The Use of Analytics in Analyzing Student Engagement in e-Learning

Mohd Hafriz Nural Azhan[1], Md Yazid Mohd Saman[2]& Noraida Ali[3]

Centre of Digital Learning Sultanah Nur Zahirah
Universiti Malaysia Terengganu
Malaysia

ABSTRACT

E-Learning web applications allow users to interact directly with any web platforms together with other users. Some learning applications and their usage in an e-learning platform have not been fully analyzed for student engagement in their learning activities. Big data is data collected in large quantities, be it in the form of structured or un-structured data. Big data can come from multiple sources. Nowadays, each application and equipment will have log data that is kept that can be translated into meaningful values. In e-Learning, each student activity will be logged and recorded. However, the raw data do not make much sense. Thus, to understand their value, analytic capabilities are highly needed. Analytics is a technology that is used to translate raw data into something more meaningful to users. Data that are being collected can be translated into data that is useful and valuable to users. This greatly depends on the translation process to statistics, computer programming and operations research in order to measure the performance of any web system. This paper reports the development of a system for the application of real-time analytics on the usage of e-learning in a tertiary institution. It includes the descriptions of the tools and statistics of the data collected by the e-learning system manager. All students' access information such as geographic information, devices used, access times, courses and activities are collected. The development of a dashboard system called Nakhoda is also described in this paper. It is a course learning analytics platform that displays summarized learning data. One finding is that devices used to access the e-learning system such as Apple Ipad, Iphone, Android-based and Symbian-based machines have shown to be the top *four mobile devices that are actively used by students. The evidence from this study suggests that the increasing use of mobile devices as a learning tool has generated a positive response from e-learning users. As a tool, analytics data can help lecturers to analyze their students' behavior, which can enhance pedagogical practices.*

Keyword: e-Learning, Analytics, Big data, dashboards

INTRODUCTION

Technology has now made learning more open where the traditional approach is now supplanted as learning and teaching enters a new era with the use of various technologies. The use of online learning and the use of web 2.0 applications have increased learning opportunities (Dalsgaard, 2006; Embi, 2012; Grosseck, 2009). Typically, to apply e-learning, most universities will use a system application known as a Learning Management System (LMS) to simplify the management of learning (Mehrabi & Abtahi, 2012). The use of this application has various advantages for both instructors and students to facilitate learning and has the potential to engage students to conduct independent learning (Mehrabi & Abtahi, 2012; Wang, Doll, Deng, Park, & Yang, 2013).

Blended learning (BL) offers an attractive educational outcome by combining teaching and learning (T&L) activities through the use of information technology. Via this mechanism, a student learns at least in part through the online delivery of content and instruction, with some element of student control over time, place, path or pace (Cashman & Eschenbach, 2003; Garrison & Kanuka, 2004). In BL, a form of learning called flipped classroom is perceived to be a suitable technique for T&L (Cashman & Eschenbach, 2003; Garrison & Kanuka, 2004). This method of T&L may also be described as "just in time teaching" (JiTT). In this method, students will have to complete certain preparatory tasks before coming to class where the lecturers will discuss the answers and comments in the face-to-face classroom sessions. With the aid of an LMS, students can undertake their learning tasks through the online contents. They may take an online quiz, do an assignment and submit it online or watch video lectures before coming to class. In the face-to-face classroom with the presence of the lecturer, the solutions to the assigned problems may then be discussed. This offers a more personalized guidance and interaction with students, instead of merely lecturing. Thus, the students come to class more prepared and motivated to learn. The lecturers can spend more time on difficult topics or common misconceptions. The Ministry of Education Malaysia (MOE) has stipulated that every course offered at public universities must implement some course contents through BL. In BL, classroom teaching is integrated with online activities (Mohd Saman & Nural Azhan, 2014). MOE has encouraged the application of BL as a pedagogical approach expecting 30% of T&L to be done through BL.

With the use of an LMS, students can access the system for the purpose of learning, suited to them. Lecturers on the other hand, can monitor the learning progress when needed (Jung, 2009; Peredo, Canales, Menchaca, & Peredo, 2011; Rodgers, 2008). Monitoring the implementation of T&L may be made on logged data stored in the LMS system. The stored data typically are student grades, activities undertaken by the students, access dates, student and course details. The data can be interpreted to show the performance of a student or the entire class that a lecturer is teaching (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Davies & Graff, 2005; Kong, 2010). With the proper implementation of e-learning, lecturers can identify the problematic students. Nevertheless, lecturers would find the data displayed by the LMS difficult to comprehend unless the data is processed and visualized in a comprehensible form (Kent, Carr, Husted, & Pop, 2011).

