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Analyzing and Comparing Online Learning Experiences through Micro-Level Analytics

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Abstract: *Learning analytics collects and uses observations of interactions, which allow course instructors to search for the underlying patterns of a student' learning progress and to accordingly optimize the student' learning progress at a micro-level. Understanding the online learning experience through the learning analytics approach is essential to inform future pedagogical decisions in online learning design. This paper attempts to define the concept of an online learning experience in three dimensions. In addition, the Experience Sampling Method (ESM) is suggested as a supplement to Web log analysis (WLA) to collect data on cognitive involvement and learning emotion as well as to collect behavioral interaction data. Then, using Clow's learning analytics cycle as a framework, this paper demonstrates how the identified cognitive, emotional, and behavioral aspects of the online learning experience can be captured and reported in the online learning experience dashboard for each individual student. In addition, the online learning experience data between two courses were compared to find evidence of different learning experiences when courses are designed with different learning tasks. The main finding from this paper is that ESM enables us to capture online learners' psychological dimensions of learning experiences and provides rich information on each learner's progress in an online course.*

Keywords: Online learning experience, Learning analytics, Web log analysis, Experience sampling method, Online course design

1. Introduction

The emergence of online learning shifted the focus of the learning process from a traditional teacher-centric process in which students primarily learn by interacting with the course instructor to a decentralized learning process in which students learn through interacting with the course structure and content (Agudo-Peregrina, Iglesias-Pradas, Conde- González, & Hernández - García, 2014). This emergence also changed how we understand the learning experience in online learning because many currently available learning management systems (LMSs) enable learners to experience multiple layers of interactions among all the different agents, including learner-instructor, learner-learner, and learner-content interactions. Such a wave of popularity of LMSs allows certain learning tasks to be technologically mediated (Pardo, 2014). The increase of technology mediation in learning experience offers the possibility of collecting and analyzing a wide variety of observations of interactions without user intervention. The analytic methods applied in a learning experience are called learning analytics (Long & Siemens, 2011). Hence, learning analytics focuses on utilizing gathered interaction data to optimize students' learning performance by applying learning interventions and helping them be aware of their learning progress (Larusson & White, 2014). The analytics results can also help the course instructor design pedagogical strategies to present effective and efficient learning content, to promote interactions among learner, teacher, and the learning content, and to support learners' affective state such as emotion and motivation.

Because the overall goal of such content design, interaction design, and motivational design is to provide learners with the optimal level of learning experience, understanding what students truly think, feel, and do in an online learning environment can elucidate certain insights on making future pedagogical decisions regarding online learning design. Without analyzing learning experience properly, the data-driven implications for online learning design (or online learning "experience" design) cannot be defined or will simply be ignored. Therefore, it is critical to properly analyze the online learning experience to better serve as the source of informed decisions.

2. Online Learning Experience and Learning Analytics

Learning, by nature, is a continuous process grounded in experience. Many prominent scholars in the 20th century, such as Dewey, Lewin, Piaget, Jung and others, accorded experience a central role in their human learning and development theories (Kolb & Kolb, 2009). The word "experience" and the idea of "user experience" are often used in designing and developing interactions between users and products (Forlizzi & Ford, 2000). Forlizzi and Ford explained "experience" in three different ways: experience, an experience, and experience as a story. What Dewey (1934) referred to in his book, Art as Experience, was "an experience", which has a beginning and an end, changes the user, and occasionally changes the context of the experience as a result.

In online environments, the learning experience cannot be separated from the learning activities and the learning tasks that provide the context of the experience. On the course level, students are assigned a series of learning tasks presented in a pre-designed sequence and are engaged in learning activities to complete the learning tasks. Through the intended learning activities that are designed to complete a certain learning task and achieve a certain learning goal, online learners experience "a task" one by one, and eventually a series of task experiences is accumulated to shape the overall learning experience within the course (Figure 1). For example, if a student is assigned a task of online discussion, she/he first needs to be involved in reading activities (a textbook or other materials), writing activities (a review/summary of the reading), and sharing activities (posting the review/summary/reflection to a discussion board and communicating these with others), and reviewing activities (reading others' discussions to understand different perspectives and viewpoints). Then, the learning cycle repeats itself for the next learning task. Learners must take necessary steps to be continuously engaged in the learning tasks to be successful in online learning.

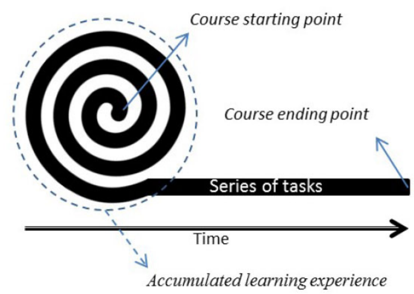

Figure 1. Learning experience in an online course.

From the situated and sociocultural perspective, learning occurs beyond the experience of an individual's reflection(Brown, 2009; Seaman, 2008). Therefore, the relationships between the participants, activity, and the learning context also need to be considered when considering learning experiences. Learning experiences emerge from the fundamental relations among cognitive, metacognitive, and affective processes (Op 't Eynde & Turner, 2006), and the complex relationships between mind, body, feeling, and the context influence cognition and learning should be noted (Barsalou, 2008). Thus, as Illeris (2003) insisted, more studies are needed to establish a connection between the cognitive, emotional, and social dimensions of learning experiences.

According to Illeris (2003), the learning process consists of three different processes of learning, which are the cognitive process, emotional process, and social process (also see Poscente, 2006). Based on Kolb's (1984) model of experiential learning theory, Illeris (2003) explains that the cognitive learning process is about "how we learn something" (p. 63). More specifically, the cognitive process is represented as an idealized learning cycle where the learner experiences, reflects, thinks, and acts in a recursive process in the learning situation (Kolb, 1984). A learner starts with a concrete experience that forms the basis for reflective observation, then the reflections are assimilated to abstract concepts which draw new implications for action. The actively tested implications serve as the source of further concrete experience. Therefore, a learners' cognitive experiences are manifested through the amounts of cognitive efforts during the cognitive process, the time taken to complete the cognitive process, and the academic artifacts created as an outcome of the cognitive process. Regarding the emotional process, Illeris (2003) uses the term 'emotional' to describe affective aspects of the learning process. According to Pekrun's (1992) conceptual model of emotions, emotions can be classified using the criteria of valence (positive vs. negative) and activation (activating vs. deactivating) in the academic learning context. Therefore, academic emotions can be depicted within the four dimensions of valence and activation. For example, emotions in an academic context can be placed within the framework of positive activating emotions, positive deactivating emotions, negative activating emotions, and negative deactivating emotions. Hence, it is critical to consider the different aspects of emotions when analyzing emotional experience in a learning context. Lastly, social components of learning from interactions within a learning context define the third dimension of learning experience, behavioral experience. Because the nature of learning interaction is defined based upon the types of tasks (Herrington, Reeves, & Oliver, 2006) and the relationship between the teacher and the learners, including the degree of a course centeredness (e.g., teacher-centered or learner-centered) (Weimer, 2002), the context of learning, whether delivered via face to face or online, determines learner behaviors. However, as Woo and Reeves (2008) pointed out, studying online learning interactions without considering the importance of cognitive and emotional experiences is limited because of the lack of evidence showing the interactions are meaningful.

