Analysis of Learning Analytics in Higher Educational Institutions: A Review

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Abstract. Learning analytics is relatively new in the field of research models, assessment/evaluation, and business intelligence. The critical analysis of literature explains that, as a consequence of more and better data, learning analytics gained significant attention in education. This paper emphasized integration of three major components: educational data mining, learning analytics, and academic analytics. It gives the comprehensive background for increasing understanding of the positive aspects of implementing the framework of learning analytics (LA) in higher educational institutions in Malaysia. Besides emphasizing LA, the role of educational data mining (EDM) in adaptive learning is also discussed. It gives an empirical-based overview with the key objectives of adopting the proposed model of LA in generic educational strategic planning by Malaysian HEIs. It examined the literature on experimental case studies, conducted during the last six years (2012–2017) for extracting recently updated information on increasing HEIs performance in Malaysia. The results have highlighted some major directions of LA, EDM, and academic analytics in driving techniques for achieving student retention and enhancing employability.

Keywords: Academic analytics · Learning analytics · Higher education · Educational data mining · Student retention

1 Introduction

The empirical framework implies that learning analytics has become an emerging domain, which seeks to utilize data analysis for making informed strategic decisions at different levels of the education system [12]. Since business analytics assesses consumer data to discover a potential range of consumers, on the other hand, learning analytics is the field involving students for creating better pedagogies [28]. Papamitsiou and Economides (2014) and Phillips et al. (2012) also indicated learning analytics as a successful domain that helps by focusing on student problems and evaluating educational programs [22, 24]. Learning analytics are designed for improving retention issues and maintaining academic attainment effectiveness. The core purpose of this document is to propose and implement the most influential constituent, learning

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analytical model in Malaysia's Higher Educational Institutions (HEIs) for increasing student retention, employability, and academic attainment.

1.1 Key Aims and Objectives

This paper aims at assessing how Learning Analytics can be implemented in the Higher Educational Institutions of Malaysia in order to improve teaching and learning. Moreover, no research has been initiated on this specific research area in the Malaysian education system; therefore, this paper aims at identifying how Learning Analytics can be implemented and what impact it will have on the Malaysian education system. The research objectives are:

- To explore the impact of Learning Analytics on the performance of Higher Educational Institutions of Malaysia
- To identify how Learning Analytics can be implemented in the Higher Educational Institutions of Malaysia
- To determine the challenges and hardships in implementing Learning Analytics in higher education in Malaysia.

1.2 Research Questions

Based on the research objectives aimed at introducing Learning Analytics in Higher Educational Institutions (HEIs) in Malaysia, the following questions will be answered by the study:

1. How do different factors of learning analytics and their adoption influence the learning perspectives in Malaysian higher educational institutions?
2. How do learning analytics impact the factors influencing student retention, attainment and employability?
3. What are the attributes for effective implementation of the learning analytics framework within HEIs in Malaysia?

2 Methodology

For this purpose, the review of articles describing or delineating LA was considered and its methods and tools (including factors affecting learning) in the university context was considered. The paper was structured in two phases: the first one focused on investigating education studies in online databases. The keywords used were learning, learning analytics, learning analytics research, educational factors, data mining, and higher educational institutions. The second phase involved scrutiny of the references in the resulting articles, which allowed discovery of topics and new specific authors related to the search objectives. Inclusion criteria included journal articles that link to LA, articles related to learning, articles related to factors influencing learning from the LA framework. Articles whose publication date does not exceed six years old, that is, from January 2012 to 2017, were considered in order to obtain a completely updated literature review, which gives an account of current field discussions, results, and trends. Papers in peer reviewed journals, by virtue of ensuring scientific rigor and quality standards in the literature, were examined.

2.1 Significance of Report

Based upon the challenging issues arising in the HEIs of Malaysia due to high rate of student absenteeism and insufficient employment opportunities, the paper is intended to conduct an exploratory research on developing an effective learning analytics model. On the theoretical foundation of Dawson et al. (2014), learning analytics demonstrated as the most impactful instrument of increasing significant consideration to converge the concepts of information technology and learning in the fields of promoting higher education, computer services, and most importantly learner personal and professional development [28]. Moreover, the report in connection with the learning aspects depicted a framework involving improving usage of the information and data with a specific end goal of enhancing academic outcomes [13].

