TPM Vol. 32, No. S2, 2025
ISSN: 1972-6325
https://www.tpmap.org/

LEARNING ANALYTICS IN SMARTSCHOOL AS A TOOL TO REDUCE EDUCATIONAL GAPS

RAÚL JOSÉ MARTELO GÓMEZ[1]
DAVID ANTONIO FRANCO BORRÉ[2]
EDWIN EDUARDO QUINTANA SALGUEDO[3]

[1]SPECIALIST IN NETWORKS AND TELECOMMUNICATIONS; MASTER IN COMPUTER SCIENCE. SYSTEMS ENGINEER. TENURED RESEARCH PROFESSOR OF THE SYSTEMS ENGINEERING PROGRAM AT THE UNIVERSIDAD DE CARTAGENA. LEADER OF THE INGESINFO RESEARCH GROUP. CARTAGENA DE INDIAS, COLOMBIA. EMAIL: rmartelog1@unicartagena.edu.co, ORCID: HTTPS://ORCID.ORG/0000-0002-4951.
[2]SPECIALIST IN UNIVERSITY TEACHING. MASTER IN COMPUTER SCIENCE. SYSTEMS ENGINEER, TENURED RESEARCH PROFESSOR OF THE SYSTEMS ENGINEERING PROGRAM AT THE UNIVERSIDAD DE CARTAGENA. LEADER OF THE GIMATICA RESEARCH GROUP. CARTAGENA DE INDIAS, COLOMBIA. EMAIL: dfrancob@unicartagena.edu.co. ORCID: HTTPS://ORCID.ORG/0000-0001-7500-0206
[3]SOFTWARE ENGINEERING SPECIALIST. MASTER'S DEGREE IN EDUCATION AND DIGITAL PEDAGOGICAL DEVELOPMENT. SYSTEMS ENGINEER. MANAGER OF THE COMPANY SOFTCOMPUTO. EMAIL: gerencia@softcomputo.com.co. ORCID: HTTPS://ORCID.ORG/0009-0008-7021-6970

Abstract
Learning analytics has become an important tool for promoting educational equity through evidence-based decision-making. This paper examines the potential of the SmartSchool platform as a learning analytics tool with the goal of recognizing and mitigating educational gaps that may arise in digitalized school dynamics. Within a qualitative framework, an analysis of the functionalities of the platform's analytical modules was conducted using anonymized data in a secure institutional environment. This analysis identified five dimensions: performance visualization, risk detection, pedagogical recommendations, progress monitoring, and support for institutional management. The results indicate that the SmartSchool platform facilitates the transformation of data into personalized pedagogical interventions, allowing teachers and school principals to take action in real time. Therefore, it is concluded that, in contexts that foster a culture of ethical and pedagogical data use, tools such as SmartSchool can be very significant in promoting the improvement of educational equity. Further research on this topic of learning analytics is recommended, in relation to its impact based on teacher experience and the concrete effects on the learning process.

Keywords: equity, data, learning, technology, teaching, academic performance.

INTRODUCTION

Within the framework of digital transformation, education is beginning to include emerging technologies such as artificial intelligence, learning analytics, and adaptive systems, not only as innovation resources but also as tools to mitigate gaps and promote inclusion (Lata, 2024). These technologies allow for the early detection of learning difficulties, the adaptation of content to individual characteristics, and the generation of evidence-based pedagogical interventions (Westwood, 2018). In this process, learning management systems (LMS) are key because they add capabilities to traditional administration that allow information to be visualized from an accessible perspective, alert about the risks of educational exclusion, and suggest automated actions that promote more equitable and student-centered teaching (Indumathy & Mujra, 2025).

Learning analytics, understood as the collection, measurement, analysis, and interpretation of data about students and the context in which their learning takes place, has been consolidated as a key strategy to make visible performance patterns, detect trajectories with low performance in time, and approach and, therefore, mitigate the so-called educational gaps (Long & Siemens, 2011; Viberg et al., 2018). Educational gaps can be associated with structural factors that generate inequality in learning, such as socioeconomic status, access to and use of digital connectivity, or the possibility of support from teachers. These factors can be exacerbated in digital environments if intervention mechanisms are not implemented (Van De Werfhorst et al., 2022; Papamitsiou & Economides, 2014).

