod_quiz\event\gradedwrong\quizid 980_3988144
Q3.5	\mod_quiz\event\gaveup\quizid 980_3988144
Q4	\mod_quiz\event attempt_summary_viewed
Q5	\mod_quiz event\attempt_submitted
Q6	\gradereport_user\event\grade_report_viewed
Q7	\gradereport_overview event\grade_report_viewed

Fig. 3 shows the process of accessing video materials via Module URL and Module Page. As you can see, the activity C6 is related to the students who have accessed the Module URL to watch/view the video teaching materials. The results show that 1,733 individuals participated in the activity (24.1% of the 7,186 students), with 777 re-participating in activities (10.8%). Activity C7 is for learners to view teaching media through the Module Page: 701 individuals participated in the activity (9.76%), and 244 individuals re-participated in the activity (3.4%). However, the initial observations of Fig. 3 do not involve some important behavioral details such as clicking Start, clicking Play, clicking Stop, clicking Change Playback Position, and clicking Close the video features. Fig. 3 also does not consider and the duration of time for watching videos. Later, in Fig. 10 we will see how all these features can be taken for further consideration.



id	idnumber	DateCreate	eventname	courseid
2918186	6201102097149	2020-06-20 08:30:20	\core\event\user_loggedin	0
2918187	6201102097149	2020-06-20 08:30:21	\core\event\dashboard_viewed	0
2918379	6201102097149	2020-06-20 09:14:20	\core\event\course_viewed	10
2918388	6201102097149	2020-06-20 09:15:23	\mod_url\event\course_module_viewed	10
2918399	6201102097149	2020-06-20 09:16:05	\mod_url\event\course_module_viewed	10
2918403	6201102097149	2020-06-20 09:16:31	\mod_url\event\course_module_viewed	10
2918408	6201102097149	2020-06-20 09:17:02	\core\event\user_loggedout	0
2946448	6201102097150	2020-06-21 19:03:07	\core\event\user_loggedin	0
2946449	6201102097150	2020-06-21 19:03:08	\core\event\course_viewed	10
2946458	6201102097150	2020-06-21 19:03:30	\mod_quiz\event\course_module_viewed	10
2946462	6201102097150	2020-06-21 19:03:49	\core\event\course_viewed	10
2946475	6201102097150	2020-06-21 19:04:19	\mod_quiz\event\course_module_viewed	10
2946481	6201102097150	2020-06-21 19:04:33	\mod_quiz\event\attempt_started	10
2946482	6201102097150	2020-06-21 19:04:34	\mod_quiz\event\attempt_viewed	10
2946509	6201102097150	2020-06-21 19:05:46	\mod_quiz\event\attempt_viewed	10
2947773	6201102097150	2020-06-21 19:45:34	\mod_quiz\event\attempt_summary_viewed	10
2947787	6201102097150	2020-06-21 19:45:46	\mod_quiz\event\attempt_submitted	10
2947789	6201102097150	2020-06-21 19:45:50	\mod_quiz\event\course_module_viewed	10
2947802	6201102097150	2020-06-21 19:46:05	\core\event\user_loggedout	0

Fig. 2. Event log data from the online learning process through the e-learning system stored in LMS Moodle's el_logstore_standard.

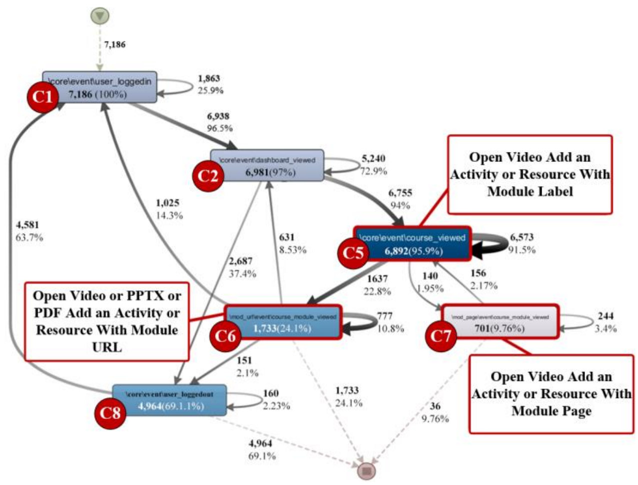


Fig. 3. Process map behavior of learning through an e-learning system that adds an activity or resource with module URL and module page (activity name is in Table I).

Fig. 4 is the exercise entry process starting from A1, an activity in which learners click to start performing exercises. In this activity, 4,548 learners participated, representing 63.3% of the 7,186 learners, and 1,285 re-entered the activity (17.9%). Activity C6 usually occurred after the learner completed the C5 activity; the A1 activity was usually followed by the A2 activity. In A2, 4,548 students participated, representing 63.3% of the 7,186 learners and 3,135 students re-entered participating in the activity (43.6%).

