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An Analytics-Based Approach to Managing Cognitive Load by Using Log Data of Learning Management Systems and Footprints of Social Media

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ABSTRACT

Traces of learning behaviors generally provide insights into learners and the learning processes that they employ. In this article, a learning-analytics-based approach is proposed for managing cognitive load by adjusting the instructional strategies used in online courses. The technology-based learning environment examined in this study involved a video conferencing system and learning management system (LMS) for hosting course content and discussion forums. The social networking software Line was used to enhance the social presence of learners. Students (N = 869) enrolled in a summer course participated in a 9-week experiment. Their LMS log data and social media footprints were recorded, and content experts assessed the intrinsic cognitive load (ICL) of each content module through a consensus process. A learning analytics method was applied to identify candidate parameters relating learning behaviors to cognitive load. The instructor assessed the learners' cognitive processes and adjusted the instructional strategies according to the results of statistical, discourse, and qualitative analyses. Practical guidelines related to various cognitive load effects were designed to assist the students with managing their cognitive load by using learning behaviors and analytics data as signals for making a change in learning processes. Teachers of online courses can use the proposed approach as a support tool to identify learning problems and assist learners with maintaining a cognitive load that is conducive to learning.

Keywords

Cognitive load, Element interactivity, Cognitive load effects, E-learning analytics

Introduction

The cognitive processing capacity of human memory is limited, as discussed in the literature on limited capacity assumptions (Mayer, 2005). Students participating in online learning experience changes in their cognitive load over time. Instructional activities as well as the topics discussed on forums and the interaction during synchronous video conferences contribute to the cognitive load of online students. Cognitive load varies dynamically with the learning process. Paas and van Merriënboer (1994) proposed an instructional design model for providing instructional strategies for controlling cognitive load during training in complex cognitive tasks. Mental-effort-based measures were recommended as suitable tools for investigating and determining the cognitive load of instructional manipulations. In our research, an analytics-based approach was proposed for measuring and managing cognitive load. Measurements of cognitive load were associated with learning behaviors that were captured by learning management system (LMS) log data and social media footprints.

LMSs enable teachers to monitor online student learning through system-generated reports. Teachers may query the system to determine the amount of time that their students have spent browsing course content or the number of discussion forum posts to which they have contributed. The size and value of the log data from LMSs can be called a type of big data, as discussed by Snijders, Matzat, and Reips (2012). Theories and technologies have been developed to mine actionable information from big data in various application areas. In this research, we explored the possibility of using educational platform log data to manage the cognitive load of learners.

Managing cognitive load by using knowledge of learning behaviors and analytics computing

Cognitive Load Theory (CLT) is a psychological learning theory that has provided a basis for exploring instructional design and learning processes with human cognitive architecture (Sweller, van Merriënboer, & Paas, 1998; Sweller, Ayres, & Kalyuga, 2011). Three sources of cognitive load were identified in CLT: intrinsic cognitive load (ICL), extraneous cognitive load (ECL), and germane cognitive load (GCL) (Sweller et al., 1998). ICL is determined by the inherent nature of the learning material and learners' prior knowledge. ICL cannot be changed by instructional interventions. ECL is determined by instructional design, including how instructional content is designed and the activities required of learners. Sweller et al. (1998) described GCL as the effort involved in relating prior knowledge to current instructional content in order to construct schemas stored in the long-term memory. The three types of cognitive load are additive and contribute to a learner's global cognitive load that cannot exceed his or her cognitive resources. Otherwise the learning process will fail. On the other hand, learning is ineffective with no or low cognitive load. Although high ICL and ECL is detrimental to the learning process, GCL can help learners to construct schemas that are stored in long-term memory and can be retrieved later in learning or problem-solving. According to CLT, the aim of the instructional design is to reduce ICL and ECL, and to induce GCL while keeping the global cognitive load under the limit of learners' cognitive resources.

The level of ICL for a learning task is determined by the level of element interactivity and learner's prior knowledge (Sweller, 2010). An element can be a concept or a procedure that needs to be learned. Low element interactivity materials allow individual elements to be learned with minimal reference to other elements and impose a low working memory load. The concept of element interactivity can be used to explain why some material is difficult to learn or understand (Sweller, 1994).

Figure 1 illustrates the relationships among learning behaviors, log data, and students in a technology-based learning environment. In online courses, students are provided instructional material, a learning schedule, and learning activities. In following the schedule, students browse the course content and participate in course events and activities. Because all of these tasks are performed online, learner behaviors can be recorded as LMS and social network log data. In this research, we assumed that patterns in learning behavior indicate changes in cognitive load. Paas and van Merriënboer (1994) described the causal factors of cognitive load as characteristics of a task or those of the person performing the task. In our research, the tasks performed by learners include browsing course content, participating in asynchronous discussions and synchronous video conferences, and interacting through social media platforms. Completion of these tasks left traces in system log data, and these traces represent learning behaviors. To assess the cognitive load of learners, learning behaviors must be related to the assessment factors in such measurement dimensions as mental load, mental effort, and performance.