Platforms like SmartSchool are already introducing analytical tools that allow teachers to gain insights from automatically generated data. Individual progress dashboards, alerts for at-risk students, report exports, and assessments in a continuous assessment phase are some of these features (Bergamaschi et al., 2025). While these tools represent an important technological advance, their true potential to contribute to educational equity from a pedagogical perspective still needs to be critically analyzed.

Several studies have shown that educational analytics can support the implementation of pioneering interventions and appropriate remedial actions that contribute to closing achievement gaps between student groups (Tsai et al., 2020; Apata et al., 2025). However, the positive effects depend on the quality of the algorithms, how they are implemented in teachers' routines, and the willingness of schools that agree to use the data to transform pedagogical decision-making.

This article analyzes the use of learning analytics within the SmartSchool platform, assessing its usefulness in reducing academic achievement gaps. It is based on a functional, documentary, and ethically controlled study, focusing on how teachers can use available data to guide more inclusive and personalized educational processes.

METHODOLOGY

This research is framed within a mixed methodological approach (Hernández, 2024), with a predominance of the qualitative-descriptive approach complemented by quantitative analysis tools based on educational analytics (Deckert & Wilson, 2023). The choice of this perspective allows for an accurate understanding and description of the ways in which learning analytics is developed in the SmartSchool platform and its pedagogical impact in real-life usage scenarios, specifically with regard to reducing educational gaps.

The design adopted is exploratory-descriptive, since it sought to analyze the ways in which teachers use the SmartSchool platform to identify, intervene, and document differences in academic performance, participation, risk of dropping out, and academic progress (Adedoyin, 2020). Since it is a tool in continuous progress and innovation, it was necessary to have a design that would allow collecting evidence from institutional and pedagogical praxis, relating observable indicators with interpretations of use.

Furthermore, data collection was conducted through systematic observation of student behavior on the platform over a full school year, making intensive use of its various analytical modules: personalized assessment, absence analysis, progression by unit, dropout prediction, automated remediation, and pedagogical recommendations. These data were complemented by documentary analysis of reports exported from SmartSchool, comparative graphs, individual progress lines, heat maps, historical intervention records, and evaluative visualization screenshots.

Each module was evaluated based on its capacity to generate evidence that would identify educational gaps in real time and trigger differentiated pedagogical responses. The visualizations provided by the system were analyzed through critical reading of graphs, individual trajectory monitoring, peer comparisons, and documentation of the effectiveness of strategies implemented by teachers based on the recommendations suggested by the platform.

This mixed approach was relevant because the phenomenon studied requires both the measurement of objective indicators (performance, attendance, progress) and a qualitative interpretation of the pedagogical meaning of its use in real-life contexts. The combination of these perspectives allowed not only to describe the type of information SmartSchool offers, but also how this information is used to reduce learning inequalities and support contextualized pedagogical decision-making.

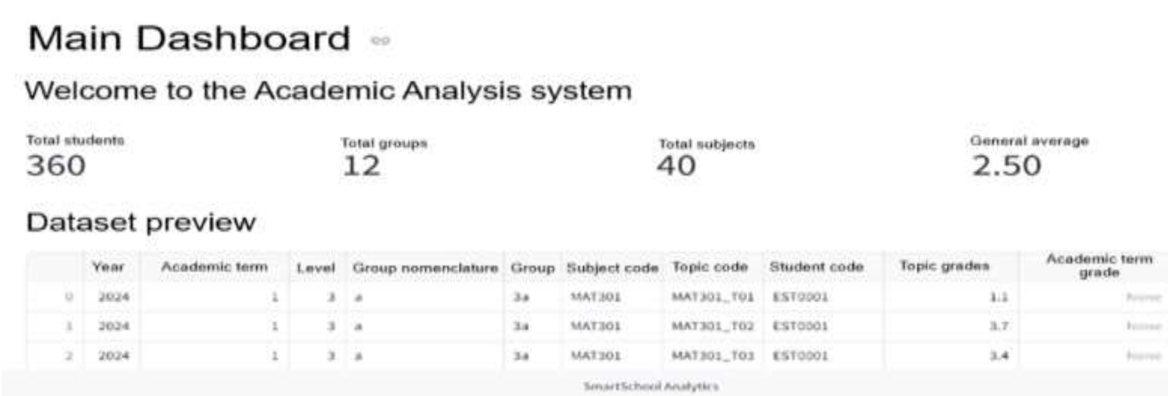
Finally, the choice of SmartSchool as the object of study is based on its architecture, focused on formative assessment, automated monitoring, and pedagogical data visualization, making it a suitable tool for research on the potential of learning analytics as an optimal tool for improving educational equity. The research was conducted in compliance with ethical principles of anonymity and confidentiality, and all data were used solely for research purposes.

