ICIC Express Letters
Part B: Applications
Volume **13**, Number **11**, November **2022**
 ISSN 2185-2766
pp. 1155–1164

LEARNING BEHAVIOR VISUALIZATION OF AN ONLINE LECTURE SUPPORT SYSTEM

Jaruwat Pailai[1] and Warunya Wunnasri[2,*]

[1]Department of Computer and Information Science
Faculty of Science and Engineering
Kasetsart University
59/5 Moo1 Chiangkrua, Muang Sakon Nakhon, Sakon Nakhon 47000, Thailand
jaruwat.pa@ku.th

[2]Department of Computer Science
College of Computing
Khon Kaen University
123 Vidhayavibaj Building, Mitraparp Road, Muang Khon Kaen, Khon Kaen 40002, Thailand
*Corresponding author: waruwu@kku.ac.th

Received March 2022; accepted May 2022

Abstract. *Online learning is a primary strategy for learning during the COVID-19 pandemic, which takes advantage of the physical distancing and contactless among lecturers and learners. Technology-enhanced learning is widely utilized over the Internet, while the demand for video communications applications has increased as a crucial tool for education. Even the video communication application supports to create a virtual classroom environment instead of an onsite classroom, the learning behavior is invisible. In this paper, an online lecture support system for visualizing the learning behavior is proposed. The system can provide learning materials as similar as the traditional lecture. The system allows learners to access the learning materials and take their notes in class period and overtime. Moreover, the system can visualize the learning behavior regarding the number of visiting and re-visiting of each material. The spending time is calculated to illustrate the learners' engagement in the course. The word cloud is generated by using note-taking of learners to visualize the recording information. Furthermore, the clustering of learning behavior was conducted for demonstrating the pattern of behavior in the online lectures. The system can inform the learning behavior to the lecturers, which describes how their learners learn in the virtual classroom.*
Keywords: Lecture support system, Online learning, Learning behavior, Behavior visualization

1. **Introduction.** Social distancing is a primary policy to prevent the spreading of coronavirus during the COVID-19 pandemic, and online learning is applied for distancing learning instead of general lecture in a classroom. Many technologies were utilized to enhance learning before the emergence of the COVID-19 pandemic, but the coronavirus pandemic has stimulated and forced educators worldwide to change their ways of learning activities. For instance, the alternative approach of online learning is Massive Open Online Courses (MOOCs), which are open-access online courses for providing education to learners who are separated by distance and in which the pedagogical material is planned and prepared by educational institutions [1]. On the other hand, the Learning Management System (LMS) facilitates learning material management. The activities on LMS are collected as the information for representing the learning behavior, identifying the engagement of learners, and finding a valuable insight learning process [2,3]. All learning materials are digitized in the form of files such as lecture slides, lecture videos, and

DOI: 10.24507/icicelb.13.11.1155

assignment statements. Meanwhile, several video communication applications are also utilized to facilitate lecturing and attending a virtual classroom over the Internet. However, the learning behavior of learners is invisible such as how the learners spend the time on the learning materials during the class period or what is the recording information of each learner when the online lecture was conducted. The supporting tool for education is required not only for facilitating the lecturer but also required to gather the learning evidence for visualizing and describing the learning behavior of learners.

In this paper, we propose the online lecture support system for facilitating the lecturers and learners when the traditional lecture was conducted in an online virtual classroom. The primary goal is facilitating the lecturers to provide each course's learning materials to their learners, while the system allows the learner to take notes of what they want to record in each learning material as similar as a note-taking function. The note-taking function encourages the self-monitoring of learners, which leads to increase motivation and participation [4,5]. Subsequently, the interactions of learners on the system are collected for visualizing the learning behaviors and informing the lecturers. The number of visiting and re-visiting of each learning material is counted, while this system calculates the spending time on each learning material. The note-taking of learners is processed to generate a personal word cloud. This information represents the general overview of the class. The learning behavior information is visualized in the system for informing the lecturers as the overview of their online learning class. The visualized information encourages the lecturers to recognize a better sense of learners in the class.

The remaining details of this paper are organized as follows. Section 2 reviews related work of learning platforms and note-taking applications. Section 3 describes the design of the online lecture support system, while Section 4 demonstrates the collected learning behaviors via the system and the discussion. Lastly, Section 5 makes the conclusions.