Previous studies explored students' online learning experience using varied constructs without a consensus of what represents such experience. Some examples from recent studies include online learning engagement (Thomas, Lasen, Field, & Skamp, 2015), perception and motivation in a learning community (Kuong, 2015), online communication difficulties and coping strategies (Symeonides & Childs, 2015), time, teaching clarity, and course design (Tang, Wong, & Wong, 2015), motivation, emotion, and learning strategies (Cho & Heron, 2015), deeper learning (Czerkawski, 2014), and self-efficacy and learning satisfaction (Shen, Cho, Tsai, & Marra, 2013). Also, the community of inquiry (CoI) model proposed by Garrison, Anderson, and Archer (1999) has been widely used as a research framework to investigate the three types of presence, which are teaching presence, social presence, and cognitive presence, in online teaching and learning. Although those previous studies and the CoI model offer a great research framework to study online learning experience, none of the studies analyzed the online learning experience from the three aspects of cognitive, emotional, and behavioral experiences using a learning analytics approach, which can provide the in-depth analysis of online learning experience during the entire semester.

Learning analytics is an emerging field of educational research (Johnson, Adams, & Cummins, 2012). Although the concept of learning analytics and the implications of analytics for improvements in teaching and learning may differ from one person to another (Anderson, 2003; van Barneveld, Arnold, & Campbell, 2012), there appears to be a consensus on the object of learning analytics as contributing to improvements in learning processes and outcomes (Siemens et al., 2011). In an online LMS or virtual learning environment (VLE), "learning experience" data can be gathered from the huge quantity of digital traces that are generated while learners complete a series of learning tasks and interact with other peers and information (Richards & DeVries, 2011; Siemens et al., 2011). Weblog data analysis or Web usage analysis has been one of the most commonly used methods in analyzing online behaviors because those digital traces can be stored in real-time and provide valuable information and insights on the actions that each individual learner performed in his/her learning process (Mahajan, Sodhi, & Mahajan, 2016). Although Web log forms of data could be valuable for providing indictors of student engagement, they do not provide insight into understanding how students are learning and what they are learning (Lockyer, Heathcote, & Dawson, 2013). Web logs are often solely limited to behavioral interaction data, and there is a need to supplement the Web logs data with psychological experience data, such as cognitive involvement and emotion to fully understand students' learning experiences (Park, 2015). Although it is challenging to capture individual learners' psychological experiences, we can explore a combined method of Web Log Analysis (WLA) and the Experience Sampling Method (ESM) as a viable approach to analyze an online learner's cognitive involvement and emotional experience as well as behavioral experience while completing each learning task.

In this paper, the researcher attempted to showcase how the WLA and ESM methods can be used in a combined manner to collect and analyze online students' learning experiences in three dimensions: learners' cognitive involvement in a task, task-related emotions, and behavioral interactions.

2.1. Web Log Analysis

Web log files provide the time-stamped list of user actions that have occurred during a certain period of time (Grace, Maheswari, & Nagamalai, 2011). Many LMS or VLE offer screens to display such actions in their platform. The vast quantity of collected action information can be used to investigate the login times per day, the participation in discussion activities, and interactions with their classmates/the course instructor. The data can be visually presented in the form of class as an analysis unit or for each individual learner (as shown in figure 2).

a successful completion rate. Previous studies show that using Web log data analysis is beneficial to understand learner behavior in the online learning system. For example, Sheard, Albrecht, and Butbul (2005) found that knowing when students access various resources can help instructors understand students' preferred learning patterns. In addition, Dringus and Ellis (2005) evaluated the progress of a threaded discussion by analyzing asynchronous discussion form usage data. Vanijja and Supattathum (2006) reported how the results of Web log data analysis can show usage patterns among various online learning courses. Recently, Wise, Zhao, and Hausknecht (2014) analyzed students' log-file trace data of speaking and listening activities visible to learners and developed selected metrics to investigate how students attend to other students' messages in online discussions.

Although Web log data can provide online learners personal information (such as profile, assignment scores, interaction data) and behavioral experience data (such as reading, writing, taking tests, performing various tasks, and communicating with peers/

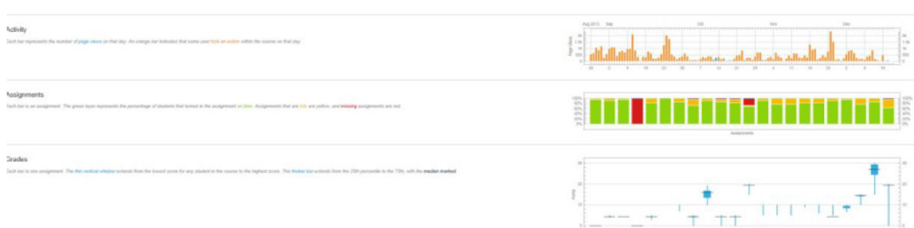

Figure 2. Example dashboard of learning analytics data on the course level.

Data visualization from Web log analysis can aid administrators and policy makers in improving the institutional efficiency in online learning. In addition, the data can help course instructors identify struggling students so that they can provide proper interventions, enhance course efficiency, and further ensure

instructor) (Mostow, Beck, Cen, Cuneo, Gouvea, & Heiner, 2005), it is still challenging to understand their cognitive experience (e.g., how cognitively a learner was involved in a learning task) and emotional experience (e.g., how a learner emotionally responded to a certain learning task).

2.2. Experience Sampling Method

Experience sampling method (ESM) is "a means for collecting information about both the context and content of the daily life of individuals" (Hektner, Schmidt, & Csikszentmihalyi 2007, p. 6), and it has been widely used in research because it "examines fluctuations in the stream of consciousness and the links between the external context and the contents of the mind" (Hektner et al., 2007, p. 6). In behavioral observations, data obtained are used to examine the activities of the observed participants and the contexts within which the activities occurred, but no other information is gained on how the participants actually experienced the activities and contexts or in what cognitive experiences or emotional experiences they were engaged.

ESM begins by requesting individuals provide written responses to both open-ended and closed-ended questions at several random points throughout each day of a normal week. Then, each individual is prompted to respond using a pre-designed signaling strategy. According to Hektner et al. (2007), the questionnaire can be tailored to meet the researchers' interest and goals; however, in general, questions often include physical context, social context, activities, thoughts, feelings, and cognitive/motivational self-appraisals. The benefits of ESM is that it allows a researcher to capture an individual's experience as it occurs; therefore, it is well-suited to measure dimensions of experience that are likely to be context-dependent. Among the three sampling methods, which are called signaling schedules (interval-contingent sampling, event-contingent sampling, and signal-contingent sampling) (Hektner et al., 2007), event-contingent sampling has been used in studies that collect data on children's experiences in school days because participants are able to focus more on the particular context of interest (Hektner et al., 2007; Turner et al., 1998; Uekawa, Borman, & Lee, 2007). Participating students can provide reports to the researcher solely after a particular event of interest has occurred, and the experience can be compared with other students' experience in the same or similar situation.

As discussed in the previous section, Web log data can provide a vast quantity of online learners' behavior data. However, other aspects of learning experience, such as learners' psychological experiences, are not captured in the Web log data. Alternatively, we can implement ESM in research on online learning experience to supplement Web log data by providing information on learners' cognitive involvement and emotion when they occur. To begin with ESM in online learning experience research, the scope of the target event in online learning first needs to be determined. After the target event is defined, the corresponding learning activities and learning experience are also defined and can be measured at certain events throughout the semester using the event-contingent sampling strategy. Next, a set of questions requesting particular aspects of learning experience needs to be designed. It can include various types of questions as Hektner et al. (2007) suggested; however, it would be ideal to focus on learners' cognitive experience and emotional experience. Finally, the event-contingent signaling strategy would be the most appropriate signaling schedule in online learning experience research, as previous studies suggested. By collecting online learners' cognitive involvement and emotion data using ESM and their behavior data using Web Logs, we can better understand the learning experience in online learning.