Analytics translates such data into more meaningful representations of information (Ali, Hatala, Gašević, & Jovanović, 2012; Kent et al., 2011). Data that are translated are data that are usually valuable but this depends much on the preparation of appropriate statistical procedures, computer programming and operation research to measure performance (Ali et al., 2012). The preparation of analytics data requires the use of mathematical and statistical techniques (Kent et al., 2011). Such translated data may be used to recommend actions or to assist in T&L decision-making. Usually, these analytical tools are used to assist the decision-making process in the business context (Muntean, Cabău, & Rînciog, 2014; Wu, Chen, & Olson, 2014) where, using such data, companies are able to identify the best investments that can be made and the amount of stock and sales materials to be added and subtracted based on purchase data trend analysis (Muntean et al., 2014).

BIG DATA IN THE E-LEARNING ENVIRONMENT

Big data refers to data collected in large quantities, in the form of structured or unstructured data. Such data can come from multiple sources. Each activity that is being performed in the T&L environment is usually kept and logged for analysis purposes. In e-learning, data comes from the learners when they access and perform an activity in the e-learning course modules. Each task and activity such as accessing notes, logging into the system, taking a quiz or logging out from e-learning system will be collected and stored. For example, once a student logs into the e-learning system and interacts with the learning modules, their progress, assessment results, views and other data is being produced as big data. With the implementation of statistical techniques combined with mathematical methods, these data can be analyzed and translated into comprehensible visuals to help instructors understand and determine how the learner is acquiring information, at what pace and time and reveal any problem that may exist while facilitating instructors' understanding of learners' learning patterns.

Educational Data Mining (EDM) is a technique used in computer science to discover patterns in large data sets involving multiple techniques such as artificial intelligence, machine learning, statistics and database systems (Mohamad & Tasir, 2013). The goal of EDM is to transform the large data sets into a comprehensible structure (Mohamad & Tasir, 2013; Romero, Ventura, & García, 2008). It can be concluded that EDM consists of data mining tools that can be used to deconstruct big data into smaller more meaningful units of comprehensible, and hence, useful, information (Mohamad & Tasir, 2013). Both EDM and big data are strongly related to each other. Once this big data is visualized into an understandable structure, it becomes known as analytics.

ANALYSIS AND MAPPING OF E-LEARNING ACTIVITIES FOR VISUALIZATION

Web Analytics is a tool that collects, measures and analyzes the usage of web system activities in order to understand user patterns in accessing the system (Kent et al., 2011; Rizzotto, 2007). Web administrators have used analytics data primarily for business and marketing research (Kent et al., 2011; Rizzotto, 2007; Ruipérez-Valiente, Muñoz-Merino, Leony, & Delgado Kloos, 2014) which may focus on user needs, products that have higher hits and sections haing lower hits (Rizzotto, 2007). In the e-learning context, there are data that can be used to make assumptions and to view user patterns for managing e-learning system facilities. Using analytics data, suggestions may also be offered to instructors as to the best day to give a quiz and which modules that will engage student more in T&L.

In developing an analytics system, the focus should be on translating the data obtained from the source into a form that can be understood by the instructors (Ali et al., 2012; Ruipérez-Valiente et al., 2014). This is to ensure that the data that appears in the analytics system can give value and help the instructor analyze student participation in using the content in the e-Learning system. The main problem encountered in the e-learning system is how we can analyze the behavior of students and monitoring their activities to ensure they carry out the activities (Hu, Lo, & Shih, 2014; Mehrabi & Abtahi, 2012; Rodgers, 2008). An LMS is able to track student activity, but somehow, most lack analytics tools to help the instructor monitor student participation and activeness (Awang & Darus, 2012). Table 1 shows the mapping of the data sources and the analytics outcomes used in analyzing student and lecturer activity in e-learning.

