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DIGITAL LEARNING ASSESSMENT: CASE STUDY OF AN AUTOMATED INDICATOR ON THE SMARTSCHOOL PLATFORM

RAÚL JOSÉ MARTELO GÓMEZ
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.
E-MAIL: rmartelog1@unicartagena.edu.co ORCID: HTTPS://ORCID.ORG/0000-0002-4951-0752.

DAVID ANTONIO FRANCO BORRÉ
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

JESÚS ALBERTO RODRÍGUEZ HENAO
SYSTEMS ENGINEER. STUDENT OF THE MASTER'S DEGREE IN DIGITAL RESOURCES APPLIED TO EDUCATION AT THE UNIVERSIDAD DE CARTAGENA. SPECIALIST SOFTWARE ENGINEER, SCOTIABANK.
ORCID: HTTPS://ORCID.ORG/0000-0002-0615-2465. EMAIL: jrodriguezh1@unicartagena.edu.co

Abstract
This paper presents a case study on the implementation of the automated assessment module in the SmartSchool platform, developed and implemented by the University of Cartagena with support from Colciencias. Using a qualitative methodology, the system is reviewed from the perspective of personalized learning and pedagogical decision-making. Through the analysis of the academic performance assessment module, aspects such as data presentation, the development of remedial plans, progress predictability, and automatic suggestions for improvement are identified. The findings reveal that the system makes it possible to articulate formative assessment with didactic planning, transforming performance data into concrete pedagogical actions. It is concluded that this tool acts as an effective innovation in the interrelation of digital technology in the service of evidence-based personalized teaching.

Keywords: digital assessment, personalized learning, educational platforms, learning analytics, educational technology, SmartSchool, pedagogical automation.

INTRODUCTION

In recent years, the digitalization of education has created dynamic, adaptive, and flexible learning spaces, resulting from the incorporation of technologies such as artificial intelligence, machine learning, and academic management systems. This has also entailed new challenges for educational assessment (Strielkowski et al., 2025). One of the most relevant challenges is how to manage assessment processes that are not only accurate and continuous but also personalized and pedagogically useful (Bingham et al., 2018; Csapó & Molnár, 2019). In this sense, there is a recognized need to transform traditional assessment systems with automated systems that offer real-time feedback, assist teachers in decision-making, and adapt individual student trajectories (Song et al., 2024).

For Paiva et al. (2022), the automation of assessment in digital environments produces predictive analysis for academic success and the personalization of teaching processes in complex school systems, especially if integrated with state-of-the-art educational management platforms. The SmartSchool platform, within the framework of a collaborative project involving the University of Cartagena and Colciencias, is a benchmark within this transformation, achieving a learning ecosystem adapted to individualized teaching based on

automated performance indicators. One of its most important modules presents, analyzes, and compares student performance by subject, academic term, and level of achievement, in order to propose a set of pedagogical recommendations to the teacher based on the information obtained.
Learning assessment that integrates digital technologies has been extensively reviewed in multiple research studies, such as those by Shoaib et al. (2024), Bennett (2011), and Aithal et al. (2024), which have demonstrated its potential in terms of the possibility of promoting continuous, differentiated, and anticipated feedback. Other recent research shows that pedagogically designed automated indicators benefit the quality of training processes (Bulut et al., 2023). Also, authors such as Redecker (2017) propose that integrated digital assessment systems should be oriented not only to the control of academic performance but also to support teachers in making more informed pedagogical decisions.
The literature also highlights the importance of new technologies for the design of adaptive assessment systems where data are converted into results to modify the way of teaching in the classroom (Van der Kleij et al., 2015). Thus, platforms such as SmartSchool represent an operational response to these theoretical recommendations, offering a means by which teachers can observe, interpret, and make decisions based on learning data in a personalized manner.
Despite the evolution of educational technologies, many educational institutions still struggle to implement systems that can truly incorporate personalization with real-time assessment (Makinde et al., 2024). Thus, the following question arises: To what extent does the use of an automated academic performance indicator, such as the one proposed in the SmartSchool platform, contribute to personalizing teaching-learning processes and improving pedagogical decision-making?
In this sense, this study is justified by the need to generate knowledge regarding the impact of technological tools that not only seek to digitize processes but also transform the logic of teaching and assessment. The case study of the SmartSchool automated indicator allows for understanding how these solutions can be integrated into real-life teaching contexts, especially in Latin American educational systems that seek to innovate without losing sight of educational quality. Therefore, the main hypothesis is that the implementation of an automated academic performance indicator in digital environments has a significant impact on the learning personalization process, as it facilitates both continuous assessment processes and differentiated performance analysis, and suggests pedagogical activities in real time.
The results of this study are expected to contribute to the literature on innovation in education with a practical analysis of a real, concrete tool; identify the functionalities and pedagogical principles relevant to automated assessment; provide suggestions for its use in school settings from a quality and equity perspective; and finally, provide design elements for application to other similar platforms.

