Application of Learning Analytics in Higher Education

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APPLICATION OF LEARNING ANALYTICS IN HIGHER EDUCATION.

Thematic line: Technologies for education.

Summary

Learning analytics are tools that have gradually gained importance in the context of higher education, especially with the momentum of e-learning and its tools, it is increasingly important to have the ability to analyze in detail what the student does (and does not do), during his stay in the training scenarios. In this sense, the objective of this paper is to analyze the characteristics in relation to the application of Learning Analytics in Higher Education. For this, a systematic review of scientific articles published in Scopus journals in English or Spanish language, during the last 5 years (2017-2022) is developed. The results yielded a total of 200 articles, of which 14 were chosen, considering the inclusion and exclusion criteria previously defined. The findings showed that, although the benefits of Learning Analytics are notorious, there is not enough evidence to affirm that they lead to significant improvements in educational processes.

Resumen

Las analíticas de aprendizaje son herramientas que han ganado importancia paulatinamente en el contexto de la educación superior, sobre todo con el impulso del e-learning y sus herramientas, cada vez es más importante contar con la posibilidad de analizar en detalle lo que hace (y no hace) el estudiante, durante su permanencia en los escenarios formativos. En ese sentido, el objetivo de esta ponencia es analizar las características en relación con la aplicación de las Learning Analytics en la Educación Superior. Para ello, se desarrolla una revisión sistemática de artículos científicos publicados en revistas Scopus en idioma inglés o español, durante los últimos 5 años (2017-2022). Los resultados arrojaron un total de 200 artículos, de los cuales se escogieron 14, considerando los criterios de inclusión y exclusión previamente definidos. Los hallazgos evidenciaron que, cuando las bondades de las Learning Analytics resultan notorias, no hay suficiente evidencia para afirmar que las mismas conllevan mejoras significativas en los procesos educativos.

Keywords: Learning Analytics, Higher Education, Application, Students, Teachers.

1. Introduction

Learning analytics can be used to uncover a wide range of issues and get answers to a variety of questions about a higher education institution. For example, learning analytics helps to monitor and evaluate a student's progress and proficiency.

For Gutiérrez-Priego (2015),

"Learning Analytics is a new tool -related to the analysis of social networks (SNA) and Big Data- that through the registration and critical study of certain student and teacher indicators, contributes to the personalization and adaptation of learning as well as cooperates in educational planning with the aim of improving the development of competencies and the significance of what is learned".

Learning analytics then consists of collecting learning data from different sources, such as study records and learning systems used by the institution, and analyzing the collected data using different methods. Material can also be obtained from data sources outside the educational institution, for example from Country Statistics.

As can be evidenced in the different conceptions of the nomenclature addressed, in the analytical concept of learning concur both a multidisciplinary perspective and diverse purposes ranging from the improvement of learning as the scientific study of the totality of educational processes (Sabulsky, G. , 2019).

An essential part of the learning analytics process is the use of the results in teaching or in the management of the educational institution, which may mean, for example, choosing appropriate working methods and guiding support. Continuous development of the learning analytics process is also important.

Thus, learning analytics can be used both in planning the learning process and as a management tool in evaluating the operations of the educational institution. With the help of learning analytics, it is possible to better identify support needs and allocate resources, however, "one of the main barriers to systematic implementation by institutions and educators is the high multidisciplinarity and complexity of the field" (Ferguson, 2012). Therefore, the paper aims to analyze the characteristics in relation to the application of Learning Analytics, specifically in the context of higher education.

2. Development

2.1 Theoretical framework

2.1.1 Definitions

Learning Analytics is the measurement, collection, analysis and reporting of data about learners and their contexts in order to understand and optimize learning and the environments in which it occurs (Rojas, 2017). It can also be conceived as is an educational web analytics application for student profiling, the process of collecting and analyzing details of individual student interactions in online learning activities (Guzman et al, 2021).

The rise of online learning since the 1990s, especially in higher education, has driven the development of Learning Analytics, as student data can be collected and made available for analysis. When students use LMS, social networking or similar online tools, their clicks, browsing patterns, homework time, social networking, information flow and concept development can be tracked through discussions. The rapid development of Massive Open Online Courses (MOOCs) provides researchers with additional data to evaluate teaching and learning in an online environment. (Guzmán-Valenzuela et al., 2021).

2.1.2 Learning Analytics as Predictive Models

One of the definitions previously discussed by the community suggests that Learning Analytics is the use of intelligent data, student-generated data and models. This is a definition that has received various criticisms from experts such as George Siemens.

