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Review

Learning Analytics and Potential Usage Areas in Education

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ABSTRACT

The purpose of this study is to define learning analytics, to introduce concepts related to learning analytics and to introduce potential study topics related to learning analytics. Today's education model has changed with evolving social and economic conditions over time. This change in education has created such new situations as individualized learning, determination of student behavior and the use of alternative assessment tools. One of the learning tools that can be used is to learning analytics. Learning analytics is defined as measuring, collecting and reporting data related to learners and learning environments to understand and improve learning and the surrounding environment. The use of learning analytics creates opportunities for individualized learning, to determine the student behaviors associated with success by examining the student behaviors affecting success, it serves as an alternative assessment tool. The main subject of the learning analytics is to obtain meaningful results from the virtual learning environments to improve student outcomes in online learning environments.

INTRODUCTION

Today's education model, developed to meet the needs emerging with the industrial revolution, has changed with changing conditions over time. There is a change from time-based student development to proficiency-based student development, norm-based tests to criteria-based tests, passive and teacher-directed students to active and self-supervised students and more (Reigeluth & Karnopp, 2013). This change in education has created new situations such as individualized learning, determining student behaviors and using alternative assessment tools (Lee, Huh, Lin, & Reigeluth, 2018).

Nowadays, the concept of individualized learning increasingly appears in educational environments scene. Today's living conditions require special and individual solutions for special and individual problems (Dabbagh & Kitsantas, 2012). The privatization and personalization of the problems require the knowledge of individuals to be able to solve these problems. Traditional school systems are based on ensuring that everyone spends an equal amount of time on learning, and this causes accumulation of learning deficiencies for students who have to continue without fully learning course subjects (Bloom, 1968). The primary purpose of schools is to ensure that everyone's potential is revealed and individualized learning is one of the best ways to do this (Miliband, 2006).

The purpose of individualized learning is to customize learning according to the characteristics and needs of students and to reach everyone's highest potential (Miliband, 2006). There is also a growing body of evidence that individualized, student-centered education can significantly improve learning outcomes (Lee et al., 2018). The rich learning opportunities offered by learning analytics, supporting the learning of students and personalized, are an important step in the individualization of learning (Bienkowski, Feng, & Means, 2012; Oblinger, 2012; Sedrakyan, Malmberg, Verbert, Järvelä, & Kirschner, 2020; Siemens, Dawson, & Lynch, 2013; Tobarra, Robles-Gómez, Ros, Hernández, & Caminero, 2014).

Another important situation related to education is the determination of student characteristics. Analysis and determination of student behavior provides the opportunity to determine the behaviors related to learning success and to make arrangements about them. These analyzes provide important opportunities for improving learning outcomes, especially when used to identify students who may fail rather than predict success (Carter, Hundhausen, & Adesope, 2017). Following student behaviors and creating meaningful patterns from the information obtained helps the teacher to identify the strategies that should be used in the lesson (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017). Analysis of student behavior and the determination of behaviors that affect success also provide information about students who are at risk of dropping courses, and students who need additional support to increase their success (Siemens & Long, 2011). One of the methods to determine student characteristics is learning analytics (Verbert, Manouselis, Drachsler, & Duval, 2012).

Another important concept related to learning is the evaluation of learning. The success of education is largely based on evaluation (Jonassen, 1999). Therefore, evaluation is an important part of education. Assessment is more prominent, especially since assessment of constructivist learning environments requires alternative assessment tools (Perkins, 1991). According to Jonassen (1999), the use of classical assessment methods causes students to memorize the information and students fail when they need to use this information in their real-life situations. Therefore, alternative assessment methods should be used in constructivist learning environments. Alternative assessment allows to measure whether high-level educational goals are achieved that require the use of knowledge in real contexts (Reeves, 2000). There are many studies showing that learning analytics can be used as an alternative assessment tool (Castellanos, Haya, & Urquiza-Fuentes, 2017; Abelardo Pardo, Han, & Ellis, 2017; Strang, 2017).

