Learning Analytics and Learning Technologies

Abstract

Emerging technologies continue to influence education in the way that instruction is designed, delivered, and consumed. As online learning has become a common mode of instruction delivery (Martin & Ndoye, 2016), more data has become available, as well as faster, more efficient tools to analyze it. Learning Analytics is one such technology, and is defined by the Society for Learning Analytics Research (SOLAR) as "the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing, learning and the environment in which it occurs" (SOLAR, 2012). This paper discusses the role of learning analytics in instructional design, the role that Learning Management Systems (LMSs) play in learning analytics, the benefits of learning analytic tools, and the limitations and future implications of this emerging technology.

Introduction

Emerging technologies continue to influence education in the way that instruction is designed, delivered, and consumed. As online learning has become a common mode of instruction delivery (Martin & Ndoye, 2016), more data has become available, as well as faster, more efficient tools to analyze it. Learning Analytics is one such technology, and is defined by the Society for Learning Analytics Research (SOLAR) as "the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimizing, learning and the environment in which it occurs" (SOLAR, 2012).

Learning analytics is a fairly new interdisciplinary field, encompassing some aspects of big data, Business Intelligence (BI) and data mining (Divjak & Maretic, 2015). Shum and Ferguson (2012) map its history by explaining that BI and data mining were the originating analytic tools, although both are largely unrelated to education. Rather, they are used as a means to understand consumer behavior in relationship to internal organizational data (Shum & Ferguson, 2015). Once Learning Management Systems (LMSs) became more widely adopted as a vehicle for delivering content in the electronic learning environment, data mining was leveraged by educators, administrators and other stakeholders as a means for driving decision-making (Czerkawski, 2015). With the vast amounts of information that became available through data mining practices, researchers were able to gain deeper understanding into student learning (Greller, Wolfgang, Drachsler, & Hendrik, 2012). As more and more learning institutions began to use data warehouses to store data across multiple platforms, thereby gaining an ability to analyze data in a more dynamic way, the idea of learning analytics was beginning to take shape (Shum & Ferguson, 2012). The *1st International Conference on Learning Analytics and Knowledge* was held in 2011, and the tool shifted from benefitting primarily administrators and heads of departments, to the inclusion of teachers and learners (Shum & Ferguson, 2012). Karanth and Mahesh (2015) posit that while analyzing large amounts of data sets once required a strong background in statistics, the internet and other widely available data sources have given non-experts the ability to do so as well. Karanth and Mahesh (2012) also point out that data can be more readily interpreted, as the technology for graphic renderings have also advanced. While Avella, Nunn & Kanai (2016) acknowledges the benefits of learning analytics, they warn that educators should become more familiar with the various challenges in its implementation before embracing it. Ifenthaler and Widanapathirana (2014) echo the sentiment in stating that "theoretical concepts and empirical evidence need to be generated" (p. 221) within this quickly growing field. Indeed, while the literature reveals the power of learning analytics to more effectively direct student education through data analysis (Marks, Al-Ali, & Rietsema, 2016; Wilson, Scalise & Gochyyev, 2016; Yen, Chen, Lai & Chuang, 2015), it is also clear that great amounts of effort must be applied to its proper use and administration (Gasevic, Dawson, & Siemens, 2015; Olmos & Corrin, 2012; Stefan, Moldoveanu, & Gheorghiu, 2016). This paper discusses the role of learning analytics in instructional design, the role that Learning Management Systems (LMSs) play in learning analytics, the benefits of learning analytic tools, and the limitations and future implications of this emerging technology.

Implications of Learning Analytics in Instructional Design

Instructional design (ID) is simply defined by Nunes and Schiel (2014) as "the planning and sequencing of activities in a course" (p. 383). The power of learning analytics to effectively inform ID can be seen across various studies (Martin & Whitmer, 2016; McKenney & Mor, 2016; Nunes & Schiel, 2014). Rodriguez-Triana, Martinez-Mones, Asensio-Perez and Dimitriadis (2015) make a distinction between learning design and learning analytics, which provides insight into how learning analytics changes the ID approach. In a learning design approach, learning tasks and scaffolding events are scripted into the lesson before the student ever interacts with the material. In a learning analytics approach, interactions with the material are being monitored so as to inform any necessary interventions. The data gleaned from the analytics, in other words, is what drives the instructional design and makes feedback formative, as pointed out by Wise, Vytasek, Hausknecht, and Zhao (2016), rather than summative only.

