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RESEARCH ARTICLE

Investigating the Potential and Challenges of Learning Analytics Tools in Brazilian Education Through Developer Insights

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ABSTRACT Learning analytics (LA) tools hold promise for transforming educational practices, providing insights into student performance, and aiding instructional planning. Despite the growing body of literature, the integration of these tools into daily educational processes remains a complex challenge. Latin America has experienced a significant expansion in its literature on Learning Analytics, with Brazil being one of the most important exponents. This study investigates the viewpoints of developers behind learning analytics tools in Brazil, in order to understand their perceptions about the potential and limitations of the tools. Using a multiple case study design with a qualitative approach, we conducted in-depth interviews with six developers actively involved in creating learning analytics solutions. Our findings reveal three overarching categories: (i) Functionality of the Learning Analytics Tools, which includes applications such as predicting dropout risks, automated feedback, and didactic course planning; (ii) Motivations and potentialities, highlighting integration with academic systems and the facilitation of pedagogical interventions; and (iii) Limits and barriers, identifying challenges from socioeconomic, technical, and pedagogical perspectives. This research underscores the significance and potential impact of learning analytics tools in the educational landscape. As a next step, we recommend expanding the scope of investigated tools and further exploring the effective utilization of analyzed data, as well as assessing the overall effectiveness of interventions. This study contributes valuable insights to both the academic discourse on learning analytics and the practical implementation of these tools in educational settings, particularly within the context of Brazilian developers' perspectives.

INDEX TERMS Latin America, Brazil, learning analytics adoption, qualitative research.

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I. INTRODUCTION

Over the past two decades, we have witnessed significant changes in our communicative and social structures. Scientific and technological advances have given rise to a new form of society, the information society. This new social organization is based on the integration of people through digital networks that employ Digital Information and Communication Technologies (DICT).

This trend can be observed in different domains, including education. Although the use of DICT in the educational process is not new, its widespread adoption has become more evident during the COVID-19 pandemic. The need for social distancing to curb the spread of the virus has required the continuation of pedagogical activities through virtual means, mediated by digital technologies [1], [2].

The digital age has led to the expansion and improvement of computer systems, which includes managing the teaching and learning process. Learning Analytics (LA) has been collaborating with this process, using both static and dynamic data from students and their contexts to support decision-making in learning and teaching [3], [4].

According to the Society for Learning Analytics Research (SoLAR), LA can be defined as the "measurement, collection, analysis, and communication of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [5], a definition that is adopted in this investigation.

The benefits of LA include: 1) improving the efficiency of the overall institutional functioning; 2) strengthening the regulation of the teaching and learning environment, leading to positive impacts on practice; and 3) providing teachers with methods and tools to perform their tasks more effectively [6]. Learning Analytics draws on principles from various disciplines, including computing, statistics, social sciences, pedagogy, psychology, and education, as noted by [7] and [8].

Taking into account the above, LA can serve as a vital instrument for modifying learning projects and supporting teachers and managers in (re)planning, with the ultimate goal of improving pedagogical processes and improving learning outcomes. However, the implementation of LA tools is not without challenges, and it remains limited to a small number of institutions [9], [10], [11], [12]. Therefore, understanding the adoption of LA tools in educational institutions and how they help to make administrative and pedagogical decisions is crucial [13], [14].

Latin America has also experienced an expressive grown in this field, with Brazil ranking first in the absolute number of scientific papers related to LA in Latin America and fifth in scientific papers per million inhabitants [15]. This valuable academic contribution emphasizes the importance of adopting LA while being aligned with institutional principles and the learning design of disciplines [12].

However, despite the significant number of publications, the implementation of LA in the daily practice of the educational process is more complex. According to [14], the implementation of ICT in education in Brazil faces several barriers, such as i) lack of government investment, ii) insufficient digital literacy of teachers, iii) scarcity of human resources trained in handling technologies, and iv) disparities between public and private education. [16] pointed out that, even with large amounts of data collected about students' digital traces, most of the LA solutions implemented in Higher Education Institutions in Brazil still are of small scale. Taking into account the scarcity of empirical studies that examine the practical and real possibilities of using LA [17], this investigation intends to better understanding this aspect from the perspective of LA developer in Brazil. The following research questions are proposed:

- **RQ1**: Which are the characteristics of some Brazilian Learning Analytics tools under usage nowadays and how they relate to the literature of the field ?
- **RQ2**: How do developers of Learning Analytics (LA) tools in Brazil view the potential and limitations of these solutions?

Based on this problem statement, this study employs a qualitative approach with a multiple case study design conducted through interviews. The central objective is to understand the developers' perspectives on the application possibilities and limitations of LA tools developed in Brazil. The remainder of this paper is organized as follows. Section II presents the relevant literature on the implementation of LA in practice. Section III outlines the research methodology adopted in this study, and Section IV presents the findings of the analysis. Section V discusses the results in light of existing literature and experiences. Finally, Section VI concludes the study and suggests directions for future research while also highlighting its limitations.

II. RELATED WORKS

In recent years, there has been a growing body of research on Learning Analytics (LA), as evidenced by the works of [18], [19], [20], and [21]. However, there is a pressing need for further exploration of the practical implementation of LA, particularly in the context of higher education institutions. This necessity arises from the presence of various socio-technical challenges, as highlighted in the studies of [10], [12], and [22].

Despite the growing interest and research in the field, the impact of LA in the real world is still limited, particularly in Latin American and developing countries, where small-scale adoption predominates [15]. This phenomenon is attributed to the complex nature of educational systems, the emphasis on analytics over learning, high demands on technological infrastructure and resources, stakeholder engagement, and concerns regarding ethics and privacy of the data [23].

In the initial stages of its development, research in the field of Learning Analytics was predominantly concentrated in North America, Europe, and Australia. A pivotal turning point occurred in 2017 when [24] demonstrated that Latin

American universities had initiated the analysis of teaching and learning processes through Learning Analytics, albeit at a relatively small scale. Subsequent works emphasized the significance of comprehending Learning Analytics tools in Latin American countries, highlighting the region as promising for the field's advancement [25], [26].

Over recent years, various scientific initiatives have played a crucial role in fostering the growth of Learning Analytics in Latin America. Notable examples include the LALA project (Building Capacity to Use Learning Analytics to Improve Higher Education in Latin America) [27], the LALA conferences (Learning Analytics for Latin America) [28], and dedicated special editions in prestigious journals such as the British Journal of Educational Technology [29] and the Journal of Learning Analytics.[1] These endeavors collectively contribute to the heightened visibility and advancement of Learning Analytics within the Latin American context. As indicated by [15], Brazil holds a significant position in the region, leading in the number of published papers among the countries. Additionally, Brazil maintains robust collaborative connections, extending its partnerships not only within Latin America but also with countries on other continents.

