Needs Analysis on Using Data about Learner Behaviors in the Perspective of Learning Analytics

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***Abstract*—Learning Analytics has emerged as one of the educational technology as affecting higher education, the interests in the theoretical and practical aspects are heightened. Most of the learning analysis study is to investigate the effects of providing learning and behavioral data visualization on learning. The information provided to learner have been determined by the teacher and researchers based on preceding review of the literature. However, the information provided to the learner through learning analysis should be designed by the needs of the teacher and learner but it is hard to fine relevant studies. In this study, learning activities and learning behavior was defined in conjunction with concept of learning analytics, whether the difference between teachers and learners' learning activities, and also between teachers and learners' needs on information based on learning analytics.**

***Index Terms*—learning analytics, e-learning activity, learning behavior, needs analysis**

I. Introduction

Being able to easily collect and analyze digital data on the learning behavior of learners in the learning environment, e-learning, in the practical and theoretical aspects is increasing interest in Learning analytics.

According to the 2016 NMC Horizon Report, learning analytics is presented in educational technology affecting higher education within one year [1]. Long and Siemens [2] defined learning analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purpose of understanding and optimizing learning and the environments in which it occurs." By analyzing the data related learning behavior of learners in e-learning training environment, the learning process can be understood more objectively [3]. It may also provide a useful reference data to the appropriate intervention for facilitating learning and decision-making [4], [5]. There are countless digital traces left by learners as the learners progress their learning in e-learning environment [6].

Previous research of learning analytics has generally analyzed the effect of learning by providing the result from collecting/analyzing some data that affects learning. However, it is hard to find a needs analysis study that what kind of information is useful to the learner and the instructor which is informed through real learning analytics. The purpose of this study is to analyze the needs for learners and instructors can be derived by analyzing the digital learning behavior data in e-learning environment. The study would provide significant implications for the future study based on analysis of information visualization and dashboard development research.

II. Literature Review

A. Data for Learning Analytics

Historically, the learners are leaving a lot of digital traces/log data to proceed with the study in current educational environment than ever. The digital traces/log data which are generated in the computer-based learning can be analyzed to identify patterns in learning behavior [7]-[9]. It may provide a wide range of insight into the learner motivation and behavior learner [10]. Learning analytics is an academic approach to predict and control learning outcomes by providing an educational implication which is figured out by analyzing the data related to the learning activities of students [5], [11].

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Learning analytics has a greater interest and significance in the qualitative data resulting from the learning behavior even though learning analytics analyzes the various quantitative data for the learner generated in the learning process [12], [13].

There are several classifications for learning analytics data collected form not only the computer data base, but also the learner's digital interaction: digital trace data from learners, the data from the interaction of learners with educational and information technology, and log data from computer data base. Digital trace data from learners is defined as evidence of human and human-like activity that is logged and stored digitally. Learner's digital trace data is record of activity undertaken through an online educational and information system [14]. 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 [15]. In a computing context, a log is the automatically produced and time-stamped documentation of events relevant to a particular system. Virtually all software applications and systems produce log files. Based on the data is recorded on learners' web log data, the various learning analytics research have been conducted. Learning analytics research has been conducted by implementing an analysis system for individual learning progress of learners, learning patterns, participation in learning, learning environment, etc. [16]. As the internet based game with an increase in interest in the education field, educational games site usage patterns using a web log data mining is analyzed [17]. It is that data preprocessing, extracting and analyzing the log file are applied to learning analytics research. Depending on learning sequence of instructor and learner, web-based teaching support system were analyzed [18]. Studies have been consistently reported based on the learning data which is already existed in the LMS by the activities of the learners. For example, Purdue University's Signals [19] and University of Maryland – Baltimore County's "Check My Activity" [20] both rely on data generated in Blackboard.

