Learning Analytics for Student Success: Future of Education in Digital Era

Myint Swe Khine, Emirates College for Advanced Education, United Arab Emirates

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Abstract
In the increasingly competitive and changing world, efficient education system that drives the human development in the country is the key to a nation's progress. The education providers – schools and higher learning institutions must focus on student success and design instruction that considers the individual differences of the learners. In recent years, learning analytics has emerged as a promising area of research that extracts useful information from educational databases to understand students' progress and performance. The term Learning Analytics is defined as the measurement, collection, analysis and reporting of information about learners and their contexts for the purposes of understanding and optimizing learning. As the amount of data collected from the teaching-learning process increases, potential benefits of learning analytics can be far reaching to all stakeholders in education including students, teachers, leaders and policy makers. Educators firmly believe that if properly leveraged, learning analytics can be an indispensable tool to narrow the achievement gap, increase student success and improve the quality of education in the digital era. A number of investigations have been conducted and reported the strategies, techniques, and approaches of learning analytics in the literature. This paper examines the recent attempts to conduct systematic and multidisciplinary research in learning analytics and present their findings. The paper also identifies privacy concerns and ethical issues and recommends further research and development in this area.

Keywords: Learning analytics; student performance; interaction; privacy; learning design

Introduction

Ever since the digital revolution has begun, endless opportunities arise in creation and delivery of new knowledge contents in different level of educational enterprises. The communications between the learners and educators have been improved tremendously both in terms of speed and time. Learning Management Systems (LMSs) and social networking micro-blogs are commonly used in educational institutions to mediate the learning process. In these communication processes and transactions, huge amount of data have been crated as the digital traces or footprints of the providers and users. These data can be captured and analysed to observe their trends and patterns. The type and magnitude of data that generated from the interactions are so massive that often refers as Big Data (Reyes, 2015; Daniel, 2016).

The term Learning Analytics has emerged to describe the process in understanding the behaviours of learning process from the data gathered from the interactions between the learners and contents. The term can be defined as as the measurement, collection, analysis and reporting of information about learners and their contexts for the purposes of understanding and optimizing learning (Siemens, 2013). Another simple definition states "*learning analytics is about collecting traces that learners leave behind and using those traces to improve learning*" (European Commission, 2016). A number of authors have considered the importance and impact of learning analytics in the future of education (Pardo, 2014: Becker, 2013). In their view, Gašević and Pechenizkiy (2016) note that the field of learning analytics is the confluence of knowledge drawn from related disciplines such as educational psychology, learning sciences, machine learning, data mining and human-computer interaction (HCI). Brown (2011) traces the development of learning analytics and predicts that the concept will be adopted rapidly in the coming years, particularly when the analytical tools are becoming more practical and affordable.

Potentials of Learning Analytics

In recent years, the potentials of learning analytics have been discussed in the educational research community. Most educators agree that learning analytics can facilitate evaluation of the effectiveness of pedagogies and instructional practices. Some suggest that learning analytics has the potential to contribute the quality of teaching and learning by designing innovative and adaptive lessons to suit the individual students' cognitive abilities. The Learning Management Systems (LMSs) that combine content delivery, discussion forums, and quiz and assessment allow to monitor students' learning activities and from the analysis, instructor can detect the students at risk and undesirable behaviors. Once the issues are identified, the instructor can provide remedial solutions to support the students and help increase the level of achievement.

Hwang et al (2017) describe that learning analytics can assist in identifying the status of students' learning and problems they face in the learning process. They also note that instructors will have the comprehensive view of students' interaction with the course materials, peers and instructors. This information may contain raising questions, clarifying concepts, seeking advice, making observations and providing alternative views and so on. By analyzing these learning behaviors and the interactions with the content, it will be possible to design a personalized and adaptive learning contents, practices and user interfaces to maximize the learning of individual students.

The learning analytics can be an indispensable tool for supporting informed decision making in course design and development. The information and analyses generated from the data can assist instructor to improve the course contents and instructional resources regularly. It is the responsibility of instructors to know the behaviors of their own students. By analyzing the source of data, the patterns can be established to understand the interactions between students, resources, and peers within the course. Providing timely feedback is a key feature in the learning process and important for both learners and instructors. The results from learning analytics can indicate when to provide feedback to specific learners.

