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Learning Activities and Learning Behaviors for Learning Analytics in e-Learning Environments*

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Most of the learning analytics research has investigated how quantitative data can affect learning. The information that is provided to learners has been determined by teachers and researchers based on reviews of the previous literature. However, there have been few studies on standard learning activities that are performed in e-learning environments independent of the teaching methods or on learning behavior data that are obtained through learning analytics. This study aims to explore the general learning activities and learning behaviors that can be used in the analysis of learning data. Learning activities and learning behavior are defined in conjunction with the concept of learning analytics to identify the differences between teachers' and learners' learning activities. Learning activities and learning behavior were verified by an expert panel review in an e-learning environment. The differences between instructors and learners in their usage were analyzed using a survey method. As results, 8 learning activities and 29 learning behaviors were validated. The Research has shown that instructors' degree of utilization is higher than that of the learners.

Keywords: Learning Analytics, e-Learning Activity, Learning Behavior

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Introduction

There has been increasing interest in the practical and theoretical aspects of learning analytics, especially the capacity to easily collect and analyze digital data on the learning behavior of learners in learning environments, which is also known as "e-learning." According to the 2016 NMC Horizon Report, the inclusion of learning analytics in educational technology can affect higher education within one year (Johnson, Adams Becker, Cummins, Estrada, Freeman, & Hall, 2016). In the 1st International Conference on Learning Analytics and Knowledge, Simens and Long (2011) defined learning analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts, for the purpose of understanding and optimizing learning and the environments in which it occurs." By analyzing the data that are related to the learning behavior of learners in e-learning training environments, the learning process can be more objectively understood (Castro, Vellido, Nebot, & Mugica, 2007). It may also provide useful reference data for appropriate interventions to facilitate learning and decision-making (Johnson & Witchey, 2011; LaValle, Lesser, Shockley, Hopkins & Kruschwitz, 2011). There are countless digital traces that are left by learners as they progress in e-learning environments (Shum, 2012).

The previous learning analytics research has generally analyzed the effects of learning by providing results from collecting and analyzing the data that affect learning. However, there have been few studies on the types of learning activities that are generally performed in e-learning environments and the types of learning behavior data that can be useful for learners and instructors. The purpose of this study is to explore the learning activities and learning behaviors that can be used in the analysis of learning data. The specific research questions were as follows: 1) what type of learning activities are performed in the e-learning environment? 2) what are the learning behaviors to be performed for each learning activity?, and 3) what are the differences between instructors and learners in the usage of learning activities and learning behaviors?. The results of this study are expected to provide significant guidelines in the research on learning analytics such as learning analytics modeling and dashboard development.

Literature Review

To achieve the objective of the study, we review the types and features of the data, e-learning activities, and learning behaviors that pertain to learning analytics. The effects of learning analytics have been summarized from the perspective of e-learning.

Data for learning analytics

The definition of data analytics

The system of learning analytics was developed to organize and understand the complexity and quantity of data that accumulates in higher education institutions. To draw meaningful conclusions from the analysis of large and complex learning data, data analysis techniques were introduced into educational research. There was a rapid increase in the range and types of learning analytics that were available, which resulted in an increase in the use and importance of this approach (Shum & Ferguson 2012; Siemens 2012). Learners leave more digital traces and log data in the process of study in the current educational environment than ever before. The digital traces and log data that are generated in computer-based learning can be analyzed to identify patterns in learning behavior (Baker & Siemens, 2013; Siemens, 2012; Elias, 2011). These data can provide a wide range of insights into the learners' motivations and behaviors (Gašević, Dawson, & Siemens, 2015). The purpose of educational data mining is to analyze the collected data. However, the purpose of learning analytics is to analyze the use of the collected data (Swan, 2012). To provide an optimized learning environment and to understand the learning process of learners, learning analytics is used to measure, collect, analyze, and report data on learners and learning environments (Siemens, 2010; Siemens & Gašević, 2012). Learning analytics is an academic approach to predict and control learning outcomes by providing the educational implications that are is determined through analysis of the data that are related to the learning activities of students (Elias, 2011; Kwon, 2013; LaValle et al, 2011). Learning analytics focuses on the qualitative data that result from learning behavior, although it also analyzes the various quantitative data that are generated in the learning process (Becker, 2013; Gibson & De Freitas, 2016).

Characteristics of learning analytics data

There are several classifications of learning analytics data, which are collected not only from computer databases but also from learners' digital interactions: these are digital trace data from learners, i.e., the data from the interaction of learners with educational and information technology, and log data from computer databases. These concepts are used interchangeably, and each of the concepts includes the other. Digital trace data from learners is defined as evidence of human and human-like activity that is logged and stored digitally (Howison, Wiffins, & Crowston, 2011). Learners' digital trace data constitute the record of activities that are undertaken through online educational and information systems (Howison, et al., 2011). This record is created when learners "hit" an online database. It can be released in many forms depending on different learning and technology situations. It is produced through and stored by information systems. Digital trace data can track users' IP address, the time when they are created, and the users' location, which can be used for later analysis. Most online users leave a digital trace. Digital trace data makes visible social processes that are much more difficult to study in conventional organizational settings (Agarwal, Gupta, & Kraut, 2008). The availability of such trace data, together with dynamic domains and the appropriate analysis techniques, form an excellent opportunity for research, which might be considered to be a "21st Century Science" (Watts, 2007).