In recent years, there has been notable growth in research focused on the adoption of LA, particularly within higher education institutions. The majority of these studies have mostly concentrated on the contexts of Europe, North America, and Australia (e.g. [30], [31], [32]). As an illustration, [33] conducted a review of 18 distinct Learning Analytics (LA) adoption frameworks, pinpointing five primary challenges encountered by teachers when incorporating LA in classroom settings. These challenges include: i) difficulties in integrating technical and pedagogical expertise in LA use; ii) a lack of connection between LA and educational theories or pedagogies; iii) the failure to align LA with teachers' practice; iv) ethical and privacy concerns; and v) the burden of additional workload and a shortage of time.

In Latin America, a discernible shift has occurred, characterized by an increasing number of studies exploring the adoption of LA in educational institutions. For instance, [12] investigated perceptions and concerns surrounding the adoption of Learning Analytics (LA) in four Latin American universities. The findings highlighted key needs associated with LA implementation, encompassing: i) a demand for quality feedback and data-driven support from teaching staff to enhance learning outcomes; ii) the necessity for data to inform support interventions; iii) a call for timely alerts from managers to better support struggling students; iv) the importance of meaningful performance evaluation of teaching quality; and v) the requirement for actionable information from staff to assess the effectiveness of support interventions. In the same direction, [34] delineates 13 significant themes addressing current obstacles in the practical application of Learning Analytics (LA) tools. The author proposes categorizing these topics into five main areas: i) data management; ii) administration and training; iii) pedagogical support; iv) data analysis; and v) legislation, privacy, and law. This data elucidates more concrete actions that can assist institutions in adopting LA, particularly by pinpointing the necessary institutional measures, the individuals involved, and their respective responsibilities.

In the Brazilian context, [13] investigated the expectations about LA from a Brazilian Higher Education Institution and considering three different stakeholder groups: students, teachers, and teachers assistant. Here, even though all participants agreed on the potential of LA to improve learning and personalized processes, they mentioned the need for simple and powerful visualizations, and suggestions of pedagogical actions by the LA tool as requirements for the adoption of LA solutions, and the risk of invading students privacy as one of their main concerns. Continuing within the context of Brazil, an initial survey carried out by [35] in the south and southeast regions with Higher Education Institutions (HEIs) revealed that only half of the participant institutions have implemented some form of Learning Analytics (LA) solution. Moreover, merely 6% of them employed these solutions systematically.

Given the prevalent challenges associated with Learning Analytics (LA) adoption in Latin America, coupled with its nascent implementation in Brazilian institutions, this paper aims to complement existing literature by delving into the challenges and possibilities of LA solutions in Brazil. The unique perspective offered here stems from the insights of the creators and developers behind these tools. As observed previously, much of the existing literature on LA adoption primarily focuses on the perceptions of students and teachers. To our knowledge, this work represents the first attempt to compile insights directly from the creators and developers of these solutions.

III. METHODS

The research paradigm encompasses the theoretical and practical frameworks that guide the constitution and execution of the investigation, leading to the production of new scientific knowledge. The choice of the research paradigm is not only determined by the research problem but also by the researcher's assumed intersubjectivities [36].

Based on the objectives and the chosen paradigm, this investigation is based on a qualitative approach. Qualitative research is ideal for studying subjective aspects of a certain group of participants, enabling a deeper understanding of a specific topic and allowing researchers to comprehend the complexity of the studied phenomenon [37].

Referring to the research methods, a qualitative approach using a multiple case study design was employed, and data were collected through semi-structured virtual interviews. The interview guide consisted of 17 open-ended questions (available at https://bit.ly/LAtoolsinterview) that aimed to explore the identification, functionality, data collection, analysis, and intervention of LA tools. The questions also addressed the participants' motivations, perceptions,

[1] https://learning-analytics.info/index.php/JLA/announcement/view/181

FIGURE 1. Steps in the interview script.

limitations, and barriers regarding the use of LA tools (see Figure 1).

The semi-structured virtual interviews were conducted remotely via the Google Meet web conference platform, and were recorded with the participants' consent during the months of January and February 2023. Once the recordings were collected, they were transcribed, and qualitative data was analyzed using the content analysis method proposed by [38]. Content analysis plays a fundamental role in scientific research, providing a robust methodology for exploring, interpreting, and understanding the content of different forms of human expression. Its application is broad, and its flexibility makes it a valuable tool for researchers seeking rich and contextualized insights [39], [40], [41]. It is widely used in educational research and can even be employed in mixed-methods research [42].

This method involves three stages: i) data preparation; ii) thematic coding and categorization; and iii) descriptive and/or comparative analysis. To facilitate qualitative analysis, statistical software tools, namely NVivo® (version 11) and Iramuteq® (version 0.7 alpha 2), were used. A sentiment analysis was conducted as the fourth stage to gauge the researchers' sentiments concerning their tools. Figure 2 illustrates the comprehensive methodology used in the study.

The research sample was composed of six Brazilian researchers who were actively engaged in Learning Analytics projects and had experience in research and development in Higher Education Institutions. The identification of participants was based on a review of literature on Learning Analytics in Brazil and the Workshop on Practical Applications of Learning Analytics in Educational Institutions in Brazil [43]. The six participants (refer to Table 1) were chosen through a purposive sampling technique and assigned codes (D1, D2, D3..., D6). The sample comprised five men and one woman, all of whom volunteered in response to an invitation. These participants possessed substantial expertise in developing and implementing computational solutions for Learning Analytics, along with the ability to train and educate others in this domain.

To ensure compliance with ethical recommendations for scientific research, this investigation adhered to the standards recommended in Resolution n° 510/2016, which is specific legislation for investigations in the areas of Human and Social Sciences [44], and Circular Letter No. 2/2021 of the National Research Ethics Commission in Brazil, which provides guidelines for research in virtual environments. At the beginning of the recorded interviews, participants provided consent by reading and agreeing to the points contained in the Free and Informed Consent Form.

The ethical principles assumed in this research are also in accordance with the American Educational Research Association (2011) and with what is advocated by [45], which include professional capacity, integrity, social, professional, educational, and scientific responsibility, respect for the rights, dignity, and diversity of participants. Confidentiality, transparency in storage and handling, as well as precision in the use of data, are prioritized, without falsifying data, fabricating results, or plagiarism. All the participants also agreed this paper directly cited their respective LA tools and papers.