RESULTS

The implementation of SmartSchool Analytics enabled the implementation of a comprehensive learning analytics system with an institutional, individual, and predictive approach, aimed at reducing the educational gaps that accompany the learning processes. As the research progressed, multiple dimensions emerged in which the platform itself not only highlights existing inequalities in learning and student participation, but also proposes differentiated, sustained, and evaluable intervention pathways. It should be noted that this section presents the main findings from the use of the various modules offered by the platform, highlighting both their analytical value and their pedagogical potential.

Among the most used modules is the institutional dashboard, which provides an overview that allows for the detection of highly significant deviations from global averages, as well as critical trends at the group or level. The platform allows for filtering and comparing data in real time, ensuring a useful analysis for systematic and contextualized monitoring of the academic progress of the educational community. Figure 1, corresponding to the main dashboard view, which includes a summary of the institutional indicators, offers a comprehensive view of the magnitude of the educational system and initially shows an initial warning about poor academic performance, with an average of 2.50 on a scale of 5, which can be translated into the existence of various structural problems.

Figure 1. View of the main SmartSchool dashboard



Source: Own capture from SmartSchool environment.

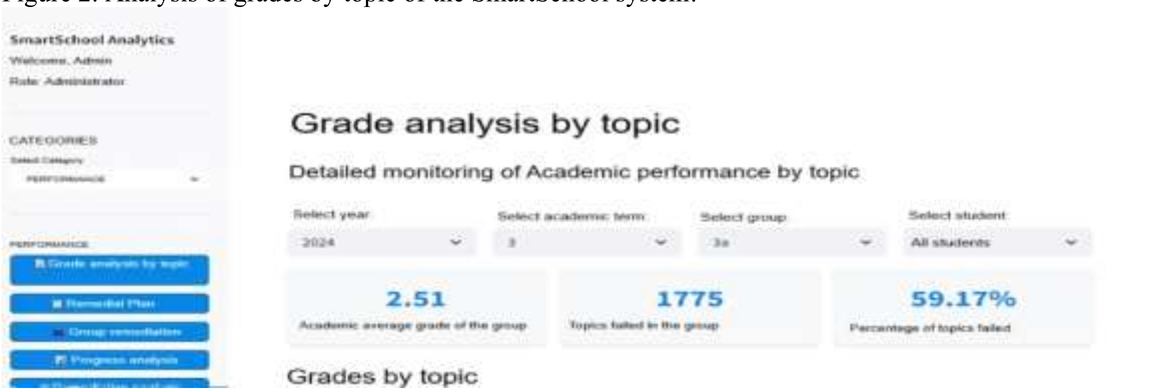
In analyzing academic performance, the Grade analysis by topic module allows for breaking down the analysis by topic or competency, highlighting the most difficult topics for each group. This analysis is invaluable when designing and planning remedial work, both individually and as a group. Using the Remedial plan module, SmartSchool automatically generates remedial plans, prioritizing them based on their estimated impact.

Furthermore, the panel in Figure 2 provides a record of academic performance by year, period, grade, group, and student, offering an analytical projection for more personalized pedagogical decision-making. At the top center of the panel, drop-down selectors allow users to select the year of interest, the academic period, the group, and the student, suggesting, although only in part of the panel, a type of dynamic analysis environment. The following three indicators can be generated from the filters: Average grade of the analyzed group, Total topics failed in said group, and Percentage of topics failed (59.17%), which indicates a high rate of poor academic performance.