From the examples in current literature (Olmos & Corrin, 2012; Stefan, Moldoveanu & Gheorghiu, 2016), one can see that the data is informative in the way that it is collected, assimilated, and returned. For example, Stefan et al. (2016) conducted an evaluation of a mixed-reality 3D virtual campus by employing tracking objects as a way to store data in a Microsoft SQL database, which was then integrated with two other data sources (Moodle SQL and Open Similator's MySQL). The activities of the virtual campus, student engagement and teacher activity were measured and viewed on dashboards, created as a visualization tool for each of the three measured components. The data tracking, data integration, and visualization tools served to inform the researchers on teacher and student preference and performance.

Using data as a driver for instructional design is often an undertaking that requires extensive planning and multiple iterations since data is typically pulled and assimilated from various sources. Olmos and Corrin's (2012) study is demonstrative of such requirements, as the researchers approached the study with a careful planning of design goals, taking into consideration what data should be extracted and incorporated into the visualization rendering. The authors mapped out their anticipated challenges and the logistics for overall design and delivery before ever beginning the instructional design process. The study required four iterations before producing a finalized analytics interface.

Several studies in the literature point to the need for a framework in order to properly implement Learning Analysis tools (Greller & Draschler, 2012; Rienties, Boroowa, Cross, Kubiak, Mayles & Murphy, 2016; Scheffel, Drachsler, Stoyanov & Specht, 2014; West, Heath & Huijser, 2015; Wise et al., 2016). Rienties et al. (2016) propose an evidence-based framework for designing and implementing data-informed instruction. The researchers (2016) posit that leveraging tools based on insufficient or limited case studies is not conducive to creating successful interventions for learners, and state that a framework is needed to assist teachers and policymakers in uncovering those interventions that work well and under which circumstances. Greller et al. (2012) also subscribe to the use of a framework in the instructional design process "to ensure an appropriate exploitation of learning analytics in an educationally beneficial way" (p. 43). Wise et al. (2016) propose a framework in the implementation of learning analytics into instruction as a way to support student use of such tools by giving them context.

Learning Analytics and Learning Management Systems

Czerkawksi (2015) explains that the use of learning analytics tools within the education system can be beneficial in that the data gathered on students can provide insight and therefore inform learning paths as problems are identified. Much of the literature around learning analytics in the education system focuses on Learning Management Systems (LMSs) and how they are being leveraged for learner analysis (Firat, 2016; Gomez-Aguilar, Garcia-Peñalvo, & Theron, 2014; Macfadyen & Dawson, 2012; Marks et al., 2016; Mhichel, van Engen, Ciardubhain, Cleirsin & Appel 2014; Zhong, 2016). In Zhong's (2016) systematic review of the related literature within the context of higher education, LMS's and external data sources were found to be the most widely used sources for learning analytics data. Marks et al. (2016) state that currently, nine out of ten US higher education institutions use the top five LMS vendors, with

Blackboard having the largest market. Marks et al. (2016) conducted a study in which online surveys from twenty seven Information Technology (IT) directors and Chief Information Officers (CIOs) were gathered and ten semi-structured interviews were conducted with IT directors and academic chairs. Of these populations, the authors found that the most common learning analytics functionalities being leveraged within the LMSs were curriculum coverage and mapping, alerts and early warning systems, goal performance, and interactive rubrics – the first two of which are discussed below.

Curriculum mapping. Curriculum mapping as a function of the LMS was found to be useful in the Marks et al. (2016) study because it allowed for a curriculum design based on an association between curriculum goals and other metrics. Administrators reported that utilizing a manual process for this type of tracking revealed inconsistencies as well as higher maintenance costs. To this point, Piotrowski (2011) discusses the use of content mapping in medical schools and other higher education institutions; however, this is discussed within the context of a curriculum management system, and not within the LMS. Piotrowski's (2011) study used a qualitative methodology to collect data from IT directors or deans of medical schools and other higher education institutions. At the time of the study, it was reported that content mapping was a primary adoption driver in the use of the LMS within the medical schools interviewed; however, this was not because the LMS already contained the content mapping functionality, but rather was based upon how well the LMS would integrate with the content management systems. This is demonstrative of the importance of interoperability between systems for data analytics.

Alerts and early warning systems. Yen et al. (2015) posit that the power of learning analytics resides within its ability to extract data that will help to improve online instruction. Displaying the data on dashboards using visualization tools and representations also make it more consumable (Lavigne, Gutierrez Ruiz, McAnally-Salas, Sandoval, 2015; Verbert, Govaerts, Duval, Santos, Van Assche, Parra & Klerkx, 2014). Once student behaviors are recognized, instructors will be able to more quickly identify any issues and adjust their teaching strategies accordingly. As an example, Poitras, Naismith, Doleck, and LaJoie (2015) conducted a study with medical students using a tool called MedU, applying early detection techniques by creating an algorithm for analyzing the learner responses to multiple-choice questions throughout the lesson. The data was then used to inform the feedback to each individual.