2. **Literature Review.** Online learning is designed to support distance learning as an alternative learning approach, which is available anywhere and anytime on the Internet. MOOCs have entered the mainstream of distance learning or distance education, which emerged as a popular learning mode since 2012 [6,7]. Especially, MOOCs have reached a broader population with wider interests during the COVID-19 pandemic [8]. The enrollment is a primary procedure of access authorization, in which the users must register and enroll in their interested courses. There are several MOOCs available worldwide on platforms for online courses such as Coursera [9] and edX [10]. For Thai learning contents, there are many available MOOCs such as Chula-, CMU-, and PSU MOOC [11-13]. The LMS is mainly used to manage the learning materials and collect learners' interactions on the system. There are several available modules such as authoring, browsing, presenting, and analyzing [3]. However, the analyzing or monitoring module still needs to improve for understanding the e-learning environment's activity in depth [4].

The video communication applications are widely used for business conferences and group meetings, which are also adapted to enhance learning as a tool for creating a virtual classroom or an online learning class. Many video communication applications are available for utilizing to produce an online classroom, such as Cisco Webex [14] and Zoom [15]. Moreover, education suites are also available such as Google Meet with Google Classroom [16] and Microsoft Teams with SharePoint [17]. Accordingly, the most proper video communication application depends on the utilized objectives of users and available functions of the application.

The note-taking application is the tool that allows users to take their notes freely with or without media content. Several applications are available as note-taking applications such as Google Keep [18], Microsoft OneNote [19], Evernote [20], and GoodNotes [21]. In the learning aspect, the note-taking application should be linked to the learning material to create the relationship between the learning content and the learner's understanding for helping the learners to understand clearly.

The lecturers can utilize the abilities of those mentioned technologies together for creating a virtual classroom environment. Nevertheless, the ability to track learning behaviors might be unavailable from the video communication application. On the other hand, using the general online learning platforms in online learning might lose some interaction between the lecturers and learners. Accordingly, this paper proposes an online lecture support system that allows the lecturers to create their courses and provide the learning materials to their learners. The learners can access the learning material quickly and simply take notes to record the information on the concentrated learning materials. Moreover, the learning behavior information will be promising information that can be applied to describing the learning style based on the evidence from the supporting tool. The lecturers can investigate the learning behavior and adapt the information to empower the suitable teaching strategy.

3. **Methodology.** The usual onsite classroom is lecturing in an actual classroom with prepared learning materials. Thus, the basic functions of the online lecture support system should facilitate the lecturer to provide the learning materials to his/her learners, while the system should also facilitate the learners to access the learning materials readily. Accordingly, the online lecture support system is developed for educational purposes and aims to visualize the learning behavior of learners from the online lecture classes. The user interface is designed with the simplicity concept and user friendly for facilitating the learners to access the learning materials. On the other hand, the system automatically gathers the learning behavior to visualize the information and inform the lecturer. Figure 1 demonstrates the system architecture and the available functions of the online lecture support system. The left-hand side of Figure 1 shows available functions for the learner role where the user can access the system by using the prepared specific link address or prepared quick response code of each class. Subsequently, the user can log in to the system by using their educational email account for accessing the learning materials and individual analyzer. The system allows the learners to take notes on each learning material. The right-hand side of Figure 1 presents the available functions for the lecturer role where the users can access learning material management, learning behavior visualizer, and individual visualizer. The procedure of the online lecture support system comprises