This visualization highlights a gap in student content mastery, as more than half of the topics covered show failure rates. Furthermore, the dashboard design shows that the system can access remediation pathways, remedial plans, and progress analyses, as seen in the left sidebar under the "Performance" category.

Taken together, this image illustrates how learning analytics can be used not only to observe outcomes but also to trigger timely pedagogical intervention mechanisms, especially in contexts where low performance threatens to deepen educational inequalities.

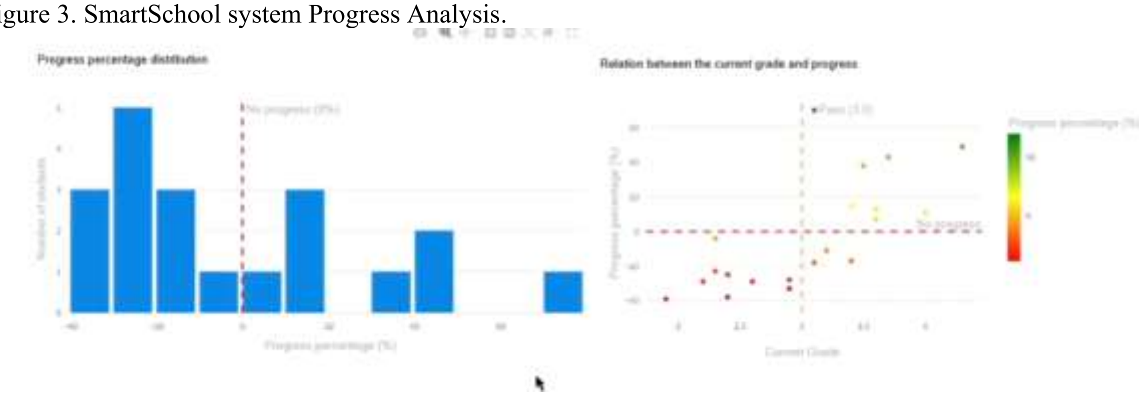
Figure 2. Analysis of grades by topic of the SmartSchool system.



Source: Own capture from SmartSchool environment.

On the other hand, the Progress Analysis module made it possible to track the evolution of academic performance between different academic terms. Line graphs made it possible to visualize key moments when interventions began to reflect real improvements. This was complemented by the Remediation Analysis module, which compares grades before and after applying remedial strategies. Figure 3 shows a timeline of academic progress compared between the current grade and the progress; a positive inflection is shown after the teacher intervention.

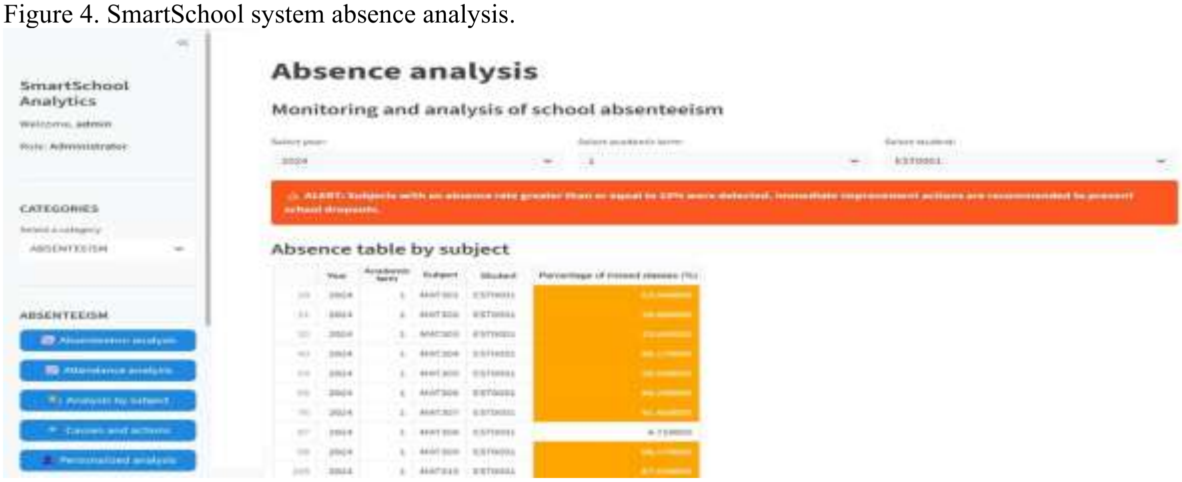
Figure 3. SmartSchool system Progress Analysis.



