The added value of Learning Analytics in Higher Education

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Abstract—Learning Analytics (LA) is a field of research and practice that uses data analysis to comprehend and optimize learning and the environment in which learning takes place. As an AI tool in higher education, LA is expected to improve student learning and support the academic community in teaching delivery, institutional management, long-term research and development, innovation, data-driven decision-making, and more. We have conducted a literature review to explore these issues and examine the added value of LA in higher education. We have focused on the key issues that educational institutions need to consider to get the most out of LA use. The findings of this review reveal that the proper use of the LA toolkit can enhance the development of an appropriate educational environment through the careful determination of ethics and policies that support the main institutional objective, and the study of opportunities, challenges, and trends in the sector. The key challenges of using AI tools like LA in Higher Education are data privacy and protection, data ownership, data heterogeneity, potential biases in AI algorithms, and the need for alignment of institutional strategies for LA with pedagogical approaches. The trends highlight the current advances in LA that give added value in higher education.

Keywords—Artificial Intelligence, Challenges of Learning Analytics, Date-Driven Decision Making, Data for Learning, Higher Education, Learning Analytics, Trends of Learning Analytics

I. Introduction

Artificial Intelligence (AI) is an upgraded technology tool that promises to transform higher education leading to changes in the educational paradigm, such as the optimization of teaching methodologies, the adaptation of learning to students' competences [1], and the automation of administrative processes, [2].

Higher Education can be supported by AI through different methods including the implementation of intelligent tutoring systems [3], the application of natural language processing for student feedback analysis [4], and the application of machine learning algorithms for the prediction of students' performance, [5].

Learning Analytics (LA) applies data analytics to Higher Education, [6]. 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 environment in which it occurs", [7]. LA is a data-driven field that uses techniques such as statistical techniques, data mining, machine learning, and visualization to improve decision-making, [6]. LA provide upgraded data analysis to reveal patterns of student behavior, predict student performance, predict personalized learning needs, and support curriculum development, [6]. However, more evidence is needed on the provided results of LA such as the improvement of learning outcomes, the support of learning and teaching, their broad deployment and their ethical usage, [8].

The use of LA in Higher Education, as all the new technologies and tools, have significant benefits like LA enhanced innovation, personalized learning, the analysis of learning behavior, the provision of immediate feedback, the prediction of student performance, the evaluation of learning theories, and the development of learning applications. Nevertheless, there are points like a) concerns over students' data privacy [9], b) the correct use of data due to heterogeneity to draw safe conclusions, c) the need for significant investment [10], and d) potential biases in AI algorithms [11] that require special attention. Practical strategies and policy frameworks should be considered to deal with these issues and ensure fairness, transparency, and accountability, [11], [12].

This paper aims to demonstrate the added value of LA tools in higher education and to identify priorities to maximize their impact in any education system. Due to constraints of time, cost, and stakeholder effort, is essential to determine the appropriate LA tools for each education system. The use of LA tools in teaching, institutional management, research and development, data-driven decision-making, dropout management, or student academic support is already a reality in universities. The paper also focuses on the opportunities and the challenges, which must be addressed by the academic community to exploit the benefits of LA and on the current trends of LA, which highlight the directions of practical use of LA by all stakeholders. Previous literature reviews have examined each of the above-mentioned issues. In this paper, we explore contemporary studies and reviews in an attempt to combine these issues and suggest new directions for LA in higher education.

The remainder of the paper is structured as follows: Section 2 presents the methodology of the paper; Section 3 discusses the AI techniques used in LA; Section 4 discusses the ethics and policies created in academic environments; Section 5 analyses the opportunities that LA offers to higher education and the challenges that should be faced; Section 6 focuses on the role of LA in decision making; Section 7 mentions the trends of LA in higher education; Section 8 includes the discussion of the main findings and finally, in Section 9 the conclusions are given.

