Evaluation of Academic Performance Based on Learning Analytics and Ontology: a Systematic Mapping Study

Laécio A. Costa
Federal Institute of Sertão Pernambucano - IFSertão
Petrolina, Brazil
laecio.costa@ifsertao-pe.edu.br

Laís N. Salvador
Computer Science Graduate Program
Federal University of Bahia - UFBA
Salvador, Brazil
laisns@ufba.br

Ricardo R. Amorim
University of the State of Bahia - UNEB
Petrolina, Brazil
amorim.ricardo@gmail.com

Abstract— **Educators face significant challenges related to monitoring academic performance and providing instruction in online courses. Due to spatial, temporal and interactive distance, this type of education requires that students have greater dedication, responsibility, and self-regulation of learning so that educational goals can be met. In this sense, educators seek instruments to consistently monitor and evaluate the student's academic performance. The present work aims at systematically mapping studies that use techniques of Learning Analytics and Computational Ontologies, allied to a Taxonomy of Educational Objectives, to monitor the student's state of knowledge. The evidence, methods, ontologies and taxonomies found will assist in the development of an educational software architecture that aims to assist educators in supervising academic performance. Three hundred and twenty studies were retrieved, of which we identified 21 (6.56%) works relevant to this research. This mapping shows that there is a research gap regarding the coordinated use of Learning Analytics and Ontologies in the field of learning assessment.**

Keywords— learning analytics, ontology, learning management system, taxonomy of educational objectives

I. Introduction

With the growth and evolution of Distance Education supported by Information and Communication Technologies (ICT), the execution of the courses in this modality have become more effective and efficient. This growth is also reflected in the research area related to the consistent assessment and monitoring of academic performance of the student's interactions in the Learning Management System (LMS).

According to [1], LMS is a work environment used to support the management of content, assist in the teaching-learning process and enable the monitoring of learning. This platform is currently widely used in education, either for the execution of e-Learning courses, b-learning or just as a content repository for classroom support. The volume of data generated from the interactions of the students in the LMS, if properly exploited, can provide useful insights into the relationship between planned educational goals and students' academic performance. Accordingly, with the high demand for consistent evaluation of academic performance, some lines of research (e.g. Big Data, Data Mining, and Analytics) are converging to the educational context to help educators in the evaluation of academic performance with focus on learning gains.

The assessment process requires monitoring of student progress throughout the instructor's planned instruction sequence in the LMS [2]. The objective of the evaluation is to infer, from the students' behavior, what learning objectives were achieved and the level of student knowledge. In this process, the use of a Taxonomy of Educational Objectives is highly recommended [3].

The search for a consistent assessment of academic performance has motivated renewed interest in research relating to Learning Analytics (LA) and Data Mining techniques to assist educators in interpreting raw data from the online environment. Siemens [4] defines LA as "techniques for assessing, predicting and advising on learning from the use of intelligent data (produced by students), models of analysis to discover information and social connections".

On the other hand, computational ontologies defined as a formal specification of a shared conceptualization: formal specification means something that is readable to computers, conceptualization represents an abstract model of some real-world phenomenon and shared means consensual knowledge [5]. Ontologies have been used in the area of Informatics and Education [6,7,8,9,10,11,12] with encouraging results. The use of computational ontology was motivated by the fact that it can conceptualize a Taxonomy of Educational Objectives so as to aid the automatic analysis of the student's interactions in an LMS.

The focus of this work is to understand how the coordinated use of LA and Computational Ontologies, guided by a Taxonomy of Educational Objectives, can contribute to the evaluation of the student's academic performance. We perform a Systematic Mapping (SM) to extend our understanding of methods, ontologies, taxonomies, and indicators used in the monitoring of academic performance. This paper consists of the first methodological step of a research in progress that aims to develop a software architecture for the educational context that consistently monitors and evaluates a student's academic performance.

The sections are organized as follows: Section II details the research method used, then the results are discussed in Section III; threats to validity are described in Section IV; and, finally, Section V presents the conclusions and future work.

II. Research Method

In this section, we describe the steps taken to run this SM. According to Kitchenham [13], SM is a research method used to identify, evaluate and interpret available studies related to a research question, topical area or phenomenon. Kitchenham suggests a five-step process: i) definition of the research question; ii) conducting the research; iii) sorting of the works; iv) extraction of data; and v) production of the report and publication. The initial four

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steps will be detailed below. The fifth step will not be detailed.