B. e-Learning Activities and Learning Behaviors

e-learning activities for learning analytics should focus on the learning behavior of learners, rather than earlier conceptual distinction. According to [21], learning activities are achieved through completion of a series of tasks in order to achieve intended learning outcomes and consist of three components: context, pedagogy, and task. Instructional Measurement Systems Global Learning Consortium [22] suggested Learning Activity Metrics that represents measurements specific to actions within each genre of activity. The idea behind learning activity metrics is that most learning activities can be grouped into one or more genres, e.g. reading, assessment, Collaboration, etc. This metrics focus on learning activities rather than computer log data [23].

In the following Fig. 1, the learning activities matrix include context, pedagogy, and task which are three components of learning activities. It is also presented separately data calculated by the learning activity result to participation and performance.

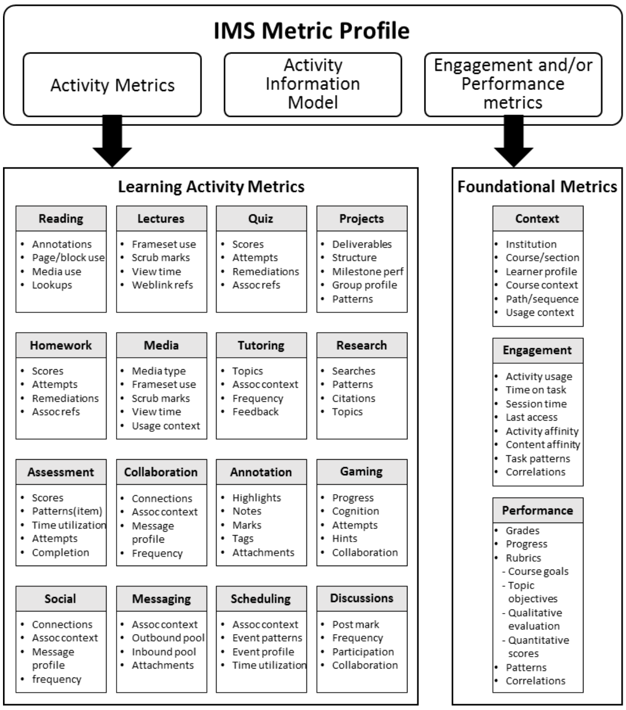

Figure 1. IMS metric profiles [22].

IMS Metric has been presented learning activities (such as homework, assessment, etc.) and learning behavior (such as reading, annotation, etc.) are mixed. Learning behavior refers to the observable behavior of learners to perform a learning activity. It could be called as a learning traces data for learning analytics. In this study, the learning activity and learning behavior are organized separately in e-learning environment and also based on the organization, it attempts to analyze the learners and instructors' needs.

C. Learning Data Usage for Supporting Self-directed Learning

One of the ultimate goal of learning analytics utilizing the learning data in e-learning activities is to promote self-directed learning. Self-directed learning ability of students is considered to have significant ability to successfully complete the e-learning since e-learning has been performed in a unique learning environment that in which not only instructor and learner but also learner and learner are separated respectively. Self-directed learning has been established by Knowles who constructed a theory of andragogy. Self-directed learning which draws from Knowles [24] is the process involving for learners to have the initiative to learn on their own, diagnose their learning needs and set learning goals, ensure the human and material resources necessary for their learning, choose the appropriate learning strategy and execution, and also evaluate their learning results of their achievements. Self-directed learning has been studied to reveal the psychological characteristics of learners such as the intrinsic motivation and emotion of the learners and cognitive characteristics of learners such as meta cognition and critical thinking [25], [26], and also to identify learning processes, procedures, techniques, and strategies [27], [28]. To review their overall research, self-directed learning has been identified as the composition of emotional regulation, motivation regulation, cognitive regulation, meta cognitive regulation, and environment regulation, etc.