II. Methodology

This study is a literature review that tries to identify the added value of LA tools in higher education. Key words and search strings, like, “Learning Analytics”, “Artificial Intelligence”, “AI”, “Higher Education”, “HE”, “Higher Education Institutions”, “HEI”, “challenges”, “opportunities”, “added value”, “trends”, “advances”, “and review”, among others, combined with “AND” or “OR” Boolean operators, are used to search different databases, including JSTOR, ScienceDirect, Web of Science, and Scopus.

Furthermore, the specific key phrases are used to search Google Scholar to locate relevant publications from various international journals and conferences. Multiple systematic reviews [13], [14], have demonstrated the importance of selecting studies that are indexed by reputable libraries. In this vein, the analysis incorporates journals with an H-Index of 20 or higher after searching Scimago Research Centers Ranking for the journals hosting the publications. The H-Index is a measure of scientific output at the author level based on publications and citations and, subsequently, contribution to science and scholarly activities; the higher the index, the more distinguished the journal and its contributors are.

Examples of international journals with high H-index, which have published articles studied in this review are the following: Computers in Human Behavior, Computers and Education, Decision Support Systems, Journal of Learning Analytics, Higher Education Analytics, Educational Technology Research and Development, Journal of Educational Technology, Journal of Interactive Online Learning Journal, Journal of Computer Assisted Learning, Journal of Computers in Education, International Journal of Advanced Computer Science and Applications, Studies in Educational Evaluation, Assessment and Evaluation in Higher Education, Journal of Interactive Online Learning, Journal of University Teaching and Learning Practice.

Following the application of an eliminative procedure, a total of over fifty papers—covering scientific publications, and official and administrative reports, —were chosen.

III. AI Techniques for LA

Although researchers investigate the application of AI in education at least three decades ago [15], [16], [17], recent studies state that AI is the most recent stage of digital transformation in higher education, enabling the “smart university” evolution. AI has provided the application of new practices for learning and teaching at any level of education, [17]. LA and Educational Data Mining (EDM) are two data-driven fields that represent AI in education. Some researchers consider LA and EDM as different disciplines with some common goals [15], while others consider LA and EDM as overlapping disciplines, [18]. EDM applies machine learning, data mining, and statistics to educational tasks, focusing mostly on the technical issues, while LA mostly concerned educational perspective, [15].

Some popular LA techniques that contribute to Higher Education are the following:

1) Statistics: Analyzes and explains educational data, [18], [19], [20].
2) Visualization: Provides data representations using graphs to make results understandable, [18], [19], [20].
3) Machine Learning (ML): Predictive modeling identifies at-risk students early, while clustering groups students based on learning behaviors for targeted interventions [15], [17], [19], [20], [21]. Examples of predictive models are Decision Trees, Neural Networks, Random Forest, Bayesian Classifier, K-Nearest Neighbor, Support Vector Machines, Logistic, and Linear Regression, and k-means clustering, [15], [18].
4) Recommender Systems: Suggests relevant learning re-sources and peer collaborators based on individual preferences and learning history [15], [18], [20], [21].
5) Knowledge tracing: Estimates students’ knowledge on a topic, employing a cognitive model and logs of students’ responses [18], [20].
6) Deep Learning (DL): Recognizes complex patterns in student data and analyzes visual data for engagement assessment [15], [17].
7) Data Mining (DM): Identifies patterns and relationships in large datasets, informing instructional strategies and discovering associations between variables. Text mining,

relationship mining, and process mining are also reported by [18], [19], [20], [21].

8) Social Network Analysis: Analyzes the structure and relations of students' collaborative activities, [18], [19], [20].
9) Outlier Detection: Detects values out of the expected range. Students with extreme performance are easily noticed, [18], [19], [20].

IV. Ethics and policies of LA in Higher Education

A. Ethics

Important questions emerge about what is being assessed, the reasons for its significance, its impact on learning, the ethics of extensive monitoring, and the moral implications and advantages of personalized learning or enforced social interaction. Crucial topics for thorough debate and critical examination are the ethics of AI, some of which are the following, [22]:

1) Privacy: Ethical concerns include the accumulation of private data, and the authorized access to such data.
2) Control human behavior: Algorithms may produce information that influence the behavior of particular individuals.
3) Transparency and accountability: AI decision support systems and predictive analytics produce outputs without human intervention and without identifying clearly their reasoning.
4) Autonomy: Issues that arise in autonomous systems include the determination of the person who controls and the person who is responsible of the system.
5) Fairness and bias: AI systems may preserve bias that preexisted in the data, may include cognitive bias, and may produce bias when use a dataset for a different kind of issue than the initial one.
6) Singularity: The ability of AI systems to develop other more intelligent AI systems is called singularity. A question is if singularity is a science fiction or there is a low possibility to occur.

