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A Literature Review of Experimental Studies in Learning Analytics

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Abstract

The purpose of this literature review is threefold: (a) to conduct a critical review of the published scientific literature on Learning Analytics (LA), (b) to identify current trends, gaps, and research questions in the field, and (c) to summarize the existing empirical evidence of the LA adoption. From a sample of 390 articles, 118 were included in the review after searching online bibliographic databases. The selected empirical evidence articles were examined for their research questions, stakeholders, and limitations using qualitative content analysis. The results demonstrated that LA is an interdisciplinary field and that developing efficient techniques is a new research challenge for the educational community. This study discusses the results of defining and analyzing five conceptual dimensions: the object of analysis, technology, objectives, stakeholders, and ethics. It provides guidelines from the literature for scholars, faculty, course designers, researchers, and other educational stakeholders interested in developing responsible, efficient, and pedagogical LA approaches.

Keywords: Learning analytics, pedagogy, ethics, educational stakeholders, literature review

Introduction

This study conducted a literature review to map Learning Analytics (LA) research area, which raises benefits and challenges. This research aims to summarize existing empirical evidence, identify gaps in current LA research, and provide critical dimensions. This qualitative content analysis is expected to guide all key educational stakeholders interested in learning more about this emerging field. This study's main contribution is the analysis of how issues for LA are defined. The section that follows (Background) introduces the concepts of data analytics and LA. The research questions for this work are then defined, emphasizing the purpose of our work. The subsequent three sections are concerned with our research design and execution of our review. The methodology of the current review is presented in the third section (Method), referencing the criteria that resulted in the final 118 selected articles. The fourth section (Results) provides insights into our study with the dimensions listed below: the object of analysis, objectives of LA, stakeholders, technology, and ethics. The final section (Discussion) discusses the findings, summarizes the benefits and drawbacks of this work, and suggests the next steps.

Background

Data analytics is a mature technology that is being used in real-world financial, business, and health systems. Big data is defined as large amounts of data that cannot be managed using traditional management software tools (Asamoah et al., 2017). Furthermore, big data analytics is the application of analytics techniques to large datasets to generate meaningful conclusions, make better decisions, or evaluate models for improving organizational processes (Jantti & Heath, 2016). Big data analysis is the evolution of computation and has been applied to various industries (Zhuhadar et al., 2013). Higher education, a field that collects massive amounts of learner data, has used analytics with on-time feedback delays (Siemens & Long,

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2011). Attempts to envision the future of education focus on new technologies such as ubiquitous computing devices and flexible, smart classrooms. However, big data analytics is the most emerging factor we cannot touch or see (Zhuhadar et al., 2013). Every button clicks data entry or a social-network action is captured and may leave digital trails (Siemens & Long, 2011), increasing the quantity and veracity of student data. As a result, many innovative analytic tools and platforms based on advanced algorithmic techniques have emerged (e.g., clustering, neural networks, text mining) to assist students in concentrating on their studies where they are most needed, and instructors adapt their teaching. As universities expand their student populations, they will put more strain on infrastructure, support resources, and academic workload.

Learning analytics

LA is a discipline at the intersection of data analysis and learning sciences, allowing students to reclaim decades of educational research as a valuable daily practice (Akhtar et al., 2017). LA is an educational application that combines sophisticated technological techniques such as information retrieval, machine learning (ML), data visualization techniques, and statistical algorithms to uncover complex data and support teaching (Khousa et al., 2015). Society for Learning Analytics Research (SoLAR) defines LA as collecting, analyzing, and reporting big data about learners and their behaviors to understand learning and the environments in which it occurs (Liu et al., 2017).

The benefits of LA adoption are highlighting students' problems, improving pedagogical strategies, providing a personalized learner experience, and predicting future performance (Liu et al., 2016). According to Jantti and Heath (2016), LA is a subfield of Technology-Enhanced Learning (TEL) research concerned with the educational application of big data analytic techniques that use intelligent, learner-produced data and analysis models to uncover meaningful patterns. LA uses educational technologies, methods, models, and algorithms to convert large amounts of educational data into useful information (Ifenthaler & Widanapathirana, 2014). It is a five-step process engine: the capture of learning actions, report, predict, act, and refine. Finally, the LA tasks are a set of tools in a smart classroom that establish indicators of teaching quality and student engagement (Aguilar et al., 2017).

