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Analysis Of Learning (Learning Analytics - La) And Educational Data Mining (Edm) Applied In Education

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Abstract:
Background: *Learning Analytics (LA) and Educational Data Mining (EDM) have emerged as research and application areas with great potential to transform teaching and learning processes. These approaches enable the collection, analysis, and interpretation of large volumes of educational data, with the aim of better understanding the phenomena related to education and proposing improvements.*
Materials and Methods: *To develop the research, a qualitative approach was adopted, using the bibliographic research procedure. Relevant scientific sources were researched, such as articles presented at scientific events, articles published in scientific journals, dissertations, and theses. The analysis of the collected data followed an interpretative perspective, seeking to identify trends, challenges, and opportunities in the use of LA and EDM in education. The general objective of this study is to investigate how Learning Analytics (LA) and Educational Data Mining (EDM) techniques can be applied in the educational context to improve teaching and learning processes.*
Results: *The impacts on the learning sciences were evident, with EDM and LA contributing to a deeper understanding of the phenomena related to teaching and learning. These approaches have enabled the development of predictive models, the identification of factors associated with student success, and the proposition of personalized interventions.*
Conclusion: *The study demonstrates that Learning Analytics and Educational Data Mining hold significant potential for advancing educational practices. By leveraging these approaches, educators and researchers can gain valuable insights into student performance and educational processes, leading to more informed decisions and enhanced educational outcomes.*
Keywords: *Learning Analytics; Educational Data Mining; Qualitative approach; Bibliographic research; Teaching and learning processes.*

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I. Introduction

Learning Analytics (LA) and Educational Data Mining (EDM) have emerged as research and application areas with significant potential to transform teaching and learning processes. These approaches enable the collection, analysis, and interpretation of large volumes of educational data, aiming to better understand phenomena related to education and propose enhancements.

The selection of this topic for the present scientific article is justified by its relevance in the current educational context. With the increasing digitization of teaching and learning processes, the availability of educational data has grown exponentially. In this scenario, EDM and LA emerge as powerful tools to extract valuable insights from this data and support evidence-based decision-making.

This research adopts a qualitative approach, utilizing a bibliographic research procedure. Relevant scientific sources such as articles presented at scientific events, publications in scientific journals, dissertations, and these were examined. The analysis of collected data followed an interpretative perspective, aiming to identify trends, challenges, and opportunities in the use of LA and EDM in education.

The overall objective of this study is to investigate how Learning Analytics (LA) and Educational Data Mining (EDM) techniques can be applied in the educational context to enhance teaching and learning processes.

The structure of this article is organized as follows: following this introduction, sections covering theoretical foundations and methodology are presented. Subsequently, final considerations are discussed, providing a synthesis of key findings and proposing future research directions. Finally, the bibliographic references used in this work are listed.

II. Material And Methods

For the development of this scientific article, a qualitative approach was adopted, employing the procedure of bibliographic research. The analysis of data collected during the bibliographic research focused on identifying trends, challenges, and opportunities in the use of LA and EDM in education.

Relevant scientific sources such as articles presented at scientific events, articles published in scientific journals, dissertations, and these were investigated. The bibliographic research was conducted using academic databases including Google Scholar, Scielo, Scopus, and Web of Science, using keywords related to LA and EDM applied to education.

Works published between 2017 and 2024 by Brazilian and international authors investigating the same themes addressed here were prioritized. Among them, notable contributions include Bakhshinategh et al. (2018), Filatro (2023), Campos et al. (2020), Romero and Ventura (2020), Bertoncelo (2022), Campos and Gomes (2022), Ozyurt, Ozyurt, and Mishra (2023), and Irala; Ortega (2024). The theoretical contributions of these authors provided the foundation for the discussions presented in the article. The results were organized and presented in a structured and commented manner, aiming to contribute to the advancement of knowledge in this area.

III. Literature Review

The topics and subtopics of this theoretical foundation aimed to develop a comprehensive understanding of the development of research communities, considering methods, techniques, and primary tools, as well as their effects on learning sciences and educational practice.

Firstly, the development of research communities was addressed, emphasizing the importance of interdisciplinary collaboration and knowledge networks to advance scientific and educational discoveries. Subsequently, the discussion focused on the main methods and tools used in the analysis of educational data.

Furthermore, specific tools were presented for conducting methods within two types of research community: Educational Data Mining (EDM) and Learning Analytics (LA), with a focus on their practical applications. Lastly, the effects on learning sciences were highlighted, addressing issues of engagement and disengagement, collaboration and learning, and their subsequent impacts on educational practice.

Development Of Research Communities

Initially, it is worth noting that the two research communities discussed here follow complementary perspectives regarding the analysis of educational data. This phenomenon is observable because researchers within these communities investigate similar topics, believing that the impartial appreciation of research results conducted within the required scientific rigor directly benefits students, ensuring reliable information and advancements in learning sciences[1].