In a computing context, a log is defined as the automatically produced and time-stamped documentation of events that are relevant to a particular system. Virtually all software applications and systems produce log files. A range of learning analytics research can be conducted based on the data that are recorded on learners' web logs. Learning analytics research can be conducted by implementing an analysis system for the individual learning progress of learners, learning patterns, participation in learning, and learning environment (Shin, Jeong, & Cho, 2003). Internet-based games have been increasingly of interest in the education field, and educational game site usage patterns have been analyzed with the use of web log data mining (Jung & Jo, 2003). Data preprocessing and extraction as well as the analysis of log files are applied to learning analytics research. Web-based teaching support systems are analyzed based on the learning sequences of teachers and learners (Eom, 2008).

Studies have been consistently conducted based on the learning data in the LMS (Learning Management System) of learners' activities. For example, Purdue University's Signals (Arnold, 2010) and the University of Maryland–Baltimore County's "Check My Activity" (Fritz, 2010) both rely on data that are generated in Blackboard. Studies have been consistently conducted based on preexisting data in the LMS of the learners' activities. Recommender systems, such as Degree Compass (Denley, 2012), similarly draw on data that are captured in existing information technology systems in universities.

Learning analytics are designed to provide not only production data and intelligent data from learners but also personalized learning (Dawson, 2010). In addition, they are designed to provide information for decision-making at all levels of an education system, and they use a model to analyze or to find social connections and the meaning of learning information as well as to generate advice for estimating learning impact (Siemens, 2010; Elias, 2011; Becker 2013; Johnson et al., 2016). As the importance of the data that are used for the purposes that are mentioned in the learning analysis increase the efficiency of teaching, some practitioners have begun to discuss and find preferable the application of analytics at any point in a study. The importance of using the learning data analysis research for the purposes of increasing teaching effectiveness has been mentioned. Thus, a discussion has begun as to the preferred data application analysis methodologies at any point in the course of research (Gibson & De Freitas, 2016).

Learning analytics refers to educational 'Big Data'. The analysis of Big data uses statistical methods, and big data research was initially developed for market research to understand consumer trends through the analysis of experience. The application of big data analysis to learning analytics originated using data from students' learning processes to understand the student experience. As a result, it has become possible to personalize learning and improve students' academic results through a wide variety of uses, such as predicting learning plans (Siemens, 2010; Siemens & Gašević, 2012). Big Data were thought to have been the answer to important questions based on access to large amounts of data, but this has not been the case (Elias, 2011).

Data mining technology has existed in higher education for more than 10 years. Unlike data mining, learning analytics provides information for educators, policy decision makers and administrators to improve the learning process (Swan, 2012). To find an alternative to the larger question, educational data mining focuses on data analysis methodology and modeling that is developed in the present educational environment. In contrast, learning analytics focuses on the use of data and analysis (Swan, 2012; Siemens, 2012). Data mining seeks to organize and reduce educational data. However, learning analytics attempts to analyze entire collections of data from a systemic standpoint (Swan, 2012; Siemens & Gašević, 2012).

Learning activities and learning behaviors

There are diverse criteria in distinguishing among e-learning activities. The first classification is based on a teaching-learning model that can be divided into problem-based learning, project-based learning, and discussion learning. The second is divided according to the number of participants and activities such as single-person activities (such as writing an online journal), one-to-one activities (such as interviews), one-to-many activities (such as lectures), and large group activities (such as discussions). The third is divided according to the purpose of an activity. Harris, Mishara, and Koehler (2009) suggested the division of technologically integrated learning activities into knowledge formation, convergent knowledge expression, and divergent knowledge representation. Additionally, Horton (2006) suggested the separation of learning activities into acquisition-type activities learners gain knowledge by viewing a lecture, reading a text, or performance types of activities that learners can perform to see what they have learned, and connection-oriented activities by which learners can connect and apply previous learning experiences to their business or daily lives.

Learning analytics aims to support learning and teaching by revealing the meaningful data on the learning behaviors of learners in e-learning environments. Therefore, the classification of e-learning activities for learning analytics should focus on the learning behavior of learners, rather than on earlier conceptual distinctions. According to Conole (2007), learning activities are achieved through the completion of a series of tasks to achieve intended learning outcomes and consist of three components: context, pedagogy, and task. Context includes the courses, difficulty levels, intended learning outcomes, and educational environment. Pedagogy refers to the teaching and learning methods. Tasks include the teaching skills that are needed to perform the tasks that are supported by the challenges that are presented to students, such as resources, tools, interaction, and assessment. From this perspective, e-learning activities can be defined as performing a series of tasks in accordance with planned learning support to achieve the learning objectives.