New technological tools are needed for individualized learning, determining student behaviors and alternative assessment approaches to work successfully (Reigeluth et al., 2015). One of these technological tools is learning analytics. The use of learning analytics is thought to be an alternative solution to these problems in education (Siemens & Long, 2011).

LEARNING ANALYTICS

The widespread use of technology and internet today also increases the data that is obtained from their usage. In our daily life, many behaviors and movements are recorded by computers and allow huge amounts of information to be collected. This collected information constitutes an important source for advertising, marketing, etc. Similarly, in the field of education, there are resources to collect huge amounts of data (Siemens & Baker, 2012).

Learning analytics expresses the reflection of big data studies on education, which are encountered with the widespread use of computers and internet. Technological developments, together with all fields, provide big data collection opportunities to obtain solutions based on data for educational purposes especially in higher education. There are two trends that lead to the emergence of learning analytics: One is the use of virtual learning environments in educational institutions, and the other is the application of data mining techniques to corporate learning systems (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014). The use of these data is thought to have a major impact on higher education as a framework for making learning-based decisions (Siemens & Long, 2011).

The use of the obtained data first appeared as educational data mining (EDM) (Siemens & Baker, 2012). The first workshop on EDM was held in Pittsburgh, Pennsylvania in 2005, followed by annual workshops and the 1st International Education Data Mining Conference in Montreal, Quebec in 2008 (Siemens & Baker, 2012). The concept of learning analytics emerged in 2011 (Siemens & Long, 2011).

Although EDM and learning analytics seem like two identical concepts, there are some differences between them, both in terms of purpose and scope. EDM is mostly a field of study on the development of technical methods for the analysis of learning data (Baker & Yacef, 2009). Learning analytics is a field of study that deals with the interpretation and transfer of the data obtained to improve learning (Cristobal Romero & Ventura, 2007). Siemens and Baker (2012) summarized the differences between EDM and learning analytics as in Table 1.

Table 1. Comparison of EDM and learning analytics

	Learning Analytics	**EDM**
Discovery	Human intervention is benefited; automatic discovery is a tool to achieve this goal.	Automatic discovery is key; human intervention is a tool to achieve this goal.
Arrangement	Stronger emphasis on understanding systems in a complex way	Reduce components and analyze individual components and highlight relationships between them
Origin	LAK has stronger origins in semantic network, "smart curriculum", outcome prediction, and systemic interventions	EDM has strong origins in education outcomes and student modeling, and has a meaningful community for predicting course outcomes.
Compliance and Personalization	Greater focus on informing and empowering instructors and students	Greater focus on automatic adaptation
Technique and Method	Social network analysis, sensitivity analysis, impact analysis, discourse analysis, learners' success prediction, concept analysis, sensitivity models	Classification, clustering, Bayesian modeling, relationship mining, discovery with models, visualization

Learning analytics is defined as the measurement, collection and reporting of data about learners and learning environments to understand and improve learning and the environment in which it is located (Siemens & Gasevic, 2012). Technological advances allow us to collect vast amounts of information about learners and learning environments. The size of the data collected makes it difficult to obtain meaningful patterns from these data. Learning analytics is a field for developing, researching and applying computer-aided methods to find meaningful patterns from educational data in quantities that cannot be obtained meaningful information by other methods due to its size (Cristobal Romero & Ventura, 2013). It allows us to obtain information from data that seems to be meaningless.

Learning analytics allows teachers, course designers, and administrators to explore themes that cannot be directly observed and basic information in learning processes (Agudo-Peregrina et al., 2014). It plays an important role in the planning and accountability processes of higher education institutions (Wilson, Watson, Thompson, Drew, & Doyle, 2017). Situations that require focusing on data in universities are increasingly explained as learning analytics (Siemens & Long, 2011).