2.1.3 Learning Analytics as an Overall Design Framework

Siemens (2006) makes a comprehensive proposal that is a common design framework and can act as an analysis service in support of educational practice and student guidance, in quality equipment, curriculum development and teacher performance improvement. It uses a general morphological analysis (GMA) division for a subject area into six "critical dimensions".

2.1.4 Learning Analytics as data-driven decision making

The broader term "Analytics" has been defined as the science of examining data for the purpose of drawing conclusions and, when used in decision making, to present ways or courses of action. From this point of view, Learning Analytics is defined as a special case of analytics, where decision making is aimed at improving learning and education. In the 2010s, this definition of analytics was expanded to include elements of operations research, such as decision trees and strategy maps to create predictive models and determine the probabilities of certain actions (Guzman et al, 2021).

2.1.5 Learning Analytics as an Analytics Application

Another approach to defining Learning Analytics is based on the concept of analytics which is interpreted as the development of actionable knowledge through the identification of problems and the application of a process of statistical modelling and analysis of usage and/or modelled future data. From this perspective, Learning Analytics is a type of analytics (as a process) in which data, problem definition and knowledge are linked to learning (Guzman et al, 2021).

In 2016, a study jointly conducted by New Media Consortium (NMC) and EDUCAUSE Education Initiative (ELI) - EDUCAUSE program - on the next six new technologies that will have a significant impact on higher education and creative expression by the end of 2020. As a result of this study, learning analytics is defined as an educational web analytics application aimed at student profiling, the process of analyzing and reasoning the details of individual student interactions in online learning activities.

2.1.6 Learning analytics as an application on data

In 2017 Gashevich, and the Consolidated Learning Analytics Model is used. The model states that learning analytics involves the use of computational methods and techniques to collect, preprocess, analyze, and present data. In 2015, Gashevich and Siemens argued that the computational aspects of learning analytics should be related to psychology, sociology, and philosophy. Existing educational research to ensure that Learning Analytics delivers on its promise to understand and optimize learning.

2.2 Problem statement

The study of analytics as a field has several disciplinary roots. While the fields of artificial intelligence (AI), statistical analysis, machine learning, and business intelligence provide additional narrative, the main historical roots of analytics are directly related to human interaction and the educational system. Specifically, Learning Analytics brings together the history of four social sciences that converged over time.

1. The definition of the learner to meet the learner's need and understanding.
2. Follow-up of knowledge, on how to transmit the knowledge acquired in the learning process.
3. Efficiency and personalization of learning, which is about how to make learning more effective and personal with the help of technology.
4. Learner: comparison of content to enhance learning to use actual use experience (Siemens, 2006).

During the last decades in these 4 aspects of the diversity of disciplines and research activities. Over the last decades, the development of learning analytics. Some of the most defining disciplines are Social Network Analysis, User Modeling, Cognitive Modeling, Data Mining and E-Learning. Learning analytics can be understood from the history and development of these areas.

Also, when looking at the history of analytics, it highlights several communities from which the learning of analytics originates. Methods, mainly during the first decades of the 21st century, including:

1. Statistics, which are a well-established means of testing hypotheses.
2. *Business Intelligence*, which has similarities to learning analytics, but has historically aimed to improve reporting efficiency by providing access to data and summarizing performance metrics.
3. Web analytics tools, such as *Google Analytics*, report on website visits and links to websites, brands and other key terms on the web. A more "subtle" exposure of these methods can be used in learning analytics to explore learners' paths through learning resources (courses, materials, etc.).
4. Operational research that aims to identify design optimizations to maximize objectives through the use of mathematical models and statistical methods. Such methods are used in learning analytics, which seeks to create real-world behaviors for practical use.
5. Artificial intelligence methods (combined with machine learning methods based on data mining) discover patterns in data. In learning analytics, learning methods as learning methods and learning methods as "course suggestion" systems modeled on collaborative filtering.
6. Information visualization, which is an important step in many analytical methods for understanding used in most methods.

Considering all these contextual aspects, this paper questions the application that has been given to Learning Analytics in Higher Education so far, based on the research report developed in scientific journals.

2.3 Method

The systematic literature review method was used for this paper. The object of this type of research is other works or articles describing original research on a given topic. When creating a systematic review, it is necessary to keep in mind the main goal: to provide a concise, but extremely reliable and relevant digression on a limited problem, to help colleagues navigate the current trends in this topic. To do this, you must strictly follow several rules for creating a review.