A systematic literature review that examines the ethics of LA is conducted in [23] and also analyzed in [24]. Some common ethical issues related to LA, include privacy, transparency, responsibility, consent, minimizing adverse impacts, validity, and enabling interventions. Some researchers consider privacy as a general category, while others focus on aspects of privacy, such as data ownership and control, transparency of data collection, usage and third-party involvement, anonymization of individuals, etc., [24].

Some of the above issues are analyzed in the next section.

B. Policies

Policies have been developed to highlight the need for higher education institutions to enhance the implementation of learning analytics within legal and ethical boundaries. However, there is a shortage of policies specifically designed for learning analytics to address privacy and ethics issues. A considerable study [25] identifies eight policies related to learning analytics. The authors argue that these policies cover four key areas in higher education: Strategy (including goal setting, methods, impact evaluation, validity assurance, communication and support, and user roles), Obligations (both legal and organizational), Privacy Protection (covering data anonymity, informed consent, and opt-out options), and Data Management and Governance (addressing data handling processes and access). The widespread acceptance of learning analytics policies fosters a supportive environment in higher education for adopting learning analytics and other beneficial AI tools.

V. Opportunities and challenges

A. Opportunities

Enterprises exploit data on customers' purchasing behavior from e-commerce websites to predict future purchases. Similarly, institutions can utilize LA to predict student performance in new courses, providing enhanced learning opportunities, [26].

This new evidence is being explored to reshape the way education responds to the needs of individuals. It is indicated that "these educational datasets offer unrealized opportunities for the evaluation of learning theories, learner feedback, and support, early warning systems, learning technology, and the development of future learning applications", [27].

LA can be used for student assessment through monitoring and analysis of learning behavior, providing feedback, predicting academic performance, and providing new assessment forms [28]. Technology-rich environments pose opportunities for innovative forms of assessments. For instance, stealth assessment is a continuing, embedded form of assessment that collects process data during various student activities such as gaming, interactions in forums, and virtual laboratories. This form of assessment can provide more accurate information on students' authentic skills and competencies, [28].

In parallel, a SWOT analysis has been developed for LA and educational data mining research, [29]. More specific, the authors identified a list of opportunities, including the development of generalized platforms through the exploitation of Open Linked Data to achieve data standardization and compatibility among various applications, and the transfer of LA outputs to other data-driven systems to support decision-making.

B. Challenges

Even though LA is crucial for the Higher Education revolution, we must consider several challenges as the following:

1) Data and database heterogeneity, as many data need

significant processes to be useful, [30]. Objectives like country, socioeconomic backgrounds, sex, age, and level of education system compose part of the picture. As education managers attempt to build a database of key components to plan a growing education program, data collection can be at a stretch. Moreover, data should be delivered timely and accurately to support educators during student evaluation, [31].

2) Data ownership, as the source of it and the way that data has been collected, used, and stored are crucial issues [30]. Who is the legal owner, how data is passed on hands, and how is used, are questions with tremendous meaning for the outcome. Many times, educational institutions pointed out that many of these resources create an additional cost when budgets are already stretched and at the same time, they need consistency in data and between systems, but a level of flexibility must be allowed as well. Institutional strategies should take into consideration data ownership issues, [32].