LA follows a data-driven cycle from engaging students in learning, generating data, and processing it into interventions (Chou et al., 2017). It results from two convergent trends: the increased use of learning management systems (LMS) in educational institutions and the application of artificial intelligence (AI) and data mining techniques. In addition, LA assists institutions with resource allocation, student success, and financial management. These institutions collect data for analysis and make predictions to set actions. Consequently, this data-driven decision-making interprets data to inform educational practice based on objective data rather than stereotypes (Liu et al., 2017). It combines principles from various computing disciplines with those from social sciences, pedagogy, and psychology (Aguilar et al., 2017). Finally, big data opens up new opportunities to support personalized learning based on data rather than rules.

Educational data mining, teaching, and academic analytics

This section discusses how LA interacts with other related fields. Many of the same methodologies are used in Educational Data Mining (EDM) and LA. LA focuses on the human interpretation and visualization of learning data, while EDM focuses on automated methods for extracting information from massive sets of learning data rather than on pedagogical issues (Kennedy et al., 2013). Researchers have identified EDM as a method for developing student models, and LA has gained insights into the effects of pedagogical support on learner achievement (Akhtar et al., 2017). Finally, the LA and EDM communities form a method ecosystem with similar goals and focus where learning science and data-driven analytics intersect (Papamitsiou & Economides, 2016).

Academic Analytics (AA) is more general than LA. AA is concerned with data analysis at the institutional or national level, whereas LA is concerned with the learner process, course, or faculty level (Olmos & Corrin, 2012). Furthermore, LA refers to collecting and analyzing data in educational settings to inform decision-making and improve learning. In contrast, AA refers to the process higher education institutions (HEIs) use to support operational and financial decision-making (Lawson et al., 2016). Finally, AA uses learner, academic, and institutional data to improve organizational procedures and resource allocation (Akhtar et al., 2017). In addition, teaching analytics (TA) necessitates instructors' educational data literacy to analyze and improve course design and empower educational data literacy. It is the ability to accurately observe and respond to different types of data in order to improve teaching and learning. Finally, LA provides a method for analyzing how students interact with learning resources, with one another, and their teachers (Goggins et al., 2016), allowing for self-reflection and feedback.

Related reviews

We summarize previous LA literature reviews in this section. Avella et al. (2016) described an overview of methods (visual data analysis, social network, and semantic analysis), benefits, and challenges of using LA in HEIs in a systematic literature review. Khalil and Ebner (2016) examined articles from LAK conferences and described a survey of different methods (data mining, visualization, social network analysis) supporting that emerging for LA to define its research methods, objectives, and challenges in a meta-analysis study. Furthermore, Papamitsiou and Economides (2016) reviewed the LA effect of adaptive learning. An examination of empirical evidence using 40 experimental case studies using non-statistical methods is carried out. This study's most common data mining methods are classification, clustering, and regression. The field's goals are behavior modeling, prediction, and self-reflection. Finally, a systematic review of 39 empirical studies on predictive LA (Shahiri et al., 2015) presents findings. The goal is to determine which methodologies are effective in which situations.

Research questions (RQs)

Empirical evidence is necessary for theoretical models to adopt LA in the scientific, academic, and industry communities. A search of the relevant literature yielded no large-scale reviews of empirical evidence, which was our motivation. Our contribution is to draw attention to this research gap. As a result, the selected articles were studied, filtered, and compared to extract research questions and results. The following RQs guide this review:

- RQ1: What, why, and for whom is critical in LA?
- RQ2: What are the methods for effectively implementing LA?
- RQ3: What are the difficulties in LA adoption?

Method

Research design. We followed the PRISMA framework (Page et al., 2021) for our review. Extensive research on the literature on LA was conducted for this review to understand and document current trends in the LA domain. The following selection criteria were used. The search term "Learning Analytics" was primarily used in the candidate articles' titles, abstracts, and author keywords. The searches were restricted to articles published in leading journals in English, excluding conferences.