In the sample data, the instructor defined the method of sending exercises in three formats: 1) AT1, AT2, and AT3 sent by text message as an online answering question via the system; 2) AF1, AF2, and AF3 sent as an Upload File; and 3) A4 sent by other means such as a document or presentation. In the case of submitting an Upload File, the learners perform activity AF1, AF2 to click submit exercises, and activity AF3 when exercises are edited and submitted. In the case of sending by text message, the learners type their answers in the given text boxes, click to perform activity AT1 to Upload the answer into the system, and then in activity AT2 click to confirm the answer submission. If the submitted exercise was edited, learners perform activity AT3 to revise their answers and resubmit. After the learners perform activity A2, they go to activity A4 to return to activity A1 or C5. Activity A3 is the activity in which the learners check the results of the submitted exercises. If the submission time has not expired, learners can edit and resubmit their answers in this activity, then the system returns to activity A2.

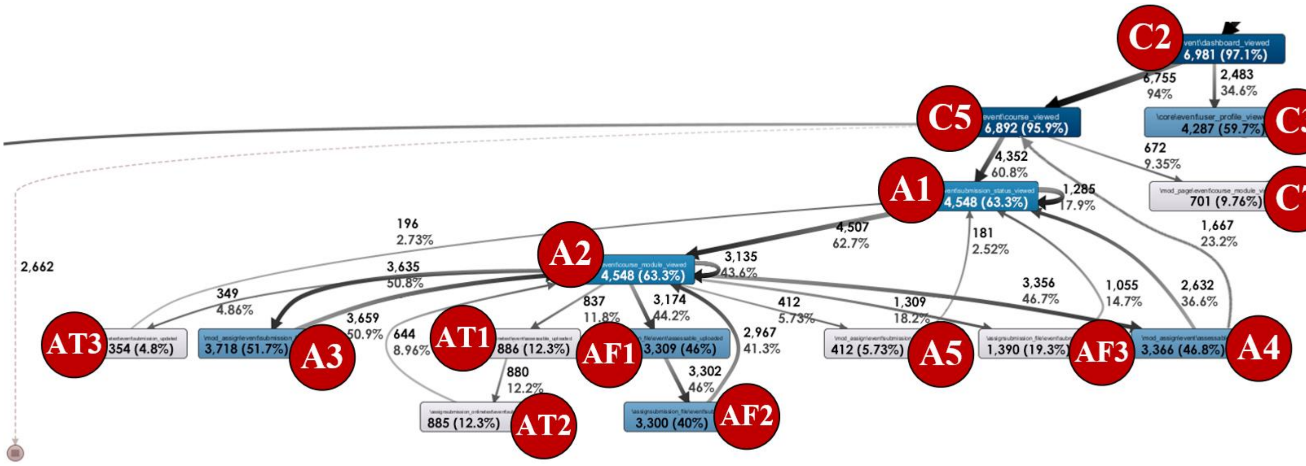


Fig. 4. Process Map Behavior of performing exercises through e-learning system (activity name is in Table I).

Fig. 5 shows the entering exam process when learners start clicking to take the exam in Q1, which shows conditions such as date, time, open and close exam, or other conditions that the instructor has set for learners to understand before clicking on the start menu to take the exam. Of 7,186 learners, 5,951 participated in this activity, representing 82.8%, and 3,384 learners re-entered this activity (47.1%). For activity Q1, learners could not see the questions on the exam until they clicked to start the test in activities Q2, Q3, and Q4, respectively. When the test is complete or timed out, the system enters the Q5 activity, saves and sends the exam, and returns to the Q1 activity. Learners can click to view the score of that test in activity Q6 or their overall score in activity Q7.

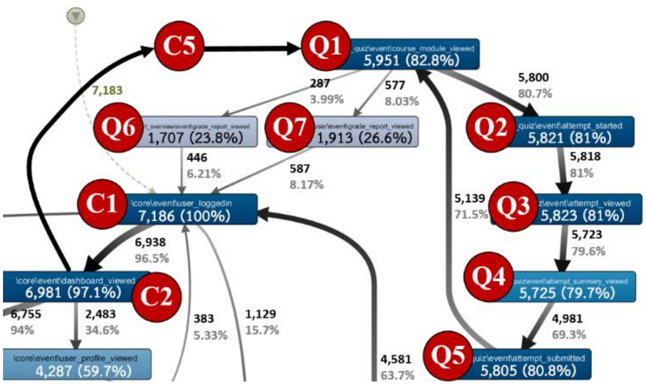


Fig. 5. Process Map Behavior of taking the exam through the e-learning system (activity name is in Table I).

The study of the event logs in Fig. 2 cannot show the subprocesses in each course in which exercises or tests are completed by the learners, Moreover, Fig. 2 does not reveal detailed behavioral aspects on the students who have taken the test, nor is the average duration needed to complete each question considered. We studied the process of in-depth data collection and found that these subprocesses are stored in several tables: the 1) el_assign table that stores exercise data; 2) el_user table that stores system user data; 3) el_assign_submission table that stores exercise submission data; 4) el_assign_grades table that stores the instructor's scoring data; 5) el_quiz table that stores exam data and the conditions; 6) el_quiz_attempts table that stores test entry data; 7) el_question_usages table that stores the grouping of questions in each set of tests taken by learners each time; 8) el_question_attempts table that stores each test entry to observe which questions were obtained; 9) el_question_attempt_steps table that stores clicks for each question; 10) el_question table that stores questions and answers; and 11) el_Course table that stores course data.