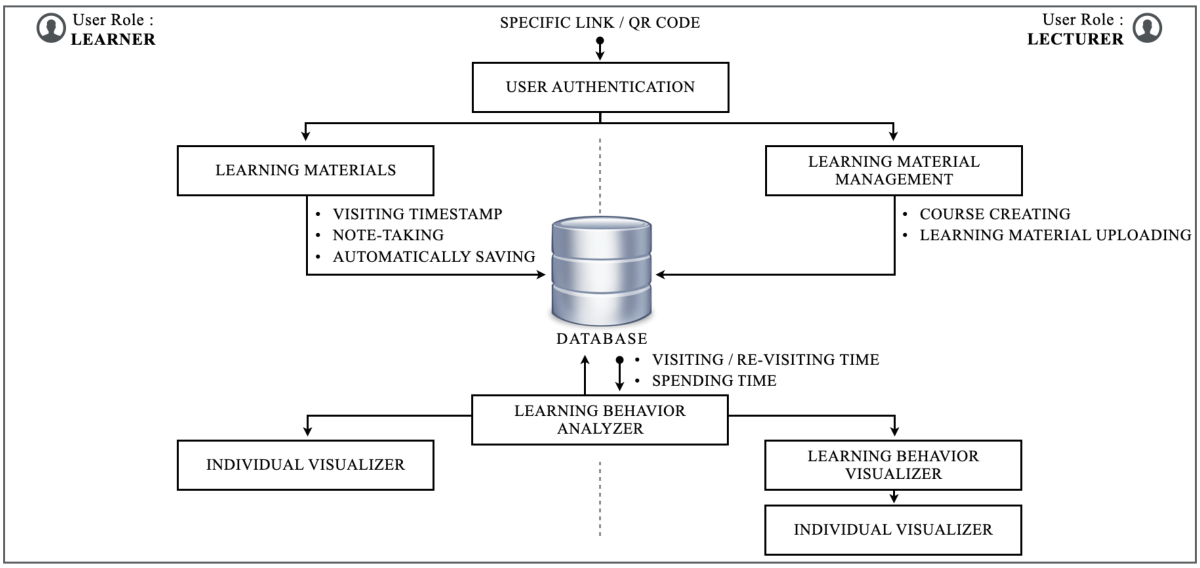

Figure 1. The system architecture of the online lecture support system

three steps. First, a lecturer creates a class and uploads his/her learning material. Next, the learners can access the learning material via the system by using a specific link that is generated after the lecturer uploaded the learning material. Lastly, the learners access each page of learning material and take notes during lecturing or later on each material. Moreover, the system allows on-demand access to learning materials. Figure 2 illustrates the user interface of the learning material viewer where the learning material is displayed on screen, while the learners can control the material viewer by themselves and take notes on each page of the learning material.

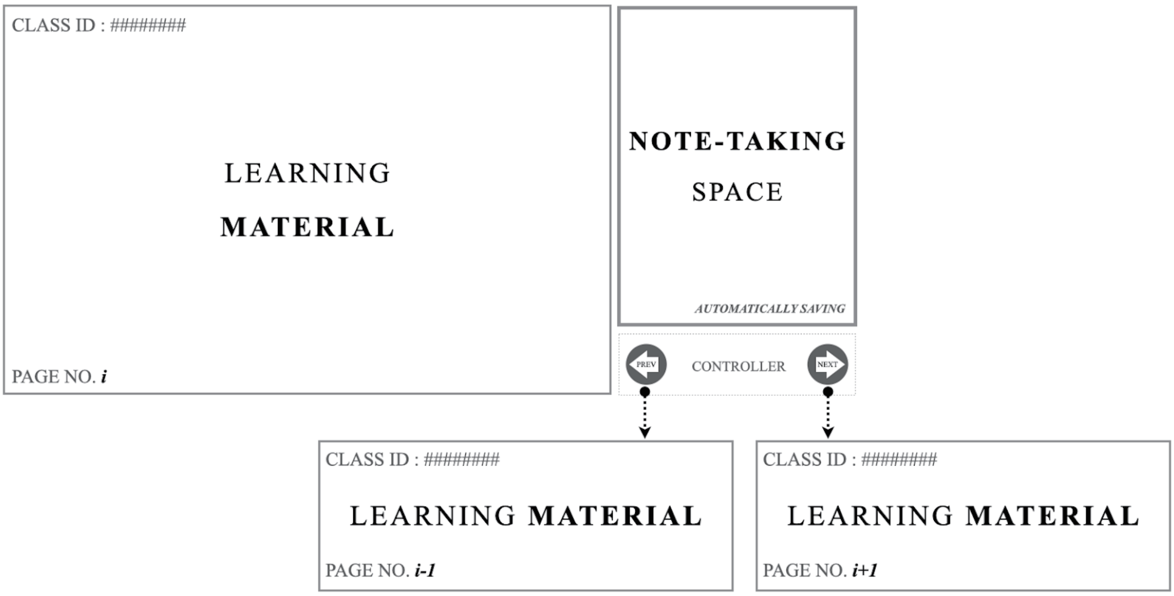

Figure 2. The illustrator of the learning material viewer

The design of the online lecture support system aims to encourage the learner to access the learning material rapidly and take their notes comfortably. The interactions of learners on the system will be automatically collected as the learning behavior whenever they access the learning material. In addition, the system asynchronously stores the accessing timestamp and the note-taking of the learner every thirty seconds of each concentrated learning material.