Article selection process. Following a systematic search of the articles, 390 initially met the criteria, intending to detect as much relevant literature as possible. After thoroughly studying their abstracts and conclusions, we selected 118 papers covering critical LA principles, excluding duplicates and conference proceedings. The selected group of 118 empirical articles was thoroughly studied and analyzed.

The remaining articles were excluded because they could not be used to answer the RQs and the quality of the study (e.g., articles that do not present empirical data). Spreadsheets were used to organize and analyze our data (we used non-statistical methods) and summarize the articles' findings to create clusters that will lead to significant dimensions of LA. The following information was extracted from each article based on our RQs: Grade level of education; Target course; LA technique; Type of intervention; Stakeholders; Classification of the study type.

Results

The dimensions of LA. This section presents the findings as a list to answer the RQs, including the critical LA perspectives discussed in the 118 evidence-based articles. The analysis includes the pattern of definitions and significant views. Our bottom-up comparative analysis of the selected literature resulted in a classification scheme describing LA.

Object of analysis (RQ1)

The primary consideration for LA is educational data capture, collection, and organization. This can include helpful information about students, institutes, and instructors from qualitative and quantitative analysis methods. Passive data is collected using sophisticated tools that do not require input from learners (Akhtar et al., 2017). Historically, HEIs have collected active data, frequently more useful for AA. Dynamic student data includes behavioral, engagement, interaction, and assessment data (Hsiao & Lin, 2017) and can be considered a measure of a student's performance. E-assessment activities, social learning tools, virtual learning environments (VLE), and student information systems are used to collect data. In addition, data from learning management systems (LMS) is a ready-made meaningful real-time data source for LA research. These traces at various scales connect learning actors and learner data (e.g., videos, tests, quizzes) with interaction behaviors (Ali et al., 2013). Students are sometimes reluctant to provide data for LA purposes (Ifenthaler & Schumacher, 2016). Furthermore, big data does not equal meaningful insights, so we must select meaningful data types to ensure a good signal-to-noise ratio. Finally, data preprocessing is a challenge to ensure data quality and extract sophisticated metrics for analysis.

Data processing technology (RQ2)

This section examines the processing for the LA parts, such as data mining, aggregation, and clustering. Data processing methods are concerned with the backend of LA, whereas input data is meaningless unless processed. Specifically, ML methods build a model from a set of instances, attributes, and classifications that can be used to predict new classifications for cases with similar characteristics. ML interprets big data instead of humans using supervised (regression, classification) or unsupervised (clustering, association) models. ML can provide new concepts in human learning, LA, and cognitive science, improving student personalization and learning outcomes. The most common ML analyzing methods are subgroup discovery, Bayesian network knowledge, Nave Bayes Classifier, artificial neural networks, support vector machines, and text mining. Finally, natural language processing techniques are used to analyze and discover course concepts, such as qualitative data collection and text analysis, to uncover hidden patterns within online student comments, essays, and discussions. Finally, we identified the following LA categories based on data processing: Social LA, content analytics, and visual LA.

Target of intervention (RQ1)

From a pedagogical standpoint, we investigate the benefits of the front end of LA, such as personalized learning, student engagement and commitment, motivation, self-regulated learning (SRL), and actionable feedback. Student engagement, as an indicator of participation in educational activities, refers to the amount of time and effort students devote to their academic lives, and it is linked to how students feel and behave (Pursel et al., 2016). Commitment has two dimensions: the first is related to the student's participation in the learning process, and the second is related to the student's responsibility and willingness to participate (Iglesias-Pradas et al., 2015). In addition, motivation is a complex personal psychological trait that cannot be measured directly. It is dynamic and can change depending on an individual's emotional state, self-confidence, or teaching support (Nistor et al., 2015). Then, SRL is a cognitive procedure in which learners manage complex learning activities to achieve academic goals (Kim et al., 2016). Students must learn to locate what they require as part of the do-it-yourself skills necessary throughout their careers. Finally, feedback is required for students to understand their performance and the benefits and drawbacks (Sedrakyan et al., 2014). Feedback is informative if two conditions are met: it is predictive and allows for intervention (Tempelaar et al., 2015).