Data were stored according to a database design technique that organized the tables in a Normalization style. Creating queries for retrieving multiple tables with large amounts of data makes the processing show which data to use but requires high server resources and a long time. Therefore, we designed a denormalized storage table called AllEventLogs for collecting event log data from more than one correlated table to avoid data-intensive queries and mainly consider the speed of data processing [26], as shown in Fig. 9.

B. Development of a Plug-in for Storing Event Log Data into Video Media and Integrating Event Log Data according to Process Mining Analysis Data Requirements

Based on the study of learner accessing process in the LMS Moodle system, the researcher developed a plug-in to record learning event logs via embedded video media in component mod_ULR and designed a table structure considering the data requirements of process mining analysis. Defined by the Minimum Requirements for an Event Log, it must contain at least three components: "Case ID", "Activity", "Timestamp" and "Other". The "Case ID" determines the scope of the process. The "Activity" names determine the steps in the process map and their granularity. The "Timestamp" determines the order of the activities in a process. The "Other" specifies any additional attributes related to the course, students, or grades [43, 44].

Consequently, the newly designed event log data table for this research is divided into two parts: 1) the video learning event log table and 2) the event log data table that includes all process activities occurring in the system as shown in Fig. 6 and Fig. 9.

Fig. 6 is the logstore_video table that organizes Timestamps of clicking video behavior, such as clicking Start, Play, Seeking, Pause, End. Fig. 6 includes Attribute ID as the order of behavior when clicking to view a video; PageN as the lesson title; StartAttemptDate as the record of Time stamps that start video media activity; EndAttemptDate as the record of Time stamps that end video media activity; TimePlay as the recorded time of clicking activity on video media in seconds, for example, with a video length 4,352.7 s, the learner clicks pause at 287.762 s; intduration as the length of the video in seconds; eventname as the behavior related to such video, for example, clicking Start to enter a video lesson without clicking Play, Play to Start video to learn, Seeking to click across video content to view the point of interest, Pause to temporarily stop the video, clicking Change Volume to adjust the volume, Volume off to mute, Volume up to increase the volume, and End to close the video; STDID to the student ID that accesses the video media; and COURSEID as the course ID that the learners use to access the video material. Next, we use the method to create a trigger embedded in the database system by specifying the data record when inserting into or updating, as shown in Fig. 7.

ID	PageN	StartAttemptDate	EndAttemptDate	TimePlay	intduration	eventname	STDID	COURSEID
24311	LS2	2021-03-12 11:16:22	2021-03-12 11:16:24	0	0	Start LS2	6301102317021	315
24316	LS2	2021-03-12 11:16:50	2021-03-12 11:16:51	1.91461	4352.7	Play LS2	6301102317021	315
24317	LS2	2021-03-12 11:16:51	2021-03-12 11:16:51	2.10227	4352.7	Seeking LS2	6301102317021	315
24318	LS2	2021-03-12 11:16:51	2021-03-12 11:17:06	2.68437	4352.7	Play LS2	6301102317021	315
24320	LS2	2021-03-12 11:17:06	2021-03-12 11:17:06	0.179	0	Play LS2	6301102317021	315
24321	LS2	2021-03-12 11:17:06	2021-03-12 11:20:17	0	0	End LS2	6301102317021	315
24420	LS1	2021-03-12 12:48:42	2021-03-12 12:49:02	0	0	Start LS1	6301102317021	315
24422	LS1	2021-03-12 12:49:06	2021-03-12 12:50:23	0.027746	1823.5	Play LS1	6301102317021	315
24442	LS1	2021-03-12 13:04:08	2021-03-12 13:04:36	901.942	1823.5	Pause LS1	6301102317021	315
24455	LS1	2021-03-12 13:12:20	2021-03-12 13:14:14	901.999	1823.5	Play LS1	6301102317021	315
24465	LS1	2021-03-12 13:27:42	2021-03-12 13:30:16	1823.5	1823.5	End LS1	6301102317021	315

Fig. 6. Example of newly created video event log data (logstore_video) from the developed plug-in.

Fig. 7 is divided into two cases. Case 1 focuses on inserting into data only, consisting of triggers for system access behavior and triggers for learning through video media. Because the system's operation records additional entries without editing and deleting the data, both sets of data are suitable for creating triggers in the form of AFTER INSERT Triggers. Case 2 focuses on inserting into and updating, consisting of exercise submission triggers, and test trigger triggers. Both sets of data are inserted into the activity or updated activity. For instance, when the learners submit the exercise for the first time, the record status is inserted, but when they return to edit status, the record is to update the data, and so forth. Obtaining the information in real-time is possible using the embedded trigger method, as shown in the trigger example in Fig. 8.