Many studies have been reported the positive contributions of learning analytics. The encouraging results confirm that if properly used, learning analytics can help instructors to identify the learning gaps, implement intervention strategies, increase students' engagement and improve the learning outcomes (Merceron et al, 2015).

Applications of Learning Analytics

From the abstract and citation database of peer-reviewed literature, Wong (2017) identifies case studies that report empirical findings on the application of learning analytics in higher education. A total of 43 studies were selected for in-depth analysis to discover the objectives, approaches and major outcomes from the studies. The study classifies six aspects that learning analytics can support to improve the education process. These are (i) improving student retention, (ii) supporting informed decision making, (iii) increasing cost-effectiveness, (iv) understanding students' learning behavior, (v) arranging personalized assistance to students, and (vi) providing timely feedback and intervention. These aspects are not to consider in separate entity, but are inextricably linked.

(i) Improving student retention

In educational settings detecting early warning signs for students who are coping with their study can be an advantage for the instructors. The issues and problems that students are facing may varies from social and emotional issues to academic matters or other factors that may lead to giving-up from the study. Those students can be provided with remedial instructions to overcome some of the problems. For example, Star and Collette (2010) report that knowing the circumstance and understanding the causes, instructor can increase the interaction with the students to provide personal interventions. As a result the students showed better academic performance and significantly increase the retention rate. In a similar study Sclater et al (2016) describe that increase interactions with students promote sense of belonging to the learner community and learning motivations. It was found that in the process the students' attrition rate dropped from 18 to 12%.

(ii) Supporting informed decision making

The results from learning analytics can also be used to support informed decision making. A study by Toetenel and Rienties (2016) at the Open University in UK involves analyzing the learning designs of 157 courses taken by over 60,000 students and identify the common pedagogical patterns among the courses. The authors suggest that educators should take note of activity types and workload when designing a course and such information will be useful in decision making of specific learning design. However, the authors conclude that further studies are needed to find out whether particular learning design decisions result in better student outcomes.

(iii) Increasing cost-effectiveness

With the funding cut and raising expenditure, cost-effective has become the key indicator for sustainability in the education sector. One of the effective ways is to take advantage of the learning management systems that not only deliver the course materials, also keep track of the learners' activities. Instructors can analyze the activities and report the progress to the students and other stake holders in a cost-effective manner. As Sclater et al (2016) note, after conducting the analysis, notifications were automatically generated and send to students and their parents on students' performance.

(iv) Understanding students' learning behavior

To better understand the students' learning behavior, instructors can explore the data collected from the learning management systems and social media networks. Instructors can examine the relationships between students' utilization of resources, learning patterns and preferences and learning outcomes. This approach has been adopted by Gewerc et al (2014) when attempted to examine the collaboration and social networking in a subject for education degree course. The study analyzes the intensity and relevance of the student's contribution in the collaborative framework by using social network analysis and information extraction. The authors concluded that findings from the study help to understand more clearly how students behave during the course.

(v) Arranging personalized assistance to students

Given the advantages of data mining techniques and algorithms that are used in business and manufacturing industry, learning analytics has emerged as educational data mining of students and the courses they study. An investigation into the application of such technique in education domain was conducted by Karkhanis and Dumbre (2015) to discover the insightful information about the students and interaction with the course. They report that after analyzing the students' study results, demographics and social data, instructors are able to identify who need assistant most to provide individual counselling.

(vi) Providing timely feedback and intervention

Providing feedback to students is an important role of teachers in any educational settings. This process enable students to learn from their action and can have a significant impact on motivation of the learners. The quality and timeliness of feedback are crucial in the learning process. From the learning analytics, teachers can identify students who are in need of assistance and provide appropriate intervention to the specific students. Dodge et al (2015) report that interventions through emails to the students work best and found that such approach impact on student achievement.