The Instructional Measurement Systems Global Learning Consortium suggested Learning Activity Metrics that represent measurements of specific actions within each genre of activity (Lukarov, Chati, Thus, Kia, Muslim, & Schroeder, 2014). The idea behind learning activity metrics is that most learning activities can be grouped into one or more genres, e.g., reading, assessment and collaboration. Learning activity metrics focus on learning activities rather than computer log data. Fig. 1 shows the learning activities matrix including context, pedagogy, and tasks, which are the three components of learning activities. It also presents separate data that are calculated from the learning activity results in participation and performance. The IMS Metric presents combined learning activities (such as homework and assessment) and learning behavior (such as reading and annotation).

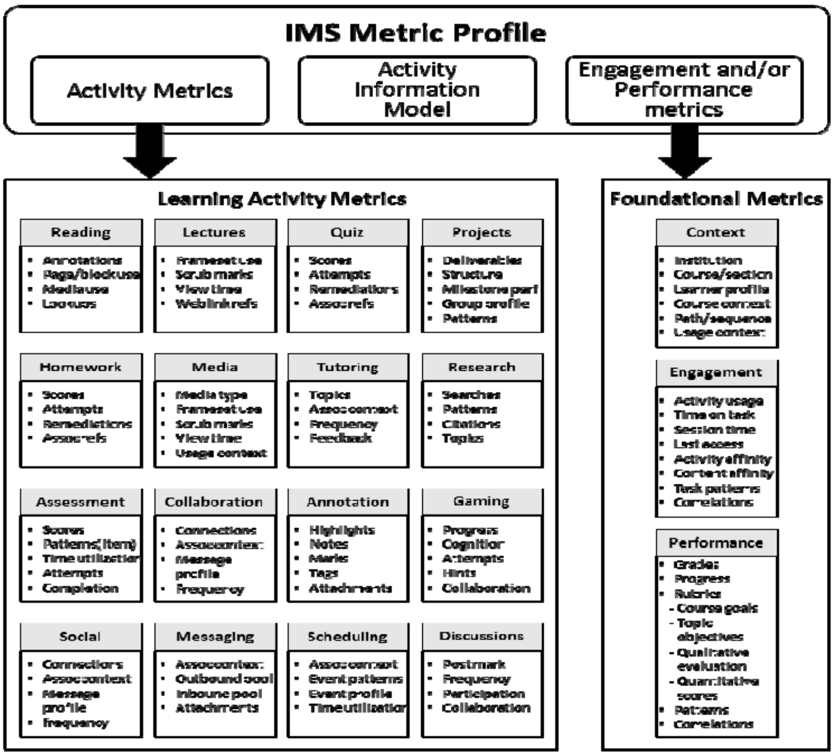


Figure 1. IMS metric profiles (IMS global learning consortium, 2013)

Rha and others have presented modifications of the study (2015) to be applied to elementary and middle school textbooks based on digital learning activity indicators, which are suggested by the IMS as follows: see Figure 1. The activity indicators at the national level are composed of an input-process-output model. Depending on the input data, the participation in an activity affects the performance level as output. The activity metrics consist of tools, basic activities, and multiple activities. In this case, "tool" means the elements that are necessary to proceed with a study. "Basic activity refers to the basic units of teaching and learning. "Combined activity" means activities that are conducted that combine several basic activities or activities that are added to a basic activity.

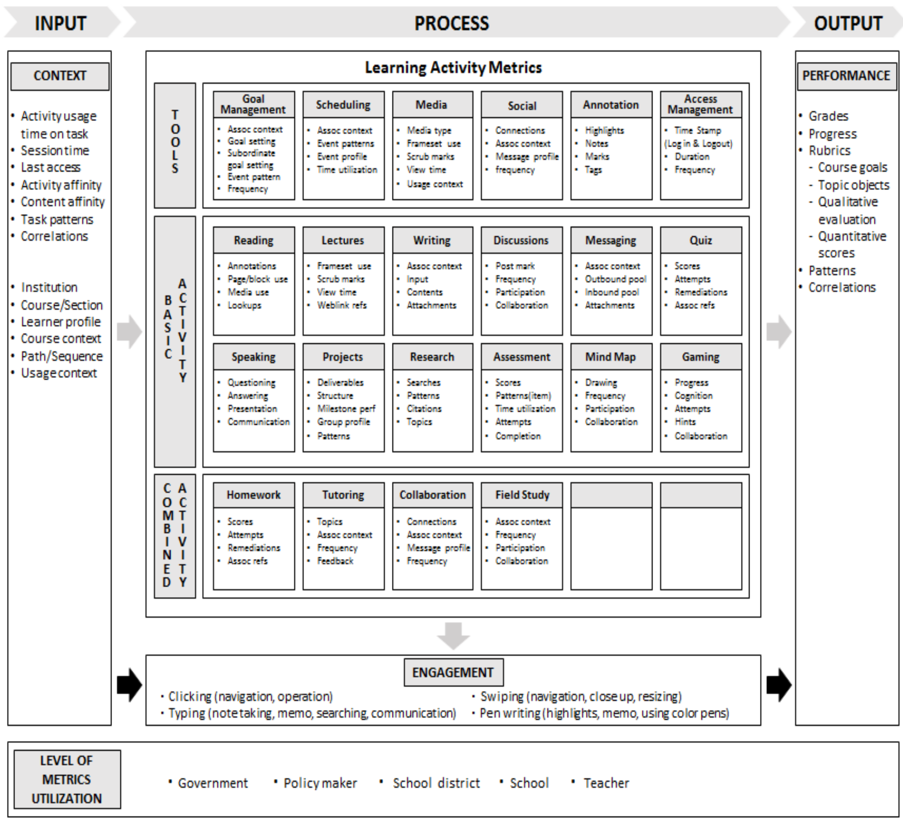


Figure 2. National learning metrics framework (Rha et al., 2015)

In this study, it is significant that the activity indicators are presented separately as input (context), courses (learning activities + participation), and output (performance). However, the learning matrix framework has limitations that do not suggest specific research methods for how the components are derived; the components that are contained in the matrix include: tools, basic activities, and combined activities.