After developing the plug-in and designing the table structure according to the data requirements of process mining analysis, the system started to store the event log data from the sample of 247 individuals from May 28, 2021, to April 10, 2022, and the CSV file was obtained as the example Fig. 9.

In Fig. 9, event log information in the AllEventLogs table consists of the 1) idnumber column that stores learner id information identifying the who have entered through the system for whom we defined the Case ID of the sub-activities arising from the behavior of each learner; 2) datecreate column that stores the year-month-day-time data of the learner's learning process activities; 3) eventname column that stores the entry behavior data; 4) courseid column that stores the course code and 5) the grade column that stores the learner's grades.

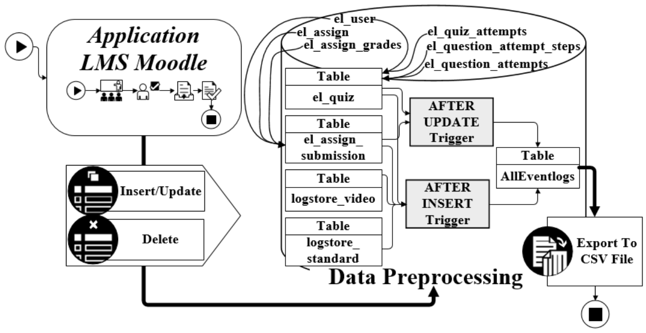


Fig. 7. An illustration of the proposed data aggregation structure for generating event logs supported by process mining platforms.

```
AFTER INSERT ON el_logstore_standard_log
FOR EACH ROW

BEGIN

INSERT INTO tb_AllEventLogs
VALUES (new.userid , from_unixtime(new.
timecreated), new.eventname, new.courseid, '0',
new.ip);

UPDATE tb_AllEventLogs as l,
(SELECT id, idnumber FROM el_user) as u
SET l.idnumber = u.idnumber
WHERE l.idnumber = u.id;

END
```

Fig. 8. Example of creating a trigger for storing event logs.

Case ID | Timestamp | Activity | Other Attributes

idnumber	datecreate	eventname	courseid	grade
6301104367023	2021-03-07 13:49:21	core/user/loggedin	0	A
6301104367023	2021-03-07 13:49:21	core/dashboard/viewed	0	A
6301104367023	2021-03-07 13:49:58	core/course/viewed	811	A
6301104367023	2021-03-07 13:57:21	mod_url/course_module/viewed(Play Video)	811	A
6301104367023	2021-03-07 13:57:24	mod_url/Start LS1	811	A
6301104367023	2021-03-07 13:57:28	mod_url/Play LS1	811	A
6301104367023	2021-03-07 14:05:10	mod_url/Pause LS1	811	A
6301104367023	2021-03-07 14:05:34	mod_url/Play LS1	811	A
6301104367023	2021-03-07 14:09:19	mod_url/Pause LS1	811	A
6301104367023	2021-03-07 14:09:22	mod_url/Play LS1	811	A
6301104367023	2021-03-07 14:11:02	mod_url/Pause LS1	811	A
6301104367023	2021-03-07 14:11:53	mod_url/Play LS1	811	A
6301104367023	2021-03-07 14:31:55	mod_url/End LS1	811	A
6301104367023	2021-03-07 14:33:12	core/user/loggedout	0	A
6301104367023	2021-03-10 21:36:15	core/user/loggedin	0	A
6301104367023	2021-03-10 21:36:15	mod_quiz/course_module/viewed	811	A
6301104367023	2021-03-10 21:36:18	mod_quiz/attempt/viewed	811	A
6301104367023	2021-03-10 21:36:18	mod_quiz/attempt/started	811	A
6301104367023	2021-03-10 21:48:25	mod_quiz/attempt_summary/viewed	811	A
6301104367023	2021-03-10 21:48:37	core/user/graded	811	A
6301104367023	2021-03-10 21:48:37	mod_quiz/attempt/submitted	811	A
6301104367023	2021-03-10 21:48:37	course_module/viewed	811	A

Instances | Events

Fig. 9. Example of event logs based on process mining analytics data requirements.

C. Online Learning Event Log Analysis via e-Learning System with Process Mining Technique

From the development of plug-ins for storing event logs into video media that are important for behavioral analysis of the learning process, we retrieved the event log data into the process search using process mining techniques. Because, in this study, we were interested in investigating and assessing the order and sequence of events within a case, the fuzzy miner algorithm was used and applied to create a dependency graph rooted in the frequencies of the activities and the frequency of times that each activity is followed by another activity [32]. By considering predefined limits, dependencies are eventually added (or maybe not added) to the generated dependency graph, which illustrates/demonstrates the "backbone" of the entire process model. This backbone is applied to reveal (and discover) details of the student events' behavior throughout the e-learning experiment. The most common method to apply process mining algorithms is through tools created for this purpose; the most used tools are ProM and Disco Fluxicon [32]. The ProM platform provides numerous algorithms through add-in extensions and plug-ins, and Disco Fluxicon is commonly applied in discovering process models/graphs by means of a single algorithm, the so-called Inductive Miner, derived from the fuzzy miner algorithm [32].