Chatti et al. (2012) described that learning analytics is a possible key of future trends in delivering competent learning and teaching, which borrow techniques from different fields – contributing to fulfillment of learning objectives. This report defines how learning analytics will develop the connection between the varying elements of academic analytics, action for research, mining of educational data, recommendation systems, along with personalized adaptive learning system in HEIs of Malaysia.

2.2 Problem Statement

Malaysia is considered as one of the biggest hubs of education providers. The government of Malaysia has always developed effective measures to enhance the education system. Implementing Learning Analytics in the education system is regarded as the new but most important measure to improve the education system. Many challenges exist in implementing Learning Analytics in Malaysia; therefore, this research has been initiated to identify and recommend the most effective ways for Higher Educations Institutions in Malaysia to implement such systems. This fact entails numerous challenges and barriers towards the completion of this research topic. While the education sector in Malaysia is highly supported by the government and university management, obtaining in-depth information is very challenging.

To meet this challenge we intend to carry out interview sessions with university management. The limitation associated with this study is obtaining information regarding the experience of individuals (Macklem, 2015). Since no research has been initiated earlier on implementing Learning Analytics in the Higher Educational Institutions in Malaysia, this might also bring challenges for this study; we thus need to rely on primary data only. Another challenge is to gain a maximum number of participants (international and local) to widen knowledge and information. Because of time constraints, it is possible that limited amount of information will be gathered for this research.

3 Emerging Concept of Learning Analytics

The term Analytics of Learning (Learning Analytics) was coined by Mitchell and Costello in 2000, as an emerging concept in its investigation of the visible opportunities in the international market, in the creation and distribution of educational products through the network [7, 19]. Learning Analytics has been defined as "the use of intelligent data that have been produced by the learner, as well as model analysis, with the aim of discovering information and social connections and predicting and advising on learning." [29] Learning Analytics is entrenched in higher education due to the growing popularity of educational processes taught through the Network [29]. Educational institutions have understood the importance of monitoring their platforms to retrieve information produced by student interactions with the learning system [23]. Despite facing a complex task, statisticians and researchers are constantly working on developing new tools to allow management of these data as input to adapt educational processes and enhance the learning process [10].

According to Wagner and Ice (2012) learning analytics serves as an educational tool that provides the teacher with data on personal, interaction, navigation in the system, with whom or with what resource, and how it interacted, location and context data and data on the texts created. Information provided by LA allows customizing of the training activities and design of learning environments accordance to the needs, interests, and forms of interaction between teachers and students and between students themselves [32]. Learning analytics can also provide students with timely information and recommendations as to their interests with two essential objectives: reflection and prediction [20]. It allows visualizing of interactions and identifying patterns of student behavior. Learning analytics will enable an iterative process of feedback, visual and effective, just-in-time feedback that allows the teacher or student to adopt correct teaching or learning strategies [18]. Having information on how people learn results in improved quality of education [3, 33]. Learning environments customized and designed according to learning styles and disciplines are feasible with LA [10]. Learning analytics can provide individuals and groups with a basis of undeniable value for a much more precise investigation of learning processes [8]. The analysis of institutional learning will allow better decision making [12] in two areas. First, instructors can decide the level of demand for different plans and curricula. Second, the academic field will have information to identify elements affecting student performance to strengthen positive factors and reduce negative factors, hence supporting development of new pedagogical models [19, 30].