Source: Own capture from SmartSchool environment.

The attendance area also yielded significant results. The Absence Analysis module in Figure 4 visualizes absence patterns by student, group, day, and subject. This view displays an immediate alert announcing that an absence rate greater than or equal to 12% is detected, offering the opportunity to take corrective action.

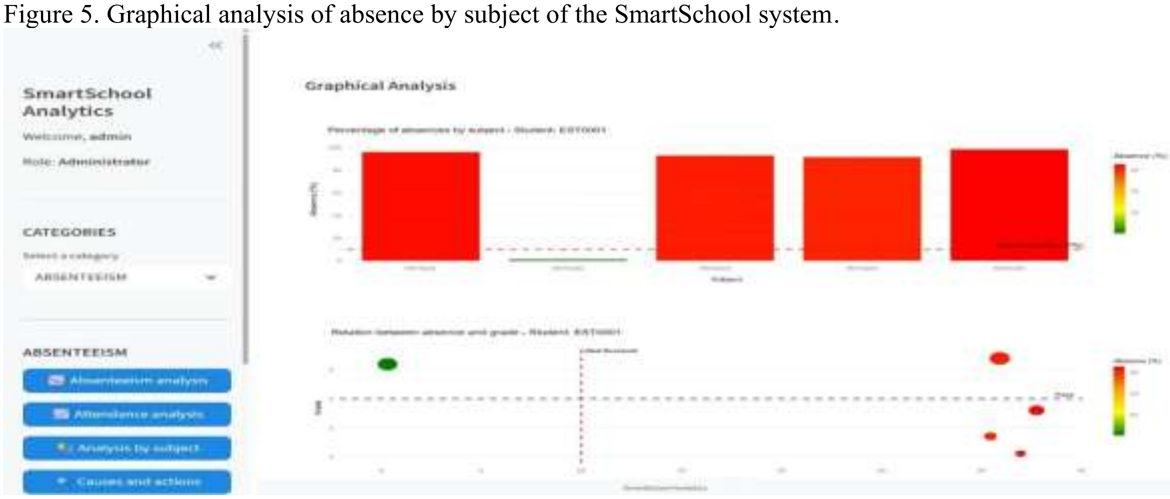
Figure 4. SmartSchool system absence analysis.



Source: Own capture from SmartSchool environment.

Figure 5 shows the visualization of absenteeism at the subject level, generated from the SmartSchool visualization module. The panel is divided into two large sections: At the top of the panel, a vertical bar graph displays the percentage of absences by subject. The subjects are arranged in color columns with a different spectrum between green and red, like a scale that reflects the severity of the situation based on the percentage of absenteeism. Subjects such as Mathematics, English, and Physics were found to be red, which shows that the percentage of absenteeism is high. Other subjects, such as arts and physical education, are located in yellow or green zones, indicating lower levels of absence.

Figure 5. Graphical analysis of absence by subject of the SmartSchool system.



