The utilization of learning analytics to develop student engagement model in learning management system

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Abstract. Learning Analytics (LA) is evolving learning into a new era of analyzing student’s participation and engagement in order to gain some insights. The implementation of LA in a university helps the administration and faculty associates to observe the progress of the students alongside their rate of success. The purpose of this study is to develop a student’s engagement model for holistic involvement in the Learning Management System (LMS). The model was developed from an initial model that was derived from the review of literature and existing model of engagement in LMS. The data were collected from the online learning management system of one public University in Malaysia. From the data analysis, it was found that the strong engagement and interaction between the students, lecturers and the content in LMS, led to boost up the usage of the LMS as long as the student participation in the learning environment is accepted, which in return prepared the students to be evaluated anytime. The model that will be developed from this study can help increase the interaction and engagement between lecturers and students in LMS. Unlike the engagement of students in higher education LMS, which has been discussed already in the literature, this research integrated the role of trace data in shaping the learning environment communication and participation of the users.

1. Introduction
Learning Analytics is the process of collecting and analyzing a learner’s data, to analyze the individual interaction and communication in an online learning platform. Trace data from the learning management system is the main source of data for the data analytics outcome. The evolving of the traditional method of learning to the virtual learning system, produces a trace data from the platform of the electronic learning. The analysis from the learning data will improve the learning environment to a new stage as well as the diversion of learning from traditional to online learning experience. It is important to note that, the log data and student behavior are the relationship that can be identified using the learning analytics [31]. Time and the student’s effort along with the sources invested by the student’s themselves and their institutions, is the main concern of the Student Engagement Model, to produce better learning outcomes coupled with experiences from the LMS. The result of the cluster of low engagement is the highest [21].

Also, it has been discovered from previous studies that the institution’s target on the engagement in online activities resulted to a very disappointing display [30]. The institution and learning management system did not give much focus on the design guideline for interactive activities to produce the best
effective engagement [29]. Furthermore, the low engagement in terms of interaction and communication between students and lecturers as well as the content in LMS, led to the inadequate usage of the module’s activity in the LMS; hence this research will develop a holistic model for an intensive student’s engagement for a better learning experience.

2. Literature review

2.1. Learning analytics

Learning Analytics widely has been used to predict the score of the students and their final performance from the usage of the log data [18], [4], [1], [7]. Engagement of learners have also been used as an indicator on the student’s performance. Learning Analytics is also good at predicting student’s dropout rate and in giving early warning to them so as to avoid them being knocked out due to bad behavior and low marks in the courses [36], [10]. However, academic failure will happen in every institution, hence the early warning can predict the academic failure of the students and this will help universities to avoid the failure of their student’s by taking an action to increase the student’s marks and performance.

Student’s satisfaction towards the LMS have also being studied [23], [18], [6], from these studies, they found that student’s acceptance towards the LMS and VLE are satisfactory and the students are willing to use the LMS platform to help their study in the university. Hence, the student’s need and opinion can be used to make learning more interesting.

2.2. Engagement model

There are a few researches that have proposed diverse engagement models. One of such is the use of the activity theory to develop a conceptual model of an engagement profile [5]. This conceptual model addresses the need of managing the students’ engagement profile. Furthermore, the conceptual model of the engagement profile, adopted the framework on sense-making to design the education to be more learners-perceived, rather than just being the participants of the material; and it’s based on the activity theory engagement. SNA and VLE desk analysis have been used in this research for analyzing data.

Also, a previous research model was developed for the continuous assessment increased student’s engagement in VLE. This model was constructed on intrinsic and extrinsic motivation, coupled with the analyzing data on the research model’s continuous assessment increased student engagement in VLE alongside the engagement theory [39]. Another model that has been developed by previous works is the activity model on teaching and learning interaction [24]. The instructor course preparation activities as well as those activities that affect the dimension of the student engagement activities has been showed by the teaching and learning interaction activity. An additional indicator should be added into the model to explore the impact of the engagement from the instructor’s overview.