Table 1. Learning activities and learning behaviors in e-learning environments

Learning activities			Learning behaviors
IMS	Rha et al. (2015)	LA^{LA}	
Lectures	Lectures	Lectures	Watching/Listening learning materials (Video lectures) Listening lectures (MP3 lectures)
-	Field study	Experience	Simulation and hands-on learning contents
Annotation	Annotation	Annotation	Taking notes in lectures Emphasizing (Highlighting)
Reading	Reading	Reading	Reading learning materials Reading opinions/Comments of others
Discussion	Discussion	Discussion	Present opinions Comments and reply
Homework	Homework	Task Performance	Posting task performance results
Research	Research		
Project	Project		
Collaboration	Collaboration	Collaboration	Collaboration (Wikis, etc.) Finding and sharing information Chatting
Assessment	Assessment	Evaluation	Quiz Exam Course evaluation Peer evaluation Self-evaluation
Quiz	Quiz		
Tutoring	Tutoring	Q & A	Question Answer
Messaging	Messaging	Messaging	Sending text/e-mail/SNS Receiving text/e-mail/SNS

This study aims to separately define learning activities and learning behaviors in e-learning environments. “Learning behavior” refers to the observable behavior of learners in the performance of a learning activity. This can also be referred to as learning traces data for learning analytics. This study presents the learning activities and learning behaviors in Table 1, referring to the IMS metrics and the national learning metrics framework proposed by Rha et al. (2015).

The exception to the proposed learning activities in precedent studies may be included in the existing learning activities with regard to the meaning of the learning analysis. However, it has not addressed the current environment of LMS e-learning in higher education in Korea. For example, projects and research could be assigned when they are performed individually, but there could also be cooperative learning activities that are performed as a team. In addition, management aspects, scheduling and access management are data that can be calculated through other activities. Media, gaming, and SNS were excluded because they include the tools that produce learning activities and learning behavior. Therefore, we summarize the ten most basic learning activities based on the extant research.

Research Methods

Learning activities and learning behavior were verified by an expert panel review in an e-learning environment. The differences between instructors and learners in their usage were analyzed using a survey method.

Validation of learning activities and learning behaviors

Participation

Two types of expert validation surveys on e-learning activities and learning behaviors were conducted, which were derived from the literature review. Ten experts with over five years of e-learning teaching and research experience participated in the expert validation survey. To collect more in-depth opinions about the revised results of the primary expert validation survey, an expert seminar was held with three experts with the most professional e-learning teaching and operating experiences. The results were confirmed by a second expert validation survey.

Table 2. Profile of experts

Experts	Degree	Exp. of e-learning	Context
Expert A	Ph.D in educational technology	13 years	Higher education
Expert B		13 years	Higher education
Expert C		9 years	Higher education
Expert D		10 years	Higher education
Expert E		16 years	Gifted education
Expert F		14 years	Higher education
Expert G		10 years	Higher education
Expert H		5 years	Higher education
Expert I	M.S in educational technology	5 years	Cooperative education
Expert J		5 years	Cooperative education

Instruments and Analysis

The instrument for the first expert validation survey was designed to evaluate the appropriateness of 10 learning activities and 22 learning behaviors using a 5-point Likert scale. The instrument was composed of 34 items: 10 items for the appropriateness of 10 learning activities, 22 items for the validity of 22 learning behaviors, and one item to request the experts' comments on these items. The first validation survey results were discussed in the expert seminar. As a result, the definitions of learning activities and learning behaviors were revised. The instrument for the second expert validation was modified by reflecting the first expert validation results as well as the expert seminar. It consisted of 8 learning activities and 28 learning behaviors to perform learning activities. The collected data were analyzed as technical statistics such as the means and standard deviations. The statistics for the learning activities and learning behaviors were modified to reflect the opinions of the experts.

Usage of learning activities and learning behaviors

Participation

To investigate the differences between instructors and students in the usage of learning activities and learning behaviors based on their e-learning experiences, 10 instructors and 187 students (male: 94, female: 93) participated in this study. Among the 10 instructors, 8 e-learning instructors had an average of 9.3 years of e-learning operating experience in higher education and 2 experts were in charge of e-learning in cooperative education. The students were selected to include 84 students who were taking e-learning courses at University A, 52 university students who were studying "educational technology" at University A and 51 university students who were studying "educational technology" at University B.