IV. RESULTS

After transcribing the interviews, a textual statistical analysis was conducted using the qualitative data analysis software Iramuteq® (version 0.7 alpha 2). The use of Iramuteq software assists in the treatment of textual data and offers various analysis possibilities based on text statistics or lexicometry. This process involved lemmatization, which searches and relates words by their root, ignoring tense, gender, plural, and supplementary formations [46].

The general corpus was formed from six transcripts, totaling 682 text segments aligned for analysis. The examination identified a total of 21,511 occurrences of words and forms, with 2,084 being distinct words and 959 occurring only once. In Figure 3, the frequency distribution of words used

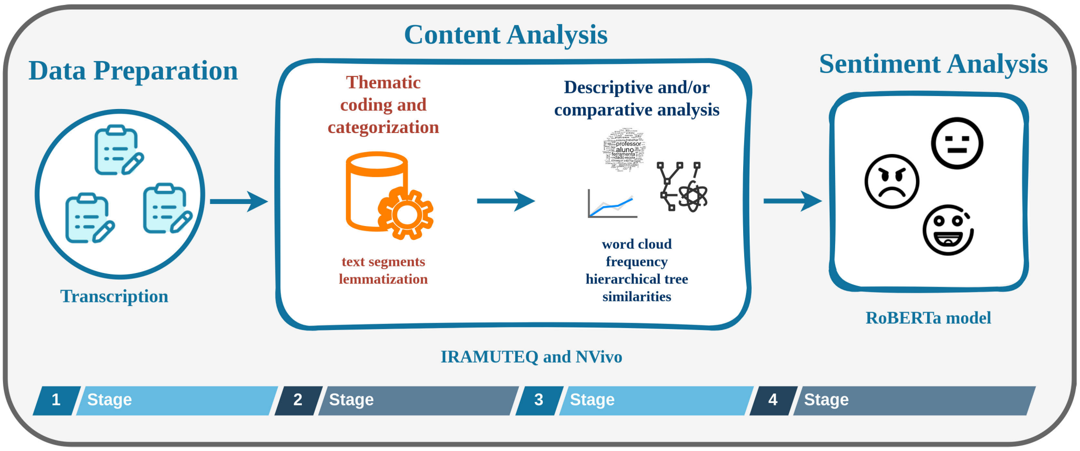

FIGURE 2. Stages followed in the methodology.

TABLE 1. Profile of the researchers participating in the research.

Respondent Code	Education	Type of Linked Institution	Brazilian Region where the institution is located
D1	PhD in Electrical Engineering. Master in Electrical Engineering. Degree in Computer Engineering	Federal Public	North East
D2	PhD in Computer Science. Master in Computer Science. Bachelor in Informatics.	Private non-profit	South
D3	PhD in Computer Science. Master in Informatics and Graduation in Data Processing.	Federal Public	North
D4	PhD in Computer Science. Master in Computer Science. Degree in Computer Science.	Federal Public	North East
D5	PhD in Computer Science. Master in Computer Science. Bachelor of Systems Analysis	Federal Public	South
D6	PhD in Computer Science. Master in Computer Science. Bachelor's Degree in Computer Science.	Federal Public	North East

in the interviews is depicted. The coordinates represent the logarithmic function of the order of occurrence and the logarithmic function of the frequency of these words.

The figure illustrates a pattern where numerous words are repeated a few times, while only a limited set of words are repeated frequently.

A word cloud was generated (Figure 4) to identify the most frequently used words in the interviews. The top five words in terms of frequency were "Student" (Estudante), "Teacher" (Professor), "Tool" (Ferramenta), "Data" (Dado), and "School" (Escola).

Through the utilization of a similarity analysis (Figure 5), it became apparent that these words exhibit a robust interconnection, consistently appearing together in the word cloud. The analysis unveils occurrences and relationships between words, contributing to a more comprehension of the textual corpus. Among the statements made by the interviewees, "Student," "Teacher," "Tool," and "Data" emerge as the most prominent terms. Elaborating further can yield additional words and enhance the articulation of their relationships.

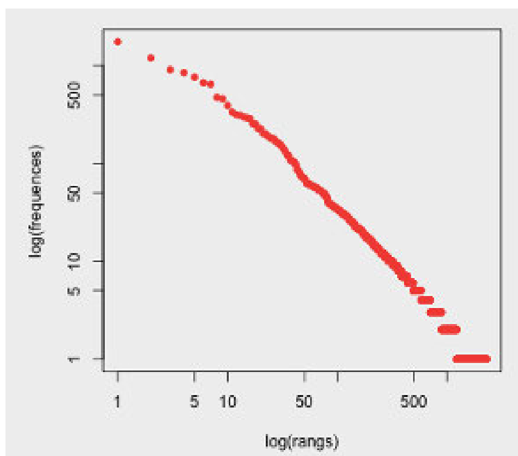

FIGURE 3. Analysis of the number of repeated words in the textual corpus.

The terms "develop" (desenvolver) and "use" (usar) are closely tied to the tool, representing integral processes in

FIGURE 4. Word cloud of the most frequently occurring words in the interview transcripts.

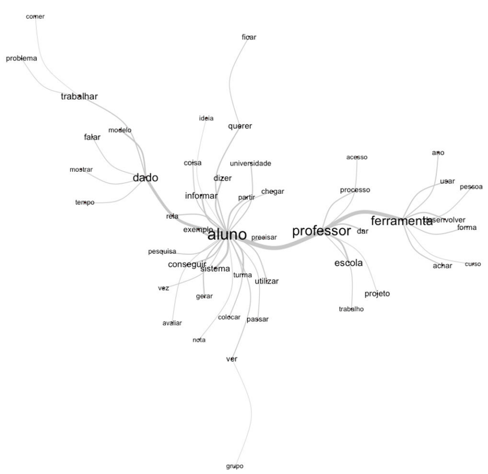

FIGURE 5. Relationship between most frequent words in the interview transcripts.

the practical application of learning analytics tools. These tools played a pivotal role in providing data for diagnosing ''problems'' (problema) and constructing predictive dropout and failure ''models'' (modelo). Moreover, these tools proved advantageous for educators in both ''universities'' (universidades) and ''schools'' (escolas), facilitating a deeper understanding of students' learning trajectories. Through the analysis of student activities and behaviors, teachers can intervene more effectively and with greater precision.