RELATED WORKSPACES

When we examine the definitions related to learning analytics, we see collecting data from learning environments, analyzing these collected data and interpreting how the results will be used in the educational environment. These three concepts transform learning analytics into a multidisciplinary field and require people from different specialties to work together (Dawson, Gašević, Siemens, & Joksimovic, 2014).

Learning analytics is primarily a big data implementation area. It includes all processes such as data retention and evaluation specific to the big data field and this field is a specialty in itself. In this respect, learning analytics has a relationship with computer science (Dawson et al., 2014).

On the other hand, it should be known how the results obtained will be used in education. This part enables training specialists to step in. The point that enabled the learning analytics to be separated from educational data mining emerged from this requirement.

IN WHICH CONTEXT LEARNING ANALYTICS WORKS?

The main field of study of learning analytics is learning management systems (LMS) (Siemens & Long, 2011). LMS is software prepared to perform distance education. In LMS, there are components such as students' basic information, course contents, and chat environments. Students log into these systems using their own user accounts. Thus, the movements of each student on the system can be easily followed.

Using LMS in learning analytics makes this area directly related to distance learning and its derivatives. It gives general information about the system, especially in environments with a high number of participants such as MOOC.

DATA SOURCES

Data presented to the use of learning analytics is largely derived from learning management systems (LMS) (Carter et al., 2017). Many learning analytics apps use data from student activities such as clicks in these systems, student participation in discussion forums (Tempelaar, Rienties, & Giesbers, 2015).

Data used in learning analytics as well as LMS are social sharing platforms (facebook, twitter, wiki etc.) (Xiao, Weng-Lam Cheong, & Kai-Wah Chu, 2018), wearable cameras, wearable sensors, biosensors (e.g., skin conductivity can be obtained from sources such as heart rate and electroencephalography measurements), gesture detection, infrared imaging, and eye tracking technologies (Blikstein & Worsley, 2016).

All data that can be used in learning analytics can be classified as in Table 2 by using Castellanos et al. (2017) and Scheffel et al. (2017) works.

Table 2. Classification of data sources

Code	Explanation
W1	Records about forum, discussion, opening wiki title or making the first post of these topics
W2	Records of posts other than the first post to the forum, discussion, wiki titles
W3	Records about the time to view, watch and realize resources such as pages, videos, etc.
W4	Records about situations such as messaging, sending friend requests, and accepting with people using the system.
W5	Records such as the number of logins to the system, the frequency of logging, the duration of the system
W6	Records about voting for sources such as pictures, videos, files, content etc.
W7	Records about adding files, pictures, video assignments etc.
W8	Records about demographic (age, experience, success score etc.) information about learners
W9	Records of information obtained from social media
W10	Other records that are not in the other 9 categories

DATA ANALYSIS METHODS

Learning analytics uses advanced analytical tools and processes in the research and visualization of large data sets and in the service of improving learning and teaching (Brown, 2011). Although the data used in learning analytics are usually easy to obtain, the data size is quite large for performing an analysis using typical database tools (Manyika et al., 2011). Special methods are required to evaluate these data (Agudo-Peregrina et al., 2014).

Educational data mining in learning analytics (Cristóbal Romero, Ventura, Espejo, & Hervás, 2008), machine learning, classical statistical analysis techniques, social network analysis, decision trees, artificial neural networks, regression analysis, artificial intelligence (Shum & Ferguson, 2012) or methods such as natural language processing can be used (Greller & Drachsler, 2012). In addition to aforementioned methods, there are several methods that can be used.

One of these methods is text analysis or natural language processing (Blikstein & Worsley, 2016). Text analysis is used to interpret writing tasks such as open-ended exams. This method enables open-ended exams to be an alternative to multiple choice tests when collective evaluation is required. Considering that it is technically and logically easy to collect text from students, text analysis is one of the important methods for learning analytics (Blikstein & Worsley, 2016).

