Learning Analytics for Whom? A Reflexion On the Retrieval of Learning Information by The Student

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Abstract

The present work aims at addressing how the use of Learning Analytics (LA) has enabled the retrieval of learning information by the student oneself, by analyzing data availability, self-management and student autonomy in learning processes inside and outside virtual environments. The bibliographic research conducted had a qualitative nature and consisted of a narrative literature review anchored in the theoretical foundations of information (information retrieval and representation) and Learning Analytics. Two relevant user case studies that dealt with LA were selected from the researched articles - the first analyzed the user approach in an adapted learning context with LA whereas the second analyzed the user approach in a personalized learning context with LA. One concluded that the student, as an information user, still has little access to an effective retrieval of what was consolidated throughout one's own learning process. Besides, in relation to the effectiveness of LA, in the context of adapted and personalized learning, there was a perceived increase in student performance with regard to the use of activities and tasks.

Keywords: Learning Analytics, Information Retrieval, User Study, Personalized Learning, Adapted Learning.

1. Introduction

Learning technologies have moved from simple learning systems institutionally managed to learning environments mediated by personal and social tools (Chatti & Muslim, 2019). The growing number of digital tools used in daily learning activities generates data on an unprecedented scale, offering challenges for information and education scientists.

In the educational context, a large amount of data produced by students can be collected, making it possible to carry out various analyzes related to students' behavior in order to support teaching and learning processes. In spite of being a relatively new research field, in which data produced by students are analyzed inside and outside Virtual Learning Environments (VLE), Learning Analytics (LA) has gained prominence in educational literature as an auxiliary process in adapted learning or as a process of pedagogical alternation, in which traditional teaching is hybridized with virtual platforms. Computational methods are increasingly used to analyze student data and learning dynamics, as well as to create predictive models and test theories (Buckingham Shum & Ferguson, 2012). The drive for LA in all education sectors requires academic research that clearly demonstrates the value proposition implicit in this field for parents, students, teachers and managers (Teasley, 2019).

This study aims at answering the following questions: How has Learning Analytics been applied in order to enable the student to retrieve information? Students are the main providers of the data used by LA, but are they exercising the use of this information? Is the data also available to students? Can students self-manage their learning process?

Thus, the general objective of the present study was to describe how the application of Learning Analytics has enabled the retrieval of information by students. The specific objectives were to (i) identify what LA data is available to students; (ii) explain students' interaction with these data and (iii) report evidence of the effectiveness of LA to the student.

2. Information Retrieval and Users Study

The approach of information retrieval by the user is associated with studies on Information Representation. When characterizing information, Setzer (1999) states that it is an informal abstraction, in the sense that it cannot be formalized through the principles and foundations of Mathematics or Logic (Philosophy). Based on this characterization, the author considers that information representation can occasionally be achieved by means of data, thus enabling its computer storage. In this case, the author reinforces that the representation can be transformed, but the meaning remains. This representation cannot consist of attempts to create an information context in view of information retrieval programs, since Cornelius (2003) highlights the disadvantages of limiting such representations in the light of what the context comprises.

Data representation in information systems aims at supporting certain human activities, such as those associated with the retrieval of information by the user. In this sense, information should be considered as a reflection of the social function of the information system (Capurro & Hjørland, 2007).

Regarding information as a reflection of the social function, Capurro (2010) questions for whom information is intended in this global society. Apparently, there is communication of everything with everyone, since Information Science seems to be situated "between the utopia of a universal language and the madness of a private language" (Capurro, 2010, p. 259).

Knowing who will use certain information implies understanding a scenario of changes, uncertainties and challenges. Therefore, with the growing advances in technologies, Alvarenga (2003) reiterates that the present century will undergo countless innovations that will directly interfere in the processes of recognition, codification, transmission and retrieval of knowledge. Due to these changes, user studies have consolidated a model that privileges the study of certain subjects in certain contexts of use, such as platform users in virtual learning environments and the increased performance in their learning (Araújo, 2008).

The key concept for user studies is interaction, because according to Araújo (2012), it highlights the evidence that an action or influence exerted by something can also be affected by that something. In this interactionist perspective, Araújo (2012) asserts that the user is not totally determined by the context in which one is inserted, nor completely isolated, nor even alien to it. One infers the need to consider information and its social function within the information system, as approached by Capurro & Hjørland (2007). Likewise, the user is social, which means, according to Araújo (2012), that one is not completely determined by the collectivity nor isolated from it, since one contributes to the construction of this collectivity (built by the concrete subjects inserted in it) and receives contributions through collective constructions. In this scope, Araújo (2012) states that accessing and using information are simultaneously cognitive, emotional, cultural and contextual actions.