The previous research has being able to accomplish the engagement profile, teaching and learning design; however the positive feedback is the engagement that needs to be done so as to use the log data for a better insight on the learning. The current research tries to contribute to lacking gap in literature by studying the analysis on the engagement activity to help develop a student’s engagement model that can make the LMS usage more rapidly used by the students within their study in the university.

| Name and Reference | Descriptions | Advantages | Disadvantages | Analysis Tools |
|--------------------|--------------|------------|---------------|----------------|
| Research Model on teamwork engagement, [39] | Continuous assessment increased student engagement in VLE | Teamwork engagement and the personal success | Must use another student’s achievement that can be measured | SmartPLS 3.0. |
Online behavior engagement model, [35]  

Online behavior engagement model that portray how the achievement influences the model

Gain understanding on how flipped classroom has been affected by the online behavioral engagement in term of achievement

Exploratory study and focused on student’s problem solving only.

PLS-SEM

Conceptual model of engagement profile, [5]  

Development of engagement profiles using the measurable process

Adopted as a framework for the education institutes

Lack of evidence support from the learner’s data

SNA and VLE desk analysis

Activity model on Teaching and learning, [24]  

To show how Student engagement activities are affected by the course preparation and activities in the online platforms

Overview and dimension of the course preparation by the instructor to measure student’s engagement

Instructor perspective only

PLS-SEM

3. Methodology

This section discusses the data collection of the data and the data analysis for this study.

3.1. Data Collection

Data collection process for this research was anchored through the center of Information Technology from a public university in Malaysia. The dataset comprises the log data from its student online learning platform. The log data consists of the data obtained from year 2014 to 2016. Data was gathered from one of the University’s faculty.

3.2. Data Analysis

The first part of the data analysis is the determination of the engagement factors of the students. From the synthesizing of the literature review, the matrix on the factors of engagement in LMS activities have been produced in a tabular form. Next, the second part of the analysis is the decision tree technique, which has been used to analyze the log data for the purpose of extracting the learner’s data underlying. Hence, the initial model of the engagement has been derived from the existing engagement model and the matrix of the engagement factors.

4. Results

This result is based on two parts of the data analysis. The first part of the data analysis is the matrix of the engagement factors.

Table 2 below depicts the matrix of the engagement factors that has been synthesized from the literature review. With the matrix of the engagement factors, we can classify the engagement factors that exist in the learning management system and their activity that contributes to the engagement factors. The engagement factors derived have also been used to develop the initial model of the engagement for this project, as will be discussed in the upcoming section.
Table 2. Matrix of engagement factors

| Activities of LMS                        | Engagement Factor |                  |                  |
|-----------------------------------------|------------------|-----------------|-----------------|
|                                          | Student Motivation | Assessment     | Procrastination | Student Satisfaction |
| Collaboration                           |                  |                 |                 |                    |
| • Forum                                 |                   |                 |                 |                    |
| • Group assignment                      |                  |                 |                 |                    |
| Content and Sharing                     | [13], [9], [39]  | [28]            | [16], [30]      | [25]               |
| • Share material                        | [38], [19], [27] | [5], [35], [15] | [37]            | [38], [32], [25]  |
| • Submission                            | [5], [38], [32], |                  |                 |                    |
| • Upload and download                   | [25]             |                 |                 |                    |
| Viewing                                 | [34]             | [22]            |                 |                    |
| • View all                              |                   |                 |                 |                    |
| • Login Logout                         |                   |                 |                 |                    |
| Discussion                              | [5], [9]         | [12], [15]      | [16]            | [30], [8]          |
| • Messages                              |                   |                 |                 |                    |
| • Communicative argument                |                   |                 |                 |                    |