In this paper, ESM was utilized to collect online learners' cognitive and emotion data. In addition, Web logs were used to collect behavior data in two different online courses. Then, the learning experience analysis for each individual student was conducted at a micro-level, and the resulting analytics were presented in a visualized dashboard. Additionally, the overall learning experiences between the two different online courses were compared with each other to examine whether students indeed showed different learning experiences in the two courses.

3. Method

3.1. Learning Analytics Cycle

Campbell and Oblinger (2007) defined analytics in educational contexts in five steps: capture, report, predict, act, and refine. The researchers explained each of the steps as follows. The first step, capture, utilizes the required measures to ensure the information regarding learning events occurring in LMS is stored properly. In the second step, report, the stored data are processed through simple visualizations or more complex algorithms that summarize or combine data. In the third step, prediction, analytics data are customized to provide answers to previously formulated questions by stakeholders, such as learners, instructors, administrators, or decision makers. The fourth step, act, generates practical actions to change any aspect of the learning activity. Finally, the refinement step revisits previous stages and ensures the necessary supervised and adjustments are included to improve the accuracy of the results.

Based on the five steps in learning analytics, Clow (2012) suggested a learning analytics cycle with four components: learners, data, metrics, and interventions (Figure 3). The first step in the cycle is to identify learners and the learning setting. Once the scope of the learning setting is defined, data regarding the learner are generated and captured. Next, the collected data are processed to provide useful insights in understanding the learning process. Last, which Clow emphasized as the most important step, the analytics results are used to design and implement interventions to affect the learning process. In this paper, Clow’s learning analytics cycle was used as a framework to analyze the online learning experience in two different learning courses. The unit of analysis was course tasks that were presented to students on a weekly basis. The dimensions of analysis included the behavioral experience, the cognitive involvement, and the emotional experience.

3.2. Learner and Learning Setting

Twenty two graduate students enrolled in two 8 week-long online courses were

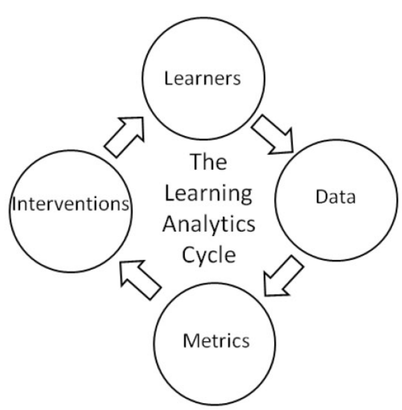

Figure 3. Learning analytics cycle (Clow, 2012).

identified as learners in this analysis. Twelve students were enrolled in a "Program evaluation" course (Course A), which focused on textbook reading and discussion activities, whereas 10 students were enrolled in the other course, "Instructional multimedia design and development" (Course B), which primarily required in-depth and hands-on activities in developing several multimedia projects. Because two students dropped from each course, data reported in this paper concern 18 participants, 10 (4 male and 6 female) in Course A and eight participants (all female) in Course B, with a mean age of 32.60 years (SD = 5.76) and 35.25 years (SD = 9.66), respectively. The average number of online courses that participants in each course had previously taken were 11.40 (SD = 4.88) and 11.38 (SD = 12.28), respectively, which was not significantly different. However, it should be noted that the number of students who have not taken more than 10 online courses previously was higher in class B (five participants) than in class A (three participants). Fifteen participants were teachers, including five in elementary school, five in middle school, and five in high school; additionally, there was one administrative assistant, one curriculum director, and one instructional designer.

Two online courses, A and B, were purposefully selected as the unit of analysis. The first course (Course A) primarily involved tasks such as book chapter readings, weekly discussion postings, quizzes, and writing an evaluation plan. Students enrolled in this course were expected to read the textbook, participate in weekly discussion activities, and complete a program evaluation plan. The other course (Course B) consisted of a series of hands-on tasks with a final Web-based multimedia unit development project. Students were required to review journal articles on multimedia design during the first week of the semester and participated in several multimedia development projects in the remaining weeks. Two courses were purposefully selected in this study because of the differences in the course objectives, nature of weekly tasks, required class activities, and the type of instructional approaches (see Table 1; in addition, refer to the Appendix for detailed course tasks). Both courses were developed according to the Quality Matters (QM) standards (Bento & White, 2010) and then approved by a certified QM reviewer. The courses were then delivered via Moodle LMS, which is an open-source LMS adopted by the university to create online learning courses. Moodle has been used as a popular alternative to proprietary commercial online learning solutions and is distributed free under open source licensing (Romero, Ventura, & Garcia, 2008). Moodle has been installed at universities and institutions all over the world (Cole, 2005). QM specifies as a standard set that is designed to certify the high quality of online courses. Both courses analyzed in this study achieved more than 10 points above an acceptable evaluation score after the rigorous review process. Because the analysis was intended to collect online learners' experience data in two different online courses, it was critical to note the differences in terms of required course tasks between the two courses.

Table 1. Comparison of two selected online courses

	Course A	***Course B***
Course objectives	By the end of the course, students will recognize and interpret evaluation models in the following levels:	This course provides an in-depth focus on the design and development of multimedia instructional materials. Emphasis will be

	satisfaction, knowledge, behavior, and result. Students will learn how to recognize and interpret various evaluation models that gather quantitative and qualitative data and that include the diversity of the faculty/student bodies and the dispositions. Students will adapt established evaluation models to accommodate technology employed in teaching and learning. Further, students will apply different data-gathering strategies to distance education settings and to traditional classroom settings in which technology is a significant element.	placed on the design of technology rich learning environments that support meaningful learning. Individual projects include instructional design and multimedia development using multimedia design principles along with hands-on activities in instructional multimedia tools such as Powerpoint, Audacity, Photostory, and Web authoring tools (Dreamweaver. Pagebreeze, and/ or Google sites, Wordpress etc.).
Key learning outcomes/ deliverables	• Program evaluation overview • Document review, online discussion • Textbook reading, article review, online discussion • Quizzes • Evaluation plan progress report • Final evaluation plan	• Audio based learning module design/ development • Visual learning module design/development • Personal Website development • Instructional Web based learning module design/development • Usability testing report
Learning tasks	• Students were guided to a real world scenario and contextualized data for weekly discussions. • Discussion topics were ill-defined and open to multiple interpretations. • Students were given a week of time for each discussion topic. • Students were encouraged to use a variety of related documents and Web resources. • Students were required to create a course outcome (program evaluation plan proposal) that can be used in their own organization.	• Students were guided to design and create instructional multimedia materials to solve a performance problem that they identified in their own fields. • Students had to determine the scope of each multimedia project to solve their unique performance problems that they had identified. • Students were encouraged to try different multimedia programs and apply various design principles that are related to their own projects. • Students were required to create a Web based learning module that can be used as an intervention to solve the identified performance problem in their own organizations.
Example of learning activity directions	[Week4] Knowledge question: Read chapter 4/5 and respond to the questions below. • Why an evaluator should use multiple variables? Explain your answer using your own example. • Define validity and reliability and provide one example for each. Discussion question: Please post your answer directly to the discussion board. • As discussed in this chapter, data-collection methods must be sanctioned by the proper authorities that include protection of human subject such	[Week3] Multimedia instructional material development using audacity and photostory: First, define a human performance problem: Use the GAP analysis and cause analysis to identify performance problems. • The performance problem will be solved by the multimedia instructional material you develop . • Determine how the multimedia instructional material can be an appropriate performance improving approach (versus requiring full scale training sessions, environmental corrections, etc) • Describe your performance problem in a word document. Justify it with the above rules. • Second, create a multimedia instructional