In view of the technological advances that influence the information area, new techniques of representation and recovery by the end user have emerged (Bräscher, 2002). Therefore, there is a tendency for the development of intelligent systems that contribute to information retrieval based on natural language processing, considering the availability of full texts on the machines and the availability of more favorable interfaces for the end user. Bräscher (2002) highlights the need for systems that recover models of knowledge representation that allow the contextualization of the meanings described in the stored texts.

Bearing in mind the development of intelligent systems, Learning Analytics (LA) appears as a possibility to address the question of the interface designed for the end user. According to Biagiotti & Baldessar (2017), properly developed smart LA systems are able to promote the presentation of a friendly interface, as well as data mining and data crossing as a result of an interdisciplinary data analysis technique that allows the convergence of knowledge areas such as Education, Psychology and Computer Science.

3. Learning Analytics

As discussed at the 1st International Conference on Learning Analytics and Knowledge, which took place in 2011 in Canada, there has been a growing demand for technological transformation in education at a global level. The following indicators justify the creation of a specific forum for researching Learning Analytics: the inability of organizations to understand data on knowledge, teaching and learning at the same pace as they arise; the inefficiency of learning institutions and corporations with regard to the use of data that students "discard" in the process of accessing learning materials, interacting with educators and colleagues and creating new content; and the growing pressure on educational institutions to reduce costs and increase efficiency (Long & Siemens, 2011; Teasley, 2018).

In this context, Learning Analytics presents itself as an alternative that helps "measuring, collecting, analyzing and reporting data about students and their contexts, for the purpose of understanding and optimizing learning and the environments where it occurs" (Long & Siemens, 2011). According to Andrade and Ferreira (2016), LA focuses on issues related to learning and, for Long & Siemens (2011), LA promises to be important lens through which one can visualize and plan changes in the levels of courses and institutions.

According to Teasley (2018), the data analyzed by LA systems can represent both the learning process - records of student activity, use of the library, accessed resources, etc. - and the learning products - evidence of learning found in discussion posts, blogs, tweets, hashtags, etc. - , thus providing a very rich image of the student's behavior. According to Teasley (2018) when advanced data repositories are formed by integrating data from various student information systems with data from other online educational systems, it is possible to extract valuable information for the identification of trends, patterns and anomalies.

The complexity of educational systems, which encompasses very different data and users, requires a careful analysis and assessment of the real effects of LA on the learning of users involved in the processes where this technology is used. Therefore, during the development of a LA-based system, it is necessary to understand what data will be collected, who will have access to this data, why and for what purpose this data will be needed and how it will be captured and made available. The “What? Who? Why? How?” proposed by Chatti, Dyckhoff, Schroeder & Thus (2012) aims at assisting and systematizing the identification of opportunities and possibilities for data collection and analysis in a LA system according to the following dimensions:

- "What?" - Definition of what data will be used for analysis;
- “Who?” - Identification of the targets or stakeholders of the analysis;
- “Why?” - Evaluation of the objectives of each analysis type;
- "How?" - Identification and definition of the techniques that will be part of data analysis.

The model presented aims to assist users in the evaluation of intelligent systems supported by LA, attempting to achieve the effectiveness and the advantages of the system as presented by Andrade and Ferreira (2016): (i) early detection of students at risk (students who do not comply with delivery times, have negative results or do not manifest themselves in activities); (ii) personalization and adaptation of the learning processes; (iii) the positive effects on student motivation, confidence and achievement; (iv) maximizing the use of teachers' time and effort; (v) improving curriculum development processes; and (vi) interactive visualizations of complex information.

The first academic works in the field of LA focused on the identification of key variables to predict student results, such as retention and time to obtain degrees. Over time, in addition to predicting performance results, LA researchers began to create systems that visually presented performance metrics, making it possible to monitor student progress and identify students who indicated the need for academic intervention. In recent years, however, there has been an increasing number of systems developed to provide "actionable intelligence" for instructors, academic advisors and, more recently, directly for students themselves (Teasley, 2018). With the maturation of research in LA, there has been a change in the perception of student's role in the learning process; the student is no longer a mere supplier user, but also a user who actively uses one’s own information.