The learning behavior visualizer of the online lecture support system illustrates the number of visiting time, re-visiting time, and spending time on each learning material. The note-taking of each learner is segmented into word token form for counting its frequency and displaying in the form of the word cloud. The overview of learning behavior is displayed when the lecturers access the learning behavior visualizer, and the lecturers can also access the individual learning behavior of each learner.

4. Learning Behaviors and Discussion.

4.1. Data collection and preparation. The preliminary study of the online lecture support system is to collect the learning behaviors of 222 learners from three online lecturing courses and statistically analyze the collected data. The lecturers used the Google Meet or the Microsoft Teams for lecturing and uploaded the learning materials to the online lecture support system. The accessing logs of the system present that the accessing timestamp is 154,400 times and more than 1,278 spending hours on the learning materials. The number of note-taking is 1,457 records. Figure 3 presents the heatmap of the accessing percentages from the accessing timestamp for demonstrating the accessed days and accessed times on the learning materials from learners. The accessing percentage means the number of accessing timestamps at that period per the total number of all timestamps.

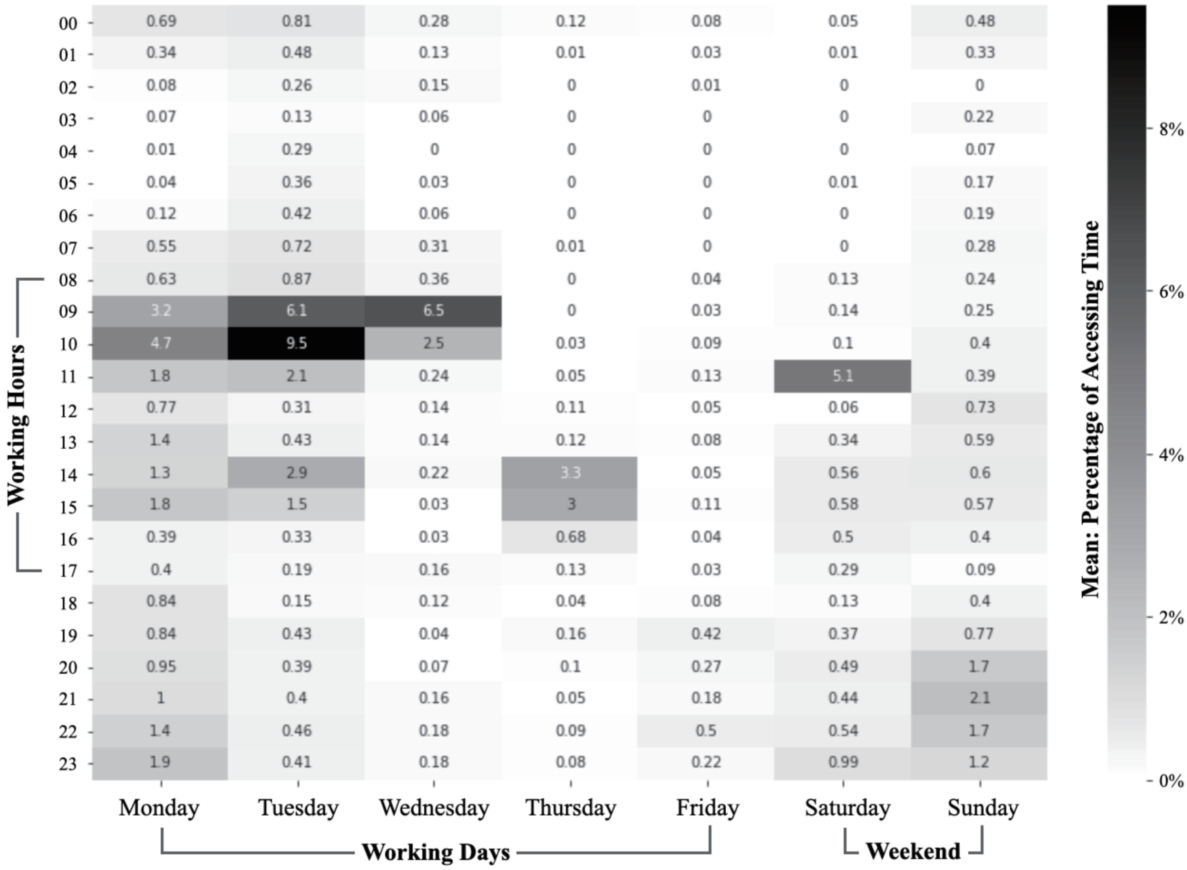

Figure 3. The heatmap of the accessing timestamp

The working days gained the main proportion of accessing percentage in the working hours regarding the lecture time of each course. The heatmap visualizes some accessing percentages on the non-working hours, especially after 5 P.M. on Monday. On the other hand, the accessing also occurs on the weekend. The highest accessing percentage on the weekend is during 11:00-11:59 A.M., while the accessing percentages are distributed almost all time on Sunday. The information on the heatmap can be interpreted that the learners accessed the materials during the lecture times and whenever they desired again, even on weekends.

Consequently, the accessing timestamps on the learning materials can be classified into visiting time and re-visiting time. The visiting time is the first time that the learner accessed each learning material, while the re-visiting time means the accessing timestamp of each material after its first time. The classified result indicates 42,354 visiting times and 112,046 re-visiting times from all accessing timestamps. Furthermore, the learning material accessing timestamps are calculated to represent the spending time on each learning material as additional learning