	as IRB committees or other review committees. In addition to seeking approval through proper channels and following organizational policies, it is also important that the evaluator seeks the input of those who will be involved actively or passively in the collection of information. If they object to the data-collection methods or procedures or fail to understand the purpose, they can sabotage the collection of valid information by providing false or misleading information or encouraging others to do so. Others simply may not take the data collection seriously. We surely don't want this to happen! What would you do as an evaluator to solicit their cooperation in collecting valid data for evaluation?	material: The quality of your image should be professional in nature; this includes: • Technically sound: opens/viewable, multiple layers, glitch free • Titled: identifies the purpose of instructional graphic to users • Proper resolution: visual resolution is set for high resolution • Color and Lighting: the multiple layers appear to belong as part of a cohesive image (e.g., lighting is the same angle and intensity, etc) • Readability – font styles, colors, sizes, background contrast, leading, etc should be arranged so as to make the graphics/audio easy to read/ listen, follow, and interpret • Instructional Quality – texts used in your project should guide users through the appropriate steps or concepts in order to complete their task. • Layout Design: use design principles discussed in class to create a professional looking layout and interface for your project • Analysis of performance problem: in a maximum 1 page, justify why the task addressed by your project is suitable • Audio: must have some parts of it that includes audio (your original audio) • Screens: your complete instructional material should be no less than 15 screens • Interaction: project must contain interactions to engage the learner on the content.
Technology use	Students utilized the following technology to share their ideas and insights via weekly discussions. • Moodle LMS • Online discussion • Web resources	Students utilized the following technology to design and create instructional multimedia materials. • Multimedia design programs • Audio instruction design • Visual instruction design • Instructional multimedia Web design

3.3. Data

To collect behavioral experience data, archived Web log data from the Moodle LMS were used. The Web logs data included three sets of behavior data: (1) Viewing activity (course viewing, forum viewing, and user viewing), (2) Online discussion activity (discussion viewing, discussion posting, discussion responding, and discussion updating), and (3) Assignment/project activity (quiz, resource viewing, and file uploading). Additionally, students' profile information, attendance record, and performance data were collected for each weekly assignment.

To measure the psychological dimensions of the learning experience, the researcher utilized ESM to collect the data necessary to compute cognitive involvement and emotion based on the contextual and experiential aspects of the online learning process (Bassi, Ferrario, Ba, Fave, & Viganò, 2012). ESM was used for each individual student to increase the accuracy and minimize retrospective biases by providing information on both contextual and experiential variables and to further reveal dynamic learning progress (Ebner-Priemer & Trull, 2009). The researcher particularly used the event-contingent sampling strategy to assess each learner's perceived psychological learning experience during the course. Weekly lessons were identified as the target event in online courses, and then corresponding learning activities and experience were defined. Each student was prompted to respond to a set of questions that appeared in a pop-up window immediately following a critical learning activity once per week. The questions were repeated each week immediately after the pre-determined critical activities. Students in both courses completed 6 sets of repeated questionnaires for week 2, week 3, week 4, week 5, week 6, and week 7/8. The invested mental effort score and the assignment performance score were used to compute the cognitive involvement score (Paas, Tuovinen, van Merriënboer, & Darabi, 2005). The average time taken to complete each weekly questionnaire was less than 2 minutes. The learning experience dimensions, metrics, methods, and questionnaires are presented in Table 2.

Table 2. Learning experience metrics and questions

Learning experience dimensions	***Metrics and questions***	***Methods***
Cognitive involvement	• Invested mental effort While completing this week's learning activity (lesson content and assignment), I invested (1: very very low mental effort through 9: very very high mental effort) • Perceived prior knowledge My prior knowledge /skills before completing this week's learning activity was (1: very, very low through 9: very very high) • Perceived task difficulty Completing this week's learning activity was (1: very, very easy through 9: very very difficult)	ESM
Academic emotion	• Interest Working on this week's learning activity was interesting. (1: very very untrue through 9: very very true) • Confidence I felt confident while working on this week's learning activity. (1: very very untrue through 9: very very true) • Frustration I felt frustrated while working on this week's learning activity. (1: very very untrue through 9: very very true) • Excitement Working on this week's learning activity was exciting. (1: very very untrue through 9: very very true)	ESM
Behavioral interactions	• Viewing activity : number of course viewing : number of forum viewing : number of user viewing • Online discussion activity : discussion viewing : discussion posting : discussion responding : discussion updating • Assignment/project activity : quiz : resource viewing : file uploading • Attendance • Task completion time	WLA

3.4. Metrics

An example of learning experience analysis from three aspects (cognitive involvement, emotion, and behavioral activity pattern) is presented in the learning experience analysis dashboard in Figures 4 and 5. The dashboard consists of five different areas. First, the top area presents the target student's background information, including name, gender, age, work, and previously taken online courses. In addition, the top-right corner of the dashboard provides a legend for behavioral activities. The middle section is where students' behavioral patterns and occurrences are presented. The cognitive involvement per each week is presented in the bottom-left section in a graph. And finally, students' perceived emotions per each week are presented on the bottom-right section in a graph. Whether a student is in progress or has completed a course, the learning experience dashboard created by using Web log data and ESM data are capable of offering the micro-level of learning analytics. The micro-level analytics can help learners and teachers make more local decisions regarding the current learning events (Clow, 2012; Wise et al., 2014).

With this visualization data, the course instructor is able to decide when scaffolding should be properly offered to the student. Additionally, depending upon the level of weekly cognitive involvement and emotions, the course instructor can decide the type of scaffolding (cognitive or motivational) to provide to the student.

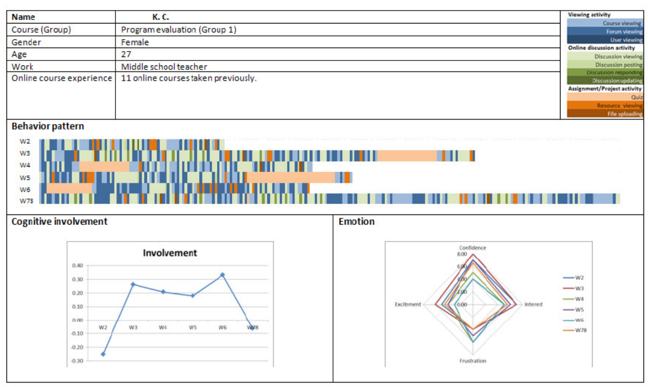

Figure 4. A micro-level online learning experience dashboard - Course A.

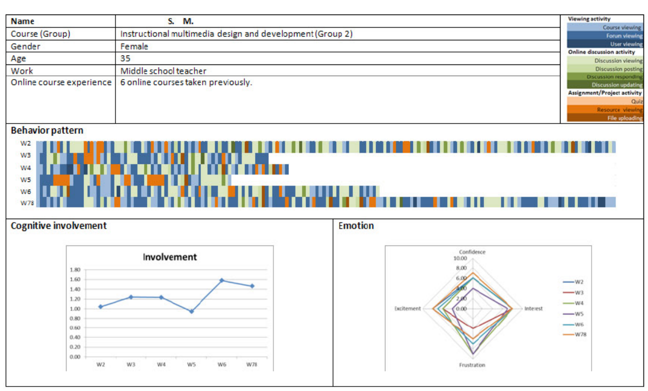

Figure 5. A micro-level online learning experience dashboard - Course B.

