Application of Learning Analytics in Higher Education Institutions: A Systematic Literature Review

Ángel Salas Martínez*, Alberto Ramírez Martinell†
School of Statistics and Informatics,
Universidad Veracruzana
Xalapa, Veracruz, México
*Email: zs22000343@estudiantes.uv.mx
†Email: albramirez@uv.mx

***Abstract*—Currently, it has been identified that two of the main learning analytical (LA) approaches are descriptive and predictive, the latter being in charge of anticipating altered behavior in the historical relationships between the variables involved. The objective of this research is to explore the most relevant works where LA is implemented in the context of the Tutorial Information System, which is executed in Higher Education Institutions (HEI), with the intention of serving as support to the student and decrease dropout rates. This article presents a systematic review literature with 11 primary studies, between the years 2000 and 2022. The results indicate the scarce existence of works witch main focus is tutoring or academic advices, the authors who have used LA, the elaboration in the improvement or optimization of learning using academic history. Therefore, an opportunity can be identified to implement LA in the information generated by the Institutional Tutoring Programs, because through them it is possible to obtain personal, economic and health information from students. That allows supporting decision-making or actions that contribute to the reduction of dropout rates.**

***Keywords*-Learning Analytics; Tutoring; Counseling; Systematic Literature Review;**

I. Introduction

The use of learning analytics (LA) in the online learning environment has increased exponentially, because its application can help institutions, teachers and tutors with problems such as decision making and measurement of student success, considering the digital footprint that can be obtained from students in each Higher Education Institution (HEI). Currently it is a reality to mention that Higher Education has been forced to retake the use of technological tools such as Learning Management Systems (LMS) due to the arrival of the COVID-19 pandemic in two thousand twenty, because although these tools are not resentful, there was a even do resistance to their use, proof of this is that LMS are style important after the pandemic, some example as Google Classroom, Microsoft Teams and Moodle some of the most implemented by HEI in the world.

LA is a recent field of study, defined by the Society for Learning Analytics Research (SoLAR) where it is defined as being responsible for measuring, collecting, analyzing and communicating data about learners and their contexts in order to understand and optimize learning and the environments in which it occurs[1]. Consequently, with the emergence of this field, work has begun to be done using such analytics to support students and teachers, identifying for example the performance levels of students, knowing their expectations regarding the implementation of learning analytics systems, improving communication between student and teacher, just to highlight some of the work that has been done so far. However, it has been observed that the subject of academic tutoring received by HEI students has been little explored.

It is worth emphasizing that tutoring is an institutional program that arises with the intention of supporting students in their academic, personal and professional processes during their education in any Higher Education Institution in Mexico. Therefore, Institutions such as Normal Schools, Universities and Technological Institutions, have their respective tutoring programs dedicated to support students during their academic life. Thus, from these systems it is possible to identify diverse situations of each student, from economic, health, academic and social points of view, problems that can directly impact their academic performance and even cause failure and in the worst case escenario, desertion. Therefore, this systematic literature review article aims to provide the reader with the following points: 1) Tutoring Information Systems (TIS) that use LA. 2) Identify the focus of these TIS. 3) What the most common interests in TIS are. 4) How TIS can be quantified and categorized. 5) How the HEI use the LA for tutoring. 6) How they interpret and visualize LA-based data in the HEI. 7) What information has been analyzed in the TIS of the HEI and what they used the analysis for.

II. Background and Related Work

For contextualization it is important to define that according to Siemens[2], LA is defined as ”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. With the implementation of LA it is possible to find out more

979-8-3503-2883-7/23/$31.00 ©2023 IEEE
DOI 10.1109/CONISOFT58849.2023.00024

hidden information about learners in online learning. For this reason, it plays a relevant role in online learning whose main interest is to identify problems with learning and improve the learning environment.

In a study conducted at a private university in Korea, where an online course was being taken, they sought to empirically validate the effects of a Learning Analytics Dashboard (LAD); where it was observed as part of the results, that students who interacted with the LAD, scored higher, compared to those who did not use it. A close correlation was also identified between the acceptance of the LAD and the academic performance of the course participants. It was also observed that high achievers who opened the LAD were less satisfied than those who used the LAD less frequently. The results guide that LAD should be revised in a way that motivates and supports students who have different levels of academic achievement[3].