METHODOLOGY

A qualitative approach based on an instrumental case study (Kekeya, 2021) was chosen because the objective is not to generalize results, but rather to deeply understand a particular phenomenon that offers a basis for other pedagogical spaces, in this case, the implementation of an automated academic performance indicator as a means of personalizing learning. This methodological choice corresponds to the exploratory nature of the object of study, which is an executable digital module within the SmartSchool platform, and the need to observe how its technical characteristics relate to pedagogical objectives. For Stake (Stake, 1995), the case study is useful to understand unique phenomena that, although they occur in specific contexts, can contribute to informing widespread practices.
From a design perspective, a descriptive-analytical design was chosen, on the one hand, to describe the system's functionalities in a test environment; and, on the other hand, to analyze the extent to which these functionalities operate in line with the pedagogical principles of personalized learning and, in turn, formative assessment. This type of design has proven to be highly useful in studies investigating technological innovations in education and, therefore, enables the discovery of relations between instructional design and the actual use of digital tools (Yin, 2017).
The unit of analysis was the SmartSchool course management platform, developed by the University of Cartagena with support from Colciencias. The study focused on the academic performance indicators module. Access to this platform enabled a systematic review of the data visualization functions, data segmentation by subject and academic term, automatic generation of teaching recommendations, and export of academic reports. The decision was made to use simulated data similar to real data. Although this does not replace participatory

research with real users, it is a valid strategy in exploratory studies when analyzing a digital tool under development or when it is necessary to focus the analysis on its functional architecture (Zhao et al., 2018).

Two complementary techniques were applied to gather information. First, a functional analysis of the platform was conducted using a pre-structured guide that allowed for observation and recording of navigation flow, as well as identifying what types of data could be displayed and the system's logic and feedback mechanisms. Then, a documentary analysis was conducted on automated assessment, learning personalization, and adaptive digital environments. This review allowed for a comparison of the indicator's functions with contemporary pedagogical approaches and theoretical frameworks that advocate for the critical integration of technologies in education (Gikandi et al., 2011).

To carry out the data analysis, a comparison matrix was prepared for five key dimensions (visualization, adaptability, customization, exportability, and pedagogical usefulness) chosen not only because they were relevant in the literature on personalized virtual learning environments (Van der Kleij et al., 2015), but also because of their connection to the functionalities evidenced by the module visualization. Each dimension was studied from the perspective of its value in pedagogical decision-making, its scope for generating differentiated learning experiences, and its degree of connection with the formative assessment process.

From an ethical perspective, the study did not collect personal data nor require the participation of subjects, so the platform's functionality was analyzed. Furthermore, the principle of responsible use of digital materials and their corresponding citation, as well as the transparency of the information processed, was strictly verified. Thus, the documentary nature of the study excludes the request for informed consent, but not the request for respect for academic integrity.

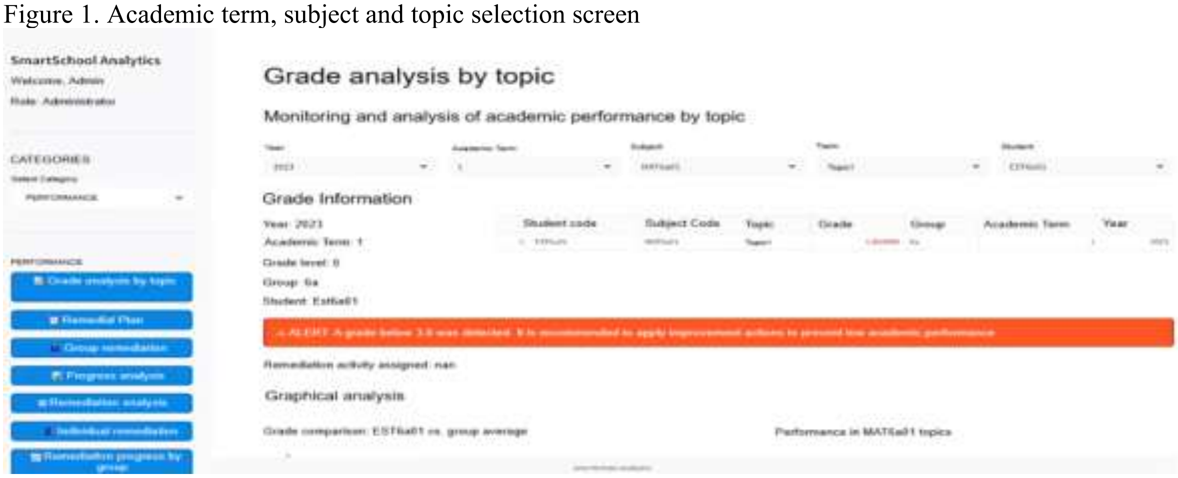
On the other hand, despite its contributions, the study is considered to have certain limitations. It is worth noting that the study was conducted in a test environment and did not gather direct use experiences with students or teachers, which limits the scope of the conclusions in terms of practical effectiveness or institutional acceptance. At the same time, the evaluation was conducted with a single technological product, without comparing it with other products or comparable evaluation models. However, the results are considered to open lines of future research aimed at empirically evaluating the pedagogical impact of this type of tool in the school context.