3) Data privacy, data protection, and legal issues about transparency, access, and use of data require strong guidelines, [15], [30], [31], [33], [34]. Researchers in [35] found that institutions were concerned about students' privacy, confidentiality, and their right to informed consent. As reported in [36], when studying the role of students, there was evidence that students were not aware of what LA is, where there was the source of data for their institution, and at what level. Their response had dual feedback, either with a sense of collaboration or reluctance and denial. Data anonymization can secure and protect sensitive data, [15].
To achieve the goal of data protection, the use of an ethical code based on six guidelines has been proposed, [37]:
   a) LA should operate as a moral practice with the aim rather to understand than measure.
   b) LA should adopt a student-centric approach, treating students as collaborators.
   c) Data on student identity and education performance should have an expiration date and be deleted at the student's request.
   d) We should consider that student performance depends on various factors and the collected data are incomplete, noisy, and biased.
   e) Institutions of Higher Education should allow visibility of the purpose of data usage, the persons who access data, and the measures of identity protection.
   f) Recognize the value of LA and its contribution to learning.

4) Potential biases in AI algorithms. For example, students' demographics may be used to predict the performance of other groups of students with similar characteristics such as gender or race. This results in systematic errors, so students take the blame even though there is a fault in instructional design, [38]. Furthermore, researchers [39] found that teachers exploited data to produce potentially biased categorizations of students. Finally, it is necessary to create "communities of practice", where teachers can exchange their experiences, exploit best practices, and perform research concerning the use of LA tools, [40].

5) Challenges related to institutional strategies and policies, such as the limited support of leadership in LA activities [25], the inadequate staff training on LA skills [25], [30], and the lack of LA-specific policies, [25]. A significant strategic issue is the lack of pedagogical approaches. Although LA seems to revolt against the way people learn and teach, LA strategies do not always include pedagogical approaches [25]. Researchers in [41] studied under what conditions a particular institution makes decisions based on LA and found that the institution may ignore basic pedagogical plans in the process of addressing technical challenges. At its core, LA in education supports the above system only if the deliverable work is helpful for all parts (students, educators, and management), and fosters a climate of cooperation, development, and innovation. In any case, LA has a role of a tool and human use is a significant factor in the equation.

VI. The Role of LA in Making Decision-Making

In the field of decision-making, it has been proposed an open research agenda for LA and advanced decision-making in higher education [42], covering various topics such as LA as AI primers, social constructs, enablers of smart education, Key Performance Indicators (KPIs), and decision-making tools. It's recommended a four-layered framework for a holistic approach to designing, operating, and monitoring LA strategies. This framework consists of 1) Technology Components, the foundational level including essential technological infrastructure; 2) Information Integration, where methodologies and strategies combine different types of educational data; 3) Educational Analytics and KPIs, where learners' behavior is analyzed using data mining, social network analysis, and sentiment analysis; and 4) Interface, the top level focusing on advanced educational decision-making and policy-making.

The decisions that educational institutions should make mainly concern the management of their resources, the selection of appropriate tools to have the most efficient and faster completion of procedures, the support of students according to their needs and the desired results, etc. [43]. For example, universities, worldwide are increasingly turning to LA to identify and intervene with at-risk students, [44]. Numerous peer-reviewed publications evaluate the effectiveness of LA interventions in higher education, focusing on student success and retention [2], [26], [28], [45], [46]. Therefore, the current demand for LA in the higher education sector may be based on scant empirical evidence of its effectiveness, [29].

Using LA in higher education also aids educators in monitoring and motivating learners, identifying undesirable learning behaviors and emotional states, and making quicker data-driven decisions, [43]. A key consideration in decision-making today is that interventions should target both student behavior and activity, as well as the existing educational facilities, emphasizing the need for a more holistic view of student growth.

It has also been found [47] that the crucial characteristics during the identification of at-risk students are students' academic history, engagement with feedback [48], first-year grades [49], academic performance [26], [28] and socio-economic disadvantage, [44]. Online student activities can be tracked, such as mouse motions and clicks, online chats, participation in discussion forums, and even visual and facial reactions, [6]. At the same time, educators and administrators may unlock big data potential and make faster and safer decisions. Having a successful organizational adaptation depends on employee support and enthusiasm for proposed changes. These findings suggest that the field is progressing, and we should build on the existing data rather than reinvent the wheel, making wise use of tools like learning analytics.