Instruments and analysis

The instrument was designed to investigate how much instructors and students perform each learning activity and exhibit learning behaviors in their e-learning courses by using a 5-point Likert scale. The instrument was composed of 38 items: 8 items for the usage of 8 types of learning activities, 29 items for the usage of 29 types of learning behaviors and one item for the experts' comments. The average and standard deviation was calculated for the usage of the learning activities and learning behavior in e-learning environments. The differences between the instructors and the students were confirmed through an independent t-test. Additionally, the differences between the instructors and the students were visualized by a multidimensional analysis.

Results

Validation of e-learning activities and behaviors

To perform learning analytics in an e-learning environment, a draft of learning activities by learning behavior was designed. It was validated by expert meetings, and an amendment was developed.

Table 3. The validation results of learning activities and learning behaviors

1st Draft			2nd Amendment		
Learning activity	Learning behavior	Question validation average	Learning activity	Learning behavior	Question validation average
Learning course materials	Watching video lecture (flash)	4.90	Learning course materials	Watching learning materials (video, flash, game, simulations)	4.67
	Watching learning materials (video, flash, gage, simulation)	4.00			
	Listening the MP3 lecture (or download lectures MP3)	4.50		Listening the MP3 lecture (or download lectures MP3)	3.67
	Reading textual learning materials (or download textual learning materials)	4.90		Reading textual learning materials (or download textual learning materials)	4.78
	Learning supplementary/enrichment materials (videos, MP3, text)	4.90		Learning supplementary/Enrichment materials (videos, MP3, text)	4.67
Experience	Hands-on learning contents (Simulation, games, and etc.)	4.00			
Remark	Taking notes in learning materials	4.50	Note taking (remember promotion)	Taking notes in learning materials	3.22
	Emphasizing (Highlighting)	4.50		Emphasizing (Highlighting)	3.22
Reading	Reading learning materials provided by instructor and learner	4.90	Checking learning activities	Reading announcements and information (assignments, exams, etc.)	5.00
	Reading other people's comments and opinions	4.90		Sending a message (note, text message, e-mail, etc.)	4.78
				Reading a message	4.56

Table 3. The validation results of learning activities and learning behaviors (continued)

1st Draft			2nd Amendment		
Learning activity	Learning behavior	Question validation average	Learning activity	Learning behavior	Question validation average
Discussion	Presenting discussion comments	4.80	Discussion activities (synchronous/ asynchronous)	Presenting discussion comments	4.89
	Comments and reply	4.80		Comments and reply	5.00
	Synchronous chatting discussion (various SNS utilization, etc.)	3.60		Reading other people's comments and opinions	4.89
				Post reference	4.78
				Reading shared materials	4.89
Cooperation activities	Collaboration (Wiki, etc.)	3.90	Collaboration activities (synchronous/ asynchronous)	Submit individual assignment	4.33
	Submit individual assignment	5.00		Reading the results of other students' assignments	3.78
	Post researched data	4.60		Post researched data	3.89
				Reading materials	3.89
				Presenting opinion	4.33
				Comment and reply	4.44
				Reading other students' comments and opinions	4.33
Submit assignment	Post task performance results	5.00	Submit assignment	Post task performance results	4.89
Evaluation activities	Quiz (formative assessment that performs intermittently)	4.80	Evaluation activities	Quiz (formative assessment that performs intermittently)	4.89
	Exam (intermediate and final performance evaluation, etc.)	4.80		Exam (intermediate and final performance evaluation, etc.)	4.78
	Peer evaluation (cooperation)	3.70		Peer evaluation (cooperation)	4.11
	Self-evaluation	4.00		Self-evaluation	4.00
Q & A	Asking a question	4.80	Q & A	Asking a question	5.00
	Answer the question	4.80		Answer the question	5.00
Message	Sending a message (note, letter, e-mail, etc.)	4.30			
	Sharing message (SNS)	4.30			
Course feedback	Course evaluation	4.70			

To analyze the learning information that can be derived through the learning behavior-related data of the learners in e-learning environments, we sought to identify the learning behaviors that are indicated by traces of digital data that are the result of e-learning activities. A total of 8 learning activities and 29 learning behaviors, which were derived through the literature review, were validated by the expert panel.

As a result, the e-learning activities and behaviors in the overall average were 4.73 (SD=.45). The average of the Q & A activity in the learning activities was 5.00 (SD=.00); the Q & A activity was recognized as being absolutely necessary by the experts. The average of discussion activities was 4.89 (SD=.29), the average of post-assignment was 4.89 (SD=.33), the average of cooperative activities was 4.78 (SD=.35), the average of checking activities was 4.78 (SD=.53), and the average of note taking (memory promotion) was 4.32 (SD=.90). These results were relatively low.

Other averages are as follows: Reading notifications and guide posts (assignments and exams), Comments and replies (in discussion), Reading materials, Comments and replies (in collaborative activity), and Asking questions, Answers the question in learning behaviors show an average of 5.00 (SD=.00). Also, a significant finding was that learning behavior in e-learning environments was found to be a result of learned behavior and expert validation.