NAKHODA DASHBOARD SYSTEM

Based on the mapping and visualization of student activity in e-learning, a dashboard system called *Nakhoda* was developed to collect and display the visualization of the student activity. *Nakhoda* is expected to help in monitoring the implementation of the 30% T&L activities conducted online. The instructor can get an idea of what going on in their courses through *Nakhoda*. The instructor can identify those activities that students find most interesting. The instructor can develop a student profile analysis based on their activity and help the student by evaluating which are the most engaging activities that can be conducted in e-learning. Figure1 shows the structure of the *Nakhoda* system. It is an extended version of the *Laksamana* system that was developed earlier (Nural Azhan, Mohd Saman, & Abdullah, 2011). *Laksamana* is a system that has applied the push-pull technology with temporal analysis with the aim of increasing student participation in an e-learning environment (Nural Azhan et al., 2011). However, despite the increase in student participation, *Laksamana* lacks strong analytics to help the instructor make appropriate T&L decisions regarding the best e-learning activities and monitor student activeness.

Table 1 : Data Source and Analysis Outcome

e-Learning Factor	Data measured & Sample	Information Outcome / Pattern Analyze
Device Access Type of device Number of Access Type of OS use What module they access	Student access log Server log Browser type OS type Device information Time access	System / Learning Management System that needs mobile view for particular devices Needed to develop native application for Mobile Device
eActivity in e-Learning	Page Access Server log Users access log Browser type eActivity track log	Temporal information on student access Statistical report which eActivity is the highest in LMS Requirement to expand e-Learning bandwidth (if using cloud) on certain time/days
Mod-blendedness measuring	LMS resource data Users data activity LMS activity Modules data	Information about courses that have achieved criteria Use the information to target the number of courses that can achieve criteria the following month based on statistical data analyzed

Entering Page	Server log Users access log	Information on user's first hit access. The highest hit page is the highest student engagement When combined with reference page information, we can find out whether the student is directly accessing or accessing after notification or instruction from email/message from lecturer.
Reference Page	Server log Users access log	This information can help administrator find out which push module helped engage the student the most This report can give us information on the external page that is most referred to before the student/lecturer enters e-learning
Exit Page	Server log Users access log	Information on last page users enter before closing the browser or the cookies expired. The entering page will reveal which module/action users interacted with and which page made users exit the LMS

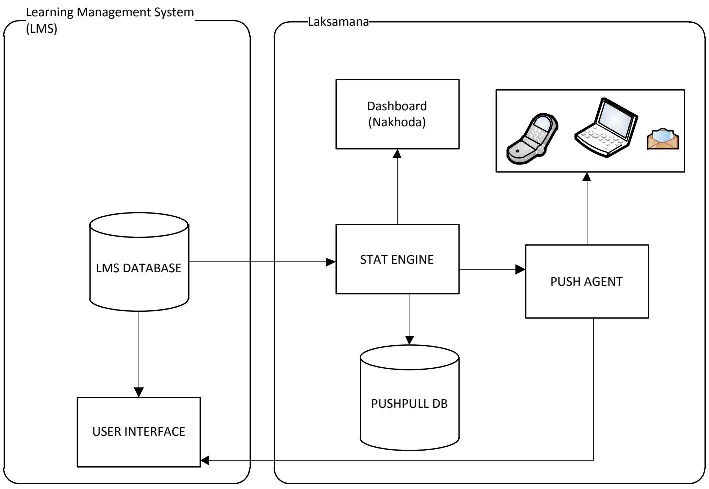


Figure 1: *Nakhoda* System Structure

Based on proposed interface and framework in Figure 1, the *Nakhoda* system was developed and integrated with *Laksamana* and the LMS. The proposed interface is based on the mapping of the e-learning information required in the analysis. This interface aims to provide an integrated meaningful visualization of the big data for lecturers to make T&L decisions. The display interfaces for *Nakhoda* were developed in a block section where each block refers to different results.

SYSTEM DISPLAYS AND ENGAGEMENT PATTERNS

Figure 2 shows the main interface for the *Nakhoda* system. Figures 3 to 5 show the various interfaces of the dashboard system with an integrated analysis that can help the instructor evaluate the implementation of the BL mode in their courses. For each student profile, the system will provide the temporal analysis of student interaction in their courses and activities provided by the instructor.