The integration of these four terms is vital in the learning analytics (LA) processes, as the primary goal of LA is to enhance student learning. By employing LA tools to analyze educational data, teachers can extract valuable insights. This, in turn, empowers them to make informed decisions, facilitating targeted interventions that support and improve student learning.

Two axes of analysis are proposed based on the research objectives and the words that emerged from the analysis.

1) Characteristics of the Learning Analytics Tool - this axis encompasses the characteristics related to the target audience, means of data collection and analysis, ways of presenting the analyzed data, and possible means of intervention;
2) Potentialities and Limitations - focuses on the motivations for developing and adopting the tool, as well as its potential for teachers and students in educational and learning management, in addition to the main obstacles to the adoption of the Learning Analytics tool. These axes align with the literature in the field and can aid in further exploration of LA in education.

A total of 124 codes were identified, comprising 82 codes related to the characteristics of the learning analytics tool (Axis I) and 42 codes associated with the potentialities and limitations of the tool (Axis II).

Hence, this section is divided into two subsections, each corresponding to the axes. Initially, we will delve into the presentation of Learning Analytics (LA) tools, with a focus on identifying their central objectives, target audience, applicable teaching modalities, and their current usage status. Additionally, we will underscore the functioning of data collection, analysis, and intervention mechanisms employed by LA tools. Following that, we will scrutinize the motivations, perceptions, limits, and barriers surrounding the use of these tools. Ultimately, we will conduct a comprehensive textual analysis, encompassing the transcription of the interviews and the identification of key words present in the dialogues. Additionally, we will explore the relationships between the interviewees.

A. CHARACTERISTICS OF THE LEARNING ANALYTICS TOOLS

In this multiple case study, we identified six learning analytics tools (LAT) developed by Brazilian research groups (Table 2). These computational solutions are applicable to both face-to-face and distance education, and are designed for students, teachers, and administrators. The main objective of these tools is to improve learning outcomes through features such as automatic grading, feedback provision, prediction of dropout and failure risks, and didactic planning of disciplines/courses.

The main motivations for developing these solutions include personal perspective and/or development opportunities, improvement and advancement of the educational process, facilitation of teaching work, promotion of learning, and educational management. These categories are supported by the statements of the developers, which are listed below:

- {...} *identify the student who has a high level of risk of dropout and low performance throughout the course, before it becomes a problem for the student* {...} (D2)
- {...} *bring a tool that interactively throughout the semester would indicate clues to teachers that could then be worked on properly* {...}, *which would meet teachers' needs* {...} (D3).

TABLE 2. Details of the learning analytics tools developed in Brazil.

Tool Code	Central objective	Target Audience	Teaching modality	Status
LAT1	Risk of Aband. and Dropout	Teachers	Face-to-face	In usage
LAT2	Risk of Aband. and Dropout	Teachers	Face-to-face and distance education	Discont.
LAT3	Activity cor. and feedback	Students	Face-to-face	Discont.
LAT4	Inst. design planning	Teachers and Manager	Face-to-face and distance education	In tests
LAT5	Risk of Aband. and Dropout	Teachers and Manager	Face-to-face and distance education	In usage
LAT6	Cor. of textual activity	Teachers	Face-to-face	In usage

- {…} *I would like to work with formalism* {…}*. So I started researching what I could work on in education. And Learning Analytics came to me. I was enchanted and I said that's what we need because we have a lot of data and we don't use anything* {…} (D4)
- {…} *the quality of education improves, we want to train better students for this, we need to have teachers who better understand what is happening in the classroom so that we can improve within the contents* {…} (D5)

To offer a more comprehensive insight into the learning analytics tools, Table 3 delineates the specific methodologies employed by each tool in data collection, analysis, and intervention. The table underscores commonalities in the approaches utilized for collecting, analyzing, and presenting data, thereby facilitating the intervention processes.

Furthermore, Table 4 illustrates the practical applications of the learning analytics tools developed in Brazil across diverse teaching modalities (including face-to-face and distance learning) and various educational levels (ranging from primary and secondary to higher education).

Considering the information outlined in Tables 3 and 4 pertaining to the content of each tool, a cluster analysis was executed to discern similarities in their central objectives and operational characteristics. The primary objective of this analysis was to highlight the proximity among the tools. To accomplish this, the Pearson correlation coefficient was computed to gauge the correlation between the tools. The resultant correlation coefficients were then utilized to create clusters, where elements within the same group exhibit similarity, while those in different groups manifest dissimilarity. The correlation coefficient data is presented in Table 5, and the hierarchical clustering is depicted in Figure 6.

TABLE 3. Specifics of data collected and analyzed by learning analytics tools originating from Brazil.

Tool Code	Data source	Data made available post-analysis
LAT1	Public database	Dropout risk percentage per class and per student
LAT2	Virtual learning environment	Dashboard with a graphical view of a series of indicators
LAT3	Virtual learning environment	Quantitative and qualitative data.
LAT4	Virtual learning environment	Quantitative data
LAT5	Virtual learning environment	Dashboard with a diversified graphical view (temperature, dispersion, line and column graphs)
LAT6	Public database	Quantitative data

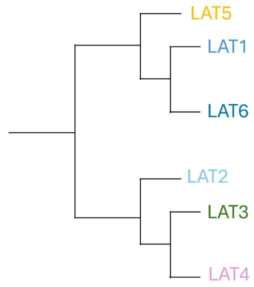

FIGURE 6. Hierarchical tree of similarity between the description of learning analytics tools.

Upon analyzing the hierarchy, it becomes evident that the tools are primarily distributed based on their applicability. LAT1, LAT6, and LAT5 are either inactive or in initial testing stages, while LAT2, LAT3, and LAT4 are in practical use.

LAT1 is predominantly used in primary education to evaluate the risk of student dropout and inform both the management group and teachers about each student's status. It was developed as a component of the National Policy for the Recovery of Learning in Basic Education, established to address the deficits resulting from the pandemic in the years 2020 and 2021. The data is acquired through a psychometric instrument, and the information is stored in a database managed by a public institution in Brazil. The Ministry of Education has access to this database and employs learning analytics (LA) tools to analyze the data across various dimensions of the questionnaire. This analysis aids in identifying potential dropout risk factors. Schools receive

TABLE 4. Characteristics of learning analytics tools developed in Brazil.