VII. Trends of LA in Higher Education

The integration of AI into LA significantly enhances higher education by creating personalized learning experiences tailored to the needs, preferences and learning styles of individual students, as well as instant feedback mechanisms that help students monitor and improve their progress in real-time. This kind of experience encourages students to participate actively in the learning process and allows them regulating their own learning speed, leading to a more dynamic and supportive educational environment [18]. LA also reveal at-risk students early, giving teachers the opportunity to intervene and provide effective support, improving retention and success rates, [16], [44].

Learning analytics (LA) in higher education provides significant value, enabling data-driven decision-making that supports student success, curriculum development, and resource allocation. Through detailed information on student engagement, progress, and achievement, LA enables teachers and administrators to improve academic programs and improve student support systems. By analyzing patterns in student behavior, course completion rates, and performance metrics, institutions can identify areas for curriculum adjustments and targeted interventions, promoting a more flexible and effective learning environment [43]. LA also boosts foundation efficiency by automating time-consuming tasks such as attendance tracking, task scoring, and scheduling. This automation frees up teachers to focus more on teaching and individualized student support, which positively impacts student learning experiences and outcomes. In addition, by analyzing data on classroom usage, course enrollment, and material needs, AI optimizes resource allocation, ensuring facilities and resources effectively match demand, [50].

Furthermore, LA can enable continuous monitoring and feedback, supporting higher education institutions to dynamically adapt and improve their provided programs. The ability of rapid adjustments of teaching strategies and curriculum content can keep educational practices updated and effective. As a result, LA can boost the quality and competitiveness of educational institutions, [50].

Learning Analytics (LA) leverages AI to significantly enhance accessibility and inclusion by offering tailored tools and resources to meet the needs of students with diverse learning requirements. For example, AI can support students with disabilities by providing adaptive content, such as text-to-speech for visually impaired learners or language support for non-native speakers, creating a more equitable educational experience. These personalized adjustments foster a learning environment where all students have the support they need to succeed, [16]. AI also facilitates lifelong learning by providing students with continuous access to tailored educational resources. This allows individuals to review learning materials, practice skills and keep abreast of new knowledge even after completing their formal education, fostering a culture of continuous self-improvement and skills improvement, [17].

Considering short-term trends of LA in higher education, universities should provide students with tools that enable active learning and self-regulated learning. For example, LA dashboards is a platform that displays comprehensive visualizations of student learning progression, based on descriptive or predictive analytics. LA dashboards can result in an increase of student engagement, facilitating the adjustment of their personal pace of learning, [51]. An approach of LA dashboard that support students to self-regulate their e-book learning activities in a blended learning environment is proposed in [52].

On the other hand, long-term trends in LA focus on individualized assessments and support. Teachers and administrators can examine data from large numbers of students to more accurately identify those who need support, [18]. In addition, predictive analytics can improve the identification of students who are likely to drop out, enabling targeted interventions to help them stay in university. Through the analysis of existing data from multiple students, predictive models can be created to alert students at risk of not achieving their learning goals, [53].

Moreover, LA enhances research capabilities by providing advanced tools for data analysis and predictive modeling, driving innovation in educational technologies and methodologies. There do exist numerous examples of popular analytics tools that have been developed by groups of researchers, [54], [55], [56]. Is also given a list of free analytics tools [20] that can use public datasets, and a list of tools that use specific educational data and are used to solve specific problems. Based on that same study, the goal of developing freely available general-purpose LA tools that can solve various educational problems has been partially achieved.

Additionally, LA can be utilized to extract useful results concerning self-regulated learning from students' online traces of activity, [19], [24], [57]. Self-regulated learning assists students in regulating the learning process independently, given the learning plans and goals. Three phases are defined, i.e. before, during, and after learning. Before learning, the learning motivation is determined. After learning, self-assessment and self-reflection occurs, [57]. Students can benefit from real-time feedback and critical self-reflection on their learning progress and goals, which enhances their self-organization skills, [18], [58].