Although there are considerable similarities, there are also pertinent differences[2]. These differences can be observed in studies by Filatro (2023) and Ozyurt, Ozyurt, and Mishra (2023)[3; 4]. Ozyurt, Ozyurt, and Mishra (2023) argue that researchers focusing on EDM are more interested in automated methods for analyzing educational data[4]. They aim to tailor their studies towards automated adjustments, where educational software identifies a need and automatically seeks to personalize certain student experiences[5]. On the other hand, Filatro (2023) indicates that researchers in LA direct their efforts towards empowering individuals (or research organizations) for better exploration of educational data[3].

It is noteworthy that researchers in EDM emphasize the modeling of specific theories (such as indicating a study process through which it is possible to infer and analyze why a particular class is not achieving good results in Mathematics), whereas those researching LA adopt a more holistic and systemic approach to research concepts. The research in LA is more closely aligned with theories that seek to understand systems in general or investigate groups of students as part of communities. This specific difference has persisted in the approaches of learning sciences researchers for over a decade[6].

Researchers in LA tend to focus their studies on sharing information that can be used in training instructors, teachers, and students, as well as proposing actions for educators dealing with specific types of students on a daily basis, especially those struggling to understand particular curriculum content[7].

As evident from the outset, EDM and LA methodologies are well-suited for educational research. The reported differences stem primarily from the applications historically of interest to researchers in each research community. EDM and LA are grounded in computational data analysis; however, researchers in these two lines of research have emphasized implications and theoretical analyses, contributing to both learning sciences and educational theory in a broader sense[8].

Techniques, Methodologies, And Key Instruments

EDM and LA employ data mining and analysis techniques to explore educational data and enhance understanding and educational performance. These methodologies differ from other areas of data mining due to their unique educational data and objectives. Techniques, methodologies, and instruments used in EDM and LA draw from various sources, with two primary sources being general data mining and analysis techniques, as well as psychometric and educational measurement techniques. Often, the unique characteristics of educational data have led to adaptations of existing psychometric methods or the use of different methods that are more pertinent in EDM/LA than in general data mining. This section reviews some of the key techniques, methodologies, and instruments in this field and provides examples of their applications.

Cluster Analysis

Cluster analysis aims to discover naturally occurring data points that cluster together, dividing the entire dataset into a set of clusters. When the most common categories within the dataset are not known beforehand, clustering is particularly useful. Each data point in a cluster set will generally be more similar to other data points in the same cluster than to data points in other clusters if the cluster set is well chosen. In education, when cluster analysis is applied, students are often grouped based on their behavior (or according to a specific characteristic under analysis)[9]. Latent class analysis is a related approach that can be used to statistically model groups in data and track changes between groups over time[10].

Network Analysis

Network analysis creates models of relationships and interactions among actors or individual components, as well as patterns that arise from these relationships and interactions. Social Network Analysis (SNA), which studies social relationships among people, is the most common application of network analysis. This instrument has been used in learning environments long before educational data mining or learning analytics became research areas[11]. Researchers have employed social network analysis to investigate the relationship between students' discussion forum usage patterns and their academic outcomes and to identify student subcommunities[12].

Factor Analysis

Factor analysis aims to identify variables that naturally group together. This is done by dividing the set of variables (rather than data points) into a set of latent factors, which cannot be directly observed. Psychometrics often uses factor analysis to validate or establish scales[44]. Factor analysis is used in EDM/LA to reduce dimensionality, decreasing the number of variables, for a variety of applications[13].

For example, Fincham et al. (2019) used factor analysis to uncover how different student behaviors in learning management systems relate to each other. Factor analysis is also frequently used to uncover domain structure, which will be discussed further[14].

Structure Discovery

Structure discovery algorithms seek patterns in data without focusing on a specific variable beforehand. The goal for this task is very different. An EDM/LA researcher aims to develop a model to predict a specific variable in forecasting. On the other hand, structure discovery does not depend on any specific variable. Instead, the researcher is trying to determine which structure naturally appears in the data; various structure discovery methods uncover a variety of structure types. Cluster analysis/latent class analysis, factor analysis, domain structure discovery, and network analysis are common methods of structure discovery in EDM/LA[15].

Domain Structure Discovery

Domain structure discovery focuses on investigating how knowledge is structured within an educational domain. This may include discovering the relationship between specific content and components of knowledge or specific skills that students possess or can develop. This could involve mapping test items to skills or mapping problems in educational software to specific knowledge components in a subject area, grouping problems for latent knowledge estimation and problem selection[16; 17].