The systems aimed at students, which are the focus of analysis in this study, are divided into two models: the adapted and the personalized models. The learning adaptation model is guided by the system; the system decides what to do. The learning personalization model is oriented to the student; the system helps the student to decide what to do (Chatti & Muslim, 2019). The following is the theoretical framework on systems that use Learning Analytics applied to both an adapted learning model and a personalized learning model.

4. Systems in the context of adapted and personalized learning

Faced with contemporary education challenges, Chiappe & Rodriguez (2017) emphasize that the “industrial education” model needs to be overcome and transformed into a model that aims at the formation of individual and unique apprentices. The current context demands individuals whose education, according to Chiappe & Rodriguez (2017), is sustained by global awareness and social and ecological responsibility, since it is necessary to educate workers capable of navigating in a world flooded with information without the risk of sinking.

Adapted Education does not focus solely on students with learning difficulties or special educational needs, since all students must advance in their learning and recreate themselves through that learning. In this context, the teaching staff, the educational administration and the society must guarantee working conditions (use of adequate spaces, sufficient time, good infrastructure, recognition), in addition to specific resources (teacher education and training, specialized services, materials) that favor the adaptation of teaching methods to a diversity of students (Coll, 2012).

Learning Analytics (LA) can provide data that contribute to possible adaptations in teaching, since they are generated by students and consist of different types of data, such as user navigation, AVA data, demographic data, amongst others (Moissa, Gasparini & Kemczinski, 2014). In this sense, the authors point out that several analysis techniques, such as data mining, statistics, information visualization, can be used in order to reach the most diverse objectives, such as prediction, tutoring, adaptation and personalization of learning. LA also allows identifying what problems occur during the learning process even if they are not explicit, thus enabling accurate decision-making on necessary interventions (Nunes, Silva, Laisa, Ugulino & Lucena, 2016; Scheffel et al., 2014).

In Adapted Education, in order to provide indications, corrections and readjustments in the learning objectives, Nogueira et al. (2018) expect students to have access to data that contribute to their self-learning and self-assessment, assisting them in the design of their study plan and allowing them to fill in gaps that are possibly associated with conventional education. Chatti & Muslim (2019) reiterate that there is a crucial need to develop intelligent learning environments that put students at the center and give them more autonomy and control over their own learning experience.

Research on personalized learning environments has gained ground in recent years, allowing the emergence of new technological solutions that put students in control of their own development and learning, such as Personal Learning Environments (PLEs), Massive Open Online Courses (MOOCs) and Open Educational Resources (OER) (Chatti & Muslim, 2019). For Kurilovas (2019), the future of education is the personalization of learning, which means creating and implementing personalized learning units, suitable for specific students according to their personal needs.

According to Chatti & Muslim (2019), personalization is crucial to achieving intelligent learning environments in different contexts of lifelong learning. Dawson, Gasevic, Siemens & Joksimovis (2014) state that the next generation of personalized learning environments should provide resources adapted to the needs of the student, thus integrating interactions, skills and competences in the mapping of academic disciplines knowledge.

In this context, Learning Analytics presents itself as an important resource in the development of personalized learning experiences. LA systems use predictive models that provide users (students, instructors and educational institutions) with actionable information based on a multidisciplinary approach to data processing, thus enhancing technology learning, educational data mining and visualization (Scheffel et al., 2014). Pardo, Jovanovic, Dawson, Gasevic & Mirriahi (2019) state that Learning Analytics systems use machine learning techniques and predictive modeling to analyze students' digital tracking in order to understand and optimize the learning process. LA systems with a focus on personalized learning provide real-time feedback to students (Avella, Kebritchi, Nunn & Kanai, 2016); which, according to Chatti & Muslim (2019), helps them to decide and continuously shape their activities to achieve their individual goals more efficiently and autonomously.

The Learning Analytics field emerged with the objective of using data to increase the perception of learning experience and to improve student support (Dawson et al., 2014), thus expanding the understanding of individual learning and creating interventions aimed at teaching and learning practices (Wise, 2014). Chatti & Muslim (2019) and Avella et al. (2016) agree and add that LA has opened new opportunities to promote personalization and adaptation, providing insights into the comprehension of how students learn and supporting personalized learning experiences that meet students' goals and needs. Finally, Scheffel et al. (2014) point out that LA increases students' awareness by helping them to make constructive decisions and to perform their tasks more effectively.