Having connected with the characteristics and factors of self-directed learning and learning data from e-learning activities, self-directed learning is widely used for the inspection and analysis of the learning activities, detection of learners' emotion, prediction and intervention of learning, tutoring and mentoring, promote socialization of learners, evaluation and feedback, adaptive teaching, individualization and recommendation, and reflection. In the e-learning activities, inspection and analysis of the learning activities, assessment, feedback, and reflection etc. are associated with meta cognitive regulation, while personification has relevance to cognitive regulation, tutoring, mentoring, and promoting socialization are related to behavioral regulation, prediction and intervention are associated with meta cognitive regulation and environmental control capabilities respectively. The following variables are available to measure the learning data: such as login place by IP address, sign regularity, how many times check the learning objectives, posting counts, tool utilization counts, comments and notes views, highlighting, the number of problem solved, read time, and the amount of information search time.

III. Research Question

The specific research questions were as follows:

1) What is the learning behavior to perform each learning activities and learning activities in e-learning environment? What is in there that can provide information through the learning analytics.

2) What is the differences in the implementation of the instructor and learner to learning activities?

3) What is the differences in needs of the instructor and learner for information that can be provided by learning analytics?

IV. Research Method

A. Validation of Learning Activities and Learning Behaviors

The two times of expert validation survey on e-learning activities and learning behavior, based on literature review, were conducted. Ten experts who participated in the expert validation survey has over 5 years of e-learning teaching and research experience. To collect more in-depth opinion about the revised reflecting in the primary expert validation survey, expert seminar was held with three experts of expert panel group who have the most professional e-learning teaching and operating experience. It was confirmed by a second expert validation survey in the final edit. The first expert validation survey tools were developed for 10 learning activities and 17 learning behaviors to evaluate the validation on a 5-point Likert scale, and also writing comments. It was discussed in depth reflection about the first validation survey results and corrected in expert seminar. The second expert validation tool, reflected the first expert validation result and expert seminar, was developed to 8 learning activities and 29 learning behaviors in order to perform each learning activity to evaluate the validation on a 5-Likert scale. Each collected data were analyzed technical statistics such as mean and standard deviation. Learning activities and learning behaviors have been modified by reflecting the opinions of experts with statistics.

B. Needs Analysis on Learning Analytics based Information

According to the Need Analysis Model of Witkin and Altschuld [29], requirements analysis consists of three phases: Pre-Assessment, Assessment, Post-Assessment. In the first phase, setting the purpose of needs analysis and developing the needs analysis methods and tools. And then in the second step, analyzing and synthesizing the collected data according to plan. In the last phase, determining the priority of needs and deriving the implications for reflecting them to the actual training.

1) Participation

Needs analysis was conducted in instructor and learner. 8 e-learning instructors, who have averagely 9.3 years of e-learning operating experience, and 2 people, who are in charge of cooperate education in e-learning, were selected for needs analysis survey. 80 University students who take e-learning course and 4 cyber university students were selected for on-line needs analysis survey. In addition, 52 university students who take "Educational Technology" in A university and 51 university students who also take "Educational Technology" in B university were selected for off-line needs analysis survey. In total 187 learners were participated in needs analysis survey for learner.

2) Instruments

Tool for the learners and instructors' needs analysis is composed of two parts. Feasibility of questions was verified from 10 experts who participated in the expert panel. First, 8 learning activities and 29 learning behaviors, which are validated from expert panel, are evaluated on a 5-point Likert scale by not only instructors but also learners. Second, the usefulness of the information (16 for instructor and 12 for learner), which is informed by learning analytics, are evaluated on a 5-point Likert scale.

3) Analysis

The average and standard deviation of experts' response was calculated by the expert validation survey on learning activity and learning behavior on e-learning. Complement the questionnaire of needs analysis was modified by reflecting the experts' qualitative feedback. Gap of needs for information based on learning analytics and also gap of utility for learning behavior between teacher and learner was confirmed through the independent t-test. And also the difference between the teacher and the learner to visualize proposed by multidimensional analysis.

V. Results

A. e-Learning Activities and Behaviors

1) Expert validation on learning activities and learning behavior

In order to analyze the learning information that can be derived through learning behavior-related data of the learners in e-learning environment, learning behavior, as digital data traces by e-learning activities, were tried to be identified. 8 learning activities and 29 learning behaviors, which are derived through literature review, are validated by expert panel.