Figure 2: *Nakhoda* Main Interface

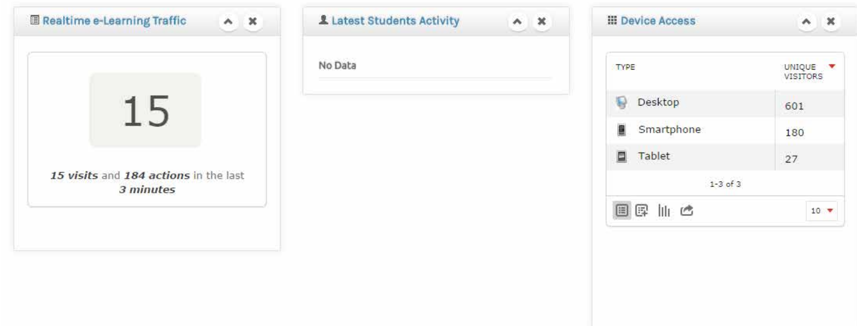


Figure 3: Some Statistical Data Displayed

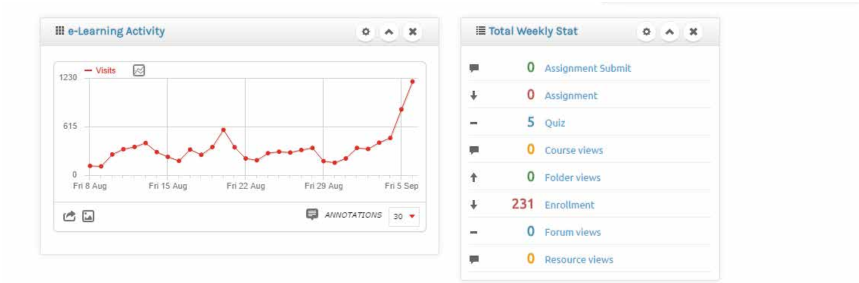


Figure 4: Some Statistical Data Displayed

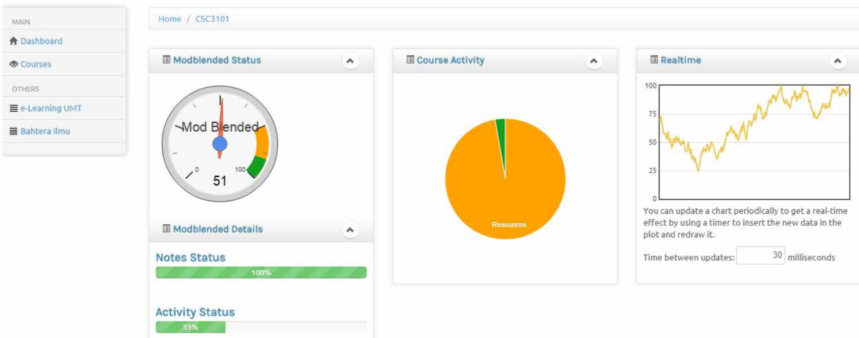


Figure 5: Course Analysis

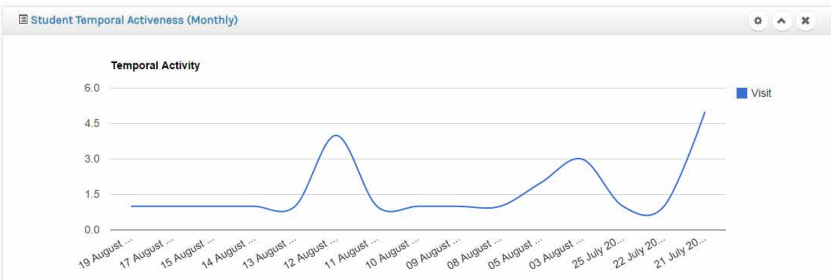


Figure 6: Temporal Activity Analysis

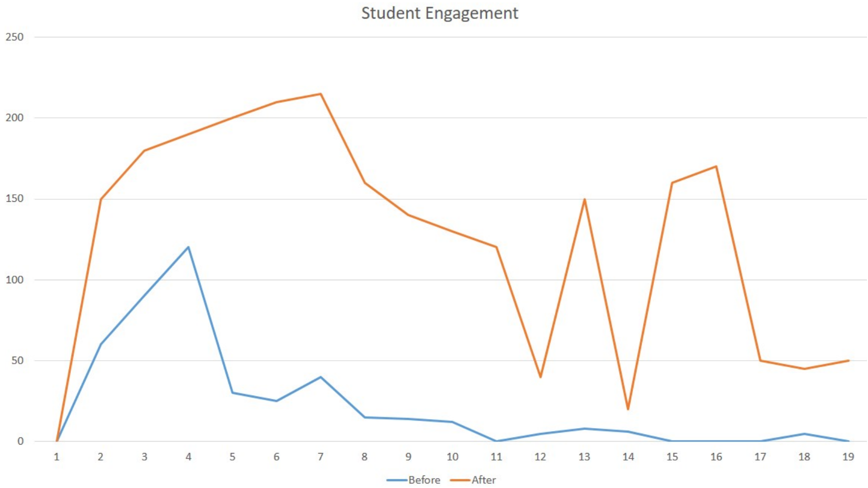
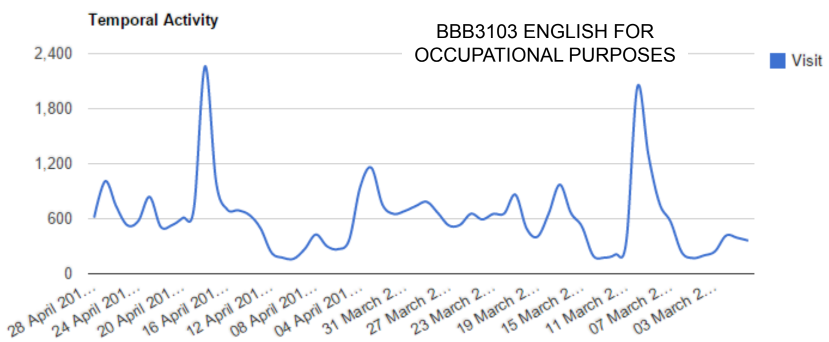
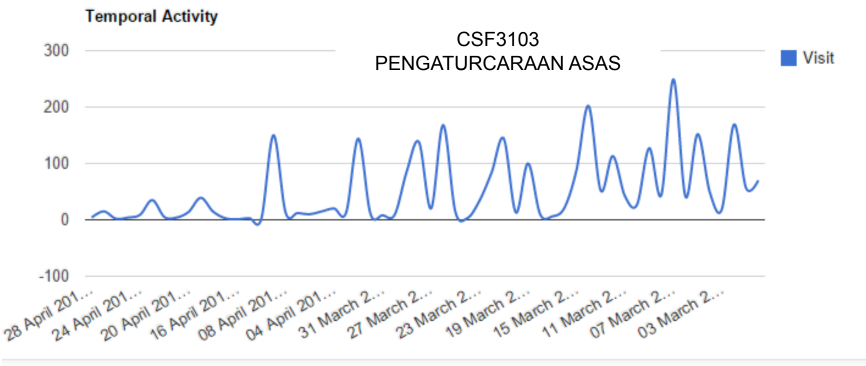


Figure 7: Increase of Student Engagement in e-learning (Nural Azhan et al., 2011)

Figure 8 shows how *Nakhoda* analyzes the patterns of student engagement based on the temporal data. These data are then compared and different patterns of student engagement are seen to emerge, assuming that each course is using a different pedagogical approach for BL. With such patterns, the best