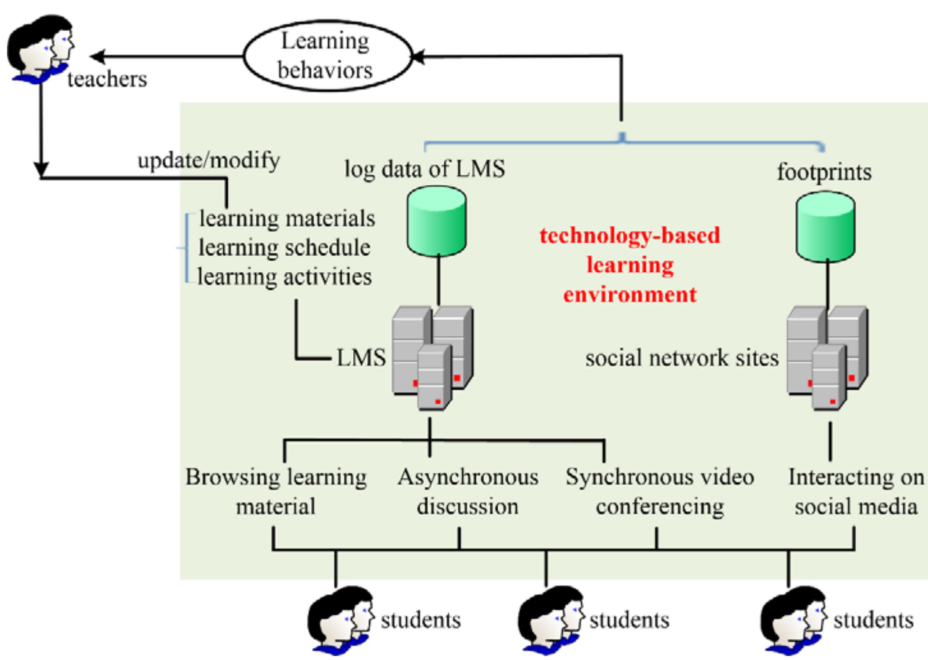

Figure 1. The learning behaviors, the log data and the students

The proposed approach is designed to assist online teachers with alleviating student cognitive load (which depletes mental resources) and enhancing students' GCL (which leads to effective learning). To achieve this goal, learning problems must be identified through feedback from analytics computing and instructional strategies must be modified to optimize the cognitive load. Technology-based learning environments facilitate computer-supported collaborative learning (CSCL). Bannert (2002) indicated that controlling cognitive overload is considerably more difficult when several learners are involved in the learning process (e.g., social learning scenarios in CSCL), possibly explaining why CLT-based assumptions are typically explored in individual learning scenarios. Because CSCL plays a critical role in online instruction, we considered scenarios involving multiple learners; which are common in asynchronous discussions and synchronous video conferences. We distinguished two views of cognitive load: micro and macro (Figure 2).

The micro view of cognitive load is focused on the cognitive load of individual learners. When log data are available, online teachers can use them as a guide to provide individualized assistance for learners. For example, if the log data show that a learner repeatedly browses the content of a certain module, then the teacher can attempt to identify the learner's problem and provide relevant assistance. Once the problem is solved, the learner's cognitive load regarding the content of the module may decrease sharply and his or her learning behavior may change (e.g., their browsing patterns may return to normal). On the other hand, the micro view of cognitive load can also be used by the learner for self-regulated learning. They may adjust the pace of learning to facilitate an internal management of cognitive load. Because the behavior of every learner is recorded in the system log, the parameters identified using analytics methods reflect learner group behavior. When these parameters correlate with learner cognitive load, they may provide an overall profile that explains the learning process.

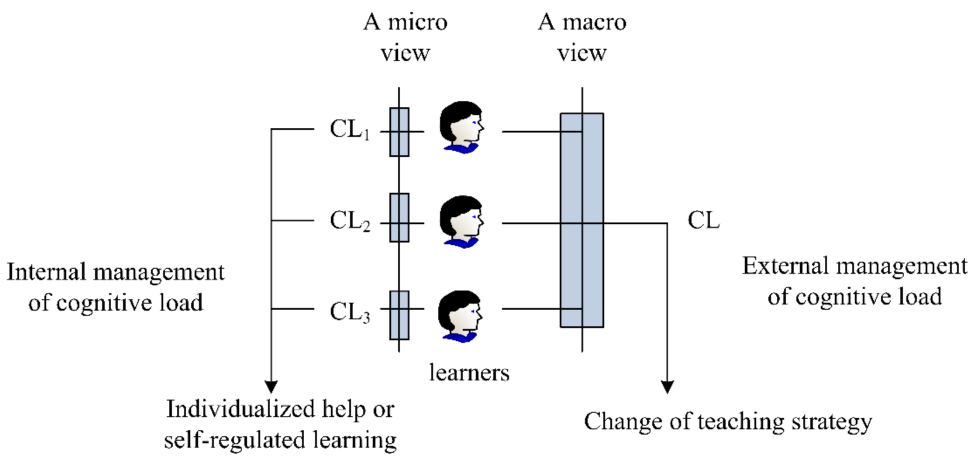

Figure 2. The difference between a macro view and a micro view of cognitive load

The macro view provides an overall assessment of the cognitive load of a group of students. The teacher can apply appropriate teaching strategies that affect the learning behaviors of the entire class to optimize learners' cognitive load. In this research, we focused on extracting information from log data to provide a macro view of learner cognitive load. An analytics approach was adopted to transform the log data into meaningful and actionable information.

Timing for assessing cognitive load and for making an instructional intervention

Cognitive load represents the resources used by working memory at a certain point in time. Previous studies have surveyed learners at the end of a learning period to assess their cognitive load for the entire learning period. To identify learning problems in a timely manner, cognitive load must be assessable at any moment in time. Van Gog, Kirschner, Kester, and Paas (2012) found that repeatedly measuring mental effort after performing individual tasks in a series was favored for tasks that take longer than usual to complete. If analytics computing can be used to relate log data with the measurement of cognitive load, then the notion of instantaneous load (Xie & Salvendy, 2000) can be implemented. The changes in temporal patterns of learning behaviors may be explained from the cognitive load perspective.

In this research, the ICL of the learning material was assessed by content experts based on an estimate of element interactivity. Under conditions of low element interactivity, instructional intervention to reduce ECL may have no appreciable consequences (Sweller, 1994). With the knowledge of the estimate of element interactivity, the timing for making a change in instruction can be adjusted to match the learning period when the level of element interactivity is high or when the temporal patterns of log data suggest a high global cognitive load.

Research goals

The approach proposed in this study provides a real-time analytics-based assessment and a macro view of students' cognitive load based on LMS log data. The design of the research imposed mental work on students gradually through a pre-planned learning organization. This study was conducted to identify the relationships among the learning behaviors, log data, and cognitive load of students. We also explored how adjusting teaching strategies affected student learning behavior and examined the corresponding changes in the log data and cognitive load. Solving these problems can facilitate controlling and managing student cognitive load at an optimal level throughout the learning period. With the knowledge of the students' learning behavior and their cognitive load, the instructional techniques based on CLT can be applied to achieve efficiency in learning (Clark, Nguyen, & Sweller, 2006; Sweller, et al., 1998).

Literature review

Management of students' cognitive load is the key to maintaining effective learning. To manage cognitive load, determining how cognitive load is assessed in CLT is essential. Cognitive load measurements must be correlated with the indicators computed from log data by using an analytics method. The students in this study were encouraged to engage in learning by using social media. The more actively the students participated in learning activities, the more log data were available for the analysis.

Measuring cognitive load with just-enough precision and in due time to spot learning problems

Cognitive load refers to the load imposed on a person's cognitive systems when he or she is engaged in a particular task (Sweller et al., 1998). To improve the learning process, CLT explains that instructional design should consider human cognitive structure and its constraints (Paas, Renkl, & Sweller, 2003). Cognitive load can be assessed by measuring mental load, mental effort, and performance (Paas & van Merriënboer, 1994). Wierwille and Eggemeier (1993) proposed three major categories of techniques for measuring mental effort, namely, subjective, physiological, and task- and performance-based indices. Each category incorporates numerous assessment techniques. Two classes of techniques for measuring the effort expenditure have been used in previous research (Paas & van Merriënboer, 1994): techniques that involve using subjective indices (rating scales), and those that involve using psychophysiological indices (e.g., pupil diameter, heart-rate variability, event-related brain potentials).