3.5. Intervention

It is expected that the learning experience analytics introduced in this paper can be used to inform the course instructor of the learning sequence that students follow and design more sophisticated interventions that can target one or more different aspects of the learning experience. For example, if a student experienced a negative emotion, such as frustration, while being involved in a certain task and showed lower cognitive involvement, it is necessary to holistically approach the issue from the aspects of cognitive, emotional, and behavioral experiences instead of only the behavioral interaction aspect. If behavioral interactions are found to be active, the student may still have high motivation to complete the learning task but suffer from a challenging learning task. The course instructor would be able to communicate such concerns with each individual student and share the learning experience dashboard to find a customized intervention to meet the academic need of the individual student.

The course instructor will be able to interpret the information that analytics provides and use it as a means to reflect on the learning design in online learning. Learning design (or learning "experience" design) describes the sequence of learning tasks, resources, and supports that a teacher designs for students over part of or the entire semester (Lockyer et al., 2013). Learning design also establishes the objectives and pedagogical plans, which can then be evaluated against the outcomes captured through learning analytics. Therefore, by investigating the behavioral interaction patterns in addition to the type of emotions and the level of cognitive involvement of all students, the course instructor can identify learning tasks that need to be revised or recreated as a result of analytics and accordingly adjust the level of task difficulty or implement motivational strategies in designing the course. Because learning design provides a model for the intentions of learning tasks and learning activities in a particular learning context, the revised course design can be used as a reference for learning analytics to support faculty in their learning and teaching decisions (Lockyer et al., 2013).

3.6. Comparison of Learning Experiences between Two Online Courses

To examine whether students experience online learning differently in two differently structured learning tasks, the collected analytics data were compared for each weekly task in the two courses. Four participants were excluded from the data analysis due to incomplete course work. A total of 18 online learners' learning experiences were included in the analysis. Several analyses were performed including descriptive analyses (i.e., means, correlations, and standard deviations) for each set of experiences of cognitive involvement, emotion, and behavior (Table 3). Then, the researcher compared the three aspects of learning experience between the two courses. A series of Mann-Whitney tests (Field, 2013), the non-parametric equivalent of the independent samples t-test, was utilized to compare cognitive involvement, emotion, and behavioral activity data between the two courses. The Mann-Whitney test was used in this study because the data did not meet the requirements for a parametric test, and the Mann-Whitney test has the great advantage of possibly being used for small samples of subjects between five to 20 participants (Nachar, 2008).

3.6.1. Cognitive involvement between two courses. Cognitive involvement scores between the two courses were compared per week using the Mann-Whitney test.

Among the six weeks compared, cognitive involvement levels in week 3, week 4, week 5, and week 6 were significantly different, as shown in Figure 6.

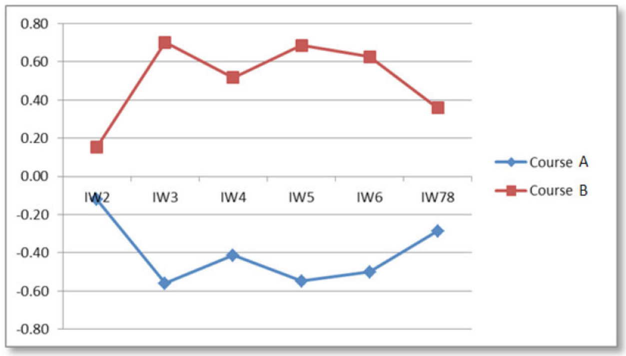

Figure 6. Cognitive involvement scores between the two courses.

Early in the semester during the week 2, cognitive involvement levels between the Course A students (Mdn = - .25) and the Course B students (Mdn = -.25) were not significantly different, U = 45.50, z = .54, ns, r = 0.19. However, as the semester progressed, cognitive involvement levels in the Course B students were significantly higher than the Course A students. In week 3, the cognitive involvement level of the Course B students (Mdn = .91) was significantly higher than the cognitive involvement level of the Course A students (Mdn = - .66), U = 66.00, z = 2.31, $p < 0.05$, r = 0.54 showing a large effect size as it is above the .5 threshold. In week 4, the cognitive involvement level of the Course B students (Mdn = .48) was significantly higher than the cognitive involvement level of the Course A students (Mdn = - .64), U = 65.00, z = 2.22, $p < 0.05$, r = 0.52 showing a large effect size.

In week 5, the cognitive involvement level of the Course B students (Mdn = 1.04) was significantly higher than the cognitive involvement level of the Course A students (Mdn = - .45), U = 66.00, z = 2.31, $p < 0.05$, r = 0.54 showing a large effect size. In week 6, the cognitive involvement level of the Course B students (Mdn = 1.37) was significantly higher than the cognitive involvement level of the Course A students (Mdn = - .69), U = 64.00, z = 2.15, $p < 0.05$, r = 0.51 showing a large effect size. Then, as the semester approached the end, cognitive involvement levels between the Course A students (Mdn = - .11) and the Course B students (Mdn = .34) were not significantly different, U = 53.00, z = 1.16, ns, r = 0.27.

3.6.2. Emotion between two courses.

Confidence: Confidence scores between the two courses were compared per week using the Mann-Whitney test. There was no significant difference found throughout the six weeks compared, as shown in Figure 7.

Interest: Interest between the two courses was compared per week using the Mann-Whitney test. Among the six weeks compared, interest levels in week3 and week6 were significantly different, as shown in Figure 8. In week 3, the interest level of the Course B students (Mdn = 8.50) was significantly higher than the interest level the Course A students (Mdn = 6.00), U = 68.00, z = 2.54, $p < 0.05$, r = 0.59 showing a large effect size. In week 6, the interest level of the Course B students (Mdn = 8.00) was significantly higher than the interest level of the Course A students (Mdn = 5.50), $U = 69.00$, $z = 2.61$, $p < 0.01$, $r = 0.62$ showing a large effect size. No significant differences were found in other weeks.

Frustration: Frustration between the two courses was compared per week using the Mann-Whitney test. There was no significant difference found throughout the six weeks compared, as shown in Figure 9. Overall, students' frustration scores were between 4 points and 5 points, which is lower than "neutral". Spearman's correlation analysis showed that the online learners' frustration in both courses was significantly correlated with perceived task difficulty ($r_s = .57$, $n=18$, $p< .05$). However, further Spearman's correlation analysis conducted for each course separately showed that the significant correlation between frustration and perceived task difficulty only existed in Course B ($r_s = .76$, $n=8$, $p< .05$). Frustration in Course A was not correlated with perceived task difficulty ($r_s = .33$, $n=10$, $p> .05$).

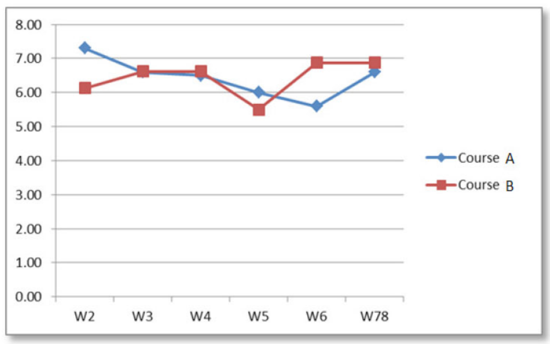

Figure 7. Confidence scores between the two courses.