way to present our content can be facilitated, knowing which content has the highest engagement according content type or through temporal interaction.





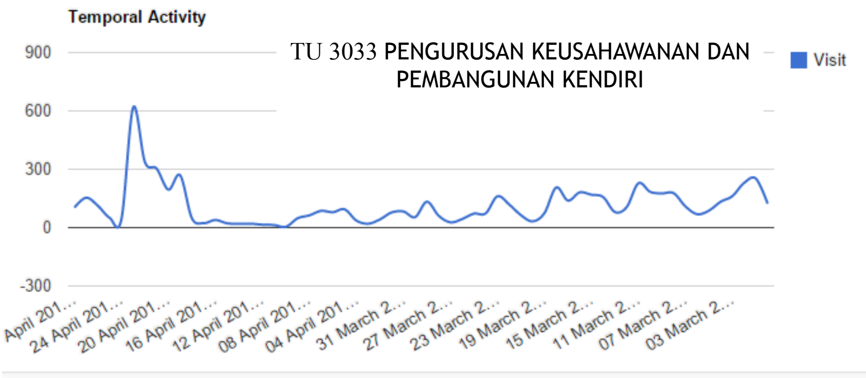


Figure 8: Different Patterns of Student Engagement in e-learning

RELATED WORK

Numerous research has been done on analyzing and translating big data into analytics. One of the tools in web analytics is Google Analytics (Educação, 2013; Google, 2015). Launched in November 2005, it is a free web analytics tool service offered by Google (Google, 2015). The main idea of Google analytics is to track and report website traffic using integrated Ad words. It is mostly used by e-commerce sites to track conversion or goals. Goals might include sales, lead generation, user views or hits to certain files hosted in the user's website (Educação, 2013; Google, 2015).