Meanwhile, Listening to MP3-type lectures (MP3 lecture downloads) (M=4.22, SD=1.09), Bookmarks (M=4.29, SD=.95), Reading the results of other student's work (M=4.33, SD=.71), Taking notes on lectures (M=4.33, SD=.87), and Highlighting (highlighting) to (M=4.33, SD=.87), were found to be relatively infrequent e-learning behaviors. An ill-structured PBL problem was also analyzed according to Jonassen's (2000a) typology of problem types. The results showed that the PBL problems in engineering courses are relatively ill structured, with complex problems and case-analysis or design problems depending on the characteristics of the course content. Nevertheless, there was no direct relationship found between the types of problem based on poor structure and the PBL tutorial process or learning outcomes.

Differences between learning activities of learner and instructor

For learning activities and behaviors in e-learning environments, we examined whether there is a difference in the actual degree of utilization by the instructor and the learner. According to Table 1, the average of the instructor's learning activities was 4.43 (SD = .40), and the average of the learner's learning activities was 3.46 (SD = .64). At the $t = -4.276$, $p < .05$ level, there is a significant difference between the two levels of learning activities. This result confirmed a very large effect size $d = 1.87$. In other words, the instructors' activities can be interpreted as being much more meaningful than the learners' activities in e-learning environments. However, there are no significant differences between instructors and learners in 2, note taking (memory promotion). The detailed results of the study are presented in Table 3 and illustrate the differences in instructors' and learners' leaning behaviors. This finding supports the intuitive understanding.

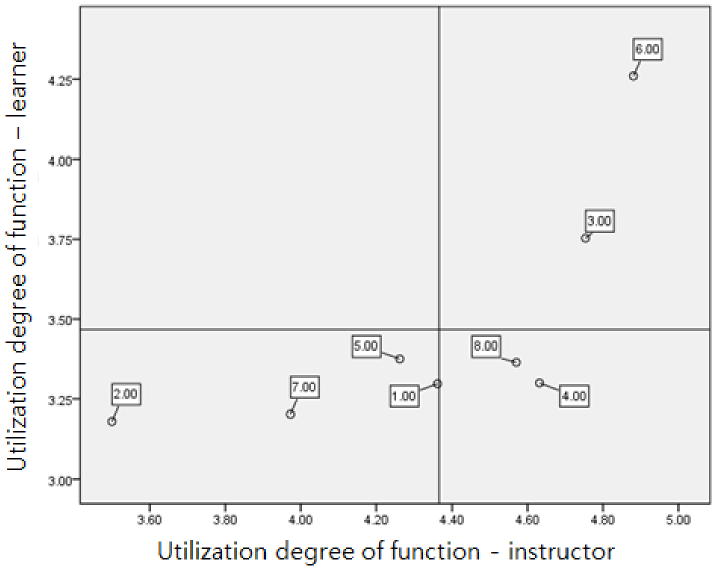
To understand the difference in instructor and learner learning activities and learning behavior, a matrix analysis was performed. The first area of inquiry was in the learning activity area, considering the difference between instructors and learners, as shown in Figure 3.

According to Figure 3, quadrant 1 refers to activities that utilize many commonalities between teachers and learners. The submission of assignments that were related to the assessment of learning performance, and the results showed 6. assignment submission, and 3. checking learning activities, and verification activities to continue with learning activities were shown to be the highest. In quadrant 4, there are many learning activities for instructors but a low utilization level for learners. Practically speaking, there are many instructor activities to promote cognitive thinking and class participation of learners such as 4. discussion