Correlation Mining

The goal of correlation mining is to find positive or negative linear correlations between variables. To avoid spurious relationships, post-hoc corrections or dimensionality reduction methods are used when appropriate.

In their studies, Patricio and Magnoni (2018) and Campos et al. (2020) examined how various correlation patterns related to learning outcomes[18; 15].

Sequential Pattern Mining

The central focus of causal data mining is to determine whether one event (or observed construct) caused another event (or observed construct). The goal may also be to predict which factors will lead a student to perform poorly in a class or to understand the impact of interventions in a learning environment[19].

Each of these techniques has the capability to uncover unexpected yet significant connections between variables. Because of this, they can be employed in a variety of situations, such as developing new hypotheses for future investigation or finding contexts for potential interventions by automated systems[20].

Association Rule Mining

The objective of association rule mining is to discover "if-then" rules, that is, "if a set of variable values is found, then another variable will generally have a specific value." For example, Oliveira et al. (2020) investigated how different behaviors and contexts in exploratory learning environments influenced changes in student behavior. They used association rule mining. According to Oliveira et al. (2020), association rule mining does not necessarily need to involve changes over time, although this specific analysis involves behavior that evolves over time[21].

Relationship Mining

The objective of relationship mining is to discover how various variables are related in a dataset composed of a large number of variables. Relationship mining is the most popular research category in Educational Data Mining (EDM) since its inception. It may attempt to discover which variables are most strongly linked to a single variable of interest or which relationships between any two variables are strongest.

In the opinion of Batista and Fagundes (2023), association rule mining, sequential pattern mining, correlation mining, and causal data mining are the four main categories of relationship mining[22].

Cagliero et al. (2021) studied data from 5,000 students using associative relationship classification models to address the machine learning model using an explanatory learning approach. The authors indicated that associative models for relationship mining produce results of similar quality to classification models and provide meaningful insights into the student success rate[23].

Tools For Conducting EDM/LA Methods

In recent years, there has been significant growth in the development of tools for data mining and analysis, both in the commercial and academic sectors. These tools, which include software applications and packages within programming languages, have been widely adopted by researchers and professionals in the EDM and LA fields[24; 25].

A notable trend is the shift of EDM and LA researchers from using software applications that offer data mining algorithm libraries to employing packages implemented in popular programming languages like Python and R. These packages support a wide range of machine learning algorithms as well as specific algorithms for educational data analysis[26; 27].

Some examples of widely used packages and tools include: 1. Packages for implementing latent knowledge estimation algorithms, enabling the inference of students' knowledge based on their performance in activities and assessments[28]. 2. Packages for epistemic network analysis, allowing the understanding of relationships between concepts in a specific knowledge domain[29]. 3. Packages for social network analysis, facilitating the study of interactions among students, teachers, and other actors in learning environments[30]. 4. Tools for domain structure discovery, aiding in the identification of key concepts and their relationships in a particular field of knowledge[31].

These tools have been extensively used in research and practical applications of EDM and LA, contributing to the advancement of the field and the improvement of teaching and learning processes. It is important to note that the EDM and LA field is constantly evolving, with new tools and techniques emerging each year. Researchers and professionals in the field should stay informed about these innovations and strive to adopt the most suitable solutions for their specific projects[32].

Impacts On Learning Sciences

Educational Data Mining (EDM) and Learning Analytics (LA) have become increasingly essential tools in the field of education, significantly impacting the learning sciences. These techniques enable the collection, analysis, and interpretation of vast amounts of educational data with the goal of gaining a deeper understanding of teaching and learning methods and suggesting improvements.

Engagement And Disengagement

Research on engagement and disengagement in educational software is an area where EDM/LA methods have proven particularly useful[33]. Prior to EDM and LA, measuring disengagement was challenging[34]. However, there are now models that can intricately infer various forms of disengagement, down to the second. This includes detectors for negative emotions and disengaged behaviors such as gaming the system[35].

Interestingly, research in educational data mining has found that certain actions are associated with poorer outcomes. For example, when a student puts in a lot of effort and engages heavily with the software, but still does not develop their skills[36].

Conversely, actions that may appear disengaged may actually be engaged; for instance, clicking hints, getting the answer, and then self-explaining it[33]. Recent studies have shown that engagement detectors can predict student outcomes up to ten years later.

Moreover, these detectors have been integrated into intelligent tutors that adapt to student disengagement. An example is the work of DeFalco (2018), which automatically detected and responded to frustration, thereby improving learning outcomes[5].

Collaboration And Learning

EDM and LA methods have aided in understanding student learning in various collaborative and group-based settings. Analyses of collaborative learning behaviors in different contexts have been conducted to determine which behaviors characterize more successful groups and learners[37].

These contexts include fully computer-mediated (CMC) learning and face-to-face collaboration activities such as working together on physical displays and nursing education with simulated patients[38].