Another similar tool to Google Analytics is *Piwik*. *Piwik* differs from Google Analytics in terms of application as *Piwik* is an Open Source Web Analytics Platform. *Piwik* offers the whole system that can be installed in users' own servers (Piwik, 2014; Scott Nesbitt, 2014). With *Piwik*, the data collected is owned by the users and secured (Piwik, 2014). The *Piwik* project was initiated in June 2007 in London and then released in September 2007. *Piwik* is used to gather and analyze important information about users that access a website. e-Commerce Analytics analyzes revenue, orders, conversion rates and detailed product statistics and sees which products are the most popular (Piwik, 2014). Dychkhoff et. al. (2012) have suggested the design and implementation of a Learning Analytics Toolkit for Teachers (eLAT). The eLAT design is to process large data sets that enables the instructor to explore and correlate learning object usage, user properties, user behavior as well as assessment results based on graphical indicators. The eLAT tool has been built for teachers to know how students react to their content and teaching approach.

CONCLUSION

This paper discusses the nature and process of learning analytics. Analytics is a technology that is used to translate raw data into something more meaningful to users which depends on the translation process using statistics, computer programming and operations research. A dashboard system called *Nakhoda* has been described to implement the analytics process. It is an extension of the system called *Laksamana* developed earlier in the project. The concept of analytics with smart business elements has been adopted and used in an e-learning environment to help analyze e-learning data to improve the development of e-learning. The T&L decisions made by the instructor using this system can help enhance and improve the implementation of e-learning in the university through increased interaction between students and lecturers. Analytics offers a way to translate data into more meaningful representations of information. Such translated data will be used to recommend actions or to assist in decision-making. Usually, these analytical tools will be used to assist the decision for the business context. It helps companies identify the best investments that can be made and the amount of stock and sales materials can be added and subtracted based on purchase data trend analysis. Future works may be focused on a fully intelligent recommender system, personalized learning, rewards system and intercepting problematic students.

REFERENCES

Agudo-Peregrina, Á. F., Iglesias-Pradas, S., Conde-González, M. Á., & Hernández-García, Á. (2014). Can We Predict Success From Log Data In Vles? Classification Of Interactions For Learning Analytics And Their Relation With Performance In VLE-Supported F2F And Online Learning. *Computers in Human Behavior*, *31*, 542–550. doi:10.1016/j.chb.2013.05.031

Ali, L., Hatala, M., Gašević, D., & Jovanović, J. (2012). A Qualitative Evaluation Of Evolution Of A Learning Analytics Tool.*Computers & Education*, *58*(1), 470–489. doi:10.1016/j.compedu.2011.08.030

Awang, N., & Darus, M. Y. (2012). Evaluation of An Open Source Learning Management System: Claroline. *Procedia - Social and Behavioral Sciences*, *67*, 416–426.

Cashman, E. M., & Eschenbach, E. A. (2003). Using On-Line Quizzes Outside the Classroom to Increase Student Engagement Inside the Classroom. In *Spring 2003 Conference Proceedings, American Society for Engineering Education*.

Dalsgaard, C. (2006). Social software: E-learning Beyond Learning Management Systems . *European Journal of Open, Distance and E-Learning*, (2). Retrieved from http://www.eurodl.org/materials/contrib/2006/Christian_Dalsgaard.htm

Davies, J., & Graff, M. (2005). Performance in e-Learning: Online Participation And Student Grades. *British Journal of Educational Technology*, *36*(4), 657–663.

Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroede, U. (2012). Design and Implementation of a Learning Analytics Toolkit for Teachers. *Educational Technology & Society*, *15*(3), 58–76. Retrieved from http://etd.lib.nsysu.edu.tw/ETD-db/ETD-search/view_etd?URN=etd-0118112-120714

Educação, P. (2013). Google Analytics. Retrieved April 14, 2015, from http://www.portaleducacao.com.br/informatica/artigos/48358/google-analytics

Embi, M. A. (2012). Web 2.0 Tools in Education : A Quick Guide. Pusat Pembangunan Akademik, Universiti Kebangsaan Malaysia. Retrieved from http://www.ukm.my/ppa/index.php?option=com_rokdownloads&view=file&task=download&id=257:web-2&Itemid=73&lang=Bm

Garrison, D. R., & Kanuka, H. (2004). Blended Learning: Uncovering Its Transformative Potential In Higher Education.*Internet and Higher Education*, *7*(2), 95–105. doi:10.1016/j.iheduc.2004.02.001

Google. (2015). How Google Analytics works. Retrieved April 14, 2015, from https://support.google.com/analytics/answer/6081186?hl=en

Grosseck, G. (2009). To Use Or Not To Use Web 2.0 In Higher Education? . *Procedia Social and Behavioral Sciences*, *1*, 478–482.