Predictive analytics examines historical data to predict what may occur as early warning signals for student reflection and regulation (Chou et al., 2017). When the outcome is meaningful and adds real value to the process of knowledge, enhanced personalization of learning and timely feedback benefit learners. Furthermore, collaboration entails exchanging ideas and skills between students with diverse interests to achieve a common goal. Approaches that stimulate and enrich collaboration are required in collaborative environments. Computer-supported collaborative learning is a learning strategy in which technology facilitates student collaboration. There is a need to make courses more collaborative to support teachers and motivate students, such as through conversational agents. This section identifies available intervention and recommendation mechanisms, such as dialogue-triggering mechanisms, recommendations on what activities students should participate in based on their progress, and the detection of students at risk of failing.

Stakeholders (RQ1)

LA results from two converging trends: the increased use of VLEs in educational institutions and the application of artificial intelligence (AI) and data mining techniques. In addition, LA is an interdisciplinary field that promotes better pedagogical practices and benefits stakeholders (students, instructors, and institutions) by fostering communication among them. Specifically, LA assists institutions with resource allocation, student success, and financial management. These organizations collect data for analysis and make predictions to establish insights. About LA stakeholders, the focus in the relevant literature is on (Hlaoui et al., 2016):

- **Student** level: triggers students' SRL skills, interaction, and retention; respects diverse ways of learning (formative assessment, differentiated learning).
- **Instructors** level: course monitoring systems, learning design, actionable decision-making, adapting teaching strategy, quality of courses; Increase the teachers' analytical skills to implementing LA activities.
- **Institution**-level (policymakers, administrators, researchers): resource allocation and evidence-based decision-making; Institution's autonomy and accountability.

The findings revealed that most LA research study participants (n = 96) were from HEI, which could be because higher-education students are more accessible to researchers. Other studies (n = 18) looked at secondary school students.

Ethics (RQ3)

Ethics are shared principles that help people distinguish between what is right and what is wrong. The classification of the LA ethical issues (Tzimas & Demetriadis, 2023), i.e., data location and interpretation, informed consent, privacy, data management, classification, and storage, is of great concern in the LA community. These issues may deter learners from participating in learning activities that do not address them adequately. Drachsler and Greller (2016) refer to learners' right to be forgotten, related to data minimization. Guidelines to protect the data from abuse must be developed to use educational data for LA in an acceptable and compliant manner and overcome the fears associated with data aggregation and processing. Specifically, the PANDORA checklist was created to support this new learner contract as the foundation for a reliable LA implementation (Tzimas & Demetriadis, 2021a). Managers and policymakers could consider the PANDORA checklist when planning the implementation of LA solutions. Furthermore, Tzimas and Demetriadis (2021b) support that learner-centered LA is a valuable tool that students own and control and is used transparently within a trust framework. Finally, learning data will not be used to stereotype learners or other stakeholders negatively.

Discussion and conclusions

We notice that the LA research community is increasingly focusing on LA year after year, with a significant increase in published articles. This review is significant because of the large sample size of 118 studies, while the findings make this review generalizable. Although LA depends on specific methods, metrics, and tools, the only LA solution may be a holistic solution that transforms learning and teaching for learners, educators, and administrators (Prasad et al., 2016). LA offers data-driven tools to assist instructors in making pedagogical decisions. Furthermore, LA will most likely be driven by administrators seeking less deceleration and higher graduation rates and students seeking more efficient learning. The responsibility for the learning procedure should be balanced among educators and learners. LA advancements highlight a high tension between data mining (analytical component) and pedagogy (learning part). There is a valid dialogue that big data alone cannot improve teaching and that more pedagogical research is required (Koh & Choi, 2016). Finally, educational agents think of big data as a quantitative shift, but a qualitative shift necessitates a transformation in educational methods.

Concluding, we wrote this review as a roadmap for a vivid dialogue on rethinking the nature of LA. LA provides opportunities to support learners but poses challenges that should not be overlooked. More empirical research is required to gather solid evidence from practitioners, industry, and researchers to develop the intersection of theory, data, and practice.

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