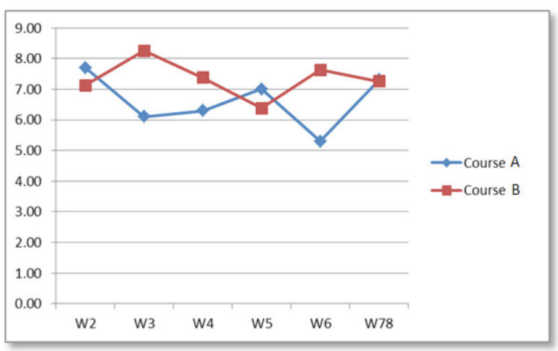

Figure 8. Interest scores between the two courses.

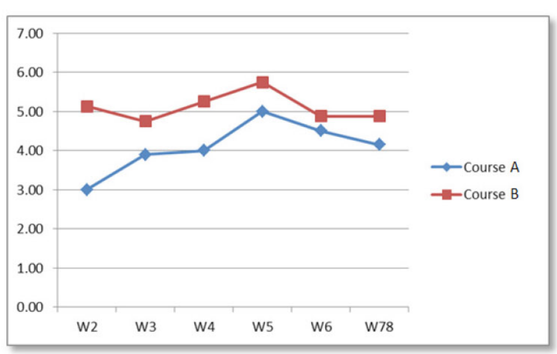

Figure 9. Frustration scores between the two courses.

Excitement: The identical results as interest were found in the comparison of excitement. Among the six weeks compared, excitement levels in week3 and week6 were significantly different, as shown in Figure 10. In week 3, the excitement level of the Course B students (Mdn = 8.50) was significantly higher than the interest level the Course A students (Mdn = 5.50), $U = 63.00$, $z = 2.10$, $p < 0.05$, $r = 0.50$ showing a medium effect size. In week 6, the excitement level of the Course B students (Mdn = 7.50) was significantly higher than the interest level of the Course A students (Mdn = 5.00), $U = 72.50$, $z = 2.92$, $p < 0.01$, $r = 0.69$ showing a large effect size. No significant differences were found in weeks 2, 4, 5, and 7/8.

Graphical representations of overall emotional experiences: The following two figures represent overall emotional experience between the two courses. Figure 11 shows the overall emotional experience of students in Course A, the discussion-focused online course, whereas Figure 12 illustrates the overall emotional experience of students in Course B, the hands-on activity focused online course. Both figures visually present how students' emotional experiences in each course were progressively changed over the semester. Unlike the individual level analysis (shown in Figures 4 and 5), this combined visualization offers an easy way to interpret students' emotional experiences on the course level. For example, we can infer from the figures that

Table 3. Descriptive statistics of cognitive involvement, emotion, and behavioral experiences

	Week2 experience		Week3 experience		Week4 experience		Week5 experience		Week6 experience		Week7/8 experience	
	Course A (n = 10)	*Course B (n = 8)*	*Course A (n = 10)*	*Course B (n = 8)*	*Course A (n = 10)*	*Course B (n = 8)*	*Course A (n = 10)*	*Course B (n = 8)*	*Course A (n = 10)*	*Course B (n = 8)*	*Course A (n = 10)*	*Course B (n = 8)*
	M SD	*M SD*	*M SD*	*M SD*	*M SD*	*M SD*	*M SD*	*M SD*	*M SD*	*M SD*	*M SD*	*M SD*
Cognitive involvement												
Invested Mental effort *	-.17 (.95)	.22 (1.09)	-.36 (1.07)	.45 (.73)	-.09 (.83)	.11 (1.23)	-.23 (.70)	.29 (1.27)	-.24 (.69)	.30 (1.28)	.14 (.84)	-.17 (1.21)
Performance *	0 (0)	0 (0)	-.43 (1.12)	.54 (.46)	-.49 (1.01)	.62 (.58)	-.54 (.96)	.68 (.54)	-.46 (.74)	.58 (1.02)	-.54 (1.07)	.68 (.12)
Involvement (I) **	-.12 (.67)	.15 (.77)	-.56 (1.09)	.70 (.77)	-.41 (.78)	.52 (.89)	-.55 (.89)	.68 (1.15)	-.50 (.63)	.63 (1.30)	-.29 (1.18)	.36 (.84)
Emotion ***												
Confidence	7.30(1.49)	6.13(2.53)	6.60(1.26)	6.63(1.51)	6.50(1.96)	6.62(2.67)	6.00(1.49)	5.50(1.77)	5.60(1.17)	6.88(1.96)	6.60(1.68)	6.88(1.25)
Interest	7.70(1.49)	7.12(1.25)	6.10(1.91)	8.25(1.04)	6.30(2.36)	7.38(1.99)	7.00(1.15)	6.38(1.99)	5.30(1.49)	7.63(1.51)	7.30(1.84)	7.25(1.67)
Frustration	3.00(2.00)	5.13(2.36)	3.90(1.66)	4.75(1.39)	4.00(1.89)	5.25(3.41)	5.00(1.25)	5.75(2.38)	4.50(2.07)	4.88(3.10)	4.15(1.96)	4.88(1.64)
Excitement	5.80(1.75)	7.25(1.83)	5.70(2.54)	8.00(1.31)	5.80(2.74)	7.12(2.10)	6.00(2.21)	6.12(2.53)	4.60(1.58)	7.50(1.51)	6.45(2.24)	7.75(1.70)
Behavioral experiences												
Discussion posting	2.70(.82)	3.63(1.30)	2.40(.84)	2.00(1.19)	2.90(1.19)	.88(1.25)	2.00(1.25)	.88(.99)	2.40(.69)	3.12(1.13)	2.90(1.10)	5.38(1.85)
Discussion response	.90(1.59)	6.00(5.18)	3.90(3.67)	4.00(4.31)	3.80(3.49)	2.25(2.66)	3.80(3.91)	.25(.46)	5.30(6.96)	1.63(1.77)	6.60(5.44)	2.13(1.46)
Discussion viewing	22.10(7.05)	43.25(18.50)	32.50(18.57)	27.88(17.63)	36.80(19.93)	13.50(10.53)	32.10(21.34)	9.13(7.43)	37.20(21.50)	26.63(9.94)	56.20(36.57)	40.75(20.84)
Resource viewing	7.40(3.63)	16.88(5.41)	9.80(5.03)	9.75(4.30)	6.00(3.94)	2.88(3.04)	7.40(4.06)	3.88(4.32)	8.50(4.43)	9.50(5.01)	14.00(5.10)	17.63(10.93)
File uploading	1.80(1.14)	3.25(1.28)	.60(.84)	2.13(1.36)	.70(.82)	.75(.89)	.10(.32)	.63(.74)	.40(.84)	2.00(1.31)	3.00(1.15)	4.88(.70)
Attendance	4.80(1.40)	5.63(1.85)	5.10(2.02)	5.13(1.73)	5.20(1.23)	4.50(1.69)	5.00(1.49)	4.50(2.14)	5.00(1.56)	4.50(1.77)	11.70(2.21)	9.76(4.20)

Note:

* *Scores are standardized (Z score) to compute an involvement score (I).*

** *Involvement score was computed using the formula* (Paas et al., 2005): $I = \frac{R + P}{\sqrt{2}}$

*** *9 point Likert scale was used*

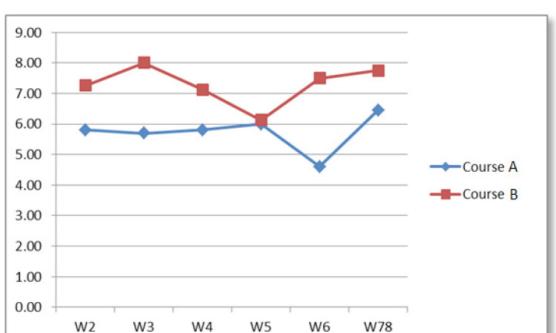

Figure 10. Excitement scores between the two courses.

students' emotional experiences in Course B were relatively more stable than the students' emotional experiences in Course A.