The level of ICL for a particular task can be determined by the level of element interactivity and learners' prior knowledge. Sweller (2010) provided an analysis of element interactivity associated with various cognitive load effects. It was also suggested that ECL and GCL can be defined based on element interactivity. In our research, the ICL was assessed by three content experts according to the element interactivity of the instructional material. We explored how learning behaviors change with the scheduled study of instructional material with varying levels of element interactivity. Pollock, Chandler, and Sweller (2002) developed a two-phase, isolated-interacting elements learning approach. Based on their findings, incorporating all the information elements required for understanding in the instructions may overwhelm a learner's limited working memory. Information was better learnt through the isolated-interacting elements instructional method for certain groups of learners. Clarke, Ayres, and Sweller (2005) explored the impact of the sequence in which the students learn on their performance. In our research, the course content was uploaded to the LMS in two batches. The students were asked to follow the announced schedule to browse the content. To select an appropriate instructional strategy, the cognitive load of learners must first be estimated. Although the estimate does not need to be precise, it should be readily available. By keeping the instructional activities relevant to the scheduled content, the estimated content ICL can be used as a rough estimate for part of students' mental load while they were participating in those activities.

Applying CLT-based instructional techniques in technology-based learning environments

CLT-based guidelines were used in the design of instructional material to enhance learning efficiency (Clark et al., 2006). Various instructional techniques also used CLT for instructional design (Sweller, et al., 1998). The availability of log data and the knowledge of learning behaviors allow us to be more confident on when and how to apply the various CLT-based instructional design in technology-based environments. The log data on browsing time provide clues on differential learning times. Darabi and Jin (2013) helped learners to make better use of their cognitive resources by providing example postings and controlling how the posts were displayed on one screen to reduce ECL. The level and quality of interaction in online instruction may correlate with the LMS log data and explain learning efficiency from cognitive load perspectives.

CSCL and collective working memory effect

Kirschner, Paas, and Kirschner (2009) indicated collaborative learning may be favored over individual learning for complex learning tasks due to a larger reservoir of cognitive capacity. Collective working memory effect was interpreted as an advantage of group learning in which information processing can be divided amongst the collective working memories of the group members (Kirschner, Paas, & Kirschner, 2011). Assessing cognitive load can facilitate the online adaptation of learning tasks in computer-based learning environments (Paas et al., 2003). In a collaborative learning environment, the concept of cognitive load needs to be extended to accommodate the situation of multiple learners and group behaviors. Because a major part of learning and instruction in technology-based learning environments is based on CSCL, the notion of collaboration load was explored by Dillenbourg and Betrancourt (2006). The effort by communicating learners to create, share, and interpret an external representation of argumentation increases the cognitive load. Various ways for managing cognitive load in CSCL were discussed in (Van Bruggen, Kirschner, & Jochems, 2002). The impact of collaborative learning in asynchronous discussion groups on cognitive processing was studied in (Schellens, & Valcke, 2005). The types of communications (task-oriented and non-task-oriented) were analyzed to explore learners' discussion behavior. Darabi, and Jin, (2013) designed strategies based on cognitive load theory to improve the quality of online discussion. Eryilmaz, Alrushiedat, Kasemvilas, Mary and Pol (2009) aimed to develop an understanding of cognitive load as a factor supporting or inhibiting students' participation in online asynchronous discussions.

Social media and social presence as a catalyst for interaction and participation

Social presence refers to a situation in which people communicate through media and are aware of the existence of other people (Short, Williams, & Christie, 1976). Social presence is a crucial predictor of learner achievement and satisfaction (Kim, 2011). Social media provide an open and cost-free platform for real-time interaction. Previous studies have shown that social media can facilitate improving the quality of interaction among learners (Lin, Lin, & Laffey, 2008; An, Shin, & Lim, 2009) and increasing the level of social presence (Hassanein & Head, 2007; Lin et al., 2008).

In this research, the social networking software Line was used to enhance the social presence of students. Students were invited to join Line groups at the beginning of the summer session. Several course activities were designed to exploit the instant messaging functions of Line. In this research, using social media was anticipated to facilitate learners' interaction and collaboration.

Learning analytics and learning behaviors

Siemens and Long (2011) defined learning analytics as the measurement, collection, analysis, and reporting of data on learners and the context of their learning, the results of which are used to explain and optimize learning and the environments in which it occurs. The behavior of learners is difficult to predict without using traces of their past behavior, and this is a critical concept in learning analytics (Yen, 2013). The importance of learning analytics lies in the information that can be extracted to facilitate improving the quality of online instruction. Collecting and analyzing learner contexts and learning profiles enables observing and realizing student learning behaviors and assisting teachers with adjusting their teaching strategies in a timely manner.

In online learning environments, interaction traces such as discussion forum posts and social media messages can be gathered. Bruckman (2006) indicated the log file data included the content of discourse that required manual inspection to retrieve valuable information. Clark, Sampson, Weinberger, and Erkens (2007) reviewed different analytics frameworks for assessing dialogic argumentation in online learning environments. The posts by learners in discussion forums were coded and analyzed by analytics methods. Dyckhoff, Zielke, Bültmann, Chatti and Schroeder (2012) implemented a learning analytics toolkit to support the iterative process of improving the effectiveness of their courses and to enhance their students' performance. Jo, Kim, and Yoon (2014) analyzed the log patterns of adult learners using learning analytics and found that an irregularity of the learning interval was proven to be correlative with and predict learning performance. Gibson, Kitto, and Willis (2014) proposed a cognitive processing framework for learning analytics. The data provided by analytics methods were used to explore the cognitive level of learners. Kalyuga (2007) indicated different types of interactivity provide means for managing various sources of cognitive load. An asynchronous communication environments allow learners to manage rate and amount of information processed at one time.

In this research, we adopted analytics computing to provide a macro view of student cognitive load based on an analysis of log data; this method is an objective approach for assessing cognitive load. However, finding evidence and a theoretical basis for correlating cognitive load with learning behaviors and log data is crucial.

Method

In this research, an LMS was used to host course content that students accessed through the Internet. The LMS also featured asynchronous discussion forums, where an online teacher assigned topics for discussion, and synchronous video conferences were held twice for the entire semester, with each conference lasting 2 hours. The research team was granted administrator privileges to access the log data containing the student learning profiles, including the time that they spent browsing specific content modules, login time, and number of posts that they made. The social networking software Line was used to enhance the social interaction among the students.

Research design

Figure 3 depicts an overview of this research. The four steps in Figure 3 indicate the main focus of this research. At Step 1, students learn through various types of virtual classroom; at Step 2, the learning process leaves traces of learning behaviors in log data that can be computed using e-learning analytics to derive actionable information; at Step 3, the online teachers verify the situation and adjust their teaching strategies on the basis of the derived information; and at Step 4, the adjusted teaching strategies affect the cognitive load of learners. In summary, the online teachers respond to the students' learning behaviors by adjusting their teaching strategies to optimize the students' cognitive load. The four-step cycle commenced only when the students were engaged in learning. When students did not participate in the learning environment, social media were used as a convenient tool to redirect them to the learning environment.