First of all, the search for publications on the subject should be as broad and comprehensive as possible. But the modern realities of science are such that there is a huge amount of work on any topic. And this is where the second point arises: already at the search stage, it is necessary to clearly formulate strict criteria for selecting articles for further review. It is important that they are precise (to get rid of unnecessary and off-topic articles) and reproducible. Finally, when all the necessary material has been collected, it is time to work with it: an assessment of the structure of the study, the characteristics, highlighting the most significant and reliable results, their generalization and interpretation: translation into an understandable working language. This is especially important.

When creating a systematic review, it is extremely important not to confuse it with a classic literature review. What is the difference? After all, both are very actively used in scientific circles. For starters, the systematic review focuses on a clear clinical question, as opposed to the broad range of questions in the literature review. The data retrieval strategy of a systematic review is rigorous and precise, as are the principles for selecting and evaluating data that strictly follow certain criteria. The generalization of the data is done on a quantitative basis, and the conclusions must be scientifically substantiated. Only by finding all these signs can you be sure that it is a systematic review.

Therefore, systematic reviews are analytical-synthetic articles that allow you to obtain a comprehensive and statistically verified understanding on a specific topic, created according to many criteria that allow you to minimize the possibility of errors. The presence of a systematic review in the dissertation can significantly increase the value of the work both in theoretical and applied terms. The use of a systematic review as a literary basis of a scientific work allows to analyze the maximum amount of data in a volume comfortable for perception and, if necessary, to resort to a more detailed study of individual publications on this topic, instead of reviewing a huge number of papers on this topic.

2.3.1 Research questions.

The systematic review on which the following paper is based, is guided by the following research question:

What are the characteristics in relation to the application of Learning Analytics in Higher Education?

2.3.2 Search process.

The search equations used were:

Table 1. Search equations.

Search	Search Equations	Database
1	(TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (Higher Education)) AND PUBYEAR > 2017	Scopus
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (University) AND PUBYEAR > 2017	Scopus
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (Universities) AND PUBYEAR > 2017	Scopus
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (Higher Education) AND PUBYEAR > 2017	Scopus
5	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (University) AND PUBYEAR > 2017	Scopus
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (University) AND PUBYEAR > 2017	Scopus
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (higher education) AND PUBYEAR > 2017	Scopus
		Scopus

	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (university) AND PUBYEAR > 2017	

2.3.3 Inclusion and exclusion criteria.

Based on the predefined research question, inclusion and exclusion criteria were defined in order to filter the studies that best meet the objective pursued in this review.

Inclusion criteria:

- Studies directly related to Learning Analytics in the context of Higher Education.
- Research published during the last 5 years (2017 to 2022).
- Publications in English or Spanish.

Exclusion criteria:

- Research unrelated to Learning Analytics.
- Research developed in a context other than higher education.
- Studies conducted before 2017.
- Articles developed in languages other than English or Spanish.
- Studies not indexed in Scopus.
- Documentary sources, such as books.
- Articles that do not provide sufficient information about the research process followed.

2.4 Results

The search process has been developed taking advantage of the potential of the Scopus database, through which it is possible to refine the search process through logical operators, as well as the storage of each search formula performed in order to develop a general analysis of the searched.

Table 2 shows a summary of the searches according to each logical operation performed:

Table 2. Search results.

Search	Search Equations	Database	Found articles	Selected articles
1	(TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (Higher Education)) AND PUBYEAR > 2017	Scopus	1	0
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY	Scopus		

	(University) AND PUBYEAR > 2017			
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (Universities) AND PUBYEAR > 2017	Scopus		1
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (Higher Education) AND PUBYEAR > 2017	Scopus	0	0
5	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (University) AND PUBYEAR > 2017	Scopus	0	0
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (Universities) AND PUBYEAR > 2017	Scopus	0	0
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (higher education) AND PUBYEAR > 2017	Scopus		
	TITLE-ABS-KEY (Learning Analytics) AND TITLE-ABS-KEY (university) AND PUBYEAR > 2017	Scopus		

The first aspect that is striking is the difference between the number of articles in English and Spanish, and those chosen for each language according to the full compliance with the inclusion and exclusion criteria. In total, 200 investigations were reflected, of which 14 strictly comply with the predefined criteria. Many of those not chosen were actually carried out in contexts other than university contexts, and a significant percentage did not provide sufficient information to be included.