A. Definition of Research Questions

Five research questions were defined to search for evidences:

RQ1: What evidence indicates the coordinated use of Learning Analytics and Ontologies as computational resources for learning assessment?

RQ2: Which indicators, extracted from the LMS, are used to evaluate student learning performance?

RQ3: What computational resources and methods are used in the evaluation process of learning performance?

RQ4: What ontological structures are used in learning assessment?

RQ5: Which Educational Objective classifications are referenced?

The RQ1 aims to provide an understanding of the main approaches developed that use LA and Ontologies in the evaluation of the student's academic performance. The RQ2 searches for indicators that enables the evaluation of the knowledge acquired by the student in LMS. The response to RQ3, RQ4 and RQ5 reports which computational techniques, ontologies, and taxonomies of educational goals, respectively, were used to assist in monitoring the student's academic progress.

B. Conducting the Search

In this section, we define a strategy for designing an appropriate search string. Kitchenham [13] presents guidelines on the definition of the string so as to reduce the search bias. Thus, we selected the keywords related to the research questions to compose the research string. According to Table I, we applied different strings obtaining a large number of papers with the second expression. The term "Ontology" was omitted from the second, third, and fourth strings, because with its inclusion, related with the other terms through the logical operator "AND", we did not obtain results in the search engines. The omission of the term Ontology keeps the string more generic and does not mean that we are excluding works that use ontological structures.

TABLE I. SPECIFICATION OF THE STRING SEARCH

#	String	Total
String **1**	("Learning Analytics" OR “Educational Data Mining”) AND Ontology AND ("educational objective" OR "instructional objective" OR "learning objective" OR "cognitive objective" OR "cognitive process" OR "cognitive learning" OR "educational theory" OR "learning theory")	0
String 2	**("Learning Analytics" OR "Educational Data Mining") AND ("educational objective" OR "instructional objective" OR "learning objective" OR "cognitive objective" OR "cognitive process" OR "cognitive learning" OR "educational theory" OR "learning theory")**	**320**
String 3	("Learning Analytics" OR "educational data mining") AND "Student Performance" AND ("educational objective" OR "instructional objective" OR "learning objective" OR "cognitive objective" OR "cognitive process" OR "cognitive learning" OR "educational theory" OR "learning theory")	74
String 4	("Learning Analytics" OR "educational data mining") AND Ontology AND "Student Performance" AND ("educational objective" OR "instructional objective" OR "learning objective" OR "cognitive objective" OR "cognitive process" OR "cognitive learning" OR "educational theory" OR "learning theory")	0

The research strategy included only digital libraries of reference in the area of computing. The choice of databases followed the qualitative analysis performed by [14]. Five digital libraries stand out in this research: IEEE Xplore, ACM Digital Library, Science Direct - Elsevier, Springer Link and Scopus - Elsevier. Table II shows the number and the studies retrieved with the application of String 2 in each database. This process was carried out from November 2017 to March 2018, and 320 documents were collected.

TABLE II. RETRIEVED AND SELECTED STUDIES

Digital Library	Retrieved	Relevant Papers	Papers
ACM Digital Library	42	3	[15, 16, 17]
Xplore IEEE	3	1	[18]
Scopus	70	5	[19, 20, 21, 22, 23]
Springer Link	123	5	[24, 25, 26, 27, 28]
Science Direct	82	7	[29, 30, 31, 32, 33, 34,35]
Total	**320**	**21**	

C. Screening of Papers

The definition of the inclusion and exclusion criteria aims to identify the primary documents that provide direct content on the research questions and reduce the probability of bias [13]. This definition is a typical strategy for sorting relevant papers. In this research, four inclusion criteria and seven exclusion criteria were created, which are presented in Table III.

TABLE III. INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	Exclusion Criteria
IC-1. Primary studies; IC-2. Studies that document methods and practical aspects of the use of LA, Ontology, and Taxonomies of Educational Objectives, in LMS; IC-3. Articles that contemplate the development and evaluation of experimental studies involving LA, Educational Objectives and LMS; IC-4. Articles that present conceptual models and ontologies in the context of this research;	EC-1. The articles that are not in English (due to the universality of this language); EC-2. The articles that do not present complete text and are not available in electronic format; EC-3. Technical reports, documents that are available in the form of abstracts or presentations as well as secondary literature reviews; EC-4. Studies that deal only with philosophical aspects in the context of research; EC-5. Duplicate paper; (consider the most current) EC-6. Redundant studies of the same authorship; EC-7. Studies that do not use LA and Educational Objectives;

In this step, we applied these criteria to filter the studies relevant and related to the object of this research. As a result of this step, we obtained a total of 21 documents. Table II also shows the filtered studies from the digital libraries.