Tool Code	Description	References
LAT1	An Early Warning System (SAP) to identify students at risk of dropping out of school. This system utilizes an Assessment Instrument for Relational Risk Factors for School Dropout (IAFREE, in Portuguese), which identifies five key relational factors for predicting school dropout risk: I. Student-School, II. Student-School Professionals, III. Student-Family, IV. Student-Community, and V. Student–Student. The study involved a sample of 15,924 Brazilian high school and middle school ; students. The findings underscore the effectiveness of the IAFREE model as an early warning system, providing a more precise and comprehensive understanding of the elements contributing to school dropout.	[47]
LAT2	Identified the potential risk of school dropout for students from 19 classes, from 4 distance learning courses. The teachers and tutors involved with the case study had access to the proposed system with dropout prediction and based on this information, triggered specific welcoming and attention actions for students. The data shows that after using the application there was a reduction in dropout rates in subjects (average of 0.33 dropped to 0.27) and an increase in the approval rate (0.57 to 0.61). In both cases with statistical significance.	[48] [49]
LAT3	It is an online judge with the purpose of automating the correction of programming exercises. Teachers can provide programming exercises to their students, who in turn can code solutions and submit them through the system interface. As soon as the student submits a solution for a given exercise, the tool informs whether it is correct or not. If the system notifies that the solution code is not correct, whether due to syntax or logic errors, the student will be able to review their code and resubmit it as many times as desired, up to the deadline stipulated by the teacher. This procedure provided an increase in approval rates, which jumped from 50% to 70% among the experimental classes, while it remained at around 30% in the control classes.	[50]
LAT4	It is a free and open-source tool allowing integration with VLEs such as Moodle. It allows one to build the Instructional Design of a course, with its sequencing, parallel or competing activities and also restrictions on the availability of such activities. Furthermore, it is possible to monitor, in real time, student performance in each activity, specifically related to quiz analysis, module access and activity history, and adapt the course to student needs. The tool is in the development phase and the next steps are its validation with real courses.	[51] [52]
LAT5	A cloud-based learning analytics service designed for Moodle enables teachers and course managers within the Virtual Learning Environment (VLE) to access student risk predictions and visualizations of their interactions in the course. This functionality is achieved through a Moodle-associated plugin (block) that gathers interactions from system logs and generates predictive models. These models are then presented on the Dashboard through graphical visualizations, facilitating the interpretation of results.	[53]
LAT6	The tool analyzes students' written production to support teachers in providing more effective and pedagogical feedback in the learning process. The analyzed elements include coherence, cohesion, readability, and the content of the essay, using Natural Language Processing (NLP) techniques.	[54] [55]

reports that showcase the results of this analysis, enabling them to intervene more effectively and mitigate the risk of student dropouts.

The tools **LAT2** and **LAT5** share a common objective, which is to assist higher education students in both face-to-face and distance learning settings. However, it should be noted that these tools have only been tested and evaluated in the context of distance education. **LAT2** is a tool developed in collaboration with an artificial intelligence-specialized startup and the graduate programs of an educational institution. This tool is integrated into the Moodle virtual learning environment, capturing data from digital traces of distance

TABLE 5. Pearson's correlation coefficient between the similarities of the words related to the tools.

	LA1	LA2	LA3	LA4	LA5	LA6
LA1	1	0,64	0,66	0,66	0,88	0,95
LA2		1	0,91	0,86	0,67	0,63
LA3			1	0,92	0,67	0,65
LA4				1	0,69	0,66
LA5	-	-			1	0,89
LA6						1

education students, utilizing approximately 36 variables. Subsequently, the collected data is employed to establish a machine learning model capable of accurately predicting the risk of student dropout. Through the analysis of this data, course coordinators and professors can access information specific to their classes and undergraduate students via a dashboard. This allows them to pinpoint students in need of extra attention on a weekly or daily basis, empowering them to intervene with pedagogical strategies and proactively prevent the perpetuation of dropout patterns or learning difficulties. **LAT5** is a tool developed through inter-institutional collaboration and co-creation with a startup. Its main goal is to support teachers in the teaching and learning process within the Moodle Virtual Learning Environment, utilizing a plugin to gather student access and interaction data. Through the analysis of various variables and dimensions within this data, a predictive model is generated, accurately identifying the risk of student failure and dropout.

A pivotal aspect of the virtual educational process involves course planning and instructional design. **LAT4** is a tool specifically crafted to enhance course design and foster effective learning outcomes. Its primary goal is to facilitate graphic instructional design planning for courses and disciplines offered in Moodle, relying on the High-Level Activities Network (Petri Net). This tool serves not only to create new courses but also to import existing Moodle courses, incorporating all registered activities into the tool. This feature empowers instructors to refine graphic instructional design through learning analytics, ensuring that the course design optimally enhances the learning experience.

The monitoring of student performance is streamlined through the use of automated tools that gather real-time data on student access and interaction in Moodle, encompassing quiz results, module access, and activity history. Instructors receive this data through descriptive statistics, enabling them to identify students at higher risk of failure. Armed with this information, teachers can intervene more proactively by conducting targeted outreach, adjusting activities, or even refining instructional design to better meet the needs of their students.

LAT4 is closely linked with two other tools, **LAT3** and **LAT6**, which concentrate on automating activity corrections and delivering automatic feedback. Despite sharing this common objective, the tools diverge in their target audience, with **LAT3** designed for students and **LAT6** tailored for teachers.

LAT3 was expressly designed to support teaching and learning in disciplines requiring the creation of computer programming codes. It provides an environment where students can test their code using their inputs and execute it. Upon deeming their code correct, they submit it for verification, and it undergoes correction using a test case as a model. Furthermore, **LAT3** offers feedback on any errors or successes in the code. This approach streamlines the efforts of both students and teachers, fostering a more efficient and effective learning process. In contrast, **LAT6** is a tool specifically designed for Android phones, employing artificial intelligence to correct textual activities. It is predominantly utilized in face-to-face basic education, with a specific focus on elementary school students, while also serving as a support tool for teachers. By automating the correction process of written assignments, **LAT6** streamlines tasks for both students and teachers, allowing them to redirect their time and effort towards other facets of the learning process. In this scenario, the student writes the textual activity on paper, and the teacher captures an image to send it to the tool. The tool then processes the information and provides feedback based on predefined criteria, such as textual cohesion, coherence, and adherence to the topic. The feedback can be tailored to each student individually or compiled for the entire class. Informed by this feedback, the teacher can make decisions that contribute to the ongoing learning of the students.