On the one hand, a second study proposes the question: How do we begin the institutional adoption of Learning Analytics, which is a question frequently asked by faculty, managers, administrators and researchers seeking to implement Learning Analytics (LA). The synthesis of the study draws on established models for the adoption of business analytics, finding two projects conducted in Australia and Europe to develop and evaluate approaches to the adoption of Learning Analytics in Higher Education (HEI)[1]. The approach proposed in the study highlights the importance of the socio-technical nature of LA and the complexities relevant to adoption in HEI[4].

A third study aims to investigate students' expectations regarding the features of learning analytics systems and their willingness to use these features for learning. In this exploratory qualitative study, 20 university students were interviewed about their expectations of Learning Analytics features. The findings of the qualitative study were complemented by a quantitative study[5]. It was found that students expect Learning Analytics functions to support their planning and organization of learning processes, provide self-assessments, adaptive recommendations, and produce personalized analyses of their learning activities[6].

Among the studies conducted, there was also Learning Dashboard for Insights and Support during Study Advice (LISSA), a LAD designed, developed and evaluated in collaboration with advisors, where the objective is to achieve communication between advisors and students in an effective and simple way through the visualization of the student's career path that are usually available in any institution. That study found that the dashboard supports the ongoing dialogue between advisor and student, successfully motivating them, activating the conversation and providing tools to add personalization, depth and nuance to the advising session, give and information on a factual, imperative and reflective level, allowing those involved as student and advisor to take an active role during the session[6].

In other study, the use of a Learning Analytics Dashboard (LAD) to inform the teaching of five university faculty was investigated, using inductive qualitative analysis to identify emergent themes highlighted in how instructors 1) asked questions, 2) interpreted data, 3) took action, and 4) verified impact. The results of the study showed that instructors did not always turn to analysis with specific questions, but rather with general areas of curiosity. The findings were synthesized into an analytical model of instructors use that provides useful categories of activities for future study and support[1].

A fourth study identified was student-oriented, providing information and promoting self-regulated learning. In this study, a dashboard design aligned with SRL (Self-Regulated Learning) theory was created, called My Learning Analytics (MyLA)[7], which seeks to better understand how students use a learning analysis tool. The study consisted of conducting a sequential analysis of student interactions with three different dashboard visualizations implemented in an LMS. The results of this study presented discriminatory patterns among different levels of academic performance with respect to LAD use, most clearly reflected in students with low academic performance and high levels of self-regulation. This work highlights the differences in students' experience with a learner-oriented LAD and emphasizes that one type of LAD does not fit all in the design of Learning Analytics tools.[8].

III. Research Method

The research process was initiated through a Systematic Literature Review (SLR) in order to use explicit and systematic procedures as opposed to traditional research. Therefore, it followed Kitchenham and Charters' [9] guidelines on SLR in software engineering and Zhang's [10] guidelines proposed under the concept of 'Quasi-Gold Standard (QGS)' applied in the identification of relevant software engineering studies. The review proposed in this paper is composed by two subsections: planning and Conduction.

A. Planning

In this phase, the formulation of the research questions was carried out, the search process was established, and described follows.

1) Research Questions: To drive the review process, the following seven research questions were generated. Where each question seeks to clarify the panorama on the application of Learning Analytics in Higher Education Institutions(HEI).

1. **[RQ1]** Are there Tutoring Information Systems (TIS) used by the HEI where LA is used?
   Justification: identify if there is any type of system that has been developed to carry out the management and/or implementation of the Institutional Mentoring Program.