RESULTS

A thorough review of the automated academic performance indicators module offered by the SmartSchool platform allowed for identifying a series of sequentially integrated interactive features, which constitute a digital assessment environment adapted to personalized learning. Navigation through the module begins with a screen that allows the teacher to select the student or group of students they wish to analyze, the academic term, and the corresponding subject. This feature is essential because it allows the analysis experience to be personalized, ensuring that the data displayed is relevant to the specific context of the teacher's work.

Figure 1 shows three fields in the form of drop-down lists: "Academic term,", "Subject", and "Topic." Once selected, the system automatically triggers a data query, allowing the teacher to contextually control the information.

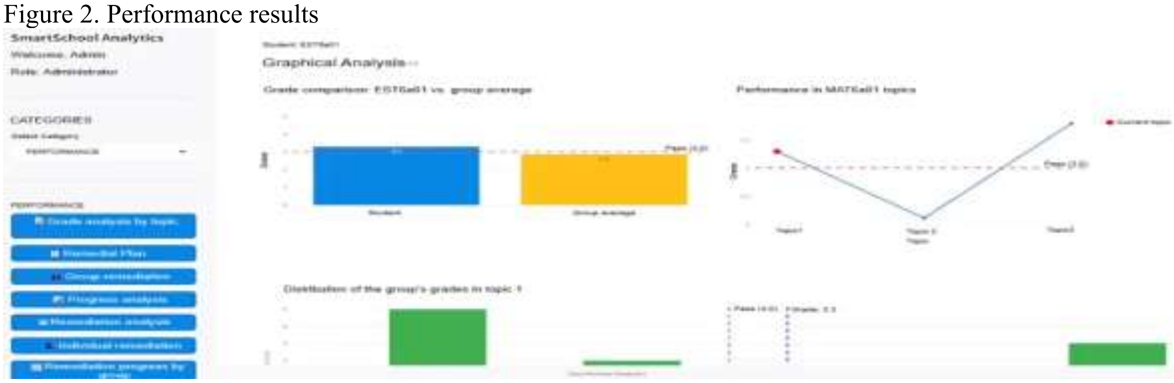
Figure 1. Academic term, subject and topic selection screen



Source: Authors

Once the filters are defined, the system displays three graphs representing a student's performance relative to the overall group. The first graph in Figure 2 shows a comparison of the grade of the student selected for evaluation against the group's overall average. The blue bar corresponds to a student, and the yellow bar corresponds to the group average. The bar for the evaluated student is labeled with the student's name or code, and hovering over it displays the numerical score or performance level achieved. The second graph represents the student's performance on the evaluated topic, while the third shows the distribution of the group's grades in the selected topic. The dashed red line represents the passing threshold, and the dashed blue line shows the grade of the evaluated student, which in this case is above the passing threshold.