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

In the learning behaviors, 3.1. Reading Notifications and guide posts (assignments, exams, etc.), 4.2. Comments and Reply, 5.4. Reading materials, 5.6. Comments and Reply, 8.1. Ask a question, 8.2. Answers to learning behaviors are all shown an average 5.0 (SD=00), and absolutely important learning behavior in e-learning was found to be a learned behavior expert validation results.

Meanwhile, 1.2. Listening to MP3-type lecture (or lectures MP3 Download) (M=4.22, SD=1.09), 2.3. Bookmark (M=4.29, SD=.95), 5.2. Read the results of other student's work (M=4.33, SD=.71), 2.1. Take notes on the lectures (M=4.33, SD=.87), 2.2. Highlighted (the highlighting) to (M=4.33, SD=.87), etc. was found to relatively low in the e-learning behaviors.

2) Expert validation on e-learning information for learning analytics

As the result of expert validation, the learning information to be provided to support the learning in e-learning environment, overall validity average was higher by 4.77 (SD=42). In a detailed study information, 2. Learning Readiness-Prerequisite average appear to 5.00 (SD=.00) were confirmed to be very important information. Next, the average of the study guide information and perform tasks to whether the information was 4.89 (SD=.33).

Thus, overall, eight of 29 learning activities and learning behavior e-learning learning environment indicators were identified as relevant.

B. Differences between Learning Activities of Learner and Instructor

For learning activities and behaviors in e-learning environment, we examined whether there is a difference in the actual utilization degree of the instructor and the learner. According to the Table. I, average of instructor's learning activities was 4.43 (SD = .40), and the average of learner's was 3.46 (SD = .64). In the t = -4.276, p <.05 level, it showed that there is a significant difference. It was confirmed that a very large effect size d = 1.87. In other words, there is instructor's activities can be interpreted as much more meaningful than learner's activities in e-learning environment. However, there is no significant differences between instructor and learner in 2. note taking (remember promotion). Detailed results of the study were presented to the actions Table I shows and illustrates the differences in instructors' and learners' leaning behaviors. It helps intuitive understanding.

TABLE I. The Differences in Instructors' and Learners' Learning Behaviors

Learning Activity	Learning Behavior	Subjects	Mean	SD	t	d
Total		learners	3.46	0.64	-4.276**	1.87
		instructors	4.43	0.40		
Learning course materials	Watching learning materials(video, flash, game, simulations)	learners	3.73	1	-2.122*	0.74
		instructors	4.5	1.07		
	Listening the MP3 lecture(or download lectures MP3)	learners	2.2	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	4.5	0.76		
Note taking(Remember promotion)	Taking notes in learning materials	learners	3.11	1.28	-1.181	-
		instructors	3.8	1.3		
	Emphasizing(Highlighting)	learners	3.25	1.31	0.076	-
		instructors	3.2	1.48		
	Bookmark	learners	2.88	1.26	-1.527	-
		instructors	4	1		
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	4.5	1.07		
Discussion activities	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	learners	3.21	1.26	-7.199**	1.72

	opinions	instructors	4.71	0.49		
	Post reference	learners	3.4	1.17	-5.161**	1.34
		instructors	4.5	0.54		
	Reading shared materials	learners	3.45	1.22	-6.065**	1.48
		instructors	4.71	0.49		
Cooperation activities	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	1.6		
	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	3.3	1.08	-2.746**	1.21
		instructors	4.43	0.79		
Post assignment	Post task performance results	learners	4.26	0.92	-4.294**	0.98
		instructors	4.88	0.35		
Evaluation activity	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	3.8	1.2	-1.683	-
		instructors	4.57	0.79		
	Peer review(cooperation)	learners	2.71	1.32	-1.53	-
		instructors	3.75	1.5		
	Self-evaluation	learners	2.72	1.3	-0.363	-
		instructors	3	2		
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		

C. Differences between Learner and Instructor Needs

The results of instructors and learners' needs gap for information provided by learning analytics in e-learning are represented by Table II.