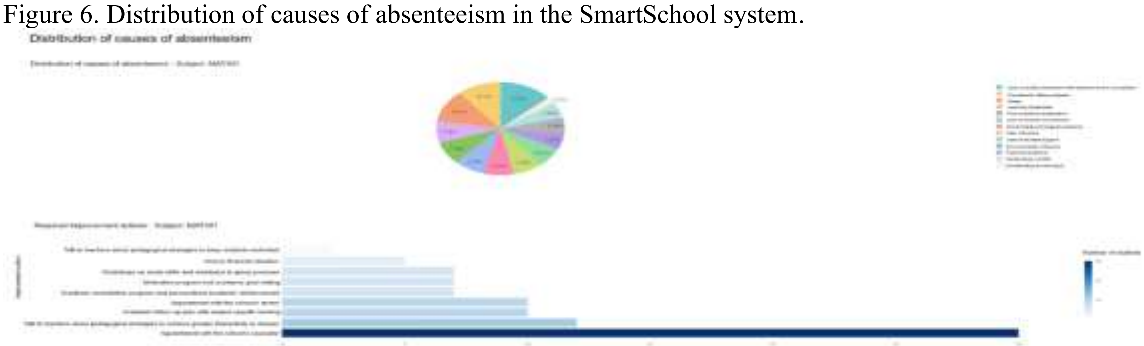
Source: Own capture from SmartSchool environment.

Below is a scatter plot representing the relation between absenteeism and grade by subject. Each dot represents a subject, and its color changes according to the intensity of absenteeism. A clear trend is evident: the higher the absenteeism, the lower the average grade, suggesting a significant negative correlation. Furthermore, the size of the dots reflects the number of sessions analyzed, which provides an additional layer of interpretation regarding the impact of absenteeism.

This visualization is particularly useful for early detection of academic risk, as it allows teachers and school coordinators to focus on subjects with high non-attendance rates through various pedagogical strategies such as adaptation, content reinforcement, or even emotional well-being. Therefore, learning analytics not only involves quantifying the problem but also directly guiding strategic educational action to reduce disciplinary and retention gaps.

Additionally, the Cause-Action Analysis made it possible to obtain a list of the most frequently associated causes of absenteeism and provided recommendations to be followed. The panel in Figure 6 contains two graphs that offer relevant information for understanding why students are absent, as well as the institution's response to this. In the upper left corner, the pie graph shows the cause that accounts for the highest proportion of absenteeism; the most notable causes include: health problems, family or financial difficulties, lack of motivation for the subject, lack of support at home, and emotional or psychological problems.

Figure 6. Distribution of causes of absenteeism in the SmartSchool system.



Source: Own capture from SmartSchool environment.

Each sector of the graph is represented in a different color, facilitating visual interpretation and rapid segmentation. This representation demonstrates that absenteeism is not a homogeneous phenomenon, but rather responds to a multitude of interrelated factors, many of them outside the direct academic context.

At the bottom of the figure, a horizontal bar graph details the improvement actions reported by the teaching staff for each cause of absenteeism. One bar stands out, significantly longer than the others, indicating that the most frequent action was personalized follow-up by the teacher, followed by communication with the family and referral to the guidance counselor. Other actions, such as tutoring, methodological adjustments, or flexible delivery times, appear less frequently.

This visualization is particularly valuable because it connects the diagnosis of the problem (causes) with institutional responses (actions), allowing for an assessment of whether the strategies applied are aligned with the real needs of students. It also offers the opportunity to evaluate the effectiveness of each action in a highly vulnerable environment, where reporting absences alone may not be sufficient in the face of a chronic pattern of school absences.

In practical terms, all these modules were integrated through dynamic filters, data exports, view customization, and the configuration of comparative reports. This technical functionality supported the analytical capabilities of managers, counselors, and teachers, which underpins evidence-based decision-making. Furthermore, the systematic use of the platform fostered a culture of continuous improvement: a shift from delayed reactions to preventive and strategic interventions was achieved, which directly impacted the reduction of achievement gaps between students from different backgrounds.

The results show that SmartSchool Analytics is not merely an assessment tool, but rather an educational data infrastructure that articulates detection, diagnosis, prediction, intervention, and monitoring. Its modular design, customization capabilities, and student-centered approach position it as an effective solution for closing educational gaps from a systemic, ethical, and sustained perspective.

DISCUSSION

The results of this study show that learning analytics systems are not only an effective means of identifying students at risk of academic failure, but are also an indispensable resource for advancing toward improving educational equity. In this sense, these empirical results contrast with an emerging trend in the academic literature: the use of tools with technologies based on artificial intelligence/predictive analytics as resources for addressing vulnerable schooling contexts.