2. **[RQ2]** In the approaches used, is was at the center the student at the center, teaching tasks or tutorial management?
   Justification: identify the approaches presented, they could be directed to the students as reinforcement or follow-up, directed to the follow-up of the teacher, or directed only a process management.
3. **[RQ3]** What are the declared interests identified in the TIS in HEI?
   Justification: identify what interest the system was created, and whether it fulfills the objective and achieves success in its execution by the HEI.
4. **[RQ4]** How can the TIS used in HEI be quantified and categorized?
   Justification: Prior to the implementation of LA in HEI, it is important to count how many systems have been developed to support mentoring, in addition to categorizing them according to the approach identified.
5. **[RQ5]** How does HEI use LA for TIS?
   Justification: learn how HEI have decided to apply LA in their tutoring programs.
6. **[RQ6]** How does the TIS use in HEI interpret and visualize LA-based data?
   Justification: identify how data have been interpreted in existing works, what techniques or methods have been used, as well as to observe how information that has already been processed through LA is thread in HEI that have already made exhibition proposals.
7. **[RQ7]** What information has been analyzed from the TIS and what was used to analyze the information?
   Identify the information considered for LA application, contemplating that there is a lot of useful information about a student, such as academic, personal, health, and social just to name a few.

2) Search Process: The search process in this article followed the *"Quasi-gold standard"* (QGS) strategy [10]. This process consists of 5 steps: i) Identify related databases, ii) Establish the QGS, iii) Define or obtain the search string, iv) Perform the automatic search and v) Evaluate the performance of the search. Each of the steps is described below in the context of the investigation.

i) **Identify related databases**
In this phase, journals were selected for the manual search and databases (DB) digital libraries and indexing services for the automatic search to. The following three journals were considered: Knowledge and Learning, Technology and Informatics in Human Behavior, for their relevance in the topic to be addressed, as well as for the Educational Institutions that participate in the edition, the impact factor they maintain and the periodicity of the journal. Other six, for the automatic search, the coverage, overlapping and accessibility of libraries and search engines. The following were included: *IEEE Xplore, ACM Digital Library, Springer Link, ScienceDirect, Wiley Online Library and EBSCOhost Academic Search*; the selected databases are available in the information resources of the National Consortium of Scientific and Technological Information Resources (CONRICyT) provided by the univercity Veracruzana México.

ii) **Establish the QGS**
In this phase, the inclusion and exclusion criteria are defined, after which a manual search is carried out in the previously selected journals, which consists of analyzing all the volumes and identifying the articles that meet the established criteria; Table I shows the criteria established in this Systematic Literature Review (SLR).

TABLE I
INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria		Exclusion Criteria	
Id	Descitpion	Id	Description
IC1	Access to the publication is through CONRICyT provided by the univercity.	EC1	The publication is an exact duplicate of a study obtained from another search engine.
IC2	The publication date is from 2000 to October 2022.	EC2	The publication is not in Spanish or English.
IC3	The publication must be a research article on software, learning analytics and tutoring in higher education institutions (Journal Article).	EC3	The full text is restricted in the retrieved publications.
IC4	The publication must reference at least two search terms.	EC4	The publication is not applied in Higher Education Institutions.
IC5	The publication must answer at least one research question.		

iii) **Define or obtain the search string**
At this point in the review, the terms *"Learning Analytics", "Tutoring System", "Academic advising", "Academic counseling"* and *"Higher Education Institutions"* were taken as reference. It should be mentioned that depending on the databases (DB) consulted, the The search string was refined and adapted depending on the fields available in the advanced search of each databases (DB). Table II shows the search string used in a general way in all the previously mentioned search engines.

iv) **Perform the automatic search**
In this phase, the search is carried out in each of the selected databases (DB) applying the specific syntax in each one of them. This resulted in a total of 71 publications, which were reviewed by applying the

TABLE II
SEARCH STRING EXECUTED

Search String
("Learning Analytics") AND ("Mentoring system" OR "academic advising" OR "Tutoring System" OR "academic counseling")

inclusion and exclusion criteria to obtain the final corpus.

Selection of Primary Studies: To carry out the selection of these studies, it was necessary to apply the process of inclusion and exclusion criteria, which consisted of three stages, as shown in Table III. This organization served to reduce the number of publications while retaining the relevant studies for subsequent analysis.

TABLE III
STUDY SELECTION PROCESS

Stages	Criterial
Stage 1	IC1, IC2 and EC1
Stage 2	IC3, IC4, EC2 and EC3
Stage 3	IC5 and EC4

The following is the selection of candidate studies after application of the inclusion and exclusion criteria, as shown in Table IV.