The Disco Fluxicon tool using the fuzzy mining algorithm and can find the activities that occurred during online learning through the e-learning system, in this case, a sample of 247 individuals and their 461,511 events and 3,445 activities. Therefore, we used filtering data with the Disco tool by dividing the data into three processes: 1) learning through video media, 2) participating in exercise activities, and 3) taking the test Fig. 10-Fig. 12.

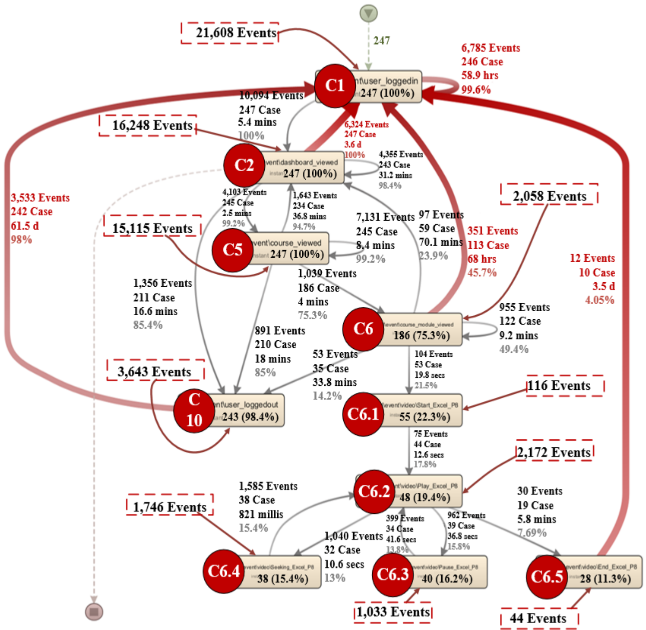


Fig. 10. Process map presents absolute frequency, case frequency, performance mean duration, and case coverage behavior depth. Only activities are related to learning in Part 20 (activity names are in Table I).

Fig. 10 provides in-depth behavioral aspects of activities related to the video of Lesson 8. It was found that for clicking on C1, the sample group logged in 247 individuals with 21,608 events, and 246 individuals reentered logins with 6,785 events; for the sample group clicking on C6, 186 individuals viewed the video through mod_url, representing 75.3% of the sample with 2,058 events; and for reentering C6, 122 individuals, representing 49.4% with 955 events, used 9.2 minutes on average. The sample group clicked into the C6.1 lesson only 55 individuals with 116 events. For clicking on C6.2, there were 48 individuals playing video with 2,172 events; for C6.3, 40 individuals paused the video with 1,033 events. For clicking on C6.4, 38 individuals were seeking a video with 1,746 events; C6.5 had 28 individuals ending the video with 44 Events. Notably, 19.4% of the sample group attended and learned the course (only for those who clicked C6.2 of Play Video). The performance mean duration of the sample used between C6.2 of Play Video activity and C6.3 of Pause Video activity was 36.8 s, 10.6 s for performing C6.4 of the Seeking Video activity, before clicking C6.5 of End video in 5.8 minutes; and 3.5 days of mean duration was observed in returning to C1 of Log in to start learning again.

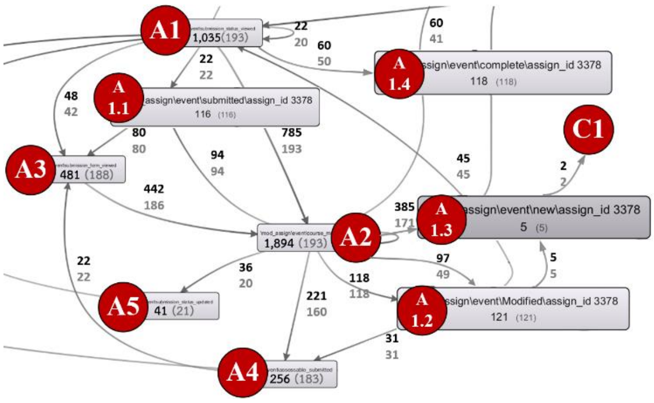


Fig. 11. Process map presents absolute frequency and case frequency in-depth behavior in practicing exercises. (Activity name is in Table I).

As shown in Fig. 11, the results of the Process Map on the behavior of participating in exercises showed that there is an additional in-depth activity from Fig. 4, which is the activity to perform exercises for each item with status A1.1: submitted, A1.2: Modified, A1.3: New, and A1.4: complete. Fig. 11 demonstrates the behavior of the sample in-depth, to the individual level of the exercise, which is not stored in the event log table el_logstore_standard, and the process of discovered exercise behavior is described in Fig. 4.