The following is a list of the selected research projects:

Table 3. Selected research

Study	Title	Author	Year	Source
A01	Learning analytics in European higher education-Trends and barriers.	Yi-Shan, TsaiDiego, Dragan Gašević	2020	Computers & Education20 May 2020Volume 155 (Cover date: October 2020)Article 103933
A02	Predicting teamwork group assessment using log data-based learning analytics	Ángel Hernández-García, Emiliano Acquila-Natale, Miguel Á. Conde	2018	Computers in Human Behavior19 July 2018Volume 89 (Cover date: December 2018)Pages 373-384
A03	Mining theory-based patterns from Big data: Identifying self-regulated learning strategies in Massive Open Online Courses	Jorge Maldonado-Mahauad, Mar Pérez-Sanagustín, Jorge Munoz-Gama	2018	Computers in Human BehaviorMarch 2018Volume 80Pages 179-196
A04	A network-based analytic approach to uncovering the relationship between social and cognitive presences in communities of inquiry	Vitor Rolim, Rafael Ferreira, Dragan Gǎsević	2019	The Internet and Higher Education13 May 2019Volume 42 (Cover date: July 2019)Pages 53-65
A05	A four-country cross-case analysis of academic staff expectations about learning analytics in higher education.	Kaire Kollom, Kairit Tammets, Tobias Ley	2020	The Internet and Higher Education15 December 2020Volume 49 (Cover date: April 2021)Article 100788
A06	From students with love: An empirical study on learner goals, self-regulated learning and sense-making of learning analytics in higher education	Ioana Jivet, Maren Scheffel, Hendrik Drachsler	2020	The Internet and Higher Education6 July 2020Volume 47 (Cover date: October 2020)Article 100758
A07	Educational data mining and learning analytics for 21st century higher education: A review and synthesis	Hanan Aldowah, Hosam Al-Samarraie, Wan Mohamad Fauzy	2019	Telematics and Informatics14 January 2019Volume 37 (Cover date: April 2019)Pages 13-49
A08	The current landscape of learning analytics in higher education	Olga Viberg, Mathias Hatakka, Anna Mavroudi	2018	Computers in Human Behavior24 July 2018Volume 89 (Cover date: December 2018)Pages 98-110
A09	An exploratory latent class analysis of student expectations towards learning analytics services	Alexander Whitelock-Wainwright, Yi-Shan Tsai, Dragan Gašević	2021	The Internet and Higher Education15 June 2021Volume 51 (Cover date: October 2021)Article 100818
A10	Stakeholders' insights on learning analytics: Perspectives of students and staff	Geraldine Gray, Ana Elena Schalk, K. C. O'Rourke	2022	Computers & Education27 May 2022Volume 187 (Cover date: October 2022)Article 104550

A11	The engagement of university teachers with predictive learning analytics	Christothea Herodotou, Claire Maguire	2021	Computers & Education12 July 2021Volume 173 (Cover date: November 2021)Article 104285
A12	Investigating prompts for supporting students' self-regulation - A remaining challenge for learning analytics approaches?	Clara Schumacher, Dirk Ifenthaler	2020	The Internet and Higher Education13 December 2020Volume 49 (Cover date: April 2021)Article 100791
A13	Connecting the dots: An exploratory study on learning analytics adoption factors, experience, and priorities	Yi-Shan Tsai, Vitomir Kovanović, Dragan Gašević	2021	The Internet and Higher Education27 February 2021Volume 50 (Cover date: June 2021)Article 100794
A14	Identifying needs for learning analytics adoption in Latin American universities: A mixed-methods approach	Isabel Hilliger, Margarita Ortiz-Rojas	2020	The Internet and Higher Education21 January 2020Volume 45 (Cover date: April 2020)Article 100726

2.5 Discussion.

Learning Analytics allows educators to assess a student's current and future performance. With this knowledge, instructors can determine the likelihood that a student will pass a given course. At this point, they can decide if students need additional support. Students who are struggling with their grades may, for example, receive additional study materials. They can be assigned essays to improve their critical thinking and writing skills. With this knowledge, educators can determine the best approach to improve students' grades.

One of the reasons students drop out of higher education is failure. Students can feel overwhelmed if they fail more and more courses and have to retake them. This leads to a backlog of work, which strains them. Seeing their peers progress without them can also create a sense of hopelessness. Learning analytics plays a critical role in improving student performance, preventing attrition associated with failure. By identifying what an individual student needs, educators can improve their effectiveness.

Learning Analytics (LA) is mainly perceived as a tool to improve teaching and institutional management. As a result, teaching and support staff are found to be the main users of LA and the target audience for learning support. In contrast, there is little evidence of active engagement with students or the use of LA to develop self-regulated learning skills. The importance of grounding LA in the learning sciences and including students as a key stakeholder in LA design and implementation is highlighted [A01].

As Rojas (2017) mentions, the essential object of Learning Analytics is the optimization of learning, however, most of the research has focused on individual learners, which has hindered the development of learning analytics for team assessment in collaborative learning contexts. From a four-dimensional view of teamwork, a set of indicators based on log data is needed to facilitate group assessment in project-based learning courses and identify relevant predictors of final project outcomes [A02].