TABLE IV
RESULTS OF THE SELECTION OF CANDIDATE STUDIES

Search String	Source	Candidate papers	Eliminated	Included
S02	IEEE Xplore	18	16	2
S03	ACM Digital Library	19	18	1
S04	Springer Link	23	9	14
S05	ScienceDirect	8	1	7
S06	Wiley OnLine Library	2	0	2
S07	EBSCOhost	1	1	0
	Totales	71	44	26

v) **Evaluate the performance of the search**
At this point the results of the automatic search are compared with the manual search (QGS). To achieve this, we used the equations proposed by Zhang et al. First, the Equation sensitivity or recovery was calculated (1), to obtain the number of relevant studies retrieved, we subtract from the total number of studies retrieved automatically, which are 71. 57 studies were not relevant. To obtain the total number of relevant articles, we divided it by the total number of Relevant studies found, thus achieving 100% of the corpus ([71-57/14]*100). Afterwards, to calculate the precision we found 14 studies found by QGS. 7 are not relevant, therefore, we proceeded to use the Equation (2) to obtain the precision, the Number of relevant studies recovered, subtracting the 71 studies obtained through the automatic search, the 7 studies that are not relevant and then we divide it by the total number of studies retrieved in the automatic search, thus obtaining 90% of the corpus ([71-7/71]*100). Therefore, it is identified that both parameters are within the suggested threshold that indicates the percentages must be greater than 70% to be acceptable, the maximum Equation sensitivity can be observed in Equation (3) and the optimal precision in Equation (4).

$$Sensitivity = \frac{NRSR}{TNRS}100\% \tag{1}$$

$$Precision = \frac{NRSR}{NSR}100\% \tag{2}$$

where:
$NRSR$ = Number of relevant studies retrieved
$TNRS$= Total number of relevant studies
NSR = Number of studies retrieved

$$Sensitivity = \frac{71-57}{14}100\% = 1.0 \tag{3}$$

$$Precision = \frac{71-7}{71}100\% = 0.90 \tag{4}$$

B. Conduction

1) Quality Assessment: At this point in of the process, the 26 selected studies are taken up again and again subjected to validation to identify only those studies that meet the necessary quality, therefore, the quality assessment instrument was prepared, which contains the quality control questions. A value of 1 was assigned to the questions that are answered with the word yes, a value of 0.5 for those questions that are considered to be partially compliant and 0 for those that are not. Table V shows the questions asked to assess the quality of the study.

All the studies found were evaluated with the proposed instrument to guarantee the quality of the chosen studies. The possible score to achieve was between 0 and 8 points. After the evaluation, all the studies that achieved a score greater or equal to 6.5 were considered. It was observed that 42% (11 studies) met the established quality criteria for the most part, while 57% (15 studies) did not meet them, therefore they were discarded from the final selection.

2) Data Extraction: This phase consisted of extracting the most relevant data from each of the primary studies identified, with the support of the Parsifal platform. Table VIII shows the bibliographic information of each study such as: title, authors, year of publication, source, type of publication, DOI, keywords and abstract. It also includes information that helps to answer the research questions.

TABLE V
QUALITY ASSESSMENT INSTRUMENT USED FOR INCLUDED STUDY EVALUATION

Id	Question
QA01	Are the objectives, research questions, and hypotheses (if any) clear and relevant?
QA02	Is there an adequate description of the context in which the research was conducted?
QA03	Is the suitability of the case to address the research questions clearly motivated?
QA04	Are the case and its units of analysis well defined?
QA05	Is the case study based on theory or linked to existing literature?
QA06	Are the data collection procedures sufficient for the purpose of the case study (data sources, collection, validation)?
QA07	Are ethical issues (personal intentions, integrity, confidentiality, consent, review board approval) adequately addressed?
QA08	Is a clear chain of evidence established from observations to conclusions?

TABLE VI
PRIMARY STUDIES QUALITY ASSESSMENT

ID	QA0								Total
	1	2	3	4	5	6	7	8	
PS01	1	1	1	0.5	1	0.5	1	1	7.0
PS02	1	1	1	1	1	0.5	0.5	1	7.0
PS03	0.5	1	1	1	1	1	1	1	7.5
PS04	1	1	1	1	1	1	1	1	8.0
PS05	1	1	1	1	1	0.5	0.5	0.5	6.5
PS06	1	1	1	1	1	1	1	1	8.0
PS07	1	1	0.5	1	1	1	0	1	6.5
PS08	1	1	1	1	1	1	0.5	1	7.5
PS09	1	1	1	1	1	0.5	0.5	0.5	6.5
PS10	1	1	1	1	1	1	0.5	0.5	7.0
PS11	1	1	0.5	1	1	1	1	0.5	7.0

IV. RESULTS

In this section of the article the answers found to each of the research questions are presented. A narrative synthesis based on the data identified in the included studies is provided.