Similar to business forecast, ability to predict students' success can be a powerful practice in all levels of education. Daud et al (2017) highlight that there is such possibility to predict student performance with the use of advanced learning analytics. In their study, a wide ranging background and personal data that includes students' household family expenditure, family income, students' personal information such as gender, marital and employment status and the family assets, are collected. By using discriminative and generative classification models, the authors are able to predict whether a student will be able to complete the course.

Privacy Concerns in Learning Analytics

While learning analytics can delve into the students' interaction data with instructors and course materials, identifying and using their behaviors and personal preferences to predict their success may amount to breaching privacy and confidentiality. Such concerns have been raised by Lawson et al (2016) and describe that identification of at-risk students using analytics and providing them intervention strategies raise ethical dilemma for the educators. However, they contend that possible ways to resolve the issue is that the institutions could obtain consent from the students at different levels and increase the transparency of the process to avoid any missteps.

Given the importance of the ethical and legal considerations surrounding the use of data from learning analytics, educators find ways to overcome the issues while still providing feedback that will benefit them. Sclater (2016) draws attention to the Code of Practice for Learning Analytics developed by the Joint Information Systems Committee (Jisc). The Code covers the main issues that educational institutions need to address to progress ethically and legally in this area. The process results in a taxonomy of ethical, legal and logistical issues for learning analytics that are grouped into the distinct areas. These include ownership and control, consent, transparency, privacy, validity, access, action, adverse impact, and stewardship. Each area is identified whether it is an ethical, legal or logistical concerns and the person responsible to deal with it. With such clear guidelines and procedures, educators can comfortably proceed with the practice in learning analytics.

From the students' point of view, they are conservative in sharing data and expect learning analytics systems to include elaborate adaptive and personalized dashboards. This was found by Ifenthaler and Schumacher (2016) when the authors conduct a study with 330 university students. The authors suggest that learning analytics should be aligned with organizational principles and values and include all stakeholders in collecting and use of data. They further suggest that data should be analyzed transparently and free of bias for the benefits of all stakeholders.

Future of Learning Analytics

The educational community is witnessing a remarkable progress in theory development, research design and technical advancement in learning analytics over the past decade. With the increase capabilities in data mining techniques and power statistics, educators can exploit the information retrieved from the students' learning experience and transform into a model that can suggest remedial actions for the learners and predict the students' success. Several studies are reported to describe the future of learning analytics in improving teaching and learning. In this regards, Strang (2017) demonstrated that by using the student attributes and their online activities, key learning engagement factors can be identified and able to develop a General Linear Model to predict the students learning outcomes. His study involves 228 university students and students' engagement data was collected from the learning management system logs.

There has been much discussion about the advantages of personalized and adaptive instruction in education in the past. However, cost-effectiveness is a hindrance in implementing across educational institutions. With the use of technology and learning analytics, adaptive instruction may become a reality in the wider scale. Min et al (2017) made an attempt to use the data to understand the behavior patterns of the learner and design an adaptive instruction for a group of 128 pharmacy students in a university. The study involves a commercially available system that uses adaptive algorithm and semantic analytics engine to take various input data from the students and generates personalized learning paths based on students' performance. The authors suggest that in designing adaptive learning, students' non-cognitive factors such as motivation and goal orientation should also be considered. Mavroudi et al (2017) conducted a systematic review of twenty-one studies to better understand the nature of adaptive learning analytics with the research questions ranging from the context, objectives and when and where adaptive learning is applied and facilitated. They report that more insightful models of complex student behaviors can be developed to create constructive-collaborative environment in the future.

Conclusion

This paper describes the potential benefits of learning analytics research, application of learning analytics in different educational settings, privacy and legal concerns, and the future of the learning analytics research. Following Wong's (2017) analysis of case studies, six themes that use learning analytics are identified. Throughout the paper, the importance of data-informed approaches in education are suggested and the role of timely feedback and intervention for the learners are highlighted. With the application of artificial intelligence, algorithm and adaptive instruction, automated teaching and autonomous learning will become a reality in the near future.

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Contact email: mskhine@ecae.ac.ae