The following tasks had to be completed before the concept was implemented. First, we determined the type of useful information that was embedded in the log data and how such information could be transformed into actionable information. Second, we determined the effect of various CLT-based teaching strategies on the students' cognitive load. Finally, we monitored the students' learning behaviors to determine whether adjusting the teaching strategies optimized their cognitive load and improved their learning performance.

In determining the relationships among learning behaviors, log data, and cognitive load, we assumed that (a) the students had no prior knowledge. (b) temporal variations in the browsing behaviors of students are related to different types of cognitive load, (c) the level and quality of interaction in the asynchronous discussion forums are related to the students' cognitive load, and (d) the level of interaction in synchronous video conferences is affected by the various cognitive load effects.

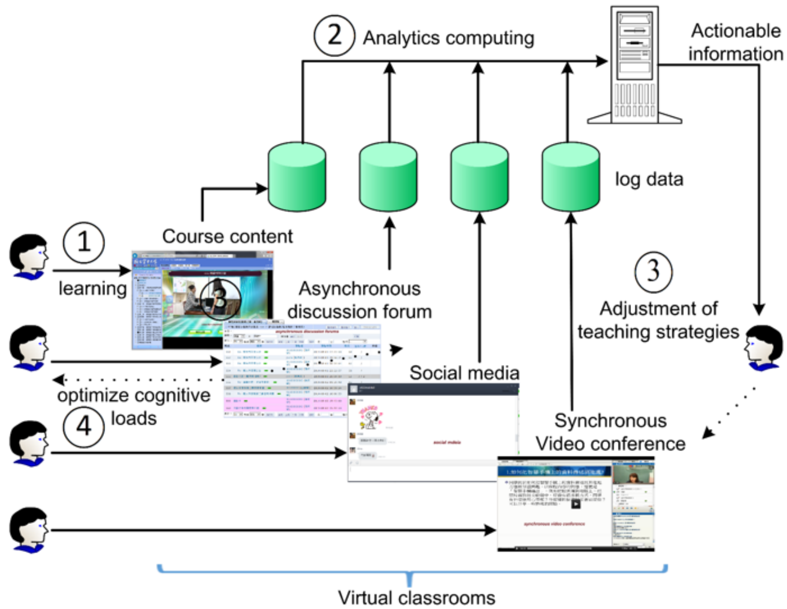

Figure 3. An overview of the scope of this research

Analysis of participants

The course "Smart Phone Operations and Applications" was offered as an online course in the summer of 2014 by the Department of Management and Information at National Open University, Taiwan. In total, 869 undergraduate students enrolled in the course, which was taught online by using digital content, asynchronous discussion forums, and two synchronous video conferences. Social media were used to enhance the students' interaction and social presence. Most of the 869 participants were female (64.5%). Most participants were aged 45–54 years (41.5%), followed by 35–44 years (32.3%), and most were adult learners that are graduates of senior high school (49.8%) and college (43.8%). Less than half (40.1%) of the participants had 1–3 years of experience with e-learning. More than half of the participants had become smart phone users before they enrolled the course.

Data collection instruments

The time each student spent browsing the content modules was automatically recorded in the LMS. The browsing time indicator, B-Time, is obtained from dividing the accumulated browsing time by the length of the module measured in the scale of time; e.g., if the accumulated browsing time of a module is 2 hours and the module takes 5 minutes to play to the end, the B-Time for this module would be 24 (module time). For each topic in the discussion forum, the number of views for each post on each day was recorded from the first day of the semester. To facilitate the analysis of the interaction in the asynchronous discussion forum, the density of posts (DP) is defined as the average of the total number of posts on that day, the preceding day, and the subsequent day. For example, if four, six, and five posts were made on 3 consecutive days, then DP = (4 + 6 + 5) / 3 = 5 (for the second day in that series). In related research, DP of a certain day was defined as the number of new posts on that day (Dringus & Ellis, 2010). Since the effect of the instructional events typically lasts for more than one day, we chose the 3-day average number of new posts to define DP. Whether the difference in the definition of DP affects the empirical results will be explored in future research. The increased number of views (IV) is defined as the total number of views for the posts on a certain date.

The messages on Line were saved as text files (one file per Line group). At the end of the semester, the students completed questionnaire surveys, which contained an assessment of ICL for the content of each module (rated using a 10-point difficulty scale), an assessment of ICL for every discussion topic (also rated using a 10-point scale), and instruments for measuring social presence (revised version of the questionnaire by Kim, 2011) and learning satisfaction (4 questions on instructional design and 6 questions on course evaluation). The pretest questionnaire comprising 20 multiple-choice questions was administered at the beginning of the summer session, and a posttest (also comprising 20 questions) was conducted at the end of the summer session.

Measurement of intrinsic cognitive load

The three content experts who taught the course and designed the content were asked to assess the ICL of the content of each module by using a 10-point scale, ranging from 1 (*very low level of element interactivity*) to 10 (*very high level of element interactivity*). The ICL was determined by element interactivity. The information recorded during the assessment process included element interactivity, element complexity, the number of elements, the type of the content (procedures, concepts, facts, processes, or principles), and the nature of the content (technical, theoretical, or practical). The assessment was not precise since we assumed that the students had no prior knowledge. Without the assumption, the estimate of element interactivity is unobtainable. Therefore, the explanation of the results should take this factor into account. The pretest was designed to evenly cover the entire course content. The pretest results were subjected to a Pearson's correlation test. The error rate correlated positively with the ICLs of the corresponding content modules with significance ($r = .447$, $p < .05$, two-tailed). In this research, the content modules with high element interactivity were the focus of the study. Under the conditions of high element interactivity, managing the cognitive load is critical to learning efficiency.

The differences in the assessment of ICLs among the content experts were resolved through repeated discussion and consultation with the grading tutors assigned to the course. The pretest results were reviewed along with the assessed ICLs in detail repeatedly. The aim was to ensure the assessment can be a reliable estimate of the mental load imposed by the content. The assessment process was designed to achieve expert validity. The ICL questionnaire was subjected to a reliability test. Because the Cronbach's $\alpha = .958 > .7$, the ICL rating scale questionnaire achieves high reliability.