5. Methodology

In order to achieve the objective of describing how the application of Learning Analytics allowed students to retrieve information, one opted for a qualitative bibliographic research, more specifically a narrative review of literature focused on case studies that addressed the theme. For Mendes-da-Silva (2019), the narrative review usually addresses one or more questions and, unlike systematic reviews, their selection criteria for inclusion of articles may or may not be explicitly specified by the researchers.

The narrative review consists of identifying the corpus of knowledge related to the objective and analyzing it to obtain answers. Wendler (2012) highlights that the clarity regarding the path adopted allows to generate an information framework that will help further researches, enabling them to identify the methods, contents and trends of the publications used. In the present research, one mapped not only classic literature, but also articles published in journals indexed at Scopus database by means of structured search procedures. The search consisted of looking for the key word "Learning Analytics" in the titles. One excluded dissertations, theses, duplicate texts, videos, images or articles whose abstracts proved them to be inappropriate for the theme of this investigation.

The time limit used was 5 (five) years, with a range from 2015 to 2019. One opted to select only articles in Portuguese, English and Spanish, as well as those whose full texts were available and consisted of case studies. After the search, 243 articles were retrieved and one analyzed their abstracts to identify case studies. Out of the 243, 36 case studies were selected and one analyzed which ones dealt with adapted and / or personalized learning. None of the studies presented a simultaneous analysis of the two learning approaches. Considering the selected articles, one opted for the analysis of two case studies. They were selected because their abstract directly referred to the adaptation or customization of learning by means of Learning Analytics and because they were recently published (2018 and 2019). The results are presented in the following topics.

6. User study in the context of adapted learning with LA

In the article entitled *What Learning Analytics tell us: group behavior analysis and individual* *learning diagnosis based on long-term and large-scala data*, Zhang, Zhang, Zou & Huang (2018) analyze the characteristics of student group behavior when performing certain tasks and the factors that influence learning and individual outcomes. The analysis considered data obtained from online learning records of 1088 students from 22 classes and they analyzed aspects associated with login behaviors, the resources used on Moodle platform, quizzes, interactive behaviors and also academic performance. The analysis period was five months, between September 2015 and January 2016. All students involved in the study attended a blended course, with traditional activities on-site and online activities on Moodle.

The research carried out by Zhang et al. (2018) was quantitative and used the following methods in order to interpret data obtained in the process and in the results of online learning: statistical analysis, analysis of visualization of social networks and correlation analysis. The results obtained by Zhang et al. (2018) are described below.

The statistical analysis initially considered the analysis of the access behavior (login). The first fourteen weeks showed a stable frequency in the number of hits, and from the fifteenth week on, the number of hits increased, having a sharp peak in the last week (nineteenth). This result showed that the teacher's intervention led some students with low attendance to increase their accesses in the final stretch. Accesses decreased with the approach of the weekend, presenting a new increase in each beginning of the week.

Then, the use of resources was analyzed, namely: questionnaire, thematic discussion, submission, expanded resource, daily communication, didactic material download and course notification. The results showed that teachers who used around 60% of the available resources presented better results in online learning in their classes. The questionnaires with tests at the end of each chapter presented a markedly higher completion rate than the other resources as they are strongly linked to the final exam.

The analysis of visualization of social networks aimed at studying interactive behavior. The peaks of interaction between students, between groups and between students and teachers occurred in the last month. Leading students presented more interactions with a larger number of people and formed small groups around their “atmosphere of influence”.

Finally, a correlation analysis was used to obtain results on academic performance. The students showed greater concern with modules and resources directly linked to the final grades. The results showed that the number of students who paid attention to different activities was deeply associated with the requirements for learning and assessment tasks.

The interaction between the teacher and the students in the four classes reinforced that online attendance could be affected by many factors, especially the adaptation of activities, methods and resources in order to arouse students' enthusiasm and initiative. This implied a rate of resource use 13.09% higher than the average use rate, with an achievement rate higher than 85% in regular, optional and final activities. Finally, the correlation between the global scores and the completion of the questionnaires was obvious.