It is important to note that all tools have ethical precautions associated with the use of data, in compliance with international legislation such as the General Data Protection Regulation (GDPR) in the European Union and the General Data Protection Law (Law n° 13.709/2018) enacted in Brazil in 2018. Data is anonymized, encoded, and encrypted to ensure privacy and security. Furthermore, teachers have exclusive access to their class data, and there is no sharing of data with all users of the tool. The ethical concern associated with the use of learning analytics is increasingly being discussed and implemented in academic research and in the technological and scientific products that result from it. In a recent study, [56] emphasized this concern and demonstrated the need for a relationship between ethics and learning analytics. The authors argue that it is necessary to expand ethical discussions and relate them to the characteristics of the different approaches used in learning analytics. This is important to raise awareness about the role of the researcher and promote conscious and responsible use of data throughout the process of collection, analysis, retention, administration, and intervention. As mentioned above, these learning analytics tools are still in the process of development and/or applied on a small-scale and experimental basis. Although developers are aware of the importance of LATs and show interest in them, there is a need to conduct further research noe research is needed on these tools to analyze and optimize their activities to improve learning and the environments in

FIGURE 7. Potentialities of learning analytics tools.

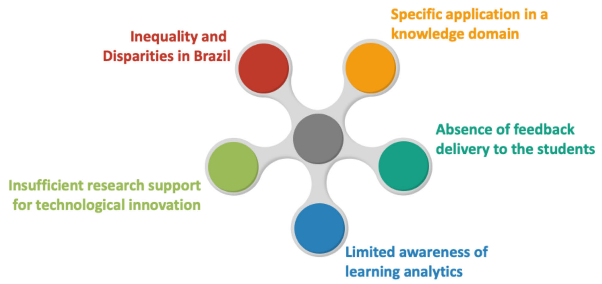

FIGURE 8. Challenges in adopting learning analytics tools in Brazil.

which where they are used. It is crucial to ensure that the tools are reliable, valid, and effective in their intended use, as well as to assess their impact on student learning outcomes. Therefore, it is necessary to continue to investigate and refine investigating and refining these tools to fully realize their potential in promoting to promote for student success in education. In summary, the examined learning analytics tools examined are versatile, applicable to both face-to-face and distance learning modalities, with a central primary focus on the benefiting of students, teachers, and administrators. These tools primarily excel in automatic and personalized activity correction, providing feedback, predictive modeling of dropout risk, and facilitating instructional design planning for courses and disciplines. To gain a deeper understanding of these computational solutions, the following section will delve into the motivations, potentialities, limitations, and barriers associated with the adoption of learning analytics tools in the daily practices of educational institutions.

B. POTENTIALITIES AND LIMITATIONS OF ADOPTING LEARNING ANALYTICS TOOLS

Upon scrutinizing the data, we have identified the primary strengths and limitations of learning analytics tools as perceived by their developers. Notably, one potential advantage is that these tools align with the requirements of two pivotal stakeholders in the learning analytics process: educational management and teachers. A more comprehensive exploration of these positive aspects of the tools can be found in the participants' statements and detailed in Figure 7.

- {…} *a complete tool, because it was integrated online with the systems that generated the data. Both the academic system and the virtual learning environment system. {…} thus, it has the potential of an intervention process that it can really* ***intervene and change reality to improve this reality of both dropout and low performance.*** (D2)
- {…} *the perception I have is always very good, people really like it because it* ***takes a lot of work off the teacher's shoulders*** {…} (D3).
- {…} *I can follow my students graphically and with a dashboard with an accuracy of 90% so that I can* ***know if this student is prone to dropping out*** {…} (D5)
- {…} *a tool that can be used in everyday life,* ***helping with text corrections and giving feedback to the student*** {…} (D6)

Nevertheless, these tools exhibit limitations, as illustrated in Figure 8. These constraints encompass technological challenges, including the requisite for reliable and efficient platforms, along with human resource limitations, emphasizing the necessity for specialized professionals to operate the tools effectively. Other drawbacks comprise infrastructural deficits, logistical challenges, and the imperative need for incentives to stimulate technological innovation. Moreover, some participants underscored that the non-commitment of education management and a lack of awareness among stakeholders in the educational process can impede the widespread adoption of these tools:

- {…} *provide information to students through a* ***dashboard*** {…} (D1)
- {…} ***access barriers both to the academic system of the university, and access to the Moodle system****, for the integration of these systems from a resource that worked effectively, quickly, safely* […] (D2).
- {…} *used* ***only for the Computing and programming areas****, for the time being* {…} (D3)
- {…} ***awareness of the community*** *in general that learning analytics is within artificial intelligence, but it has the purpose of bringing benefits of giving positive support to decision-making and not as a mechanism that can be used to generate criticism and unrelated discussions productive* {…} (D5)

According to the developers, it is imperative for school managers, teachers, and government officials to cultivate awareness and promote the dissemination of information among active participants in the educational process who contribute to the collection of educational data, aiming to enhance education. Furthermore, there is a need for incentives to expedite research on technological innovation, facilitating the training of qualified and skilled human resources for the development and improvement of tools like those mentioned here. Although the results already demonstrate the effectiveness of such tools in improving education, there remains a necessity for further development and widespread dissemination of these technologies to ensure equal and effective access to education for all. Next section will delve into the strengths and limitations of the LA solutions outlined in this study in light of developers' opinions.

TABLE 6. Sentiment evaluation by respondents.

Respondent	Neutral	Negative	Positive
D1	0.4727	0.2947	0.2325
D2	0.5009	0.2940	0.2052
D3	0.5481	0.2776	0.1742
D4	0.5167	0.2824	0.2009
D5	0.4844	0.3029	0.2128
D6	0.4876	0.3012	0.2112

C. SENTIMENT ANALYSIS

Sentiment analysis was performed over the respondents answers using multilingual XLM-roBERTa-base model [57]. RoBERTa, short for Robustly Optimized BERT Pre-training, is a pre-trained language model developed by Facebook AI, with a specific emphasis on sentiment analysis tasks. Serving as an extension of the BERT (Bidirectional Encoder Representations from Transformers) model, RoBERTa uses a transformer architecture and integrates various modifications aimed at enhancing its overall performance. For each response, the analysis returned the sentiment score for three distinct sentiments: positive, negative and neutral. The scores vary from -1 to 1 where as close they are to 1 the stronger is that given sentiment. The results of this analysis are shown in Table 6.

As illustrated in Table 6, consistent patterns emerge from the sentiment analysis. Upon reviewing the findings, it becomes apparent that all respondents conveyed neutral sentiments during their interviews. Furthermore, when contrasting negative and positive sentiments, it becomes evident that negative sentiments consistently slightly surpass the positive ones, suggesting a slight leaning towards an overall neutral sentiment with a negative undertone. These specific data points and comparisons underscore the uniformity of sentiments expressed among the respondents and may offer insights into the prevailing perspective of LA developers. This phenomenon could be attributed to several factors, such as limited widespread adoption of certain tools or the failure of LA initiatives to achieve the anticipated impact initially envisioned.