Procedures

The course was taught without a textbook. Online multimedia content was produced for the course and was organized into ten chapters. The course content was uploaded to the LMS in two batches. The first batch comprised the first six chapters and the second batch comprised the final four chapters. The first and second synchronous video conferences were held in Weeks 4 and 7 of the semester, respectively. Five discussion topics related to the scheduled course content were announced in sequence in the asynchronous discussion forum. The time that each student spent browsing the content modules was recorded in the LMS log data. The number of views for each 24-hour period for every post was recorded at 10:00 A.M. daily. The students were invited to join Line groups that were set up by the teacher. The first synchronous conference was led by the teacher without offering any topics for discussion. Three discussion topics were announced for the second synchronous video conference. Approximately 10 min was allocated to each topic for the students to interact in the Line groups and in the LMS. The leader for each Line group was requested to summarize the discussions in his or her group. The teachers monitored the progress of the discussion in all Line groups and reported to the host of the video conference.

Adjustment of instructional strategies to manage cognitive load

Instructional control of cognitive load may be triggered by temporal variations in log data. The instructional strategies can be adjusted with the knowledge of the various cognitive load effects. A summary of how learners' cognitive load was managed in our experiment is listed in Table 1. Abnormal learning behaviors raised a signal to attract the teacher's attention. The signal must be verified to remove the possibility of a false alarm (Macfadyen & Dawson, 2010). At the beginning of the semester, the number of logins and B-time indicated whether learners had started to learn. The strategy at this stage was to encourage learners to log into the LMS and browse the course content. The content modules on which the learners focused their mental effort can be identified by the statistics of B-Time. By controlling the accessibility of the course content, the learners were directed to follow the learning schedule. Increased B-time of high element interactivity content may imply high CL. The teacher should review the discourse in the discussion forum and Line to spot learning problems and try to reduce ECL. The design of topics for discussion was a common strategy to direct students' attention toward effective learning. Low IV and low DP indicated the level of interaction in asynchronous discussion forums was low. The strategy was to encourage students to participate and interact with peers while ensuring the ECL or collaboration load was kept at a low level when element interactivity was also high. Although increasing the level of interaction may also increase the CL, effective learning induced by CSCL was expected to reduce the CL.

Table 1. The management of learners' cognitive load (when and how)

Learning behaviors reflected in logs or analytics	Possible implication	Suggested actions	Expected effect
Very low number of logins	Possibly no or low CL due to lack of learning activities. Possibly high CL due to learning difficulty. May be a false alarm if other learning data are normal.	Check the students' learning profiles and verify if they are far behind the learning schedule or have no online activities. Ask students to learn by direct contact or by reminders posted on social media. Help resolve learning difficulty.	The increase in number of logins, the increase in students' online activities, and variations in CL. Impose a proper amount of stress and CL could promote learners' cognitive performance.
Very low B-time	Possibly no or low CL. Possibly high CL due to learning difficulty. May be a false alarm; e.g., learners have related prior knowledge.	Identify the learning problem to decide the proper action. Announce reading assignments and quizzes to impose a proper amount of stress. Help resolve learning difficulty.	The increase in B-time and variations in CL. Learning difficulty resolved.
Low IV and low DP	Low collaboration load. Possibly no or low CL. Possibly high CL due to learning difficulty.	Encourage participation via intervention or social media. Intervene by providing sample replies or summaries. Help resolve learning difficulty.	The increase in participation, interaction and CL. The improvement in quality of discussion. Learning difficulty resolved and CL reduced.
Increased B-time	CL may be normal. Possibly high CL due to intensive learning.	Check whether the element interactivity is high. Take action to reduce ICL. Check whether there are sources of ECL. Take action to reduce ECL.	Browsing behavior back to normal. The reduction in ICL and ECL. The increase in GCL.
High IV and high DP	Non-task-oriented issues that lead to high CL. Task-oriented issues that lead to high ECL and collaboration load.	Resolve non-task-oriented issues; e.g., resolve conflicts. Provide a summary of task-oriented posts to reduce ECL. Spot and resolve learning problems by moderation or intervention.	The improvement in quality of discussion. The reduction in ECL. The increase in GCL.
High number of task-oriented posts in video conferencing	High ECL and high collaboration load.	Provide feedbacks and summaries.	The reduction in ECL and the increase in GCL.
High number of non-task-oriented posts in video conferencing	High ECL and high collaboration load.	Direct attention to task-oriented dialogue.	The reduction in ECL and the increase in GCL.

In synchronous video conferences, we focused on inducing students' GCL. The social networking software Line was used for group discussion. The strategy was to direct students' attention to task-oriented dialogue and encourage them to participate. Although the use of Line introduced another source of information that may impose high ECL, the learners' attention was directed to group discussions in Line instead of using the LMS's text module that was difficult to use and might induce high ECL. The arrangement of learning activities should consider the effect of high element interactivity; e.g., more instruction time and learning time was allocated to allow the activities of high element interactivity content to be interleaved.

Results

Assuming that learners had no prior knowledge, the three content experts assessed the ICL of the content modules based on the level of element interactivity. A questionnaire survey was conducted to determine the ICL of the course content from the students' perspective (also measured using a 10-point difficulty scale). The results of correlation tests of the cognitive load assessed by the teachers and that assessed by the students (Table 2) indicated that the correlation was not significant (p = .1). We speculate that ECL induced from learning material may be a factor for the difference in the assessment of cognitive load by the experts and by the students. Several students complained that the streaming video content for smart phone operations was not easy to follow. They had to stop the video, tried on their smart phone, and started the video again several times. ECL affected students' evaluation of the difficulty of content. The assessment of ICL by content experts did not consider ECL. Students' prior knowledge might also be the reason for the inconsistency. The questionnaire survey was conducted after learning. This prevented students from giving a more accurate assessment of difficulty.

Table 2. The correlation test of the cognitive load assessed by the teachers and the students

	Cognitive loads by teacher	Cognitive loads by students
Cognitive loads by teacher	1	
Cognitive loads by students	.550	1

Browsing time and cognitive load

Figure 4 shows the curves of the students' browsing time (B-Time) and the ICL for all content modules (B-time was computed using the average B-time of all students; ICL was assessed by the content experts based on element interactivity). In several cases, the content modules with low ICL coincided with long browsing times (e.g., Module 7-2-1 "Management of Photos on Smart Phones" and Module 8-3-2 "Using Line on Smart Phones"). The figure provides a macro view of cognitive load and learning behaviors because all of the students were considered collectively instead of individually. Although the data shown here were computed at the end of the semester, teachers could retrieve these data anytime by querying the LMS to review the temporal variations in browsing behaviors.