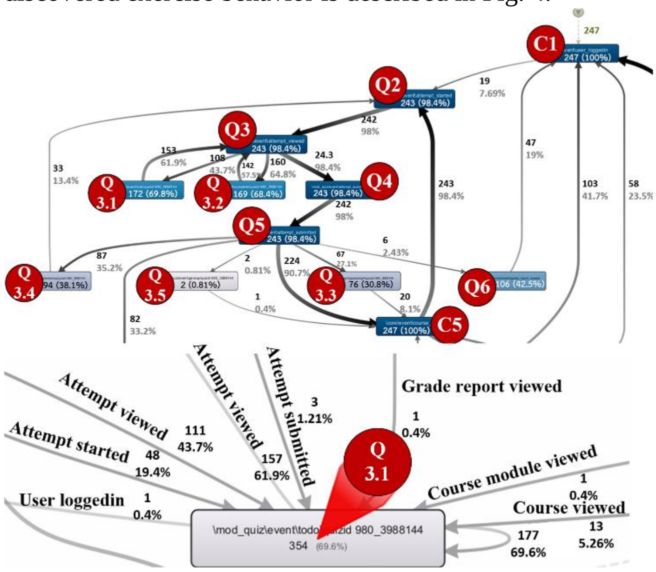


Fig. 12. Process map uses the case frequency option to ignore repetitions and observe relative numbers for how many cases passed through which activities and along which paths.

As shown in Fig. 12, regarding taking the test, 414,009 events and 3,307 activities occurred, representing 89%. Therefore, the event log behavior data at each test question resulting from the integration of the el_logstore_standard led to many activities in the sample group. Thus, we, used the Disco tool to filter the data of entering an exercise from the sample group by showing only the behavior of the test set number 980, question number 3988144, to be used as an example for analyzing the process of taking the test. Notably, 131,049 events occurred in the test set, and 17 activity events occurred, as shown in Fig. 12. As you can see, the resulting Process Map contains Q 3.1: Activity to take the exam (Todo); Q 3.2: Submit the answer (Complete); Q 3.3: Activity to answer the question correctly (Graded-as-correct) or Q 3.4: Wrong answer (Graded-as-wrong) and Q 3.5: Flag making activity (Uncertainty and hesitation) based on the data of the sample group. There were 172 individuals, representing 69.6% of the sample, who took the test series 980. For question code 3988144, it was clicked to perform (Q 3.1: Todo) 354 times and returned to review 177 times. The submission of the learners who answered this question was 169 individuals (Q 3.2: Complete 980_3988144) representing 68.4%, 76 individuals who answered correctly (Q 3.3: Graded-as-correct 980_3988144) representing 30.8%, and 94 individuals with wrong answers (Q 3.4: Graded-as-wrong 980_3988144) representing 38.1%. We can see two students or Cases marked with the flag symbol as a sign of hesitation and doubtfulness while answering a multiple-choice question online (Q 3.5: Hesitating on Question #980_3988144) representing 0.8% of total number of Cases, and one student or Case who did not submit an answer to the same multiple-choice Question #980_3988144.

D. Comparison of Online Learning Behaviors through an e-Learning System between Learners Who Scored a Total Score of 70% or More and Those Who Scored Less Than 70% on the Exam

In this section, we conduct and discuss a comparison between online learning behaviors via the e-learning system between learners who scored a total score of 70% (or more than 70%) and those who scored less than 70%.

As mentioned earlier, we used some Disco Filtering techniques applied on the event log data to analyze the activities related to the video learning process in 20 lessons of the course. The dataset comprised 85,304 Events that occurred during the learning session. There were 247 students enrolled in the sample group, and 108 activities occurred and were accordingly filtered.