A. Answers to Research Questions

1) ***[RQ1] Are there TIS used by HEI where LA are used?:*** Based in the work carried out by Chatti et al. [22] who proposes a reference model for Learning Analytics (LA) based on four specific dimensions, (i) what (e.g., data, environment and context), (ii) why(e.g., objectives), (iii) how(e.g., techniques/methods) and (iv) who(e.g., stakeholders), model that helps to have an overview of LA and its concepts of relevance, in addition to including the review carried out by Bodily et al. [13] where they categorize the works under an approach between various subfields of educational technologies. In this review we analyze the objectives and technologies that guide those interested in making effective decisions about teaching, within the analysis we can identify the following categories to classify the most relevant jobs in the educational field and LA, see Table IX

TABLE VII
PRIMARY STUDIES

Id	Author	Year	Database
PS01	Reyes et al. [11]	2015	Springer Link
PS02	Rafique et al. [12]	2016	IEEE xplore
PS03	Bodily et al. [13]	2017	IEEE xplore
PS04	Viberg et al. [14]	2018	Wiley OnLine Library
PS05	Herodotou et al.[15]	2019	Springer Link
PS06	Guerra et al. [16]	2020	Wiley OnLine Library
PS07	Ranjeeth et al.[17]	2020	Wiley OnLine Library.
PS08	De Laet et al [18]	2020	Wiley OnLine Library
PS09	Guzmán et al. [19]	2021	Springer Link
PS10	Pérez et al. [20]	2022	Springer Link
PS11	Kaliisa et al. [21]	2022	ScienceDirect

TABLE VIII
DATA EXTRACTION FORM

Primary studies data
Identifier
Title Author
Year
Source
Publication Type
DOI
Keywords
Abstract
Related research questions

TABLE IX
CATEGORIES OF SYSTEMS USING LEARNING ANALYTICS IN HIGHER EDUCATION INSTITUTIONS

Category	**Article**
Intelligent tutorial systems	[13]
Predictive systems	[15] and [12]
Academic performance system	[13] and [14]
Educational recommendation systems	[20] and [12]
Learning boards	[13], [16], [15], [12], [21] and [14]
Educational data mining system	[13] and [20]

2) ***[RQ2] In the approaches used, is the student at the center, the teaching tasks or the management of tutorials?:*** Based on the studies reviewed, it can be classified that the works where Learning Analytics (LA) is applied are mainly focused on the following actors [11]: teachers, students, tutors and researchers, with the latter having less presence in the research reviewed [19], [21]. According to Robert Bodily [13] in his review of student-oriented learning analysis dashboards and educational recommender systems, most of the systems found are oriented 74 percent to the instructor, and he also states that researchers do not conduct much research on the impact of the systems on teaching and learning. Also, Pérez Sánchez [20], Ranjeeth [17] and Rafique [12] focus on students. For example in Ranjeeth's literature study, some of the predictions that have been made are: predictions of student grade point average (GPA), prediction of student performance in graduate programs, prediction of instructor performance and likely student performance in gaining admission to college, prediction of attrition from college programs, and prediction of student grades using social network theory analysis. For his part Rafique says that student performance can be predicted from the student's digital fingerprints [16], i.e., demographics, behavior, facial emotion control records while using an intelligent tutoring system [15]. While for researchers the most predominant focus is on an online learning environment to predict student performance and timely intervention, however, Rafique expresses that it is very limited work in traditional learning environments.