In the diagnosis of collective behavior, Zhang et al. (2018) indicated that teachers who actively participated in the platform exercised a leadership and mediation role in most of the thematic forums. The participation of one of the teachers stood out and by means of the interactions with the students, this teacher promoted an environment that was favorable for student individual participation. According to the data presented and analyzed, the adaptations in the educational practice provided indications, corrections and readjustments in the learning objectives, contributing to self-learning and self-assessment. Therefore, according to Nogueira et al. (2018), adaptations in educational practice allowed to fill in the gaps of conventional education, which was evidenced in the performance of 85% in activities.

7. User study in the context of personalized learning with LA

In the article entitled *The PERLA Framework: Blending Personalization and Learning Analytics*, Chatti & Muslim (2019) presented the *Personalization and Learning Analytics (PERLA) Framework* (Figure 1). It is a conceptual framework to effectively support customization in different lifelong learning configurations. The main objective of the PERLA framework is to provide LA researchers and developers with a systematic way to design and develop indicators to support personalized learning.

Figure 1. Personalization and Learning Analytics (PERLA) Framework
Source: Chatti & Muslim (2019)

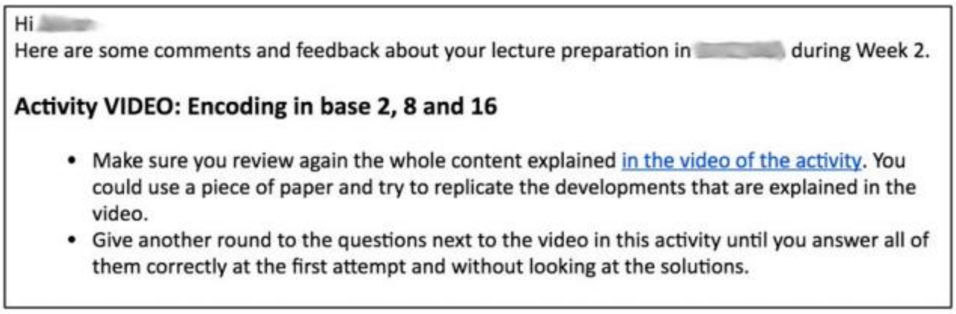
When developing PERLA, Chatti & Muslim (2019) aimed to provide a structure that could assist in measuring the efficiency and effectiveness of LA, since, according to them, although several studies revealed the importance of using and analyzing data, few highlighted how data analysis would be changed to optimize learning. In order to highlight the positive effect of LA on the personalized learning experience, one highlights the results published by Pardo et al. (2019) in the article *Using learning analytics to scale the provision of personalized feedback*. In this article, the authors conducted a case study to analyze the impact of personalized feedback on the student's academic performance and evaluate the student's perception of the quality of the feedback received.

In the PERLA structure, feedback is one of the most important mechanisms for the development of intelligent learning environments to help students achieve their goals. In the structure, this mechanism is addressed within the scope of the requirements for open assessment and assessment indicators. According to Chatti & Muslim (2019), open assessment is a generic term for different assessment methods, such as easy assessment, self-assessment, peer review and feedback. LA had the potential to support open assessment, with timely and personalized feedback, providing an explanation of how and why feedback was given, validating the peer review and making learning achievements explicit to support awareness, trigger self-reflection and promote self-assessment (Chatti & Muslim, 2019).

Hattie (2008 apud Pardo et al., 2019) also identified student-directed feedback as one of the most important factors that influence academic performance. In the article, Pardo et al. (2019) presented a new approach to providing personalized feedback based on a set of engagement indicators derived from students' activities in the learning environment. For each activity defined in the course design, instructors prepared in advance a set of feedback messages for each level of student interaction with the learning resources. For example: “if an activity contains a video, instructors will provide feedback to students who barely took a look at the video, for those who watched a significant part of the video, for those who watched the entire video and for those who watched the video several times ”(Pardo et al., 2019, p. 131). The assumption behind this approach was that instructors can use the level of involvement with the activity to modulate the feedback sent to students, so that it was much more personal and connected to their behavior. After these comments were created, an algorithm was executed at the end of each instruction cycle in order to select the appropriate comment for each student based on the student's level of participation in the activity. The comments selected for each activity were grouped in a detailed feedback message that was sent to the student through the virtual learning environment or by a personalized email. The goal was for the students to take advantage of the feedback received at the end of a cycle to improve their performance in activities in the next cycle (Pardo et al., 2019).