D. Data Extraction

In this step, we performed the data extraction to answer the research questions and find evidence. We read the selected documents in full and extracted information necessary to answer the research questions.

III. Results and Discussion

We firstly analyzed the method of research and the temporal distribution of the studies. Many of the studies (57.14% - 12 articles) were published in conferences, while 38.10% (8 articles) were published in journals and 4.76% (1 article) in Workshops. The conference on Learning Analytics and Knowledge (ACM LAK) and the journal Computers in Human Behavior (CHB - Elsevier) record the most publications.

The research method described in each selected study can indicate its stage of maturity. Thus, regarding this classification we identified 61.90% (13 articles) that performed a "Controlled Experiment", and 14.29% (3 articles) that performed a "Case Study". The "Research-Action" research method and the "Not Applied" classification were identified in 9.52% (2 articles each). The representativeness of the method Controlled Experiment indicates maturity in the field and empirical studies provide more reliable evidence on specific research hypotheses.

The temporal distribution allowed us to observe that the studies were carried out between the years 2010 and 2018. In the years 2014 and 2016, 6 studies were found each year. In 2017, 5 studies were published and in 2010, 2011, 2015, and 2018 only one article was retrieved each year. Of course, the papers appear after 2010, as the term “Learning Analytics” was defined in 2010.

A. *Answers to Research Questions*

In this section, we present the results grouped by the research questions.

- RQ1: What evidence indicates the coordinated use of Learning Analytics and Ontologies as computational resources for learning assessment?

We identified three studies that report on the use of Learning Analytics, ontological structure and some taxonomy of educational objectives, however in an uncoordinated way. A summary of these papers is presented in Table IV. Two papers present a theoretical approach, while only one describes a conceptual model with empirical evaluation.

In [20], the authors demonstrate the use of Bloom's Taxonomy to evaluate the verbs used in exam questions. They present the use of Natural Language Processing (NLP) techniques coupled with the English-language lexicon database, WordNet, and similarity algorithms to perform verification if the verbs of the assessment exam questions are in agreement with the taxonomy. The authors report that learning objectives, learning activities, and evaluations are interrelated elements that allow students to observe their learning.

TABLE IV. Summary of studies Associated to RQ1

Paper	Ontology	Taxonomy	Research Method
20	-	Bloom	Controlled Experiment
22	Learning Ontology	Learning Activity	Not Applied (Theoretical Model)
35	Student Model	Bloom	Not Applied (Theoretical Model)

The study [22] presents an approach to support students' awareness and reaction to their cognitive and metacognitive learning activities. This approach aims to make the person more aware of their learning activities unobservable by capturing and viewing observable data on student behavior during the learning process. The authors of [22] explain that the basis for the technical solution is the extraction of key actions from data recorded in the logs of the user interaction with the resources available in the learning environment. They also present the use of a specific taxonomy of learning activities derived from the self-regulated learning theory to combine the elements of this taxonomy with the actions/interactions carried out by the students. The use of the ontological structure in this work is presented to classify the interactions of students in the learning environment according to the taxonomy.

In [35], authors present a theoretical, flexible and student-centered model. This model presents an ontological network that combines information related to: i) students and their state of knowledge, ii) evaluations that depend on rubrics and different types of objectives, and iii) learning units. The model is defined as ON-SMMILE (Ontology Network-based Student Model for MultI Learning Environment) for multiple learning environments. The aim is to develop and construct the ON-SMMILE model methodologically to supervise student learning as a competency-based recommendation system, through ontological engineering.

The objective of [35] combines the Student Model ontology with Valuation Signature, Performance Indicator, and IMS Learning Design ontology. It uses Bloom's Educational Objectives Taxonomy as a pedagogical / cognitive diagnostic element to supervise the learning process. For the authors, the use of ontologies provides the ability to infer about the knowledge of the student from the information represented, besides allowing reuse and its extensibility in different learning environments.

Evidence of student academic performance assessment from the coordinated use of Learning Analytics and Computational Ontology techniques was not identified. However, two papers [22, 35] indicate the possibility of the use of Learning Analytics and Ontologies.

- RQ2: Which indicators extracted from the LMS are used to evaluate student-learning performance?

The indicators were classified into Evaluation, Productive, Interactive, Assimilative and Communicative activities, according to the taxonomy suggested by [17]. These categories represent the learning design activities and they are relevant for a student’s evaluation.