*3) **[RQ3] What are the declared interests that are identified in the TIS in HEI?:*** According to the research work conducted by Bodily [13] in 2017, it is possible to identify that there is an interest in identifying student-oriented LA reporting systems with respect to their purpose, functionality and the types of data collected. Also, Schwendimann et al.[13] mentions the interest in the mechanisms by which student-oriented systems attempt to improve teaching and learning, which requires analysis through different categories such as type of data, target users, and evaluation.Learning Analytics Dashboards (LAD) also identified by their acronym LAD were found to have evaluated categories such as: goal orientation, usefulness of information, visual effectiveness, ease of use, comprehension, reflection, motivation for learning, behavior change, performance improvement, and competency development.

*4) **[RQ4] How can the TIS used in HEI be quantified and categorized?:*** In the various works reviewed, multiple approaches and objectives have been observed, however, none of them gives an answer to this question since most of the cases where tutoring is discussed, their focus is on intelligent tutoring systems, as identified by Bodily, to this point the only ones that come closest to working with tutoring in Latin America, are the systems generated by Learning Analytics in Latin America (LALA) expressed in the research of Guerra et al. [16]. This arises from a framework called COALA [18](Context Adaptation for Learning Analytics), which is constituted by four dimensions for adapting tools: objectives of using a Learning Analytics Dashboards (LAD) (e.g., identifying subjects in which students have low or high performance), stakeholders (e.g., advisors, teachers, students and administrative staff), key moments in which the use occurs (e.g., at the beginning of the academic year, when a course is registered or when they receive grades) and the interaction of stakeholders (e.g., face-to-face sessions with the advisor-student). This project was conducted within the context of Latin America partner institutions, the participating institutions were University of Cuenca in Ecuador(Cuenca), University Austral of Chile (UACh) and Polytechnic Superior School of the Litoral in Ecuador(ESPOL)[18].

*5) **[RQ5] How do HEI use LA for TIS?:*** Among the works reviewed, there are three cases where the use of LA applied to tutorial information systems has been most closely approached. Identified in the following institutions: University of Cuenca, University Austral of Chile and Polytechnic Superior School of the Litoral. The three cases coincide in combining information from the curricular structure and academic records to observe student progress. However, the three Latin American universities adapted an advisory board, originally implemented at KU Leuven in Belgium. In all three cases, the context was the main factor for adapting the dashboard, taking up that the LALA project [16] focuses on four different elements of the context such as: Objective, Actors, Key Moments and Interactions.

*6) **[RQ6] How do TIS used in HEIs interpret and visualize the data based on LA?:*** Several institutions have begun to adopt Predictive Learning Analytics (PLA) [15], where a variety of computational techniques (e.g., Bayesian modeling, cluster analysis, predictive modeling) are used to identify which students will pass a course, and which are at risk.According to Merceron's categorization [14],

it is identified that predictive methods (regression and classification) with 32% are considered the most frequent, below are relationship mining methods (association rules, correlations, sequential patterns and causal data mining) and methods for distilling data for human judgment tied with 24% frequency, where statistics and visualization are included.According to Viberg et al. [14] the application of methods for data analysis has been increasing from 2014 to 2017, reflecting from 2017 an increase in mining methods compared to previous years. In the work of Kim et al. [23], k-medoids clustering and Random Forest classifcation followed by logistic regression were applied for the analysis of the identified cluster profiles to analyze students' self-learning patterns in asynchronous mode. Likewise, to predict whether students pass or fail the course, the following models were used: Ramdom forest (RF), K-Nearest Neighbors (KNN), logistic regression (LR), neural networks (NNETS), TreeBagging (TB) and

Figure 1. Cloud of frequent words in the corpus of primary studies.

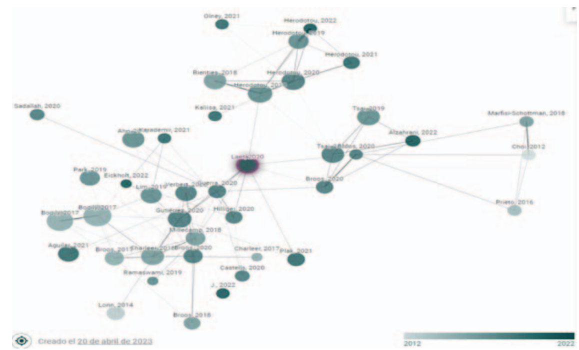

Figure 2. Mapping of previous works and derivatives of the most representative article of the corpus.