TABLE II. RESULTS OF INSTRUCTORS AND LEARNERS' NEEDS ANALYSIS

Learning Information	Subjects	Mean	SD	t	d
Total	learners	3.42	0.77	-9.543**	2.25
	instructors	4.66	0.33		
Learning readiness-Required skills	learners	3.39	0.98	-3.555**	1.65
	instructors	4.63	0.52		
Learning readiness-Prerequisite subject	**learners**	**3.55**	**1.04**	**-9.079****	**1.91**
	instructors	**4.88**	**0.35**		
Learning progress situation	learners	3.58	1.09	-5.251**	1.3
	instructors	4.63	0.52		
Learning guidance information	learners	4.28	0.85	-4.239**	1
	instructors	4.88	0.35		
Whether performing tasks	**learners**	**3.3**	**1.22**	**-7.793****	**1.73**
	instructors	**4.75**	**0.46**		
Task performance results	learners	3.51	1.28	-5.442**	1.4
	instructors	4.63	0.52		
Plagiarism result	learners	3.02	1.29	-7.024**	1.62
	instructors	4.5	0.54		
My participation information compared with entire classmates	**learners**	**3.28**	**1.2**	**-7.916****	**1.77**
	instructors	**4.75**	**0.46**		
Result of relative quiz and performance evaluation	learners	3.45	1.27	-5.712**	1.32
	instructors	4.63	0.52		
Result of each evaluation items	learners	3.76	1.14	-5.370**	1.24
	instructors	4.75	0.46		
Forecast of dropout	**learners**	**2.82**	**1.3**	**-10.209****	**2.19**
	instructors	**4.75**	**0.46**		
Forecast of grades	learners	3.05	1.29	-2.319*	1.01
	instructors	4.13	0.84		
Feedback of learning process	learners	3.46	1.32	-4.814**	1.27
	instructors	4.75	0.71		

According to the Table II, total average of instructor's needs in e-Learning was 4.66 (SD=.33), and total average of learner's needs in e-Learning was 3.42 (SD=.77). There were significant differences between instructors and learners needs for information provided by learning analytics in e-learning. $t = -9.543$, $p < .05$ level, the effect size was $d=2.25$ that is large effect. Learners wanted to get information on Result of each evaluation items

(M=3.76, SD=1.14). On the contrary, instructors wanted to have information on Learning readiness-prerequisite subject (M=4.88, SD=0.35), and Learning guidance information (M=4.88, SD=0.35). Overall, there were differences needs for being provided by learning analytics between instructors and learners. Especially, instructors need more learning information than learners in e-learning environment.

VI. Discussion and Conclusion

Learning activities and learning behavior in e-learning environment was confirmed to be very useful and relevant indicators in teacher perspectives. In needs of the teacher and learner, learning activity and learning behavior required to perform the actual e-learning, such as Q & A, discussion activities, cooperation activities, etc., are confirmed to be important to the learner. The teachers' needs appeared to be more significant than the learners' needs. However, the passive forms of learning activities such as watching and reading the lectures, was accounted for a high proportion. The proportion of active forms of learning such as presenting opinions, commenting and replying, responding, etc. was appeared to be low. Therefore, the support strategies to replace cognitive learning participation of learners with traces of digital learning information are required. In addition, utilization degree of the note taking (stimulating activity for memory) was analyzed to be low in e-learning environment because on-line note taking skill is not highly technical perfection and also it has different note taking mechanism with off-line. In the learning information part, learners often preferred the information available to determine the learning process and the learning outcomes. Teachers, on the other hand, preferred entire learner information, whether performing tasks, forecasts of dropout, etc. to operate and manage the class. Therefore, there is a need to provide divided into learning analysis information for teachers and for learners. In order to provide a more personalized learning information about e-learning activities and behaviors, it is necessary to analyze how to the result of e-learning activities, behaviors and information affect to learning progress and result of learner directly or indirectly. Depending on the learner's characteristics, the type of information to be provided is expected to vary.

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