behavior information. The sequence of accessing timestamps is gathered when the learners control the learning material viewer and is asynchronously collected every 30 seconds when the learners concentrate on the screen. The difference of accessing time between two continuous pages indicates the spending time of the last visited page. The number and average values of learning behavior are presented in Table 1. The number value of course A presents sixty-six learners who are able to access 183 pages from 8 chapters of content. The average value of course A represents 170.61 visiting times and 647.59 revisiting times. These average values demonstrate that the learners of course A accessed almost all pages of the learning materials, and they re-accessed the material more than three times on average. The average spending time of course A illustrates that the learners spent their time on each learning material around

TABLE 1. The number values and average values of learning behavior

Course	Number value			Average value		
	Learners	Chapter/ Page of materials	Note-taking	Visiting time	Re-visiting time	Spending time
Course A	66	8/183	834	170.61	647.59	135.18
Course B	23	8/180	623	103.04	391.69	175.20
Course C	133	11/220	0	215.97	453.35	84.19

135.18 seconds per each accessed page. The number value and the average number of course B present 23 learners access around 80 percent of 130 pages of the learning materials. They re-accessed the material more than three times, similar to the learners of course A, while they spent 175.20 seconds per accessed page which is more than course A. The 133 learners accessed 98.17 percent of 220 learning material pages from 11 chapters of course C. They re-accessed the learning material two times on average and spent 84.19 seconds per accessed page, which are less than the learners of courses A and B.

Following the process mentioned above, the attribute of data contains six features as the following: 1) the id of course, 2) the chapter of course, 3) the page number of each visited material, 4) the id of learner who accessed the material, 5) the spending time on each page of each learner, and 6) the number of notes on each learning material.

After investigation, there are no duplication records and missing values. Accordingly, this data is ready-to-use for descriptive analysis. For the data preparation of the clustering process, the data was separated into three pieces based on the course's id. The record of separated data was grouped by the learners' id in the following process for finding the average of their spending time and the average number of their notes. Then these two attributes were normalized by using standardization.