4 Positive Impact of Learning Analytics

A number of authors have investigated the positive impact of implementing learning analytics on education and student development. Learning analytics referred to a blend of various scenarios at different universities, introduced by management for implementing a virtual learning environment (VLE) exclusively for utilizing effective learning [23]. Dietz-Uhler and Hurn (2013) regard LA as a research model taking advantage of data analysis to inform on the actions and events taking place during the educational process [11]. It seeks to collect, organize and provide data on student performance, allowing a personalized guide, adapting the contents and activities to their abilities and identifying possible learning problems in time [4]. Analytics can reveal data such as feelings, attitudes, social connections and the wishes of users, as well as evidence of what they know, how they learn and their future actions [9]. This allows applying data collection and study techniques relevant for different fields and in particular for education, since it facilitates customization of educational processes according to student needs [12, 13, 36]. Besides making it possible to diagnose problems and identify strategies for improving a course, LA also provides indicators of educational progress at local, regional and even national or international level [22]. LA supports the education system by allowing curriculum adaptation, personalization, and prediction [3]. It enables direct evaluation of the role of learning analytics in the educational process [17] for improving training processes and increasing learning for improved productivity [24]. Having available indicators such as effectiveness, efficiency or time spent on resources, teachers can understand which educational resources failed or are difficult to understand and which are problematic [7, 34]. Resources for future courses can then be improved [23]. Teachers can better understand students, their evolution over time, their achievements, specific subjects problematic for them, profiles, and so forth. Teachers can then provide more effective feedback for them [2]. Predictive techniques allow teachers to detect students at risk and identify slow and fast learners [5, 6]. Early intervention can thus prevent cases such as dropping out of courses or poor learning [6]. Students can visualize and reflect on information about their own learning, see their profiles and make appropriate changes [24]. Adaptation and customization are enabled according to students' profiles to enhance learning [5]. Thus, different learning paths can be designed to accelerate learning [17].

4.1 Integrating Effective Framework of LA

Figure 1 illustrates the process of learning analytics. It shows learning analytics is based on four major perspectives, which include governance, higher educational institutions, online learning environment, and physical learning environment – all perform to improve the learning abilities of an individual or learner [22].

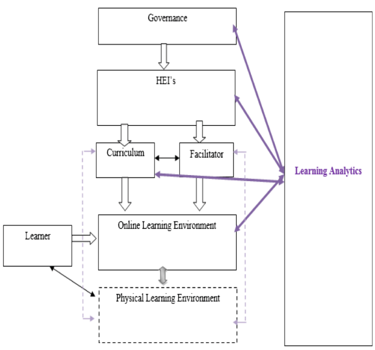

Fig. 1. Process of learning analytics

Governance involves activities related to implementing cross-institutional comparisons, developing benchmarks, informing policy making, and ensuring quality assurance processes [17]. These activities increase productivity, implement a rapid response to critical incidents, and analyze student performance. Phillips et al. (2012) stated that governance predicts high impact on organizational decision-making [24].

As for the second component of the analytic process, West (2012) suggested that HEIs be responsible to analyze processes, optimize resource allocation, meet institutional standards, and compare units across programs and faculties [34]. The model discussed helps in monitoring processes, evaluating resources, tracking enrollment, and analyzing educational outcomes. The functional processes of HEIs in Malaysia predict forecasting techniques, project attrition, model retention rates, goal attainment, employability, and gap identification [6].

The third process consists of curriculum design including the pedagogical model analysis, measuring impact of interventions, and increasing curriculum quality. These activities support education by comparing the learning design, evaluating learning materials, adjusting difficulty levels, and providing resources to learners. Curriculum design involves identifying learning preferences, planning for future interventions, modeling difficulty levels, and developing model pathways [5]. The fourth component of the model is the facilitator who is responsible for comparing the learners, cohorts, and courses, analyzing teaching practices, and increasing quality of teaching. Facilitator activities include monitoring learning progression, creating meaningful interventions, increasing interaction, and modifying content to meet student needs. Facilitators also identify learners at risk, forecast learning progress, and plan interventions [27]. The last fundamental component of learning analytics is the learner who necessitates understanding of learning habits, comparison of learning paths, analysis of learning outcomes, and tracking of progress toward goals. Learners are highly responsible for receiving automated interventions and scaffolds and taking assessments including just-in-time feedback. Recent studies suggest that interest in LA was prompted by the huge amount of data related to education and the increased computer processing power enabling collection of new information from new and different pools of data [9, 35]. Such analytics have stronger impacts by placing productive information for huge numbers of individuals besides ensuring delegated decision-making skills [19]. Besides this, Ali et al. (2013) noted how VLE has become a significant platform incorporating huge amounts of data, for instance, data obtained from academic software [2]. Numerous studies of literature [16, 21, 25] highlighted how learning analytics finds better ways to enhance everyday practice in HEIs. Instead of being hesitant due to privacy concerns, implementers must realize that LA successfully address issues of conflicting interests of different shareholders and the applicable integration [26].