Explainable AI for LA [59], [60] has become popular very recently, as a solution to the extensive use of Machine Learning algorithms in various LA applications. Explainable AI attempts to give comprehensive interpretations to decisions provided by Machine Learning models, offering personalized guidance to students [59], feedback through dashboards [51], information to teachers concerning students' capabilities [15], etc. A crucial issue is to ensure predictive models' stability throughout the years, especially when predicting student performance based on historical data.

VIII. Discussion

The added value of LA in higher education is multi-dimensional. The literature review presented in this paper, reveals the areas of the main contribution of LA in higher education, which include personalized learning, data-driven decision-making, administrative efficiency, ethics and policies establishment, research, and innovation. In the following, we discuss these findings.

LA tools provide critical insights that enhance personalized learning experiences, allowing educators to tailor instruction to individual student needs, preferences, and learning styles. This personalization not only fosters deeper engagement but also allows students to progress at their own pace, improving overall learning outcomes.

LA contributes to data-driven decision making. Using LA methods and tools, large amounts of educational data are analyzed to provide teachers and administrators with a deeper understanding of student achievement, curriculum adequacy, teaching methods effectiveness, and resource allocation. These findings direct strategic planning, taking into account that educational practices are continuously adapted and updated to satisfy the evolving educational goals.

At the same time, LA improves administrative efficiency by automating routine processes, allowing teachers to focus more on teaching and mentoring students. The result is better educational outcomes and more efficient management of institutional resources.

In addition, LA promotes ethical and inclusive practices, supporting equity and ensuring that all students benefit from AI-based information. The value of LA extends to the early identification of at-risk students, facilitating the delivery of targeted interventions to improve retention and success rates. By monitoring student behavior and performance in real-time, universities can provide the necessary support to the students who need it most, creating a supportive and adaptable learning environment.

LA also enhances universities' research capabilities by providing advanced tools for data analysis and predictive modelling. This innovation contributes to the development of new educational technologies and methods, better preparing students for future challenges.

The findings of the conducted literature review also shed light on LA difficulties and challenges that should be addressed. Data and database heterogeneity may cause difficulties during data collection and cleaning. Data ownership must be considered when developing institutional strategies. Data privacy and protection issues are also crucial since students are usually unaware of the tracing methods. AI algorithms should be carefully used to avoid large biases that may influence educators' judgment concerning students' performance. Moreover, institutional strategic planning for LA often ignores the development of pedagogical approaches.

Finally, recent advances in AI-driven LA have been found. The latest research interest concerns the utilization of LA for students' self-regulated learning. Online data are analyzed to evaluate learning motivation, learning management, and self-assessment. Another promising discipline is the Explainable AI in LA, which enhances stakeholders' trust in the LA results when ML models are adopted. Different applications of Explainable AI have been developed for various LA activities, [60].

IX. Conclusion

In this paper, we investigated the application of LA tools in higher education aiming to shed light on the contribution of LA to different dimensions of academic environment such as teaching, learning, administration, and research. We conducted a literature review, aiming to examine the opportunities, challenges, and trends of LA in higher education, and evaluate the results to drive conclusions on the added value of LA in higher education. This paper contributes to the examination of recent reviews and studies and the combination of their findings to reveal that the added value of LA in higher education is extensive and transformative. LA not only improves the quality and effectiveness of educational practices but also ensures that these practices are equitable and responsive to the needs of all stakeholders. As institutions continue to integrate LA into their operations, the potential for even greater improvements in student outcomes, institutional efficiency, and educational innovation will only increase.

Our study has some limitations. Firstly, the literature list is non-exhaustive. We have selected over fifty papers published in recognized international journals and conferences with a high H-Index, mainly from JSTOR, ScienceDirect, Web of Science, and Scopus, using predefined keywords and search strings. Therefore, some significant relevant papers may be omitted. Another limitation is related to the potential subjectivity of the authors' viewpoints expressed in the examined papers, which is difficult to be avoided.

In the future, we intend to conduct a systematic literature review to evaluate the contribution of LA in higher education, reducing bias in selecting existing literature. Additional future research can include empirical studies concerning the utilization of LA tools in academic environments.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The authors wrote, reviewed and edited the content as needed and they have not utilised artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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