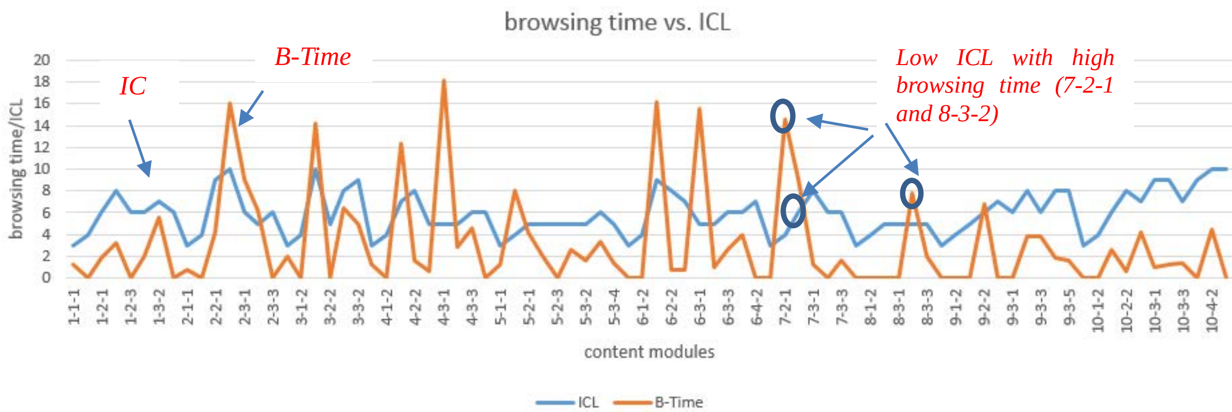

Figure 4. The browsing time (B-Time) and the intrinsic cognitive load (ICL)

Pearson's correlation test was used to identify the relationship between browsing time and ICL for each content module. The results in Table 3 show that the correlation was positive and significant. Both Module 7-2-1 and 8-3-2 contained captured screens of smart phones to illustrate the steps of operations. Several students complained that they had to listen to the instruction carefully because the position of the screen touched by the finger was not shown in the content. This could be a source of ECL. The variations in browsing time were also affected by class events. The peaks of accumulated B-time were observed close to the exam dates and two video conferences. Since ICL was assessed with a general assumption about learners' prior knowledge, it could only be used as an estimate. On the other hand, ECL also played a role. Technically, the students might click and play the module and do something else. The interference of these factors makes it hard to use B-time as a valid indicator for cognitive load. In future research, we may consider the learning time (the span of time browsing the content module) and the percentage of completion (for each content module) as candidate indicators.

Table 3. The correlation matrix of the ICL (assessed by the content experts) and the browsing time

	ICL	Browsing time
ICL	1	
Browsing time	.265*	1

Note. $^{*}p < .05$.

In Figure 5, a scatter chart shows the distribution of ICL versus B-time. The three points in the upper right corner include those content modules with high ICL and high B-time. These points are called hot spots because the corresponding element interactivity assessed by content experts is high. By checking the difficulty level assessed by students, we found that the assessed difficulty levels are also high. These three content modules all include the streaming video with captured screens of smart phones. We speculate that ECL is an issue that affected B-time. Instructional control of cognitive load should be given higher priority to reduce ICL and ECL for these modules first. The points in the lower right corners of Figure 5 correspond to those modules with high ICL and low B-time. The teacher should check and see if there are any learning problems related to these modules. The suggested actions should be taken upon the variations in browsing behaviors. For those modules with low interactivity, we assumed that the global cognitive load would not deplete the students' cognitive resources. When the log data implies that element interactivity plays the major role, the isolated-interacting elements effect or the molar-modular effect can be used to change the intrinsic nature of what is scheduled to be learned.

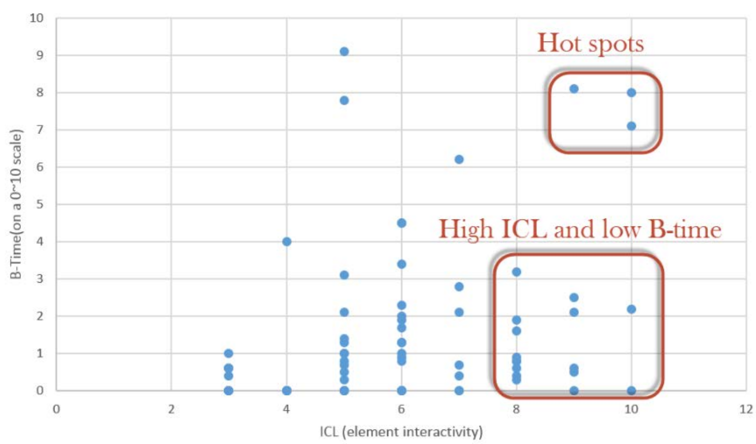

Figure 5. The hot spots that may induce high cognitive load

Asynchronous discussion and cognitive load

In the asynchronous discussion forums, the number of posts and the number of views of each post was recorded daily from the beginning of the semester. According to the syllabus, 10 chapters were taught in a 9-week summer session. The level of interaction in the discussion forums was measured using an analytics approach (Yen, 2013). The analysis involved determining the density of posts (DP), the increased number of views (IV), and the ICL (element interactivity assessed by the content experts).

Figure 6 shows the recorded data plotted as three curves. The values of the three indicators were normalized to a scale of 100. We sought to determine whether the level of interaction correlated with the corresponding ICL of the content modules for the same period. For example, the content experts rated the ICL of Module 6-2-1 of Chapter 6 with a score of 8 (on a 10-point scale). Chapter 6 was covered in early August, and, accordingly, the DP and IV curves exhibited small peaks during this period.

The course activities typically coincided with an increase in the level of interaction in asynchronous discussion forums. The forum discourse-analysis results indicated that only approximately 30% of the posts were directly related to the content of the course. In other words, we detected the temporal dynamics of the discussion forum but were unable to provide a precise explanation for the changing levels of interaction without performing a manual discourse analysis. We found the increased number of views for most posts reached a peak not long after their appearance in the forum. This implies that most students tended to browse the content of new or unread posts first. From the perspective of cognitive load, the teacher may choose to intervene and reduce the cognitive load if any learning problems were spotted in the new posts. Several students mentioned they were bothered by the increasing number of new posts. They experienced a pressure to read these posts. However, they often found the content of the posts hard to read. They were also concerned about the correctness of the content provided by their peers. When DP is high, it takes time to search for a specific post. The posts in the same thread contain redundant content of previous posts. These scenarios all contributed to ECL.