V. DISCUSSION

The main objective of this study was to investigate the viewpoints of developers on the implementation of learning analytics tools in Brazil, with a particular focus on their functionalities, potential benefits, and potential drawbacks. This section is focused on answsering the research questions proposed in the beginning of the paper.

RQ1: Which are the characteristics of some Brazilian Learning Analytics tools under usage nowadays and how they relate to the literature of the field?

Six learning analytics tools developed by Brazilian research groups were examined in this multiple case study. These computational solutions cater to both face-to-face and distance education, targeting students, teachers, and administrators. The tools, scrutinized in this study, concentrate on enhancing learning outcomes through features such as automatic activity correction, risk analysis of failure, abandonment, and dropout, as well as didactic planning of courses/disciplines. The functionalities of the analyzed tools align with three out of six scopes advocated by [58], namely prediction (LAT1, LAT2, LAT5), feedback (LAT3 and LAT6), and pedagogy (LAT4). Notably, the remaining three categories—assessment, curriculum, and social learning analytics—fall outside the purview of the investigated tools. This observation opens up new prospects for future local developments in the country, signaling potential areas for expansion and innovation in the field of learning analytics.

Failure, abandonment, and dropout represent significant challenges for the educational system, not only in Brazil but also on a global scale. In Brazil, these challenges were exacerbated during the pandemic period. Data from the National Institute of Educational Studies and Research Anísio Teixeira (INEP), responsible for the Census of Basic Education and Higher Education, reveals a troubling trend. Dropout rates in Secondary and Higher Education doubled compared to the rates observed in 2020 and 2021 [44]. In this context, it is imperative to investigate solutions that can proactively prevent or indicate the likelihood of student dropout, allowing for early intervention to avert the issue. Predictive analysis, leveraging student data from learning management systems or educational process management systems, plays a pivotal role in this regard. This approach is instrumental in optimizing the management process and fostering the dissemination and assimilation of knowledge. By identifying potential challenges early on, educational institutions can implement targeted strategies to support students and enhance overall academic success. The learning analytics (LA) tools examined in this study are aligned with the challenges outlined and draw upon solutions proposed by other researchers, such as [48], [59], [60], [61], [62], and [63]. These tools also illustrate instances of predictive models characterized by a high level of accuracy in anticipating the risk of student dropout. Encompassing both face-to-face and distance learning, as well as basic and higher education, these studies offer valuable insights through dashboards. These dashboards enable students, teachers, and management groups to actively monitor learning progress and assess the potential risk of failure and dropout.

Furthermore, findings from our study underscore the significance of aligning didactic-pedagogical planning of courses with learning analytics. This alignment encompasses various stages, including course design, evaluation, activity correction, and feedback—areas directly addressed by three of the learning analytics (LA) tools examined in this study. As asserted by [37], the relationship between learning analytics and course design should be reciprocal, fostering collaborative reflection on teaching practices and facilitating the identification of strategies that enhance the learning experience. Moreover, providing purposeful feedback on student activities is critical for their academic performance, and automated and personalized feedback can make this process more accurate and effective. Learning analytics tools have emerged to provide feedback to the most appropriate students through learning indicators, artificial intelligence [64], [65] and dashboards [66]. Moreover, the LA tools examined in this study effectively address the diverse needs of Latin America. For instance, as reported in [12], Latin American students express a desire for quality feedback and faculty support to enhance their learning outcomes. Teachers underscore the importance of timely alerts about students' difficulties, not only to provide effective support but also to make informed pedagogical decisions and evaluate their own practices based on concrete evidence. These needs are also corroborated by the findings of [13]. Additionally, [12] notes that the management team highlights the lack of quality and actionable information for interventions, as well as the imperative to analyze the effectiveness of these interventions when implemented.Notably, these are all characteristics addressed by some of the LA tools scrutinized in this analysis.

RQ2: How do developers of Learning Analytics (LA) tools in Brazil view the potential and limitations of these solutions ?

The potentialities identified in the study converge on the improvement and advancement of academic management and teaching practices. For academic management, LA tools have the potential to be integrated into academic systems and virtual learning environments, enabling better student monitoring, sometimes in real-time, with the aid of dashboards for easier visualization of data analysis. This can lead to the creation of more effective intervention strategies. As for teachers, potentialities lie in the facilitation and improvement of teaching activities, such as better planning of disciplines/courses, automated correction of activities, and personalized feedback to students.

Despite the potential of learning analytics tools, the developers mentioned limitations and barriers that hinder their widespread adoption, especially due to various sociotechnical and pedagogical challenges [12], [22], [67]. The social-technological perspective highlights the issue of social inequality and lack of digital access in Brazil, as well as the budget cuts for research and scientific development. Brazil is a continental country with different regions that present distinct and unequal sociodemographic characteristics. These factors contribute to the challenge of implementing learning analytics tools in a way that benefits all students equally.

According to [44], the Continuous National Household Sample Survey shows a significant disparity in internet access, especially in rural areas, where only 55.6% of the population has access to the internet. The situation is even more concerning in the North (38.4%) and Northeast (51.9%) regions, which also have the lowest per capita household income, approximately 11.2% lower than the national average. In contrast, the South, Southeast, and Midwest regions have the highest average per capita household income. These regional differences in income and access to technology highlight the socioeconomic disparities that exist in Brazil.

The developers of the LAT1 and LAT6 tools, which use basic education data for their analyses and decision-making, have identified several barriers to the widespread use of their tools. One major impediment is the lack of cell phones to digitize and send textual productions for analysis. Additionally, the absence of internet connectivity in schools interferes with the sending of socio-demographic data and academic performance of students to the platform, which serves as a crucial source of data for learning analytics.

In order to achieve more accurate performance analysis, it is crucial to consider the socioeconomic profile, conditions, and geographic context of students within the educational process. This is necessary to define the proposed activities, forms of evaluation, and communication, as social inequalities can affect students' basic skills and their access to necessary infrastructure [13].

It is important to note that there is a lack of support for Brazilian technological innovation research, which hinders national technical-scientific development and progress. In recent years, science has been subjected to significant budget cuts, which have directly impacted research, grants, and related activities.