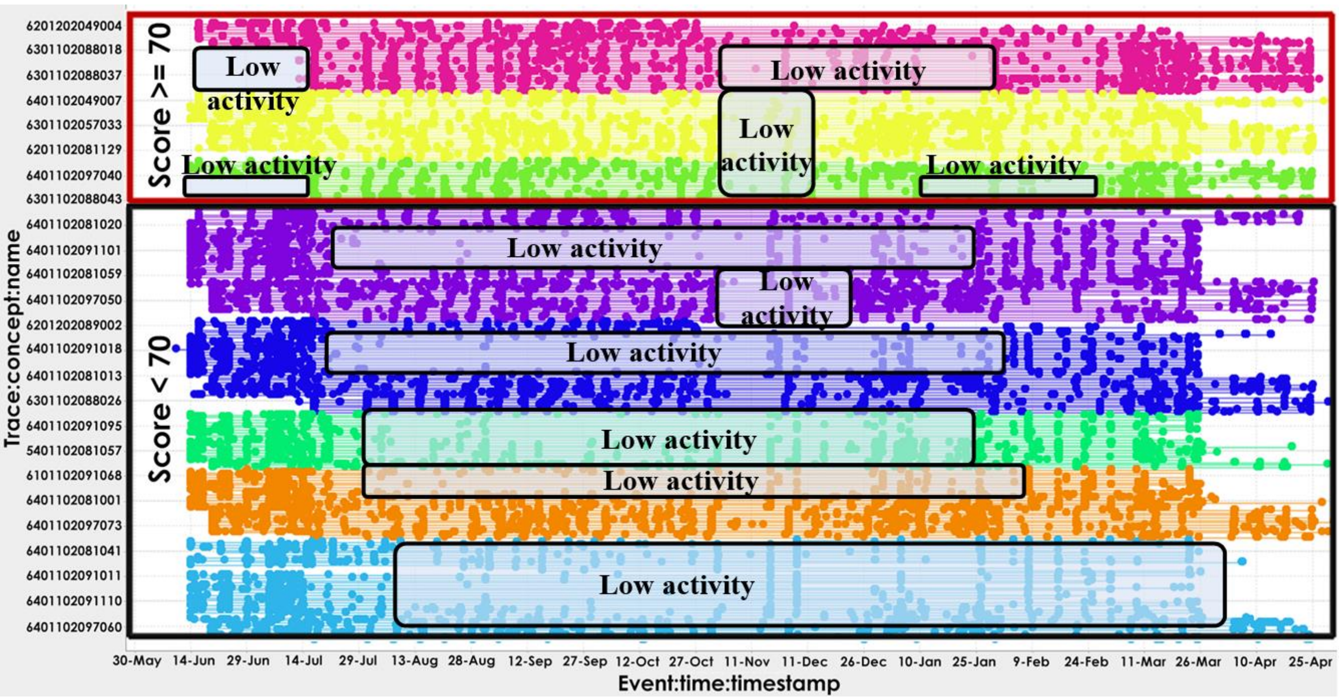


Fig. 13. Dot chart with students' activities through video material.

As shown in Fig. 9 and Table II, the sample groups were divided into two main groups of high performance and low performance, according to the final marks/grades obtained for everyone in the relevant course. The students whose grades were in "Good – Excellent" received scores ranging from 70.00 to 100.00 points. The students whose grades were in "Failure – Almost Good," received final exam scores ranging from 00.00 to 69.99 points. During the teaching and learning management process, we tested the knowledge of the learners with a formative score of 60 points and a summative score of 40, out of a total score of 100 points, including a range of scores to cluster/group of the students' grades, as shown in Fig. 9 and Table II. Group 1 had 74 individuals, representing 37,637 of Events or 29.96% of the total number of events. The second group comprised 173 individuals, representing 70.04%, and 47,677 Events occurred. We assessed exported event log data in filtered exs format with Disco tools for analysis with a dotted chart using ProM tools [32] to assess the variation in activity frequency to compare the learning behaviors of the samples. The frequency of attendance differed by the group, observed from the frequency of the point and continuity of entry points, as shown in Fig. 13, which shows the dot chart generated for the activities involved in LMS login, video access (20 learning topics), and exit. The LMS system in the chart shows each student's session corresponding to the number of cases (an instance of the process) as a horizontal line. There are 247 lines: one line represents the activities of on student. The dots in each line represent video tracking from the beginning to the end of the semester. The color of the dots indicates the difference in the student's grades. (See Table II for color grades.) Gaps between the dots indicate the frequency of the student's access to the video material. In the presented chart, X Axis Attribute Equals Event:time:timestamp, Y Axis Attribute equals with Trace:concept:name, and Trace Sorting equals with Sort on Grade of trace, and Color Attribute equals Trace:Grade. Group 1 (i.e., including students with Scores >=70) indicates continuous learning behavior starting from the beginning of the course until the end of the semester, and the frequency of the point is thin for a short period of time. For the second group, the frequency of the point in each row is dense only at the beginning of the semester and near the end of the semester. The frequency of the point is distant. and leaving a longer period than group 1 (i.e., including students with Scores >=70), indicating that group 2 (i.e., including students with Scores <70) had no continuity of learning.

TABLE II: DISTRIBUTION OF THE RANGE OF SCORES ASSOCIATED WITH STUDENT LEVEL

Score range	Grade	Significance	Student	Color
100.00 - 80.00	A	Excellent	28	Pink
79.99 - 75.00	B+	Very good	19	Yellow
74.99 - 70.00	B	Good	27	Green
69.99 - 65.00	C+	Almost good	37	Purple
64.99 - 60.00	C	Fair	45	Blue
59.99 - 55.00	D+	Almost Fair	28	Light green
54.99 - 50.00	D	Poor	22	Orange
49.99 - 00.00	F	Failure	41	Light blue

VI. CONCLUSION AND DISCUSSION

The aim of this research was to study the process of using the e-learning system from the event log data of the sample group. We found that the event log data in the el_logstore_standard table of LMS Moodle and newly created event log data in the logstore_video table can be utilized to analyze learning behaviors through e-learning systems by using process mining techniques to show the statistics of the activity. The process mining techniques used in this study to analyze the collected event log data can indicate the frequency of the students' activities, the amount of time spent between the activities, the repetition of the activity, the description of the relationship, and the connection of activities that occur in each activity throughout the learning process. Therefore, every educational institution that uses the LMS Moodle as an online education management tool can leverage the event logs discussed in this research to explore the learning process of the sample for decision-making in online education development planning.