Another method of data analysis is speech analysis. Speech analysis shares most of the goals and tools involved in text analysis (Blikstein & Worsley, 2016). However, speech analysis allows the student to perform in a more natural environment, allowing them to differentiate from traditional assessment methods.

WHAT SHOULD BE THE COMPETENCIES FOR LEARNING ANALYTICS?

In order for the field of learning analytics to be an effective tool for educational practice, the results must be interpreted correctly (Reffay & Chanier, 2003). Therefore, the efficient use of learning analysis data requires some high level qualifications in this direction (Drachsler & Greller, 2012). Drachsler and Greller (2012) determined 7 skills that learning analytics employees should have. These are: numerical skills, information literacy, critical reflection, assessment skills, ethical skills, analytical skills, self-management. Drachsler and Greller (2012) stated that all of these 7 skills are important for the interpretation of learning analytical results.

CONTRIBUTION OF LEARNING ANALYTICS TO EDUCATION

The most important contribution of learning analytics to education is that it creates opportunities for individualized learning (Greller & Drachsler, 2012). Technological advances offer new opportunities to individualize teaching (Johnson et al., 2016). When education meets the individual needs of the student, students are more likely to succeed (Baghaei, Mitrovic, & Irwin, 2007; Kerr, 2015). Learning analytics contribute significantly to the success of individualized learning especially in higher education and to make data-based educational decisions and to investigate learning processes (Aldowah, Al-Samarraie, & Fauzy, 2019; Gutiérrez et al., 2020; Liu et al., 2017). The learning analytics tools developed contribute to educators making the right decisions even if they are not a data analyst (Gutiérrez et al., 2020).

In order to understand how individualized learning systems can be designed effectively, it is necessary to investigate the behavior patterns shown by learners with different characteristics when interacting with an adaptive learning environment (Liu et al., 2017). For example, Graf and Liu (2010) stated in their study that students' browsing behavior can be determined using learning analytics and user modeling can be realized with the information obtained. Likewise, Premlatha, Dharani, and Geetha (2016) emphasized that learning analytics can be used to meet changing student behavior, styles, goals, preferences, performances, knowledge levels, learner status, content difference and feedback. As a matter of fact, A. Pardo, Jovanovic, Dawson, Gašević, and Mirriahi (2019) provided individualized feedback by using their analytes by learning in their studies, which contributed significantly to their academic achievement in the change of expression. At the same time, learning analytics can be used to improve students' self-regulation skills (Wong et al., 2019; Zheng et al., 2020).

Another contribution of teaching analytics to education is to examine student behaviors that affect success and determine student behaviors related to success (Castellanos et al., 2017; Abelardo Pardo et al., 2017; Strang, 2017). There are many studies conducted with learning analytics in this direction and examining student behavior is one of the main areas of study of learning analytics. For example, Tempelaar, Heck, Cuypers, van der Kooij, and van de Vrie (2013) showed that demographic characteristics, cultural differences, learning styles, learning motivation and participation, and learning stories have an important effect on learning mathematics and statistics. Morris, Finnegan, and Wu (2005) found significant differences between successful and non-successful students when we consider the main activities (number of clicks, number of content displayed etc.) on LMS systems and the time spent in the system. These studies provide a new model for systemic change to improve teaching, learning, organizational effectiveness and decision-making skills for universities and university administrators, as a result provides a new model for systematic change (Siemens & Long, 2011).

Analysis of student behavior and the determination of behaviors that affect success also provide information about students who are at risk of dropping courses, and students who need additional support to increase their success (Siemens & Long, 2011). Using learning analytics to identify students who may fail at the end of education and improve learning outcomes (Carter et al., 2017; Waheed et al., 2020), ensures that all students get the most out of the education provided.