5 Learning Analytics, EDM and Academic Analytics

The process of learning analytics tends to perform as a recurring system of development for the data collection, data analysis as well as interventions mainly derived from different techniques [19]. For instance, quality control is determined as a consistent process for improving teaching and learning perspectives. A close relationship exists between learning analytics, EDM and academic analytics [1, 30]. Pardo and Siemens (2014), consistent with the abovementioned discussion, also asserted the connection of learning analytics with a collection of huge data and representation of the data in the form of useful information [23]. In a similar context, Dawson et al. (2014) also investigated the significance of learning analytics in shaping positive behavior and leading toward the correct direction. Analytical application can extract knowledge in terms of utilizing different techniques of data mining along with the practices of visualization [10].

5.1 Educational Data Mining

While considering the research objective, Dyckhoff et al. (2012) explained Educational Data Mining as a process used in teaching to examine the methods of development to generate information. The process referred to the combination of data collecting techniques that focus on the attainment of student's in-depth understanding in terms of integrating different processes of learning with various settings. However, educational data mining is quite similar to learning analytics, which involves varying processes, procedures, and methodologies aimed at gaining the required information for fulfilling learning objectives [14].

Papamitsiou and Economides (2014) indicated that both fields tend to focus on domains of education and tend to work with potential data generated from the environments. Fidalgo-Blanco et al. (2015) added that processes ensure complete conversion of data into valuable information to purposively improve the learning process. Phillips et al. (2012) reflected that varying techniques are being used in learning analytics in comparison to EDM. Wagner and Ice (2012) argued that the major focus of educational data mining remains the applications developed to ensure techniques of data mining must support learning perspectives of students and teachers. West (2012) noted that these methods should be implemented for data mining and testing of usability in various possible situations. In contrast, Blikstein and Worsley (2016) differentiate data mining with learning analytics by claiming that analytics involves different methods for instance statistics tools, visualization, and techniques of analyzing social networks which ensure compilation of information to transform it into a more effective and informative context.

5.2 Academic Analytics

Blikstein (2013) signifies the role of academic analytics as an imperative aspect to enhance in-depth understanding of learning analytics. As suggested by Scheffel et al. (2014), academic analytics aims at supporting the educational institutions to address the challenging issues hindering students' future success and prosperity. Ali et al. (2013) depicted that analytical analysis also increases the accountability that allows the institutes to perform responsibilities – must be designed for fulfillment of academic objectives or goals. Academic analytics generate a huge amount of data exclusively to predict the level of student retention and the graduation percentage [21].

Meanwhile, Prinsloo and Slade (2013) depicted that academic analytics also combines a particular range of data by utilizing various statistical or inferential techniques for predicting effective models. Ferguson et al. (2014) highlighted how successful implementations of these models help the faculty advisors interpret the challenges faced by students [16]. However, the study of Romero and Ventura (2013) analyzed that academic analytics must be differentiated in a more comprehensive way to allow the educational institutions to draw a fine line among the respective fields.

5.3 Factors Influencing Student Retention

In considering the research questions, it is necessary to examine the concept of student retention as well as analysis of the factors that impact retention. As discussed by Ellis (2013), student retention is based upon core attributes, namely (1) motivation, (2) academic integration, (3) social integration, and (4) financial factors [15].

Daniel (2015) portrayed how the LA framework plays a vital role in motivating students to study and ensure retention by managing student commitment and motivation [31]. Wise (2014) suggested various attributes contribute to increasing student motivation to remain enrolled; course structure, course fee, and educational marketing are key elements to be considered [14]. According to Greller and Drachsler (2012), academic integration is another factor influencing student retention. Academic integration is seen as the involvement of physical and psychological energy that convey individuals an exceptional experience of studying or association with the educational institution [7]. It is also seen as an educational tool, integrated by academics for proper maintenance of individual's time, preparation for assessments, fostering skills and competencies, and ensuring effective critical thinking [14]. It affects student retention through collecting essential information on student progress, which in turn ensures high priority feedback from instructors [10]. Staffing is another characteristic of academic integration that assists in student retention [14]. Besides that, feedback from students enables management to meet student expectations [22]. As indicated by Phillips et al. (2012), social integration is the key component influencing student retention. Studies have supported the impact of social integration on retention, emphasizing on interaction among students, faculty and management in the context of extracurricular activities [14, 22]. Students who feel unwelcome and lack support may drop out [17]. Blikstein and Worsley (2016), in considering financial factors, analyzed that some students from lower socioeconomic groups face financial challenges [6]. These financial hardships might cause them to discontinue their studies [2, 34]. Students from lower income family background experience more critical challenges as compared to their wealthier counterparts. Fee structuring system is another core attribute highlighted by Siemens and Gasevic (2012) who argue that an economical fee structure will attract students [30].