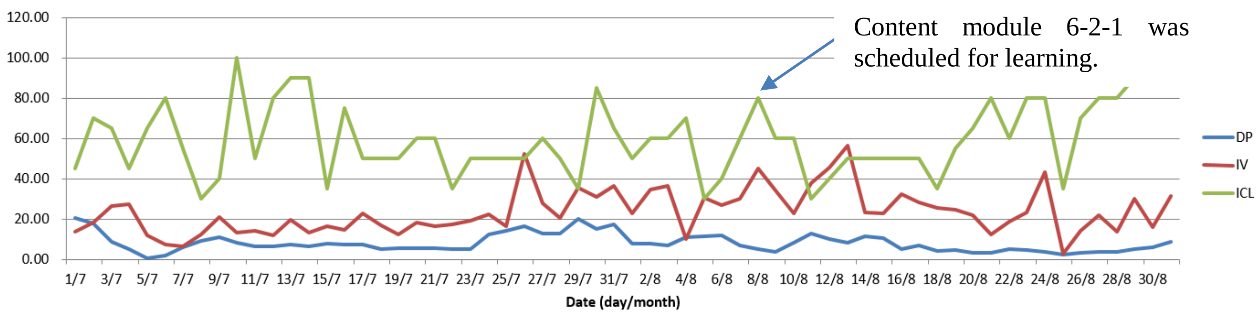

Figure 6. The temporal dynamics of DP, IV and ICL

Pearson's correlation analysis was used to test the correlations among DP, ICL, and IV (Table 4). The correlation between DP and ICL was negative and significant ($p < .05$); the correlation between DP and IV was significant and positive; and the correlation between ICL and IV was nonsignificant.

Table 4. The correlation matrix of the three indicators in analytics computing

	DP	ICL	IV
DP	1		
ICL	-.261*	1	
IV	.276*	-.112	1

Note. *p < .05.

Krathwohl (2002) discussed six categories of cognitive processes, including remember, understand, apply, analyze, evaluate and create, ordered from low to high levels of cognitive processing. The taxonomy was used as indicators of discussion quality. A total of 179 out of all the 562 posts were identified as related to the course content. Different CLT-based strategies were applied to facilitate the discussion of 5 topics. A sample reply to the topic of discussion was provided for topics 3, 4 and 5, respectively. A summary was provided for each of the topics 2, 3, 4 and 5. The sample reply strategy is analogous to the completion problem effect from the cognitive load perspective. The teacher provided the required format and part of the solution in the sample reply. The summary strategy is similar to the worked example effect in CLT. Some of other students' replies were included and commented on in the summaries.

The 179 task-oriented messages were reviewed by transcript analysis to classify each message into the categories of low cognitive processing level (i.e., remember and understand) and high cognitive processing level (i.e., apply, analyze, evaluate and create). According to the result shown in Table 5, topics 3 and 4 had the higher number of task-oriented messages. The periods of discussion corresponding to topics 3 and 4 were close to the peaks of the curves of DP and IV. We speculate both strategies had an effect on the level of interaction and the quality of discussion. The result is consistent with the findings reported in (Darabi & Jin, 2013). The period of discussion of topic 5 was close to the end of the semester. The level of interaction was low according to Figure 6.

Table 5. Number of messages that belong to high and low level cognitive processing

Topic	1	2	3	4	5
High level of cognitive processing	3	6	35	30	15
Low level of cognitive processing	4	10	36	25	14
Provide sample reply			v	v	v
Provide summary		v	v	v	v

The IVs for the sample replies and summaries were much higher than that of other posts. Several students mentioned the summaries saved them a big hassle to search through the forum for related posts. This strategy may reduce ECL. Both the summary and sample reply strategies have the effect of keeping the discussion focused on the designated topic. There were several cases where the students were diverted to non-task-oriented discussions. This might increase DP and IV while deteriorating the quality of discussion. Keeping the students focused on the topic of the discussion avoids the split-attention effect from the cognitive load perspectives.

Synchronous video conferences and cognitive load

A total of 112 students attended the first synchronous video conference on July 26, and 158 students attended the second synchronous video conference on August 16. Both conferences ran from 10:00 A.M. until 12:00 P.M. The Line groups were created on August 1. During the second synchronous conference, the discussion topics were announced in the second hour. The number of Line messages increased significantly after 11:00 A.M., and the number of messages related to the topics instead of social chat was higher in the second hour than in the first hour.

Table 6 lists the number of messages related to the assigned discussion topics. Because the three topics were announced in sequence, the correlations between the number of Line messages and the ICL of each topic (assessed by the content experts) were tested, and no significant correlation was observed. After the first topic was announced, several students expressed uncertainty regarding what to expect and when the activity ended. This might induced ECL since the students would try to find out what was going on. The teacher had to lead the discussion and coordinate the activity. The text appeared on the video conference screen along with the teacher's explanation was a practice of the modality effect to expand working memory capacity.

Table 6. Number of messages related to assigned discussion topics (23 students showed up in the five Line groups)

Sources	Topic 1	Topic 2	Topic 3
Line group 1	11	11	9
Line group 2	25	39	28
Line group 3	11	24	10
Line group 4	20	11	6
Line group 5	8	16	9
Sum	75	101	62
Synchronous video conference software	1	48	10
Mean	12.7	24.8	12.0
SD	3.5	6.32	3.26
Difficulty scale of topic	3	6	9

The second topic was announced and the starting and ending times of the group discussion were stated explicitly. Additional time was allocated for discussion, and the teacher refrained from speaking during the discussion to avoid split-attention effect. The teacher summarized the feedback from each group after every discussion. The pace of the synchronous conference might easily overload the flow of information, contributing to a high cognitive load. The discussion of the third topic indicated that the students interacted effectively. Although the topic covered highly complex sociocultural topics (specifically, the abuse of smart phones), the students addressed the key points of the topic early in the discussion. We speculate that most students became familiar with the process and ECL was reduced. The change in CLT-based instructional strategy facilitated reducing the cognitive load.

A total of 50 students began interacting on Line on August 1. The data in Table 7 indicate that the students' posts on Line were primarily social for the period of August 1 to August 15. The discussion activities on August 16 caused the students to focus on task-oriented interaction. Few of the students who did not use Line contributed to the interaction by using the default LMS module for inputting text.

Table 7. Number of messages appeared in Line (Every Line group had 10 members)

Date	8/1~8/15		8/16 (7/26 for video conf. 1)		8/17~8/31	
	Task-oriented	Non-task-oriented	Task-oriented	Non-task-oriented	Task-oriented	Non-task-oriented
Line group 1	12	65	31	15	25	87
Line group 2	6	75	92	21	39	47
Line group 3	8	46	45	13	19	23
Line group 4	14	42	37	17	36	45
Line group 5	3	22	33	19	17	38
Sum	43	250	238	85	136	240
Video conf. 1	N/A	N/A	23	25	N/A	N/A
Video conf. 2	N/A	N/A	59	37	N/A	N/A

The data and our observations indicated that students were much more active on social media. If all the conversations were to appear in the text area of the synchronous video conference software, it would be difficult for the participants to work in groups and trace the interaction. Both the teaching staff and students mentioned that scrolling up and down the text area frustrated them. The interface is inadequate and may impose ECL. One of the convenient features of video conferencing software is the real-time poll that can be used to check the students' learning performance. Although Line messages provided abundant feedbacks from the students, most of these messages were short. Very few of these messages were of high cognitive processing levels based on the taxonomy introduced in (Krathwohl, 2002).