Another contribution of learning analytics is that it serves as an alternative assessment tool. Wolff, Zdrahal, Nikolov, and Pantucek (2013) found that the results of classical assessment and learning analytics predicted students achievements in the same way, in their studies within the scope of the blended learning method. Similarly, Agudo-Peregrina et al. (2014) found that interactions with assessment tools follow interactions with peers and teachers, and active participation significantly detects academic success in six online lessons. These and similar studies show us that learning analytics can be used as an alternative assessment tool.

CRITICISM ABOUT LEARNING ANALYTICS

Ambitious words such as improving or even transforming the spoken language about learning analytics have led attention to this area and to critically address what it promises. Criticisms directed to learning analytics can be examined under 4 headings (Wilson et al., 2017).

Contradictory results: While some of the studies in the field of learning analytics show that the student behaviors examined are effective on success, in others, the situation is the opposite. this undermines the reliability of the results obtained from learning analytics.

Learning analytics and big data: Another criticism of learning analytics is its relationship with the big data area. The techniques used in learning analytics are the same techniques used in big data analysis. Therefore, it is controversial that learning analytics is an independent study subject.

Problematic data and analytical algorithms: What is measured in terms of learning analytics, why it can be useful, how it relates to learning is criticized. There is a risk that incorrect analyzes and assessments may reveal prejudices such as class, gender, and ethnicity and harm them. Also, complex data representations can mislead people.

Allowing pedagogical diversity: Different demographic characteristics, institutional cultures, different contexts should be taken into consideration and applied accordingly when applying learning analytics. Such differences restrict the creation of general analytical principles.

POTENTIAL STUDY TOPICS

The main study subject of learning analytics is to draw meaningful conclusions from the information obtained from virtual learning environments that initially seem meaningless. Study topics related to learning analytics Verbert et al. (2012) and the studies carried out in this field are summarized under six headings. These are:
- Estimating learners' performance and modeling learners,
- To suggest relevant learning resources,
- To increase reflection and awareness,
- To develop social learning environments,
- To identify undesired student behavior,
- To identify the effects of students.

Predicting learners 'performances, modeling learners: Predicting learners' performances at the end of education, modeling learners according to their behaviors in the educational environment constitutes the main study subject of learning analytics studies. The results obtained here are in the individualization of education (Bienkowski et al., 2012; Oblinger, 2012; Siemens et al., 2013; Tobarra et al., 2014), in determining the success or failure of students (Carter et al., 2017; Kizilcec et al., 2017; Siemens & Gasevic, 2012) and as an alternative assessment tool (Agudo-Peregrina et al., 2014; Wolff et al., 2013). Some study suggestions that can be made regarding this topic are as follows:

- Which interaction behaviors affect students' academic success?
- What are the working behaviors that will predict students' success?
- Do the models developed to measure success give the same results for different courses?
- How to help students who are predicted to be unsuccessful?
- How effective are the situation visualizations to be used on students' success?
- Creating structures that students can self-evaluate.

Suggesting relevant learning resources: Another study topic related to learning analytics is to offer learning resources to students according to their needs (Verbert et al., 2012). Analysis of student behavior enables the student to identify the information they need and provide content for this need. These studies take us one step closer to individualized learning. Some study suggestions that can be made regarding this topic are as follows:

- What are the necessary models for determining the individual learning needs of students?
- Determining whether students can obtain the information they need from the organized courses.

Increasing reflection and awareness: Another study topic on learning analytics is the visualization of student behavior (Giannakos, Chorianopoulos, & Chrisochoides, 2015; McCormick, 2013). With the various tools used, summary information about students' behavior is presented and students can follow their learning history using these tools. Some study suggestions that can be made regarding this topic are as follows:

- What are the data sources and types that can be used for visualization?
- What are the visualization tools that students find most impressive?
- Is there a relationship between visualization tools and educational outcomes?

Improving social learning environments: Studies on this subject are about analyzing students' interactions in learning environments they use. The data they use for communication, such as the answers in discussion forums and the answers they send to each other, are used to carry out these analyzes. This data enables to determine whether collaborative environments (Jonassen, 1999) that should be constructivist learning environments can be used effectively.