Hu, Y.-H., Lo, C.-L., & Shih, S.-P. (2014). Developing Early Warning Systems To Predict Students' Online Learning Performance.*Computers in Human Behavior*, *36*, 469–478. doi:10.1016/j.chb.2014.04.002

Jung, J. J. (2009). Social Grid Platform For Collaborative Online Learning On Blogosphere: A Case Study of eLearning@BlogGrid. *Expert Systems with Applications*, *36*, 2177–2186.

Kent, M. L., Carr, B. J., Husted, R. a., & Pop, R. a. (2011). Learning Web Analytics: A Tool For Strategic Communication. *Public Relations Review*, *37*(5), 536–543. doi:10.1016/j.pubrev.2011.09.011

Kong, S. C. (2010). Using A Web-Enabled Video System To Support Student–Teachers' Self-Reflection In Teaching Practice. *Computers & Education*, *55*, 1772–1782.

Mehrabi, J., & Abtahi, M. sadat. (2012). Teaching withMoodle In Higher Education. *Procedia Social and Behavioral Sciences*, *47*, 1320–1324.

Mohamad, S. K., & Tasir, Z. (2013). Educational Data Mining: A Review. *Procedia - Social and Behavioral Sciences*, *97*, 320–324. doi:10.1016/j.sbspro.2013.10.240

Mohd Saman, M. Y., & Nural Azhan, M. H. (2014). Blended & Flipped Learning. In *Blended & Flipped Learning case studies in Malaysia* (pp. 165 – 174). Pusat Pengjaran & Teknologi Pembelajaran, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor Darul Ehsan.

Muntean, M., Cabău, L. G., & Rînciog, V. (2014). Social Business Intelligence: A New Perspective for Decision Makers. *Procedia - Social and Behavioral Sciences*, *124*, 562–567. doi:10.1016/j.sbspro.2014.02.520

Nural Azhan, M. H., Mohd Saman, M. Y., & Abdullah, M. L. (2011). Adaptation of Content Syndication For On-Demand Active E-Learning. In *1st National Conference Of Active Learning*. Universiti Teknologi Melaka.

Peredo, R., Canales, A., Menchaca, A., & Peredo, I. (2011). Intelligent Web-Based Education System For Adaptive Learning. *Expert Systems with Applications*. doi:10.1016

Rizzotto, F. (2007). *WHITE PAPER Adding Intelligence to Web Analytics Adding Intelligence to Web Analytics*. Retrieved from www.idc.com/italy

Rodgers, T. (2008). Student Engagement in the E-Learning Process and the Impact on Their Grades. *International Journal of Cyber Society and Education*, *1*(2), 143–156.

Romero, C., Ventura, S., & García, E. (2008). Data Mining In Course Management Systems: Moodle Case Study and Tutorial. *Computers and Education*, *51*(1), 368–384. doi:10.1016/j.compedu.2007.05.016

Ruipérez-Valiente, J. a., Muñoz-Merino, P. J., Leony, D., & Delgado Kloos, C. (2014). ALAS-KA: A learning Analytics Extension For Better Understanding The Learning Process In The Khan Academy Platform. *Computers in Human Behavior*. doi:10.1016/j.chb.2014.07.002

Scott Nesbitt. (2014). Top 3 Open Source Alternatives to Google Analytics. Retrieved April 14, 2015, from http://opensource.com/business/14/10/top-3-open-source-alternatives-google-analytics

Wang, J., Doll, W. J., Deng, X., Park, K., & Yang, M. G. (Mark). (2013). The Impact Of Faculty Perceived Reconfigurability Of Learning Management Systems On Effective Teaching Practices.*Computers & Education*, *61*, 146–157.

Wu, D. D., Chen, S.-H., & Olson, D. L. (2014). Business Intelligence In Risk Management: Some Recent Progresses. *Information Sciences*, *256*, 1–7. doi:10.1016/j.ins.2013.10.008