We identified that 68% of studies (15 studies) use Evaluation Activities as the main indicator. This result was expected because this category determines the result of activities and evaluations (formative and summative). Second, the category of Productive Activities had 63% (14 studies); this category determines the production actions of students, such as to create, complete, do, among others. Thirdly, it registers the Interactive Activities category, which also shows good representativeness (54.55%, 12 studies). This result shows the interaction of students with content and with other people (teacher, tutor or student). In addition to these, two other categories represent less than 50% of the selected studies: the Assimilative category (10 studies, 45.45%) and the Communicative category (6 studies, 27.27%).

The analysis of these categories demonstrates that the use of a combined indicator or several indicators can best represent the evaluation of student engagement and participation due to the dynamism and interaction provided by the environment and teacher's pedagogical planning.

- RQ3: What computational resources or methods are used in the evaluation process of learning performance?

This question aims to identify the learning platforms and map the main techniques and statistical methods used in the evaluation of student performance in LMS.

Regarding learning management platforms, MOOC platforms (19.05%, 4 studies), Moodle (14.29%, 3 studies) and SMEUS - Semantic E-learning System - (4.76%, 1 study) stand out. More than half of the studies (61.90%, 13 studies) did not specify the type of LMS used, because the architectures proposed there aim to be generic, in order to meet the requirements of the main learning environments.

Regarding the statistical methods and techniques used in the data mining process, we found that some studies focus on methods for Classifying and Grouping data. In this SM, 38.09% (8 studies) used some Regression Analysis technique (classifier) and 4.76% (1 study) cites the use of statistical techniques of grouping data.

Regarding the techniques of prediction or progress evaluation, 38.09% (8 studies) of the studies use specific algorithms of training and data testing based on Machine Learning.

- RQ4: What ontological structures are used in the learning assessment?

This question identifies the relationship between the Computational Ontologies and the context of this research. We found two studies, (9.25%) which use Computational Ontologies, for Learning assessment. One study [22] presents a conceptual approach with the use of learning ontology to assist in monitoring unobservable actions of students' activities allied to the taxonomy of learning activities. In [35], the authors present a theoretical model using a network of ontologies to supervise student learning and recommend competency-based activities. These works were presented in RQ1 as well.

- RQ5: Which Educational Objectives classifications are referenced?

Among the works analyzed, 23.80% (5 studies) report using some taxonomy in the context of the research. Some studies (14.28%, 3 studies) cite Bloom's taxonomy, and other taxonomies (Bloom's Revised, SOLO, Learning Design Activities and Learning Strategies) are cited in at least 1 study (4.76%).

IV. Threats

SM uses a formal investigation process and is conceptualized as a more accurate approach than other methods in the literature review. However, elements may arise that pose a threat to its validity, such as keyword selection and search string constructions, if not carefully crafted/selected.

For instance, by specifying the string using the term Ontology, we did not obtain any documents in the search engines, but the omission of the term did not exclude documents referring to its use and application.

V. Conclusions

This work presents the results of a SM to answer research questions related to the coordinated use of Learning Analytics techniques and Computational Ontologies, guided by a Taxonomy of Educational Objectives. This is the first methodological step of a research in progress that aims to build an educational software architecture to assess the academic performance of students in LMS.

Using this SM, we identified 320 articles in 5 digital reference libraries widely consulted by the computing community. After applying the inclusion and exclusion criteria, we identified 21 relevant papers.

The results show that there is a relevant research gap. Among the recovered papers, we did not find an expressive number of articles which use computational ontologies and Learning Analytics in a coordinated way, and more specifically, nothing based on a taxonomy of educational objectives taxonomy to evaluate educational goals and student performance. Furthermore, the papers recovered in SM also show that there is a need for tools which help teachers to monitor the academic progress of e-learning students consistently.

SM is an instrument used to: investigate pieces of evidence, become familiar with the research area, find gaps, and answer research questions. Thus, the results presented here help in the decision making about which methods, techniques and/or learning taxonomies are more appropriate in the modeling and specification of an architecture for educational software.

Future work will model and develop an educational software architecture that uses: i) Learning Analytics techniques to extract useful information from students; ii) Computational Ontologies to represent a taxonomy of educational objectives, and iii) Data processing and evaluation techniques to infer the student's state of knowledge in a coordinated manner.

Acknowledgements

The Institutional Qualification Program of the Federal Institute of Sertão Pernambucano (IFSertão-PE) supported this research.

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