The most recent literature shows how platforms with predictive algorithms can identify patterns of behavior that precede school dropout or poor performance. For example, Green et al. (2025) demonstrated in their work with schools in the United Kingdom how the use of predictive tools is capable of reducing the dropout rate of students with a history of low performance by 26% by using interventions based on early warnings generated by a learning analytics system they had implemented. Similarly, Aileni (Aileni, 2025) developed a data architecture that consolidates multiple sources such as grades, attendance, and virtual classroom participation and showed how the integration of this data significantly improved the identification of at-risk students before academic failure became evident.

On the other hand, the principles of equity, according to Fraser (2009), require "recognition, redistribution, and representation." Learning analytics platforms are positioned precisely on the redistributive axis, allowing institutions to focus resources more efficiently on historically disadvantaged students. In line with this, the study by Gavin et al. (2024) argues that these well-designed systems can correct structural biases by offering differentiated and personalized feedback, especially in higher education environments with cultural or socioeconomic diversity.

However, the benefits must be critically analyzed against ethical challenges. Veltri and Banerjee (2024) warn about the possibility of reinforcing algorithmic biases if models are not trained with data representative of diverse populations. They propose algorithmic equity audits as a control mechanism. This point has also been developed by Peer (2024) in his analysis of public health and educational inequality, highlighting the need for regulatory frameworks that ensure that tools do not perpetuate existing inequities.

Likewise, the similarity in the approaches used in sectors such as health is striking. Iloanusi and Chu (2024) proposed a digital health model for marginalized communities based on predictive risk analysis, with results that can be extrapolated to education as parallel risk-benefit systems. Similarly, Panahi (Panahi, 2025) shows how data-driven community models can generate timely interventions from the local level, which is related to territorial educational strategies.

Finally, the literature highlights that the sustainability of these platforms depends on three key factors: data quality, teaching skills in data analysis, and institutional policies on student well-being. As Bali and Mughal (2023) highlight, many universities implement these types of technologies without a pedagogical ecosystem to support them, which can limit their reach.

The findings of this research together demonstrate that learning analytics platforms can be valuable tools for detecting academic risk and fostering equity. However, they must be implemented from a critical perspective, informed by ethical, theoretical, and social justice principles. Likewise, the spread of innovation through learning and teaching technologies must coexist with educational responsibility to ensure that these technologies do not create or amplify existing gaps.

CONCLUSION

This study allowed for observing how the smartshool tool, as a digital learning analytics platform, provides a very complete set of tools with functionality for monitoring, intervention, and pedagogical decision making based on evidence. From the critical and pedagogical point of view it can be concluded that the educational analytics, designed and implemented from an ethical intention and an inclusive approach, can significantly contribute to the reduction of educational gaps.

In particular, five key functional dimensions have been announced that leverage the pedagogical utility of the platform: visualization of academic performance, allows clear, rapid and actionable compression of group or individual behavior; the detection of students at risk, through early visual alerts and internal rankings that decrease the analytical load of teachers; automated pedagogical recommendations, which connect quantitative data with contextualized action proposals; monitoring of academic progress, through personalized visual trajectories that allow evaluating the effectiveness of interventions; and support for institutional decision making, exportable and comparative reports useful for macro management and school policy design.

The results validate that the SmartSchool tool not only organizes information, but that it transforms it into useful evidence for pedagogical practice, aligning with current framework of equity, training evaluation and data - based school governance. In addition, the use of specific modules such as absenteeism not only allows visualizing patterns of silent exclusion, but also opens spaces for differentiated and anticipatory intervention, in coherence with the values of educational justice.

Although it is also found that the real impact of these tools depends largely on the context of use, on the digital competences of teachers, and on the institutional will to convert the data into meaningful pedagogical decisions. The platform alone does not guarantee equity, but it offers the technical and visual conditions of allowing the most fair, anticipated and adaptive practice. Finally, it emphasizes that the use of anonymized data and the documentary approach allowed a rigorous and respectful approach to privacy, giving rise to an analysis model that could be replicable with other similar platforms.

ACKNOWLEDGMENTS

The authors thank the Publindex institution, the Universidad de Cartagena, and the Softcomputo company for their support and for making this study possible.