Lonn, Aguilar, and Teasley (2015) explain that retention at the university level is an ongoing issue, as a failure to graduate has negative implications for both the student and the institution from which they left, and that early warning systems are being used to help identify at-risk students before they drop out. Course Signals is discussed in the literature as an early alert system for struggling students, developed by Purdue University starting in 2005 (Avella et al., 2016; Friesen, 2013; Gasevic, Dawson, & Siemens, 2015; Verbert et al., 2014; Wright, McKay, Hershock, Miller & Tritz, 2014). According to Gasevic et al. (2013), this system was created to integrate with Blackboard LMS, and provides feedback in the form of colored "traffic" lights (green, amber, or red) to identify high risk, moderate risk, and not-at-risk students. Gasevic et al. (2015) point out that Course Signals was originally utilized as an academic analytics tool and in that capacity it serves its function, which is to predict student retention through academic performance. Gasevic et al. (2015) go on to say that while Course Signals' simplistic approach is helpful in prompting action, the design does not "have sufficient theoretically informed functionality to encourage adoption of effective instructional and intervention practices" (p. 66). This statement echoes Rienties' (2016) proposal for evidence-based design and implementation for data-driven instruction.

Other learning analytic tools mentioned in the literature are Student Activity Meter (SAM) (Govaerts, Verbert & Duval, 2011; Papamitsiou & Economides, 2015; Verbert et al., 2015), SNAPP (Conde, Hernandez-Garcia, Garcia-Peñalvo, Sein-Echaluce, Zaphiris, & Ioannou, 2015; Dringus, 2012; Firat & Yuzer, 2016; Vebert et al., 2014) and LOCO-Analyst (Ali, Hatala, Gasevic, & Jovanovic, 2012; Dringus, 2012; Gasevic, et al., 2015; Papamitsiou & Economides, 2015; Verbert et al., 2014).

Limitations of the LMS

While the literature is reflective of the positive aspects of using an LMS as an analytics tool (Firat, 2016; Marks et al., 2016; Martin & Whitmer, 2016) there are also some important limitations outlined in using this tool as a sole source of data. Gewarc, et al, (2016) explain that learning analytics goes beyond the LMS, as learning behaviors are also part of the analytical equation, and therefore having the ability to link the data to other data sets becomes important. It is the combination of data that would be able to provide such in-depth insights into learning processes within specific contexts. While it is now more common for LMS's to build a learning analytics tool into the system, students are generally not working solely in the LMS and the tools built into the LMS do not generally grab data outside of the environment (Czerkawski, 2015; Siemens & Long, 2011; Strang, 2016). This means that if instructors are relying solely on the data produced by the LMS, interpretations and assumptions may be made on incomplete data sets. One such example is a study that was carried out by Firat (2016), making use of the LMS as a tool to determine the effects of undergraduate students' LMS learning behavior on their academic achievement. The results indicate there was no correlation between the amounts of clicks into the system and academic achievement, but that there was a significant correlation between the overall amount of time that students spent in the LMS and their academic achievement. Since the data is derived solely from the LMS, it is not clear why this is the case; however, the author puts forth the implication that “trainers could contribute to their students’ academic achievement by increasing the time students spend on the LMS” (p. 85). There is no explanation given as to *what* students should be doing on the LMS. Gasevic et al. (2015) label the practice of using trivial indicators, such as number of times a student logs into the system, as undesirable. Echoing that sentiment, Dringus (2012) explains that beyond merely obtaining data, one must be able to effectively use it for meaningful feedback and student intervention.

Macfadyen and Dawson (2012) suggest a need for more progressive socio-technical infrastructures that allow for communication across systems in order to capture learning events and outcomes on many platforms. The researchers (2012) explain that such initiatives are already being undertaken to create this type of interoperability and hence more comprehensive data collection (some examples are the ADL Experience API and Learning Measurement Framework IMS Caliper).

Future Implications of LA

Looking ahead to the future of learning analytics, Czerkawski (2015) explains that because these tools make use of “intelligent online data” (p. 4), more Web 3.0 tools will likely be developed to create more open and interactive learning platforms, thereby revolutionizing education. In addition, embedded assessments with feedback systems will become more prominent in higher education institutions (Czerkawski, 2015). MacNeill, Campbell and Hawksey (2014) assert that research in learning analytics will continue to grow and branch out, as social network tools and massive open online courses (MOOCs) provide opportunities for larger scale studies. Based on the review of literature, it seems that in order to accomplish the goals of effective implementation of learning analytics tools, it will be important to apply a greater focus on utilizing frameworks within which to work (Greller, & Draschler, 2012; Rienties et al., 2016; Scheffel et al., 2014; West et al., 2015; Wise et al., 2016), as well as base implementations on more extensive research and case studies (Gasevic et al. 2015; Ifenthaler & Widanapathirana; Rienties2016).

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