The method of integrating data from the event log data of LMS Moodle and the newly created event log data of the plug-in for storing the behavior of clicking the video demonstrated that data can be combined by creating triggers embedded in the database system. The focus was recording events and updating data in the five main tables, el_logstore_standard, logstore_video, el_assign_submission, el_quiz_attempts and el_question_attempt_steps, that stored the activity data via the e-learning system for the Trigger to send the data and save it in the AllEventLogs table in real-time. As shown in Fig. 9, component is designed by means of the denormalized technique to record and query data quickly to have little impact on system processing compared with extracting data from many tables using the queries method. This approach and method are aligned with the database design recommendations mentioned in the research "Evaluating partitioning and bucketing strategies for Hive-based Big Data Warehousing systems" by E. Costa *et al.* [27], including denormalized tables that are effortlessly exported to a CSV file, allowing event log data to be imported to be immediately used for analysis with process mining techniques.

By analyzing the event log data using process mining techniques with the Disco and ProM tools, we discovered the learning behavior of the students from clicking menus to accessing various activities created by the instructors in the e-learning system. This research focused on finding a method for monitoring learning behavior through video media based on the recommendations of 103 instructors at Thonburi University who participated in the training and used the e-learning system. As shown in Fig. 10, the sample group logged into the system (247 individuals). The sample group clicked C6.1 to enter the video displaying a page on Lesson 8 (55 individuals). The system saved behavior data as a starting point to enter the lesson. When the sample group clicked on the C6.2 Play video, the system began recording their behavior as Watch Video, an activity demonstrating authentic video learning. Only 48 individuals (19.4%) clicked on the C6.2 activity. Seven individuals (2.8%), after clicking C6.1 on the video page, left the video page open without performing any activity. The frequency of those who participated by playing the video, pausing the video, and seeking video activities was low. If instructors are aware of learners' learning behavior from the discovered process, they can adopt it a guideline for adjusting learning policies and teaching conditions or setting learning objectives to encourage the continuity of learning [4]. Acknowledging the learning objectives plays a significant role that results in learners' effort and motivation to learn online under online learning, not independently [5]. Therefore, the method of creating event log data in this research can be applied in the analysis to find the in-depth online learning process through the e-learning system, as well as searching for the learning process through video media, entering the exercises, and entering the test.

From the comparison of online learning behavior with e-learning via video media, we observed that the learning processes of the two groups varied in the frequency of the learning behaviors. The sample group with continuous self-learning tended to score higher on tests than those who attended intermittent classes, which aligns with the Behavior Analysis of Students in Video Classes research by Francisco Genivan Silva *et al.* [31]. Thereby, to adjust the learning policy or set learning conditions in the e-learning system, the instructor should focus on the requirements for learning through video media or other appropriate teaching media, such as which topic, exercise, or test learners will submit. The system must first examine whether the learners have learned the teaching materials according to the specified conditions to cultivate self-directed learning by allowing the system to be the driver and encourage continuous learning.

VII. Limitations and Future Work

Despite proposing the idea of analyzing the students' video-watching behavior while they participated in an (authentic) online e-learning experiment, the research has various limitations:

Investigation and analysis of students' behavior while watching videos on an online platform is not the only (and not the most effective) means of evaluating their performance. Many other indicators and elements should be considered and investigated to improve the quality of learning, teaching, curriculum design, and managerial developments at institutions.

In this study, only two process mining techniques, namely, fuzzy miner and dotted chart techniques and algorithms, were used and applied to the collected dataset. Many other data mining techniques, such as Alpha miner, Heuristic miner, Social Network analysis, association rule mining, and association rule mining, can be considered for similar purposes.

In this course, 247 students (a limited number) enrolled in the course due to reasons discussed in the methodology part of this study. To improve the coefficients of accuracy, precision, recall, and F1-score, in the future, a larger sample of students/target audience is needed that is not limited to only one course and one learning environment.

The experiment was conducted during the COVID-19 pandemic; thus, the impact of COVID-19 on the research results is unclear.

In our further research, we plan to investigate the video-watching behavior of students by using different process mining techniques in different venues and subjects/courses through versatile scenarios, to improve the accuracy and precision of the results.

Conflict of Interest

The authors declare that the current work has no conflict of interest with other research, person, or identity.

Author Contributions

Anake Nammakhunt has developed the main concept of the research by designing a method for collecting data, pre-processing data, running, and implementing the tests and scenarios. Parham Porouhan contributed to the analytical interpretation of the findings, results, and discussions of the study. Wichian Premchaiswadi contributed to the conduction of the research methodology and supervision of the research throughout the study.

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