In order to analyze student satisfaction with the feedback received and to evaluate the effect of this feedback on students' academic performance, Pardo et al. (2019) conducted a research with students enrolled in the 2013, 2014 and 2015 editions of a 13-week first year Computer Engineering course at a university in Australia. According to Pardo et al. (2019), the interviewees were: 291 students who enrolled in 2013 (46 women, 245 men, 97.3% engineering students), 315 students who enrolled in 2014 (57 women, 257 men, 1 individual without gender identification, 93.6% engineering students) and 414 students who enrolled in 2015 (75 women, 339 men, 94.2% engineering students).

The intervention promoted by Pardo et al. (2019) was implemented in weeks 2 to 5 of the 2015 edition of the course and consisted of sending each student a personalized email (Figure 2) at the end of the week with detailed feedback on their involvement with the proposed activities. To this end, the instructor created four feedback comments for the 37 activities in the four cycles that preceded the intermediate exam (weeks 2 to 5); a total of 138 short texts (with one or two sentences). The activities were available through the institutional Learning Management System (LMS) that captured all student interactions with the activities and learning resources (Pardo et al., 2019).



Hi

Here are some comments and feedback about your lecture preparation in during Week 2.

Activity VIDEO: Encoding in base 2, 8 and 16

- Make sure you review again the whole content explained in the video of the activity. You could use a piece of paper and try to replicate the developments that are explained in the video.
- Give another round to the questions next to the video in this activity until you answer all of them correctly at the first attempt and without looking at the solutions.

Figure 2. Example of a personalized message
Source: Pardo et al. (2019)

The research hypotheses explored in the study carried out by Pardo et al. (2019) were:

• RH1: providing feedback through personalized messages based on student engagement with learning tasks increases student satisfaction on a blended learning course.

• RH2: providing feedback through personalized messages based on students' involvement in learning tasks increases academic performance.

For the first research hypothesis (RH1), the authors, Pardo et al. (2019) performed a unidirectional ANOVA test between subjects to compare the effects on the level of student satisfaction with the feedback reported in the years 2013, 2014 and 2015. The results suggested that in the 2015 edition, in which personalized feedback was included, there was a significant positive effect on how students perceived feedback. For the second research hypothesis (RH2), the authors performed a t-test of independent samples to compare the intermediate scores of students in the two editions of the course. The result suggested that providing personalized feedback messages in the 2015 edition had a small positive effect on students' intermediate scores. Pardo et al. (2019) concluded that, although the effect of the intervention was not as high on the intermediate score as on the perception of the quality of the feedback, the combination of these two results showed that the proposed approach had a significant and positive impact on the students' learning experience.

8. Final Considerations

In this study on the use of Learning Analytics it was possible to evaluate how the student, user of the system, has recovered the information by means of data on the computer. It was noticed, however, that this recovery was less intense and less representative when compared to the recovery of data by other users of educational systems, such as teachers and managers, for example. In both analyzes, it was observed that the student, as a user, still had little access to an effective recovery of what was consolidated throughout the learning process. Concerning the effectiveness of the LA, there was an increased performance in both analyzes with regard to the use of activities and tasks when the student received feedback on one’s performance in the general and social learning contexts.

In the analysis carried out with the perspective of adapted learning, the interaction between teacher and student was observed by means of small adaptations made by the teacher in the activities and tasks that already existed on the platform. But the adaptations in the system seemed only to point out which way to go, within the existing options. It was also noticed that this approach was more focused on the teacher's performance, either when they demanded tasks from students or insisted on students to use the platform due to the approaching assessment period, according to the school calendar. However, the students (as users) received information related to their performance and, thus, could compare their performance with the other performance data provided, such as average class rates and performance per activity.

Regarding the analysis that focused on personalized learning, there was a greater flow of information available to the student, by means of personalized feedbacks. In spite of not being measured, these feedbacks unveiled opportunities for information retrieval, what suggests that there is room to expand in this area and to improve the effectiveness of students' access. Based on these feedbacks, students could take decisions on the most appropriate procedures to continue their study.

This study was limited to the analysis of the impact LA had on the interaction between student and teacher in an adapted learning context and on feedback in a personalized learning context. However, there are still several other impacts and contexts to be analyzed by future research on LA, such as: interaction between students, data security, student-centered platform design, amongst others.

The question in the title of this work reinforces the importance of specifying the "what", the "why", the "how", but above all the "for whom" in Learning Analytics. It is paramount that students not only generate information but also be regarded as users of the generated information; thus avoiding the commonplace of information being institutionally appropriated with no return for the student.

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