6 Implementation of Learning Analytics Framework in HEIs

In consideration of the literature review and different facts, a new model is proposed that entails as a conceptual framework, where attributes such as motivation, social integration, financial facts, and academic integration are taken as independent variables; with student retention, employability, and attainment being considered as dependent variables (Fig. 2).

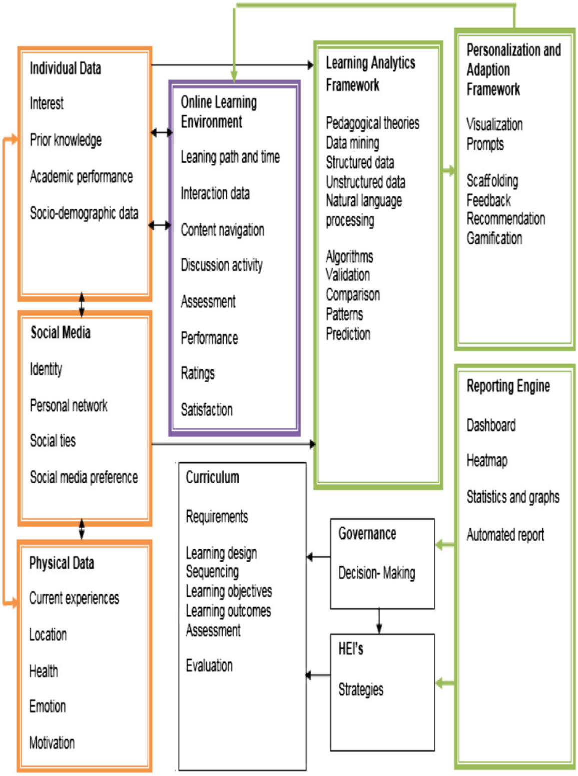

Fig. 2. Learning analytics framework to implement in HEIs in Malaysia.

The variables are selected in such a way because the study of Chatti et al. (2012) suggested that characteristics such as student retention, employability, and attainment are significantly influenced by the financial facts, motivation, academic integration as well as social integration [7]. The model also plays a crucial role in maintaining a consistent level of communication that helps institutes in keeping the functionality of the model manageable and productive. According to the framework, educational institutions need to emphasize three major aspects (1) individual data, (2) social media, and (3) physical data. Moving to the second stage, consistent with the findings of Siemens and Gasevic (2012) these three factors assist in developing an effective online learning environment, based upon interaction, discussion activities, assessment, performance, ratings, and student satisfaction [30]. This component is further directly linked to the learning analytics framework revolving around pedagogical theories, data mining, structured data, unstructured data, and natural language processing. Pardo and Siemens (2014) underscored the significance of personalization and adoption framework, which indicates the functionality of visualization prompts, scaffolding and feedback [23]. After the successful integration of both the structures within the educational system, educational institutions need to critically consider the reporting engine that intends to manage the dashboard through calculating the statistics and graphs and create automatic or auto-generated reports.

7 Conclusion

This paper has demonstrated that Learning Analytics could be an effective strategy for intelligent instructing practice – supporting and empowering instructors to conduct assessment and research. It aimed at introducing implementation of Learning Analytics in Higher Educational Institutions (HEIs) and highlighted the different factors which play a vital role in student retention, attainment, and employability. The framework adopted in this research also provided extensive support to carry out the future studies on the empirical implication of learning analytics. Factors such as motivation, academic integration, social integration, and financial factors that impact on student retention rate in higher educational institutions in Malaysia were identified. The proposed integrated practical model for LA in Malaysia depicts how the educational structure must be implemented to ensure success in higher education.

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