On the other hand, when students self-regulate their learning through LAs, a threefold phenomenon occurs: First, they become well-rounded learners, who follow the sequential structure of the course materials, which prepares them to gain a deeper understanding of the content. Second, students strategically engage with the specific course content that will help them pass the assessments. Third, students who do not use LAs exhibit more erratic and less goal-oriented behavior, report lower self-regulated learning, and underperform relative to comprehensive and focused students [A03].

When using LA, indicators of social presence have more association with the exploration and integration phases of cognitive presence. In addition, affective category indicators of social presence have stronger links to the two high levels of cognitive presence (i.e., integration and resolution), whereas interactive message indicators of social presence are more connected to the two low levels (triggering events and exploration) of cognitive presence [A04].

Given the complexity of all the processes associated with learning analytics, it is necessary to

> *"...for the true implementation and systematization of learning analytics in education it is critical to achieve the involvement of educational institutions and the generation of national educational policies, and this generates problematics that initially might not be obvious" (Macarini et al., 2019).*

Self-regulated learning skills are predictors of how relevant students find these constructs. Student goals have a significant effect only on the perceived relevance of frames of reference. Knowing what factors influence students' understanding will lead to more inclusive and flexible designs that will meet the needs of both novices and experts [A06].

In [A07] it was found that specific LA techniques could offer the best means to solve certain learning problems. The application of LA in higher education can be useful to develop a student-centered strategy and provide the necessary tools that institutions can use for continuous improvement purposes. In spite of this, and although

> *"most works agree on the high potential of the area for the transformation of the education sector, (...) on numerous occasions it is seen how studies can lose the focus of focusing on improving student learning" (Gašević, Dawson, & Siemens, 2015).*

For all the goodness that the research wields, it is striking that one of the findings of the case study is the generally low and consistent expectation and desire for academic staff to be compelled to act on data showing that students are at risk of failing or underachieving [A05]. Hence, Ruipérez-Valiente (2020) states that "achieving the true potential of learning analytics will require close collaboration and conversation among all stakeholders involved in its development, enabling its implementation in a systematic and productive way".

Also, the findings from [A09] show that students' expectations of the ethical and privacy elements of a learning analytics service are consistent across groups; however, those expectations of service features are quite variable.

The results of [A08] show that, overall, there is little evidence to show improvements in student learning outcomes (9%), as well as in support for learning and teaching (35%). Similarly, little evidence was found for the third (6%) and fourth (18%) proposition. Despite the fact that the identified potential for improving student practice is high, not much transfer of the suggested potential to higher educational practice can currently be seen over the years. However, analysis of the existing evidence for learning analytics indicates that there is a shift towards a deeper understanding of students' learning experiences in recent years.

In this order of ideas, Ruipérez-Valiente (2020) states that "one of the main barriers for the systematic implementation by institutions and educators is the high multidisciplinarity and complexity of the field", so it is not strange that each professional carries out the analysis according to his or her own individual competences.

Overall, for [A10], the results suggest that there are significant differences in the perspectives of each stakeholder. There is also a strong need for additional training and ongoing support to manage and achieve stakeholder understanding and objectives around learning analytics. More research is needed to explore the needs of a wider diversity of stakeholders.

Thus, the findings of [A11] suggested that among the factors facilitating engagement with LA were performance expectancy, effort expectancy, and social influence. Factors inhibiting engagement with LA included performance expectancy and facilitated conditions that were related to training and lack of understanding of predictive data. It is agreed, then, with Rojas (2017) in relation to "the challenge is to refine the analyses, deepen them and surface insights about the nature of learning that is feasible to develop in learning environments..."

3. Conclusions

To perform successfully in higher education, it is believed that students must engage in self-regulation, and key to this is the use of learning analytics that makes them aware of all the variables present in their learning processes. However, the research data were not able to sufficiently explain learning performance on a transfer test. Future research is needed to investigate adaptive cues using follow-up data in authentic learning environments, in addition to focusing on learners' reactions to different cues [A12].

Whereas the interrelated connections between the prevailing challenges that impede LA scaling up have been identified. It is suggested that periodic evaluations of LA adoption be developed to ensure alignment of strategy and desired changes. This, considering also that several of the researches identify areas that require special attention when forming short-term goals for LA at different phases of adoption [A13].

Finally, it is found that (1) students need quality feedback and timely support, (2) faculty need timely alerts and meaningful performance evaluations, and (3) managers need quality information to implement supportive interventions. Thus, the LA offers the opportunity to integrate data-driven decision making into existing tasks [A14].

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