4.2. **Descriptive and diagnostic analysis.** Figure 4 demonstrates the learning behavior visualizer of the lecturer role. The number of all accessing timestamps, visiting time, re-visiting time, and word cloud are visualized in this function. For instance, the upper block represents the learning behavior information of the learner who got the excellent level of class. The number of accessing timestamps is 2,463, the visiting time is 100 percent that means this learner accessed all materials, and the number of re-visiting time is 2,280. In contrast, the lower block represents the learner's learning behavior information

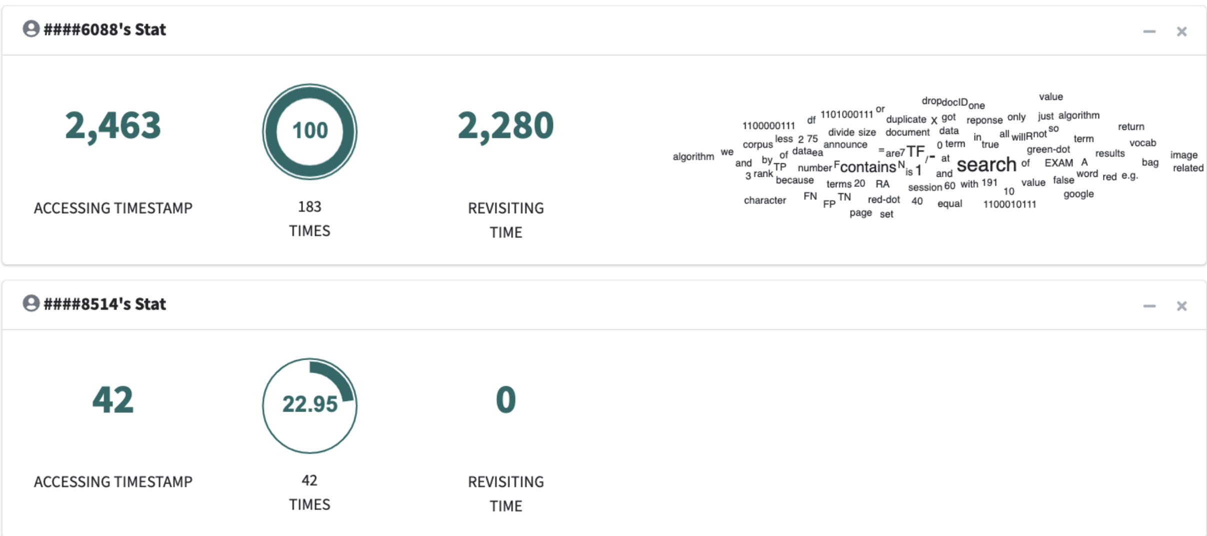

FIGURE 4. The example of the learning behavior visualizer

who got almost underperforming in class. The visualizer illustrates low numbers of accessing timestamp, visiting time, and re-visiting time, while the learner's note-taking is empty.

This preliminary study collected the logs of transactions from three online lecturing courses: courses A, B, and C, in which the first two courses are lecturing classes while the last one is a laboratory class for practicing learners' skills. In discussion, three main viewpoints are focused. The first focused viewpoint is the number of accessing time on the learning materials, and the second focused viewpoint is the learners' spending time on each learning material. The last is the number of notes that learners took during their studies.

Figure 5 comprises three comparative bar graphs regarding the average value of accessing time, spending time, and the number of notes, respectively. Figure 5-G1 shows the average of learners' accessing time on each course. This graph displays that the learners from course A used a lot of their attention to access learning materials. In comparison, the learners from course B accessed the materials less than the others on average. In Figure 5-G2, the graph represents the average of spending time. The learners of course B spent their time on the learning materials higher than course A and course C. Lastly, Figure 5-G3 illustrates the average number of notes in each course. There are no notes from learners of course C that means learners ignored note-taking. The reason might be that the contents are laboratory learning materials. The course B's learners took notes more than course A's dramatically.