The work of Renninger and Järvelä (2022), which examined how self-regulated learning manifests in group learning activities, used multimodal learning data to fill gaps in a theoretical model of self-regulated learning. It is important to highlight this study[39]. On the other hand, research shows that off-topic discussions during collaborative learning are more detrimental to learning basic facts than problem-solving alternatives[37].

These insights demonstrate how EDM and LA are not only transforming educational research but also shaping practical interventions and instructional strategies to enhance learning outcomes across diverse educational settings.

Impacts On Practice

Educational Data Mining (EDM) and Learning Analytics (LA) have emerged as significant fields of research and application with substantial potential to transform teaching and learning processes. Two practical applications of these methodologies worth highlighting are data visualization and the development of educational plans.

Data Visualization

Data visualization is a fundamental application of EDM and LA as it allows the transformation of large volumes of information into graphical and interactive representations that facilitate the understanding and interpretation of educational data. Some key advantages of data visualization in the educational context include:

- Identification of Patterns and Trends: Visualizations enable educators and administrators to identify patterns in performance, behavior, and student interactions, as well as trends over time. This leads to a deeper understanding of learning processes[40].
- Monitoring Progress: Real-time visualization dashboards can provide immediate feedback on student progress, allowing teachers and institutions to track both individual and class performance, and to intervene pedagogically in a timely manner[41; 42].
- Support for Decision-Making: Visualizations assist in identifying problem areas, evaluating the effectiveness of pedagogical strategies, and allocating resources, thus supporting evidence-based decision-making[43; 42].
- Student Engagement: When shared with students, visualizations can enhance their engagement and understanding of their learning processes, empowering them to take a more active role[42].

Thus, educational data visualization has proven to be a powerful tool for transforming large volumes of information into actionable insights, contributing to the continuous improvement of educational processes.

Development Of Educational Plans

Another practical application of EDM and LA is the development of personalized and adaptive educational plans tailored to the individual needs of students. Some key advantages of this approach include:

- Personalized Learning: Based on data analysis of students' performance, behavior, and preferences, it is possible to develop individualized educational plans that consider each student's pace, style, and difficulties[42].

- Targeted Interventions: EDM and LA allow for the early identification of students at risk of underperformance or dropout, enabling the implementation of specific and timely interventions to support them[40].
- Resource Optimization: By developing data-driven educational plans, institutions can more efficiently allocate human, financial, and technological resources, maximizing the impact of educational actions[42].
- Continuous Improvement: Continuous monitoring and evaluation of educational plans, based on data, allow for the ongoing enhancement of pedagogical strategies and educational resources[40].

Therefore, the development of educational plans based on EDM and LA represents a promising approach for personalizing teaching and improving the effectiveness of educational processes.

IV. Conclusion

The present research achieved its proposed objectives by investigating how Learning Analytics (LA) and Educational Data Mining (EDM) techniques can be applied in the educational context to improve teaching and learning processes.

Regarding the development of research communities in EDM/LA, there has been a consolidation of this field as an interdisciplinary area, with the creation of scientific events, journals, and specialized research groups both in Brazil and internationally. This has fostered theoretical and methodological advancements in this area.

Concerning the techniques, methodologies, and tools in EDM/LA, notable approaches include student knowledge modeling, pattern and trend detection, real-time assessment and feedback, and personalized recommendation of educational resources. These strategies have shown great potential to enhance the understanding of learning processes and support more effective pedagogical interventions.

In terms of the main tools for conducting EDM/LA methods, there has been a shift among researchers from using software applications to employing packages implemented in programming languages such as Python and R. These packages offer greater flexibility and support for a wide range of machine learning algorithms and educational data analysis.

The impacts on learning sciences have been evident, with EDM and LA contributing to a deeper understanding of phenomena related to teaching and learning. These approaches have enabled the development of predictive models, the identification of factors associated with student success, and the proposition of personalized interventions.

Among the highlighted practical impacts, data visualization and the development of personalized educational plans have proven to be promising applications. Visualizations have assisted in identifying patterns and trends, monitoring student progress, and supporting evidence-based decision-making. Meanwhile, personalized educational plans have contributed to the adoption of teaching strategies tailored to individual student needs.

For future research, it is suggested to investigate ethical and privacy aspects in the use of educational data, as well as to evaluate the long-term impact of adopting LA and EDM in educational institutions. Additionally, comparative studies between different approaches and tools, and the analysis of their effectiveness in specific contexts, can further enrich the field.

In conclusion, the present research demonstrated that Learning Analytics (LA) and Educational Data Mining (EDM) have established themselves as promising areas for the improvement of teaching and learning processes. Their responsible and informed adoption can significantly contribute to the advancement of education in the 21st century.

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