Identifying unwanted student behavior: Another field of study of learning analytics is to identify undesirable student behaviors such as academic failure, dropout, abuse, and misbehavior (Verbert et al., 2012). Detecting these behaviors in advance will enable us to take action on them.

To determine the emotional state of the students: By using learning analytics, the course of the student can be changed according to this information by determining the situations such as boredom, astonishment, frustration, enthusiasm, getting into the flow, and dealing with the content (Verbert et al., 2012). Some study suggestions that can be made regarding this topic are as follows:

- To make changes on the designs of the students by detecting the contents that are not of interest.

INFORMATION SECURITY AND ETHICAL ISSUES

Ethical issues in teaching analytics are generally related to the rights to collect and use the data obtained. Whether the information obtained through a LMS system belongs to the student or the institution is one of the primary problems (Greller & Drachsler, 2012). This situation brings serious restrictions in research. Many institutions do not share this information as private information for students and share it with researchers.

One of the ethical problems is to use the data as clearly as possible, and on the other hand, it is an obligation to anonymize the data legally (Greller & Drachsler, 2012). The use of anonymous data makes it difficult for us to intervene individually on students.

In the current circumstances, the data collected (before anonymizing) about a person belongs to the owner, data client, and beneficiary of the data collection tool (Greller & Drachsler, 2012). Since the consent of the person can be obtained in classical data collection tools such as surveys, there were not many ethical problems related to the use of the data. But today, data can be collected using new technologies such as LMSs, ambient sensors, location tracking or biometric facial recognition systems etc. without the knowledge of the person and often there is no consent or awareness of individuals in the process of data collection (Greller & Drachsler, 2012). This raises the violation of the "informed consent" ethical principle (AoIR, 2012).

An important ethical question that we come across is "who owns the life data of a person". Educational data collected, although lawful, can be easily exploited for improper purposes (especially in the case of minors). In principle, more access to a data subject owned by a data client, higher responsibility is to use this information precisely and ethically (Greller & Drachsler, 2012).

Abelardo Pardo and Siemens (2014) have identified four principles for classifying privacy and ethics-related issues: transparency, student control over data, security and accountability and assessment.

Transparency: It refers to informing the stakeholders how the steps of the analytical process such as data collection and analysis are carried out. Consent of students is required to collect data as a legal requirement. However, the principle of transparency eliminates this requirement.

Student control over data: This principle is the right of users to access and modify information obtained about them. Giving access to the information collected is also related to the principle of transparency. Since this principle poses certain difficulties, only the right to change on limited data is recognized.

Security: This principle is about sharing the information obtained with third parties. Occasionally, violations related to this principle have resulted in the sharing of sensitive information. Educational institutions need to develop an access policy to prevent such violations.

Accountability and evaluation: This principle states that all processes carried out in the process of learning analytics are carried out under the responsibility of the relevant institution.

CONCLUSIONS

Individualization of education has increasingly been becoming important (Dabbagh & Kitsantas, 2012; Miliband, 2006). Advances in technology make it easier for us to achieve this goal. In this study, learning analytics, which is an important step for the individualization of education, is tried to be handled in every aspect. The analysis made shows that learning analytics should be used, especially in distance education applications. It will be especially useful in multi-participatory applications to keep track of students' progress. The need for understanding the impact of student characteristics and their preferences on educational outcomes in distance education requires data driven evaluation. These data can be used in applications such as predicting student performances, suggesting learning resources, raising awareness, and detecting undesired learning behaviors. Learning analytics is a relatively new topic in terms of education. More work should be done on it.

Ethics and Consent:

Ethics committee approval is not required as it does not involve clinical researches on humans as well as it does not contain Retrospective studies in accordance with the Law on Protection of Personal Data.

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