REFERENCES

- Adedoyin, O. (2020). Qualitative research methods. . *Principles of Social Psychiatry*, 77-87.
- Aileni, A. (2025). AI-Driven Educational Equity: A Data Architecture for Addressing Achievement Gaps in Public Education Systems. *Journal of Computer Science and Technology Studies, 7(4)*, 535-540.
- Apata, O., Ajose, S., & Oyewole, P. (2025). The role of artificial intelligence in higher education: A systematic review of contributions to Sustainable Development Goals. *ResearchGate.*
- Bali, R., & Mughal, N. (2023). The Impact of Different Computing Tools on the Learning Outcomes of Undergraduate Students in Pakistan: A Cautionary View. *Journal of Educational Computing and Innovation Research, 1(1)*, 1-14.

- Bergamaschi, A., Giambruno, C., & Morales, P. (2025). Empowering Schools with Data: How Can We Achieve Effective Use of Educational Dashboards for Teachers and Principals?. *IDB Impact*. doi:Bergamaschi, A., Giambruno, C., Morales, P., Forkosh-Baruch, A., Hanuka, S., & Hershkovitz, A. (2025). Empowering Schools with Data: How Can We Achieve Effective Use of Educational Dashboards for Teachers and Principals?. https://doi.org/10.18235/0013561
- Deckert, J., & Wilson, M. (2023). Descriptive Research Methods. . *Research methods in the dance sciences/edited by Tom Welsh, Jatin, 153*.
- Fraser, N. (2009). *Scales of justice: Reimagining political space in a globalizing world.* Nueva York, NY: Columbia University Press.
- Gavin, H., Cheung, A., & Salim, M. (2024). *Optimizing AI in Higher Education: Achieving Balance Between Innovation and Inclusion.* Open Book Publishers.
- Green, D., Thompson, E., & Ocineg, I. (2025). Predictive Analytics to Enhance Learning Outcomes: Cases from UK Schools. *Journal Emerging Technologies in Education*, 34-43.
- Hernández, R. (2024). *Metodología de la Investigación. Las Rutas Cuantitativas, Cualitativas y Mixtas (2ª Edición). .* McGraw-Hill.
- Iloanusi, N., & Chun, S. (2024). AI impact on health equity for marginalized, racial, and ethnic minorities. . *In Proceedings of the 25th annual international conference on digital government research*, 841-848.
- Indumathy, I., & Mujra, P. (2025). Sustainable Learning. . *Smart Education and Sustainable Learning Environments in Smart Cities; IGI Global: Hershey, PA, USA*, 381-402.
- Lata, P. (2024). Beyond algorithms: Humanizing artificial intelligence for personalized and adaptive learning. *International Journal of Innovative Research in Engineering and Management, 11(5)*, 10-55524.
- Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. . *EDUCAUSE Review (Online).*
- Panahi, O. (2025). Predictive Health in Communities: Leveraging AI for Early Intervention and Prevention. . *Ann Community Med Prim Health Care, 3(1)*, 1027.
- Papamitsiou, Z., & Economides, A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Journal of Educational Technology & Society, 17(4)*, 49-64.
- Peer, B. (2024). Inequality and access to education: Bridging the gap in the 21st century. *Review Journal of Social Psychology & Social Works, 1(3)*, 155-167.
- Tsai, Y., Perrotta, C., & Gašević, D. (2020). Empowering learners with personalised learning approaches? Agency, equity and transparency in the context of learning analytics. *Assessment & Evaluation in Higher Education, 45(4)*, 554-567.
- Van De Werfhorst, H., Kessenich, E., & Geven, S. (2022). The digital divide in online education: Inequality in digital readiness of students and schools. . *Computers and education open, 3*, 100100.
- Veltri, G., & Banerjee, A. (2024). Harnessing pluralism in behavioral public policy requires insights from computational social science. *Frontiers in Behavioral Economics, 3*.
- Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in human behavior, 89*, 98-110.
- Westwood, P. (2018). *Inclusive and adaptive teaching: Meeting the challenge of diversity in the classroom.* . Routledge.