According to data from the Brazilian Society for the Progress of Science [68], there has been a reduction of around 37.6% in the amount allocated to scientific research in the Federal Government's Annual Budget Law from 2019 to 2022. This reduction has had a direct impact on research, grants, and related activities. The reduction in support for research on technological innovation in Brazil carries substantial consequences for the nation's progress, leading the developers of LAT2 and LAT4 to halt their efforts in enhancing their tool.

Infrastructure, time, ease of use, usefulness, personal perspectives, experiences, behaviors, skills, and abilities have been identified as factors that limit the adoption of new technologies [69] and directly impact the technical limitations imposed on the adoption process. Our study also identified technical limitations, such as the restriction of a specific tool to an area of knowledge (Computing and Programming) and students not having access to the results of data analysis, which prevents them from monitoring their own academic performance and learning. This concern is relevant, as many learning analytics tools prioritize presenting their results to teachers and management, without involving students in the implementation process. However, the central focus of learning analytics is to support students and enhance learning outcomes [10].

Providing students with access to a graphical and intuitive dashboard that presents clear and precise information on the various variables used in the analyses is essential for feedback and student ownership of their learning path and performance. Institutions must provide training to enable students to use data as a support for learning [70]. This could also encourage new innovative initiatives for LA tools, which were identified as a limitation of LA adoption for some tools in this study. It is necessary to promote and expand research to sensitize the population about the importance and potential of LA. This concern is not unique to Brazil, as evidenced by [10] who carried a study on the adoption of LA in 83 higher education institutions across 24 European countries. The study highlights that the biggest challenges associated with the adoption of LA are related to tensions and concerns around exploring innovative ways to combine skills, funding, infrastructure, people, and the culture of data use while maintaining academic efficiency and financial management.

Many of the highlighted limitations in our study align with various categories influencing the adoption of Learning Analytics as emphasized by [71]. The authors identified 14 factors distributed across 6 major groups that influence the adoption of Active Learning (AL) in higher education: User involvement and training (UIT); Project management and control (PMC); Skill mix (SKM); Organization fit (ORG); Technology planning (TEC); and Software system design (SSD). Our study identified limitations correspond to several factors outlined by the authors, encompassing all interconnected categories. Specifically: i) challenges related to technological aspects correspond to the PMC, TEC, and SSD categories; ii) issues such as the lack of infrastructure, logistics, and incentives for technological innovation are acknowledged in PMC, ORG, TEC, and SSD; iii) problems related to qualified human resources are associated with UIT, SKM, and ORG; and iv) the absence of commitment to managing education and raising awareness among educational stakeholders can be linked to UIT and SKM.

At last, in addition to the technical and methodological limitations mentioned in this study, developers also mentioned barriers related to the access of data and ethical preoccupation related to data privacy. This aligns with other researches in Latin America [37], [63] that also identified bureaucratic barriers such as the approval and certification of research, as well as difficulties in accessing data quickly and easily. These factors can hinder the use of the tool in a more widespread and efficient manner, limiting its potential for effective intervention in the teaching and learning process. The significance of aligning learning analytics (LA) development with ethical considerations, particularly in relation to data privacy, has been extensively highlighted in the literature [45], [56], [72], [73], and [74]. Trust concerns of teaching staff are specially concentrated on third parties involved with LA and how they handle privacy and ethics-related issues [75]. In the context of Brazil, this involves taking into account the General Data Protection Law, which the interviewed developers cite as a guiding framework in their investigations, development, and enhancement of LA tools.

VI. CONCLUSION

The present study investigated the adoption process of Brazilian learning analytics tools from the perspective of their developers. For that, six developers of LA tools were interviewed about the functionalities of their LA tools, potential applications, and limitations in the context of Brazil. The analysis were was conducted according to two main dimensions, which are: 1) The characteristics of the LA tools and 2) The potentialities and limitations of their adoption. As stated in during the paper, LA tools developed in Brazil and selected for this study are used in both face-to-face and distance learning, and their functionalities include predicting students at-risk of dropping out, providing automated and personalized correction and feedback, and supporting didactic planning of courses or disciplines. The intended users of these tools vary depending on the specific tool, and may include students, professors, or management groups.

Developers underscore the significant potential of these tools for interventions and driving transformative change in the applied context, ultimately enhancing the teaching and learning processes. In elucidating the tools' potential, developers specifically emphasized the following aspects: a) seamless integration with academic systems; b) enhanced monitoring of students; c) facilitation of teaching actions; d) improved visualization and interpretation of analyses through dashboards; e) streamlined intervention planning with the capacity to effect real change; and f) reduction in dropout rates and improvement in academic performance.

Nevertheless, developers also recognize various limitations impeding the broader adoption of learning analytics tools, including: a) the sociodemographic inequality inherent in the Brazilian context and the insufficient reach of the tools; b) inadequate support for technological innovation research, marked by yearly reductions in funding; c) restricted application of the tool to specific knowledge domains; d) insufficient feedback to students, as most analyses remain accessible only to teachers and administrators; e) a lack of awareness among the population regarding the importance of learning analytics and its potential impact on the teaching and learning process.

The paper has also examined how the features of the tools, their potentials, and limitations align with the current state of the field both in Latin America and globally. This is particularly noticeable as the present study presents the perspectives of the developers while the existing literature normally focuses on the opinions other stakeholders such as the teachers, the students and the managers. To the best of our knowledge, this is the first work tackling this specific group.

While this research provides valuable perspectives, there are also some limitations and areas for improvement. As the research was qualitative it is not possible to extrapolate the results found here to the whole country and region.Thus, future work should focus on quantitative approaches with a larger sample of developers and creators of other LA tools. It would also be interesting to follow up the evolution of the studied tools and contrasting the findings of the present work with data gathered with the real users of these tools, and how their interventions helped to improve learning outcomes. It would also be interesting to complement the sentiment analysis with contextual and cultural aspects of sentiment. Finally, the research could also be expanded to other countries in Latin America.

The insights presented in this paper can serve as a reference to strengthen the Learning Analytics field in Brazil and across Latin America, offering a more direct approach to addressing the challenges and issues highlighted by the developers of these tools in the region.

For future work, there is an opportunity to complement this work with an in-depth analysis of the strengths and weaknesses of various tools in educational contexts, utilizing relevant data. This approach promises to improve our understanding of the effectiveness of learning analytics tools and guide their more effective implementation in educational environments.

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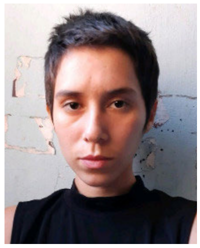

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