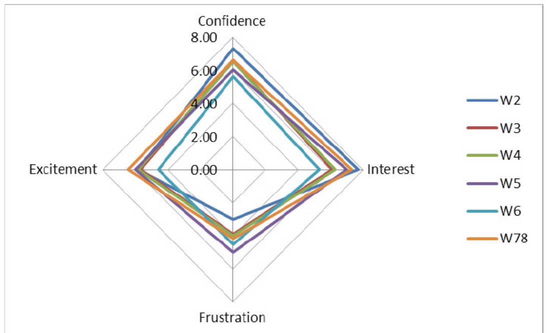

Figure 11. Overall emotional experience in Course A.

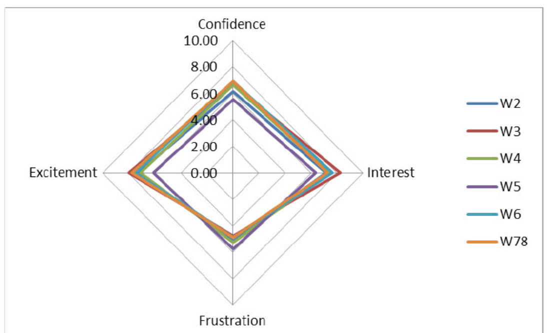

Figure 12. Overall emotional experience in Course B.

3.6.3. Behavior experience between two courses. The behavior experience was analyzed by comparing six behavior activities: discussion posting, discussion response, discussion viewing, resource viewing, file uploading, and course attendance. The six activities were selected as they were considered to support the significant learning event in the two courses.

Discussion posting: The average number of discussion postings per student between the two courses was compared per week using the Mann-Whitney test. Among the six weeks compared, the average numbers of discussion responses in week 4 and week 7/8 were significantly different, as shown in Figure 13. In week 4, the average number of discussion responses in Course A ($M = 2.90$, $Mdn = 3.00$) was significantly higher than the average number of discussion postings in Course B ($M = 0.88$, $Mdn = 0.00$), $U = 10.50$, $z = -2.69$, $p < 0.01$, $r = 0.63$ showing a large effect size. In week 7/8, however, the average number of discussion postings in Course B ($M = 5.38$, $Mdn = 5.50$) was significantly higher than the average number of discussion postings in Course A ($M = 2.90$, $Mdn = 3.00$), $U = 71.50$, $z = 2.89$, $p < 0.01$, $r = 0.68$ showing a large effect size.

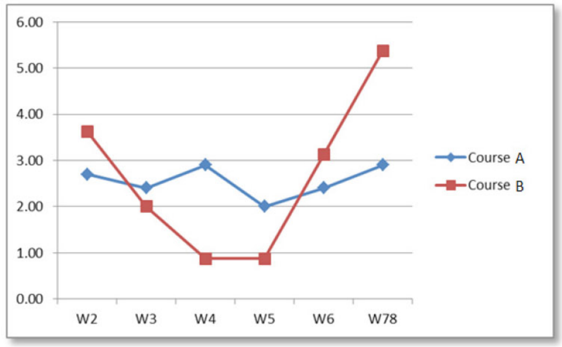

Figure 13. Average number of discussion postings per student between the two courses.

Discussion response: The average number of discussion responses per student between the two courses was compared per week using the Mann-Whitney test. Among the six weeks compared, the average numbers of discussion responses in week 2 and week 5 were significantly different, as shown in Figure 14. In week 2, the average number of discussion responses in Course B ($M = 6.00$, $Mdn = 6.00$) was significantly higher than the average number of discussion responses in Course A ($M = 0.90$, $Mdn = 0.00$), $U = 64.00$, $z = 2.23$, $p < 0.05$, $r = 0.53$ showing a large effect size. In week 5, however, the average number of discussion responses in Course A ($M = 3.80$, $Mdn = 3.00$) was significantly higher than the average number of discussion responses in Course B ($M = 0.25$, $Mdn = 0.00$), $U = 16.00$, $z = -2.29$, $p < 0.05$, $r = 0.54$ showing a large effect size.

Discussion viewing: The average number of discussion viewing behavior per student between the two courses was compared per week using the Mann-Whitney test. Among the six weeks compared, the average number of discussion responses in week 2, 4, and 5 was significantly different, as shown in Figure 15. In week 2, the average number of discussion viewing in Course B ($M = 43.25$, $Mdn = 45.00$) was significantly higher than the average number of discussion viewing in Course A ($M = 22.10$, $Mdn = 21.00$), $U = 69.00$, $z = 2.58$, $p < 0.01$, $r = 0.61$ showing a large effect size. In week 4, however, the average number of discussion viewing in Course A ($M = 36.80$, $Mdn = 32.00$) was significantly higher than the average number of discussion viewing in Course B ($M = 13.50$,

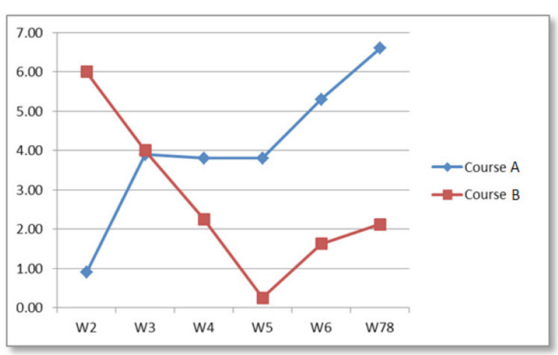

Figure 14. Average number of discussion response per student between the two courses.

Mdn = 14.00), U = 9.50, z = -2.71, $p < 0.01$, r = 0.64 showing a large effect size.

In week 5, still the average number of discussion viewing in Course A (M = 32.10, Mdn = 24.00) was significantly higher than the average number of discussion viewing in Course B (M = 9.13, Mdn = 10.00), U = 7.00, z = -2.95, $p < 0.01$, r = 0.69 showing a large effect size.

Resource viewing: The average number of resource viewing activity per student between the two courses was compared per week using the Mann-Whitney test. Among the six weeks compared, the average numbers of resource viewing only week 2 was significantly different, as shown in figure 16. In week 2, the average number of resource viewing in Course B (M = 16.88, Mdn = 8.00) was significantly higher than the average number of resource viewing in Course A (M = 7.40, Mdn = 16.50), U = 75.00, z = 3.12, $p < 0.01$, r = 0.74 showing a large effect size.