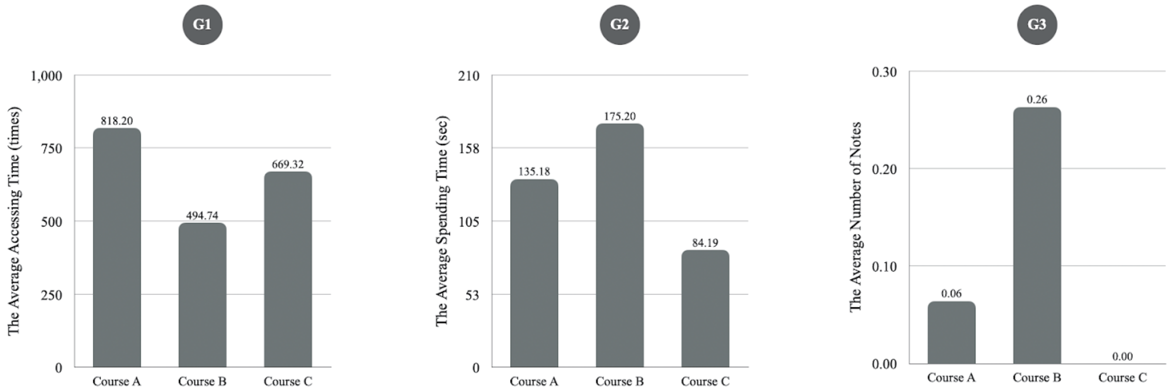

FIGURE 5. The average of learners' accessing time, spending time, and the number of notes of each online lecture course

This group of comparative bars presents the highest average value of the accessing time (Figure 5-G1) denotes to the learners of course A. However, its average spending time (Figure 5-G2) and the number of notes (Figure 5-G3) are less than B's. These results correspond with the situation that learners of course B had more engagement on the materials and took notes. In other words, the learners of course B might find it challenging to take notes on the complex content they tried to understand, which affected their average number of notes. In addition, the learners of course B took their average spending time longer than the learners of course C. The situation can be assumed that the course B learners had more engagement on the content of the course while the course C's learners interpreted the learning materials, which are the sort of practice instruction.

Based on the behaviors of learners, the average of spending time and the number of comments are utilized for analysis. The data is transformed into the vector of data and is used to calculate distortion which is the sum of squared distances to centers. Then the distortions of each number K of learners' behavior clusters are plotted to a line in a graph. The line graph is used to determine the optimum number of learners' behavior clusters by using the rapid change, which creates an elbow shape [22]. From this step, the elbow method shows the result as four clusters. K-means clustering is the algorithm to compute the centroid of the cluster and then repeats the process until finding the optimal cluster. It is applied to 66 learners of course A, which are grouped into four clusters. A silhouette score is the ratio of intra-cluster and nearest-cluster distance, which is used for examining clustering quality [23]. The silhouette score of this clustering is 0.4022 which means the quality of this clustering is acceptable. The learners' clusters are shown on the left-hand side of Figure 6. For profiling each cluster of learners, the categorized features are investigated. The first cluster contains the learners who did not pay much time on the learning materials and rarely took notes. The learners of the second cluster also rarely took notes but they took the time with the learning materials more than the former. The learners in the third cluster represent the characteristic that they used the time and took notes at an average level, which is different from the last cluster that took much time and took notes on an average.