Table 4. The differences in instructors' and learners' learning behaviors

Learning activity	Learning behavior	Subjects	Mean	SD	t	d
Learning course materials	Watching learning materials (video, flash, game, simulations)	Learners	3.73	1.00	-2.122*	0.74
		Instructors	4.50	1.07		
	Listening the MP3 lectures or download lectures MP3)	Learners	2.20	1.21	-3.233**	1.65
		Instructors	3.83	0.75		
	Reading textual learning materials (or download textual learning materials)	Learners	3.85	1.12	-1.947	-
		Instructors	4.63	0.52		
	Learning supplementary/ enrichment materials (videos, MP3, text)	Learners	3.41	1.19	-2.569*	1.26
		Instructors	4.50	0.76		
Note taking (remember promotion)	Taking notes in learning materials	Learners	3.11	1.28	-1.181	-
		Instructors	3.80	1.3		
	Highlighting	Learners	3.25	1.31	0.076	-
		Instructors	3.20	1.48		
Checking learning activities	Reading announcements and information (assignments, exams, etc.)	Learners	4.39	0.74	-3.520**	0.91
		Instructors	4.88	0.35		
	Sending a message (note, text message, e-mail, etc.)	Learners	3.39	1.25	-9.320**	1.86
		Instructors	4.88	0.35		
	Reading a message	Learners	3.48	1.24	-2.283*	0.89
		Instructors	4.50	1.07		
Discussion	Presenting discussion comments	Learners	3.25	1.26	-6.535**	1.57
		Instructors	4.63	0.52		
	Comments and reply	Learners	3.19	1.22	-6.942**	1.66
		Instructors	4.63	0.52		
	Reading other people's comments and opinions	Learners	3.21	1.26	-7.199**	1.72
		Instructors	4.71	0.49		
	Post reference	Learners	3.40	1.17	-5.161**	1.34
		Instructors	4.50	0.54		
	Reading shared materials	Learners	3.45	1.22	-6.065**	1.48
		Instructors	4.71	0.49		
Cooperation	Post individual assignment	Learners	4.14	0.96	-1.545	-
		Instructors	4.71	0.76		
	Reading the results of other students' assignments	Learners	3.1	1.28	-1.355	-
		Instructors	3.83	1.60		
	Post researched data	Learners	3.19	1.12	-1.226	-
		Instructors	3.71	0.76		
	Reading materials	Learners	3.64	0.96	-2.172*	1.05
		Instructors	4.43	0.54		
	Presenting opinion	Learners	3.11	1.08	-3.187**	1.4
		Instructors	4.43	0.79		
	Comment and reply	Learners	3.15	1.12	-2.662**	1.36
		Instructors	4.29	0.76		
	Reading other students' comments and opinions	Learners	3.30	1.08	-2.746**	1.21
		Instructors	4.43	0.79		
Assignment	Post task performance results	Learners	4.26	0.92	-4.294**	0.98
		Instructors	4.88	0.35		
Evaluation	Quiz (formative assessment that performs intermittently)	Learners	3.58	1.19	-2.184*	1.14
		Instructors	4.57	0.54		
	Exam (intermediate and final performance evaluation, etc.)	Learners	3.80	1.20	-1.683	-
		Instructors	4.57	0.79		
	Peer review(cooperation)	Learners	2.71	1.32	-1.53	-
		Instructors	3.75	1.50		
	Self-evaluation	Learners	2.72	1.3	-0.363	-
		Instructors	3.00	2.00		
Q & A	Asking a question	Learners	3.47	1.15	-2.501*	1.13
		Instructors	4.57	0.79		
	Answer the question	Learners	3.26	1.26	-2.722**	1.28
		Instructors	4.57	0.79		

*p<.05 , ** p< .01

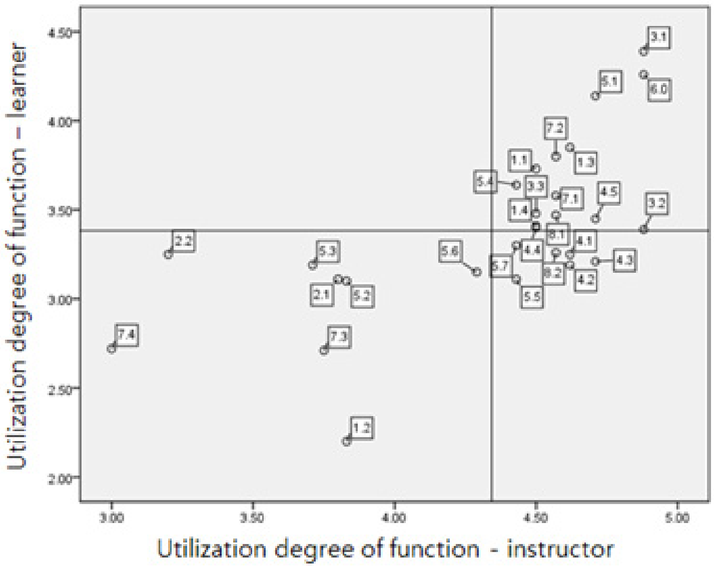


1. Lecture, 2. Note taking (Remember promotion), 3. Checking learning activities, 4. Discussion activities (Synchronous/Asynchronous), 5. Cooperation activities, 6. Submit assignment, 7. Evaluation activity, 8. Q & A

Figure 3. Matrix analysis of instructors and learners on learning activities in e-learning

(synchronous and asynchronous); 8. Q & A; and 1. teaching activity, but learners showed relatively low activity. Quadrant 3 refers to a low level of activity not only by instructors but also by learners. These are important activities in face-to-face learning such as 2. note taking (memory promotion); 7. evaluation activities; and 5. cooperation activities. However, these activities serve as limitations and represent poor activity levels in e-learning environments. Next, in accordance with specific learning behaviors in the area, please note the difference between the activities of instructors and learners in Figure 4.

According to Figure 4 quadrant 1 represents learning activities that are utilized by both instructors and learners. It was found to account for a high proportion of the activities of instructors and learners such as 3.0, Reading announcements and information; 6.0, Posting task performance results; 5.1, submitting individual assignment; 1.3, Reading textual learning materials; 7.2, Taking exams; 1.1, Viewing learning materials; and 5.4, Reading materials. In quadrant 4, there are many



1.1. Watching learning materials (video, flash, game, simulations), 1.2. Listening the MP3 lecture (or download lectures MP3), 1.3. Reading Textual learning materials (or download textual learning materials), 1.4. Learning supplementary/enrichment materials (videos, MP3, text), 2.1. Taking notes in learning materials, 2.2. Emphasizing (Highlighting), 3.1. Reading announcements and information (assignments, exams, etc.), 3.2. Sending a message (note, text message, e-mail, etc.), 3.3. Reading a message, 4.1. Presenting discussion comments, 4.2. Comments and Reply, 4.3. Reading other people's comments and opinions, 4.4. Post reference, 4.5. Reading shared materials, 5.1. Submit individual assignment, 5.2. Reading the results of other students' assignments, 5.3. Post researched data, 5.4. Reading materials, 5.5. Presenting opinion, 5.6. Comment and Reply, 5.7. Reading other students' comments and opinions, 6.0. Post task performance results, 7.1. Quiz (formative assessment that performs intermittently), 7.2. Exam (intermediate and final performance evaluation, etc.), 7.3. Peer evaluation (cooperation), 7.4. Self-evaluation, 8.1. Ask a question, 8.2. Answer the question