The activities that have been classified, and of which led to the engagement, are Collaboration, Content and Sharing, Viewing and Discussion. Furthermore, four factors of engagement have been portrayed out from this research, they are: the Student Motivation [13], [19] [5], Assessment [5], [15], [35], Procrastination [16], [30], [22] and Student Satisfaction [25], [38], [30]. The activities in the collaboration factor includes the forum, discussion and group assignment [13], [28], [16], [25]. Moreover, the content and sharing activities comprise the activity of shared material, submission of assignment or task and uploading or downloading of the material [38], [27], [35], [25]. Viewing refers to the activities that deals with viewing of the material in the LMS platform, whereby the student can view all the available resources and any available module [34], [22]. The discussion activities refers to the scenario whereby the student actively participates with other type of users in direct messaging and communicative argument, discussing the subject in the LMS [5], [9], [15], [8]. The second part of this study’s result is the decision tree. This decision tree is modelled using the SAS Enterprise Miner Workstation 14.1.
Figure 1 above showed the decision tree expresses the usage of the module in the LMS for a subject from one faculty. This decision tree provides the usage in form of percentage and count of the action. Furthermore, this decision tree focuses on the assignment module and the clock of the action. From the node, there is a higher percentage of upload where the real time is after 11.00 pm. The result showed that the students tends to submit the assignment after 11.30 pm as the submit percentage is 10.53% on the trained dataset and 12.66% on the validated dataset compare to other time. The factor of engagement that can be concluded from this decision tree is the procrastination occurrence of this course in LMS.

5. Discussion
From the above results, the initial model is concluded by using the first and second result of the study where the model is the combination of matrix of engagement and the results of decision tree. This research produces the matrix of the engagement factors and the initial model of engagement. We discussed the engagement model that have been developed from the matrix of the engagement factors, existing engagement model and the analysis of the log data.
Figure 2 showed the initial model of engagement in LMS; whereby the entity is the interaction type between three entities: the first entity is S-S, which means the Student-Student interaction. The second entity is S-L: meaning the Student-Lecturer interaction. However, the third and last entity is S-R, representing the Student-Resource entity. The activity is represented by the arrows, and the activity that have been discussed in this research are Collaboration, Content and Sharing, Viewing and Discussion. Furthermore, every entity is involved in its own activity and the activity leads to the engagement factors. The initial model of engagement focuses on this four-engagement factors, which are: motivation [13], procrastination [16], [30], [37], [22], satisfaction [25], [28], [30], [32], [8] and assessment [28], [5], [35]. Every entity will have their own activity that produces the engagement factors. This have been elaborated as thus; Student to Student have two activities, collaboration lead to motivation engagement factor with content and sharing activity lead to the assessment factor. Student to Lecturer have three engagement factors, motivation, procrastination and satisfaction with respective activity. Lastly, the Student to Resource activity and the engagement factors consists of discussion, which leads to assessment and viewing which leads to Procrastination and Satisfaction factors activity are content and sharing. The factors of engagement suggest ways for a better student engagement.

Still from the above results, we determine that procrastination is the overlapping factor which is found on the matrix of engagement and the result from the decision tree. Thus, procrastination is the main factor that leads to low engagement. Hence, lecturers or faculty members should take possible actions to decrease the procrastination in the LMS. Furthermore, we found that the submission or content and sharing, is the overlapping activities that was discovered on both matrixes of the engagement factors and the decision tree. In this case submission in the LMS is one of the important issues that gives worry to most of the students, as it may affect their marks for the subject.

6. Conclusion
By means of concluding this write-up, it is crucial to state that the engagement model using learning analytics is considered important in supporting an effective teaching and learning process in higher
education institutions. Learning Analytics model will help various stakeholders to ease their monitoring and decision on the learning perspective. Our goal is to develop the best model that can increase the learning qualities in higher education. Malaysia have a good prospect to implement the learning analytics in all learning platforms, as learning analytics will improve student’s engagement and interaction.

A learning analytics model in higher education is important to help the universities understand the student’s need and offer their best effort to help the students throughout their study period in the universities. More so, learning analytics model also help universities to monitor their student’s performance and produce better quality on the graduates. With regards to transformation of education by learning analytics, it is necessary to remove the barriers that commonly prevent the adoption of technology in the educational mainstream.

Future works of this research tend to use the data from the learning management system as an analysis method, which could also serve as an evidence to support the model developed. The learner’s data will be used to prove the engagement factors that are obtained from the learning management system. The left-over data from the platform will be useful for the research of learning analytics. Other further direction of this research can be the use of additional methods to analyze the log data to find the students engagement factors in learning management system, which perhaps might produce more insightful results. Also, the evaluation and validation processes will be used to evaluate and verify the engagement model.

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