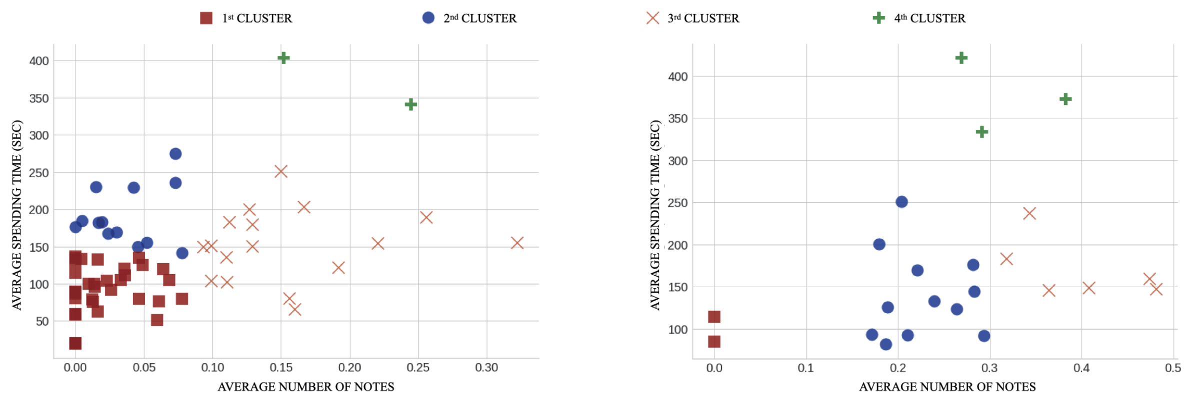

FIGURE 6. The clusters of learners in courses A and B from K-means clustering

By utilizing the same procedure of course A, the K-means clustering technique groups the learners of course B into four clusters which are illustrated on the right-hand side of Figure 6. The silhouette score of these clusters is 0.4710, which represents the well quality of these clusters and does not have critical overlapping. Learners' behavior in course B is rather different from course A even though the lecture time is provided equally; most learners like to take notes more than the learners of course A. In this course, the number of notes is mainly used to represent the cluster. For the learners in the first cluster, they did not take notes, and they took time for learning material shortly when compared with the others. The learners in the second and the third cluster took their time on the materials in the same range, but the third cluster preferred to take notes more than the former. On the other hand, the learners in the last cluster have unique characteristic. They took much time to understand the learning materials and took notes on average. Following these learners' behaviors, even they were shallowly analyzed, they can be utilized to improve the functions to support learners' studies based on their learning styles.

Nevertheless, there are some interesting research questions that the learning evidence of the system cannot describe clearly, such as the relationship of active learners' percentage on each chapter and the relationship with the number of materials' pages. Figure 7 represents the relationship of the percentage of active learners with the chapter of course as shown on the left-hand side. The decrease of active learners was noticed at the fifth chapter of course C and the last part of all courses. The right-hand side of Figure 7 illustrates the Pearson correlation coefficient which contains the relationship between the number of active learners and the number of materials' pages of each chapter in the course. The correlation values denote 0.30, 0.83, and 0.41 from courses A, B, and C, respectively. These values show the differences which might depend on the environment of each class. These

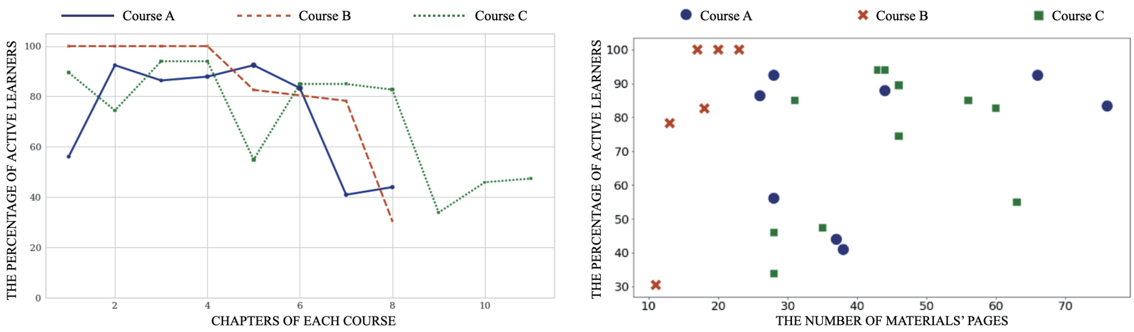

FIGURE 7. The relationship between the percentage of active learners and each other two attributes

questions require more in detail investigation with a class diagnosis from the lecturer's viewpoint regarding an objective of the class.

5. **Conclusions.** The online learning is suddenly required due to the COVID-19 pandemic. The online lecture support system is proposed for filling the lack of learning behavior visualization, when the video communications applications are utilized to create a virtual classroom for online lecturing. The lecturer can upload the learning materials, and the learners can access the learning materials via the system. In addition, the note-taking function is available to learners. The interactions of learners in the system are collected as the learning behavior regarding the accessing timestamps. The accessing timestamps can be classified into visiting time and re-visiting time. The spending time is also calculated by using the accessing timestamps. Afterward, the visualizer retrieves the learning behavior information to illustrate the number of each information, and generates the learner's note-taking word cloud. Furthermore, the learning behavior information can be used to demonstrate the characteristics of each course. For instance, the average of learners' accessing time, spending time, and the number of notes are information to imply the engagement of learners. The characteristic of each learning style is also determined by using the learning behavior information, which is promising valuable information for choosing the appropriate teaching method of each different learning style.

In future work, the learning behavior analysis will be applied in detail to supporting learners and lecturers on the online lecturing course. The other note-taking techniques will be considered for eliciting the learning behavior such as concept mapping or graphical drawing. Furthermore, the observing evidence on the system can be automatically visualized for illustrating the positive and negative current learning situation in the class. The learning information is possible to contribute the effective actions of the lecturers.

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