Bayesian additive regression trees (BART) Pérez et al. [20]

*7) **[RQ7] What information has been analyzed from the TIS and what did they use for the analysis of the information?**:* It has been identified that to date only the data available in some of the educational platforms have been used to generate conclusions from the LA perspective. Among the data identified we can find: student demographics: age, gender, disability, previous grades, ethnicity, successful completion of previous courses, previous experience of the student at the university (new versus continuing student), best score in the previous course and sum of credits earned [15]. In the work of Pérez et al. [20], characteristics such as: LMS, numbers of accesses, participation scores, learning activity ratings, submissions, published content, completed learning activities and peer reviews were contemplated, where these characteristics presented significant statistics between students who failed and those who passed.

Finally, an analysis was applied through the MAXQDA Analytics Pro 2022 tool under the following license: Creative Commons Attribution-ShareAlike 4.0 International (CC BY-SA 4.0) to generate a cloud of frequent words in the research corpus, see Fig 1. Likewise, the most representative article of the corpus was taken to be observed through the CONNECTED PAPERS web tool available at https://www.connectedpapers.com/ , where the network of authors who have previous works derived from the article analyzed with the topic raised during the systematic review can be observed, see Fig 2.

V. Conclusion

With the SRL on topic it has been identified that the term LA as we describe it today arises from the year 2011, being the most cited definition the one that arises in [2]. Therefore, we can say that it is clear at this time to identify that the objective of LA is to improve learning. It should be noted that the term Tutoring in this context, is defined as a process of group or individual accompaniment that a tutor provides to a student during her stay in an HEI, with the purpose of contributing to her integral formation, besides influencing the fulfillment of the institutional goals related to the educational quality such as: to raise the terminal efficiency rates and to decrease the failure and dropout rates. Also, in order for LA to achieve this objective, different techniques and methods are used, which are applied to the data offered by the educational platforms. It is important to mention that there are still few studies on the subject, but it has been identified that in Latin America, LA has already begun to be used in HEI. As indicated, it is still a little explored topic with great areas of opportunity. All the studies found present the common idea of the use of student information specifically related to academic history, being just a few cases where other types of information of used to predict future behaviors. This research opens a gap to resume studies where academic information and information from institutional tutoring programs can be integrated. It should be noted that the complexity of this part will depend on the ease of access to data from these tutoring programs, since there is no specific system or standard for integrating information, so each institution stores and processes its data in a unique way. The Future lines of development for this proposal include an empirical practice within a HEI in Mexico, the reflection on its availability and further documentation and analysis

References

[1] D. Gasevic, Y. Tsai, S. Dawson, and A. Pardo, “How do we start? an approach to learning analytics adoption in higher education,” *International Journal of Information and Learning Technology*, vol. 4, pp. 342–353, 2019.

[2] G. Siemens and P. Long, “Penetrating the fog: Analytics in learning and education,” *EDUCAUSE Review*, vol. 5, pp. 30–32, 01 2011.

[3] S. Aguilar, S. Karabenickb, S. D. Teasleyc, and C. Baek, “Associations between learning analytics dashboard exposure and motivation and self-regulated learning,” *Computers & Education*, vol. 162, 2021.

[4] H. Cha and T. Park, “Applying and evaluating visualization design guidelines for a mooc dashboard to facilitate self-regulated learning based on learning analytics,” *KSII Transactions on Internet and Information Systems*, vol. 13, pp. 2799–2823, 2019.

[5] C. Schumacher and D. Ifenthaler, "Features students really expect from learning analytics," *Computers in Human Behavior*, pp. 397–407, 2018.

[6] S. Charleer, A. Moere, J. Klerkx, K. Verbert, and T. D. Laet, "Learning analytics dashboards to support adviser-student dialogue," *IEEE Transactions on Learning Technologies*, vol. 11, pp. 389–399, 2018.

[7] F. S. Kia, S. D. Teasley, M. Hatala, S. A. Karabenick, and M. Kay, "How patterns of students dashboard use are related to their achievement and self-regulatory engagement," *LAK 2020 Conference Proceedings - Celebrating 10 years of LAK: Shaping the Future of the Field - 10th International Conference on Learning Analytics and Knowledge*, pp. 340–349, 2020.