Figure 4. Matrix analysis of instructor and learner on learning behavior in e-learning

instructor activities, but the utilization level of learners' learning activities is low such as 5.5, Presenting opinions; 4.2, Comments and replies; 4.3, Reading other people's comments and opinions; 4.1, Presenting discussion comments; and 8.2, Answering questions. In presenting opinions, a low level of activity for learners was confirmed. In quadrant 3, there are low levels of learning behavior for both instructors and learners such as 7.4, Self-evaluation; 1.2, Listening MP3 lectures; 7.3, Peer evaluation; and 2.2, Emphasizing (Highlighting). Such differences were confirmed to be due to the unique characteristics of the instructor and learner activities.

Discussion and Conclusion

Theoretical contributions

Learning activities and learning behaviors in e-learning environments were confirmed to be useful and relevant indicators by two rounds of expert reviews. There was a problem with the combination of learning activities and learning behavior to analyze the learning activities that have been suggested in the previous studies concerning the metrics and frameworks.

This study conceptually distinguishes between learning activities and learning behavior. There has been significant research that suggests learning behavior indicators can be measured from a learning analytics perspective. Considering the results of the expert reviews, active learning activities, such as Q & A, discussion activities, and cooperation activities, were evaluated more highly than the others; however, the note taking activity received a relatively low evaluation. Note taking is one of the most important learning strategies when a learner listens to lectures or watches learning materials in a face-to-face learning environment. Experts evaluate the note taking learning strategy as a low level of learning activity because it maybe has low potential advantages due to technological constraints. In other words, note taking on a video or in the context of text learning is not available in the current university LMS.

Research about leveraging learning behavior in e-learning environments has shown that an instructor's degree of utilization is higher than that of the learners. From the instructors' perspective, it was confirmed that they utilize teaching strategies and systems to facilitate learning and to promote learning behavior. The degree of learning behavior utilization, in passive forms of learning activities such as watching and reading lectures, accounted for a high proportion of learning behavior. The proportion of active forms of learning such as presenting opinions, commenting and replying and responding appeared to be low. Therefore, support strategies to replace the cognitive learning participation of learners with traces of digital learning information are required. In addition, the degree of utilization of evaluations was analyzed to be low in e-learning environments. The reason for this seems to be mostly due to the lecture-centered content that is presented in e-learning environments.

Practical implication

This study is conceptually divided into learning activity and learning behavior in e-learning environments, and it also provides measurable behavioral indicators from a learning analytics perspective. The results of this study are expected to provide the following as practical implications.

First, the study suggests the designing of various learning activities through a reorganization of the indicators of learning activities and learning behaviors in e-learning. Learning in an actual e-learning environment is a combination of various learning activities and learning behaviors. For example, when others post comments or questions, this can be regarded as a discussion activity. If several people participate in the process of collecting opinions at the same time, it can be regarded as a cooperative project activity as well as a discussion activity. Therefore, the development of various activities is expected to be more easily designed in accordance with the intended objectives.

Secondly, the current study provides new information about the process of e-learning. There are core activities that are required in e-learning. For example, checking notifications and guide posts, listening to lectures, and posting assignments, questions, and answers. When these core activities are executed properly, the possibility of learning success is increased. However, if these activities are not carried out properly, learners are likely to fail. Therefore, if participation information is provided to learners objectively, it is expected to enhance their level of participation in learning activities by monitoring and reflecting on the learning process.

Finally, based on the learning activities and learning behavior indicators presented in this learning analytics study, we provide criteria for standardized LMS development on the institutional and national levels. When LMS is developed, various functions can be assigned, and this study has established the criteria that should be used in the provision of information to the learner. LMS must create the appropriate meta-data to function. The indicators of learning behavior that are presented in this study should be the criteria for the creation of such meta-data. From a learning analytics point of view, meta-data and learning behavior patterns should not only be analyzed but also prescribed in a timely manner to assist in more successful learning in e-learning environments.

Limitations and future directions

In this study, learning activities and learning behaviors in e-learning environments were derived as a basic foundation for research in learning analytics. Through the modeling of behavior, learning data are identified, and learning analytics provide meaningful information about the learning process for learners and instructors. The aim is to facilitate learning and to support teaching activities. Therefore, through the modeling of learning behavior data, learning information should be provided to both learners and instructors. In addition, further research is needed on the effects of the implementation of this method. Through a needs-analysis study, the information that is needed by instructors and learners and a screening process of learning information could be determined. Furthermore, if the studies are conducted using the proxy data as a representative that can explain the sub-variables of learning, it would be expected to provide important guidelines for learning analytics on the LMS in higher education.

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