Learners' performance

A paired-samples test was used to compare the students' performance in the pretest and posttest. Cohen's *d* is listed in Table 8 to show the effect size of the experiment. The level of practical significance was determined according to the value of coefficient *d* (.2 = small, .5 = medium, and .8 = large). The students' performance in the posttest was significantly higher than that in the pretest ($t = 14.516$, Cohen's $d > .8$). Future research is planned to include a control group and an experimental group to explore whether managing the cognitive load exerted a positive effect on the students' performance.

Table 8. Paired samples test

	N	Mean	*SD*	*t* value	Cohen's *d*	Effect size
Pre-test	158	76.519	13.221	14.516^{***}	.953	Large
Final exam	158	87.505	9.539			

Note. $^{***}p < .001$

Discussion and conclusion

The assessment of ICL depends on the element interactivity of the course content. Course designers or content experts can only provide an estimate of element interactivity by assuming that the students had no prior knowledge. Moreover, the information is static, unlike the students' learning behaviors, which can change over time. Because the students learned according to the schedule arranged by the teacher, the static values of the estimated ICL for each content module can be used as a reference for the level of element interactivity of the content learned by the students throughout the semester.

Applying the framework in online instruction

Figure 7 depicts the five-step cycle of the proposed framework. The students learned through online platforms. Log data were generated for the analysis by using an analytics approach. The system raised a signal for action when certain conditions were met. The teacher needed to verify the situation by reviewing the overall picture of the students' learning process. There might be false alarms. Actionable information was then provided for the teacher to adjust the adopted teaching strategies. The adjustment affected the students' learning behavior and cognitive load, which was subsequently reflected in the log data. In this research, empirical data were collected from multiple sources, including the LMS log data, survey data, and the data from interaction on Line. Discussion topics for the asynchronous and synchronous interactions and various online activities were designed based on the teaching strategies and according to various cognitive load effects. Occasionally, the teacher provided solutions for pop quizzes on the LMS and posted a message on Line to notify the students. A sharp increase was observed in the level of interaction, first on Line and then on the LMS.

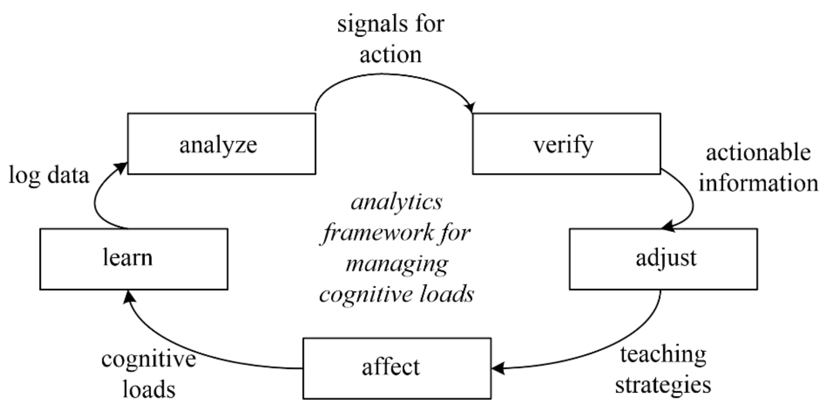

Figure 7. The five-step cycle of the proposed framework

The many facets of learning behaviors

The temporal dynamics of learning behaviors are difficult to capture because multiple factors can contribute to learning behavior. For example, students may spend additional time completing content modules that are difficult, although they may also spend additional time working on easy modules that satisfy their needs in certain applications. Some learners may spend less time on difficult content modules because they are stuck or have prior knowledge. The same situation applies to the asynchronous discussions. Through a manual discourse analysis, we found that some class events had a particularly strong effect on the level of interaction in the discussion forums; for example, many posts appeared on the LMS when the teacher announced the allocation of students to the Line groups.

Keep learning focused and on schedule

Regarding the content modules of high level element interactivity, specific discussion topics were designed and posted in the forum to elaborate on certain elements or to summarize key concepts in order to reduce the material's cognitive load. Most of the teacher interventions were intended to direct students to focus on the scheduled course content and assigned topics. If the instructions were not kept focused and the course was not conducted on schedule, then it would be difficult to capture a precise indication of student learning behaviors and cognitive load. However, the indicators obtained through the analytics approach are simply numbers for use as a quick reference; thus, they cannot be fully relied upon as indicators. To more accurately monitor the students' browsing behavior, we recommend releasing the content according to a preset schedule. For example, suppose that the lesson scheduled for Chapter 2 is held in Week 3; the content for Chapter 2 should then be made accessible during Week 1 and closed before the end of Week 3. During the scheduled learning period, the teacher may announce related discussion topics to direct the students' attention to the content covered in the schedule. Eryilmaz et al. (2009) found that anchored discussions assisted students with engaging in more effective interaction. When the generated log data corresponded to the specific content modules listed on the schedule, the ICL determined by the content experts would be a valuable indicator of students' cognitive load.

Internal management of cognitive load

Bannert (2002) described the external management of cognitive load as an approach that can be implemented by optimal instruction. On the other hand, the internal management of cognitive load is controlled by learners with their metacognitive and self-regulative competence. Although our research was focused on the external management of cognitive load, the approach can be used to help learners perform their internal management of cognitive load.

Social media as a tool for attracting more log data and reducing cognitive load

We found that the students enjoyed interacting on social media. Moreover, keeping the students informed of class events and activities through social media was convenient and effective for the teacher. Most students mentioned that they used social network sites considerably more frequently than they did the LMS. When the online students were involved in a technology-based learning environment, it was observed that using social media allowed them to receive responses or assistance in a timely manner. Furthermore, adopting social media in the course activities improved the students' social presence and learning satisfaction.

Limitations of the study

Because of the large amount of log data, computer programs are required to automate the processing of empirical data. The use of social media has been a challenge for teaching staff, particularly in synchronous video conferences. The students in every Line group became active when the discussion topic was posted. The online teacher required assistance from other staff with organizing and summarizing the interaction so that he or she could provide feedback for the students. However, joining the Line groups was not compulsory for the students, and not participating in the synchronous video conferences did not affect their academic record. The data were collected only for a segment of the student body. The novelty effect of using Line in online instruction should be considered a factor that may affect students' learning behaviors.

There were technical issues that need attention; e.g., the students may stay on the content page while doing something else. This might raise a false alarm. Not all types of cognitive load left traces in log data. Several students complained about the time that they wasted searching numerous posts to locate a certain post. They also experienced difficulty in keeping track of posts that had not been read. These problems increased the cognitive load.

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