[8] I. Jivet, M. Scheffel, H. Drachsler, and M. Specht, "Awareness is not enough. pitfalls of learning analytics dashboards in the educational practice," *Data Driven Approaches in Digital Education: 12th European Conference on Technology Enhanced Learning*, vol. 10474, pp. 12–15, 2017.

[9] B. Kitchenham and P. Brereton, "A systematic review of systematic review process research in software engineering," *Information and Software Technology*, vol. 55, no. 12, pp. 2049–2075, 2013.

[10] H. Zhang, M. A. Babar, and P. Tell, "Identifying relevant studies in software engineering," *Information and Software Technology*, vol. 53, no. 6, pp. 625–637, 2011, special Section: Best papers from the APSEC.

[11] J. A. Reyes, "The skinny on big data in education: Learning analytics simplified," *TechTrends*, vol. 59, no. 2, pp. 75–80, 2015.

[12] A. Rafique, M. S. Khan, M. H. Jamal, M. Tasadduq, F. Rustam, E. Lee, P. B. Washington, and I. Ashraf, "Integrating learning analytics and collaborative learning for improving student's academic performance," *IEEE Access*, vol. 9, pp. 167 812–167 826, 2021.

[13] R. Bodily and K. Verbert, "Review of Research on Student-Facing Learning Analytics Dashboards and Educational Recommender Systems," *IEEE Transactions on Learning Technologies*, vol. 10, no. 4, pp. 405–418, oct 2017.

[14] O. Viberg, M. Hatakka, O. Bälter, and A. Mavroudi, "The current landscape of learning analytics in higher education," *Computers in Human Behavior*, vol. 89, pp. 98–110, 2018.

[15] C. Herodotou, B. Rienties, A. Boroowa, Z. Zdrahal, and M. Hlosta, "A large-scale implementation of predictive learning analytics in higher education: the teachers' role and perspective," *Educational Technology Research and Development*, vol. 67, no. 5, pp. 1273–1306, 2019.

[16] J. Guerra, M. Ortiz-Rojas, M. A. Zúñiga-Prieto, E. Scheihing, A. Jiménez, T. Broos, T. De Laet, and K. Verbert, "Adaptation and evaluation of a learning analytics dashboard to improve academic support at three Latin American universities," *British Journal of Educational Technology*, vol. 51, no. 4, pp. 973–1001, 2020.

[17] S. Ranjeeth, T. P. Latchoumi, and P. V. Paul, "A Survey on Predictive Models of Learning Analytics," *Procedia Computer Science*, vol. 167, pp. 37–46, 2020.

[18] T. De Laet, M. Millecamp, M. Ortiz-Rojas, A. Jimenez, R. Maya, and K. Verbert, "Adoption and impact of a learning analytics dashboard supporting the advisor—Student dialogue in a higher education institute in Latin America," *British Journal of Educational Technology*, vol. 51, no. 4, pp. 1002–1018, 2020.

[19] C. Guzmán-Valenzuela, C. Gómez-González, A. Rojas-Murphy Tagle, and A. Lorca-Vyhmeister, "Learning analytics in higher education: a preponderance of analytics but very little learning?" *International Journal of Educational Technology in Higher Education*, vol. 18, no. 1, p. 23, dec 2021.

[20] C. J. Pérez Sánchez, F. Calle-Alonso, and M. A. Vega-Rodríguez, "Learning analytics to predict students' performance: A case study of a neurodidactics-based collaborative learning platform," *Education and Information Technologies*, 2022.

[21] R. Kaliisa, B. Rienties, A. I. Mørch, and A. Kluge, "Social learning analytics in computer-supported collaborative learning environments: A systematic review of empirical studies," *Computers and Education Open*, vol. 3, p. 100073, 2022.

[22] M. A. Chatti, A. L. Dyckhoff, U. Schroeder, and H. Thüs, "A reference model for learning analytics," *Int. J. Technol. Enhanc. Learn.*, vol. 4, no. 5/6, p. 318–331, jan 2012.

[23] J. Kim, I. Jo, and Y. Park, "Effects of learning analytics dashboard: Analyzing the relations among dashboard utilization, satisfaction, and learning achievement," *Asia Pacific Education Review*, vol. 17, pp. 13–24, 2016.