File uploading: The average number of file uploading per student between the two courses was compared per week using the Mann-Whitney test. Among the six weeks compared, the average numbers of file uploading in weeks 2, 3, and 7/8 were significantly different, as shown in Figure 17. In week 2, the average number of file uploading in Course B (M = 3.25, Mdn = 3.00) was significantly higher than the average number of file uploading in Course A (M =

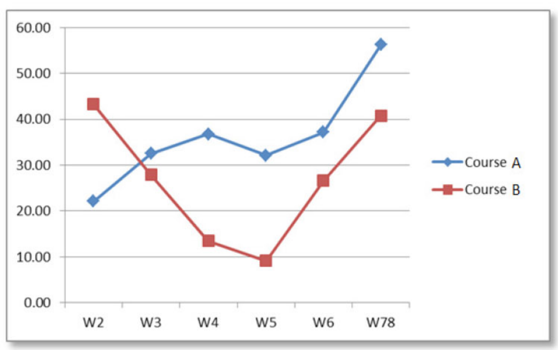

Figure 15. Average number of discussion viewing per student between the two courses.

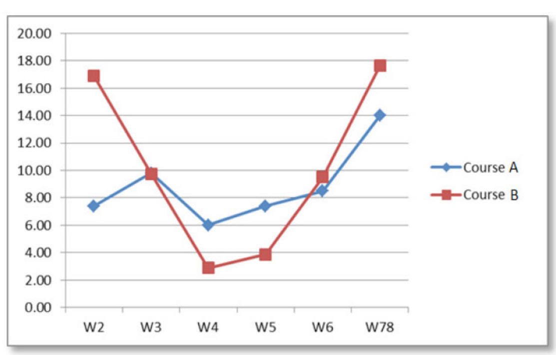

Figure 16. Average number of resource viewing per student between the two courses.

1.80, Mdn = 2.00), U = 64.50, z = 2.26, $p < 0.05$, r = 0.53 showing a large effect size. In week 3, the average number of file uploading in Course B (M = 2.13, Mdn = 2.00) was significantly higher than the average number of file uploading in Course A (M = 0.60, Mdn = 0.00), U = 68.00, z = 2.60, $p < 0.05$, r = 0.61 showing a large effect size. In week 7/8, the average number of file uploading in Course B (M = 4.88, Mdn = 4.50) was significantly higher than the average number of file uploading in Course A (M = 3.00, Mdn = 3.00), U = 68.00, z = 2.68, $p < 0.01$, r = 0.63 showing a large effect size.

Attendance: The average number of attendance per student between the two courses was compared per week using the Mann-Whitney test. There was no significant difference found throughout the six weeks compared, as shown in Figure 18.

4. Discussion

Learning analytics data can be aggregated and reported at various levels (Ferguson, 2012). Analytics can be used for administrators and policy makers to make decisions at the institutional level (a macro-level analysis), or analytics can be used for individual learners and instructors to support the tracking and interpretation of the learning process (a micro-level) (Clow, 2012; Wise et al., 2014). The level of analytics presented in this paper focused on the micro-level analytics by incorporating two combined learning analytic methods to understand the online learners' experience in three dimensions. In addition, a visualized dashboard was used to show multiple graphic elements that each focus on a

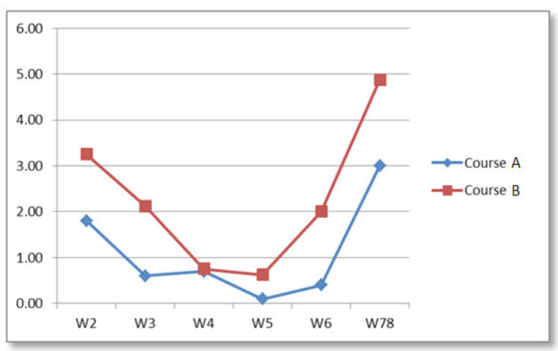

Figure 17. Average number of file uploading per student between the two courses.

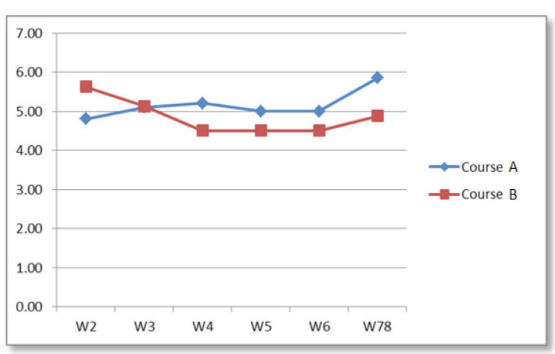

Figure 18. Average number of attendance per student between the two courses.

single aspect of the learning experience (Pardo, 2014). This paper particularly attempted to find a means to collect data on online learners' psychological aspects of learning experiences as well as their behavioral interaction experiences. Findings from this study indicate that ESM can be a useful approach to measure online learners' learning experience as a supplement to Web log data. ESM was used to capture the learners' cognitive involvement and emotional experiences during the 6 weeks of the course, while Web log data were used to examine learners' behavioral experience. Due to its unique feature that represents the quality of experience in selected activities for selected groups of people, ESM has great potential to be used to measure the cognitive and emotional aspects of learning experiences that otherwise cannot be captured using the Web log data approach.

The learning experience dashboard presented in this paper shows individual learners' cognitive, emotional, and behavioral experiences during the course and offers the opportunity to establish pedagogical recommendations for the students. The compared learning experiences between two differently structured online courses provides evidence that students' experiences are different depending on the type of online tasks and learning activities. Overall, students in the hands-on, activity focused course showed higher cognitive involvement throughout the six-week study period. Because cognitive involvement is computed using learners' invested mental effort during the target experience (in this study, weekly assignment/project) and learner performance (weekly assignment/project score), high cognitive involvement indicates that the learner was engaged in an in-depth cognitive process while achieving high academic performance. In addition, students in Course B reported two positive emotions, interest and excitement, during week 3 and week 6 while they were involved in visual multimedia development projects.

With the meticulous analysis of each individual learner's cognitive, emotion, and behavior data as presented in the learning experience dashboard, we can gain deeper insights into online learning experience design issues. Specifically, the use of ESM has enabled us to investigate the learning experience from multiple aspects and therefore can further provide rich information on each learner's progress in an online class.

There are several limitations of this study. First, the experience data collected using ESM and Web logs in this study are solely limited to internal data stored in the LMS server. External communication data, such as email correspondences between the course instructor and students or between students and students, were not included in the data analysis. Second, students behaviors while being engaged with multimedia design/development programs were not traceable as the activities occurred outside of the LMS environment. However, it provides a good rationale why only using Web log data is limited when capturing students' learning experience. Utilizing the ESM approach can supplement Web log data analysis by collecting students' cognitive experience and emotional experience after completing a task. Third, the ESM questionnaire was designed to reflect what the researcher considered the most important aspect of learning experience in the two selected online courses. Although researchers are allowed to have flexibility in designing the questionnaire (Hektner et al., 2007), there is a need for a guideline to inform researchers on effective questionnaire design strategies, particularly when employing ESM.

5. Conclusion

The findings reported in this paper are expected to lead to a new approach to understanding what an online learning experience is, what influences such experiences, and what the qualities of the learning experiences are. Using visualized learning experiences both at the individual and the group level, we will be able to better understand what types of experiences can be designed and how experiences should be shifted over time to achieve learning goals. Future research will further explore how ESM can be utilized in measuring learning experiences in different course structures and formats. Also more studies are needed to explore how learners' individual characteristics, such as prior knowledge, motivational level, interest, cognitive learning styles, influence their learning experiences. Another possible research direction would be to investigate how to utilize the learning experience analytics to design appropriate interventions and to help each learner maintain the optimal level of learning experience while participating in the course. Presenting the learning experience dashboard after each learning activities could be a suitable solution to achieve this goal.

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