Figure 2. Performance results

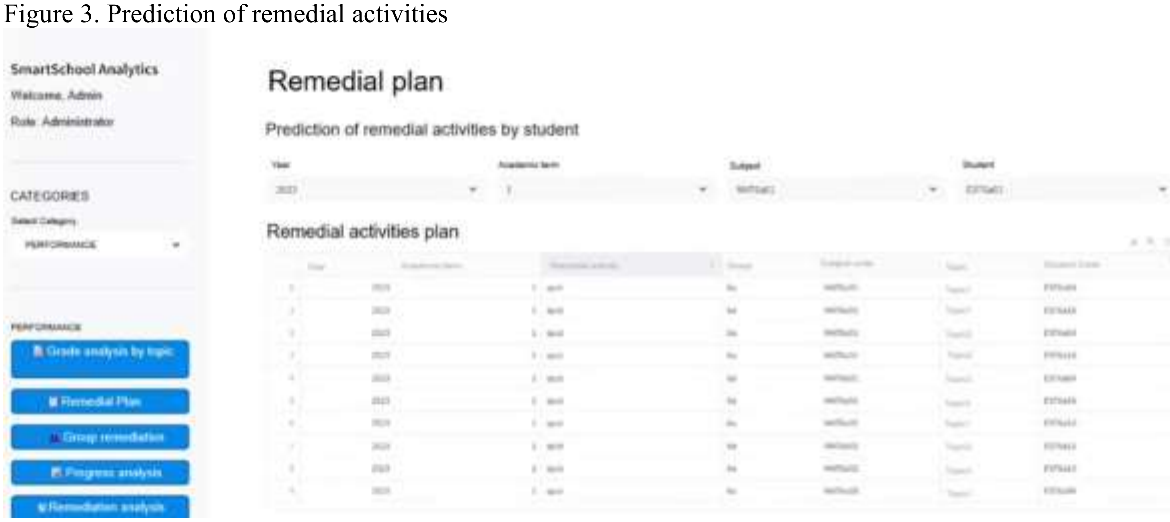


Source: Authors

The third graph at the bottom of the figure also shows that some students are below the passing threshold for the subject. For these cases, Figure 3 shows the interface of the "Remedial plan" module of the SmartSchool Analytics platform, specifically the functionality for predicting remedial activities per student. This component is part of the "Remediation analysis" subsystem, as seen in the left-hand menu. In the upper center of the screen, the user can apply customizable filters such as academic year, academic term, subject, and student, allowing for specific and targeted reports. In this case, the selected subject is MAT0421, corresponding to Mathematics. Below the filter bar, a table is displayed with a remedial activity plan, with the following fields: Year, Academic term, Type of remedial activity, Group, Subject, Topic or Remedial unit, and Student. The table lists students with their respective codes, as well as the remedial areas and competencies to be reinforced, allowing for the automatic generation of customized improvement plans. This feature turns assessment into a predictive tool, as it can anticipate remediation needs even before critical performance alerts materialize in final grades.

From a pedagogical point of view, this tool not only reports on performance but also prescribes and implements remediation and reinforcement actions adjusted to the reality of each student, making this tool a strategic resource for the design of adaptive learning paths that are especially suitable for use in formative assessment or academic monitoring processes.

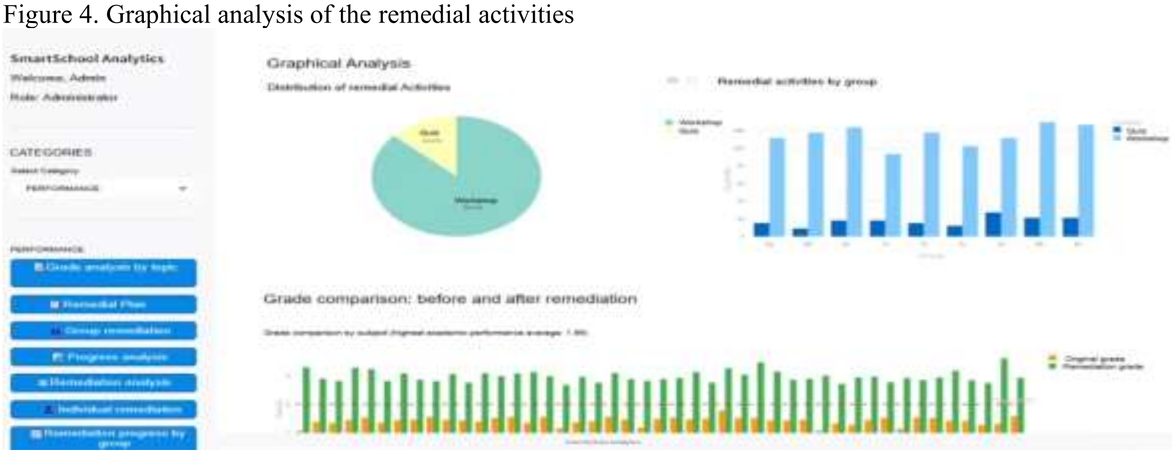
Figure 3. Prediction of remedial activities



Source: Authors

On the other hand, this same function allows for obtaining a graphical analysis of the remedial activities shown in Figure 4. This function allows for obtaining a distribution of the type of remedial activity, both individual and group, in addition to a comparison of qualifications before and after the remediation.

Figure 4. Graphical analysis of the remedial activities



Source: Authors

Figure 5 shows the interface of the "Group remediation" module, which is designed to analyze collective academic performance below established criteria. This feature is designed to allow teachers to quickly view, in detail, which students have not reached the expected achievement level in a specific competency or unit.

At the top of the screen, filters are displayed that allow you to configure the academic year, academic term, group, subject, and topic. In Figure 5, group 6A is being assessed in course MAT0421, topic topic2, during the first academic term of 2023. The center of the screen displays a table titled "Students with grades below criteria," which groups information by student, course code, group, thematic unit, remedial activity, and grade obtained. The rows are color-coded: red for grades below what is considered good performance and yellow for those grades close to reaching the minimum passing grade.

This color coding allows for an immediate visual interpretation of academic risk, facilitating teacher decision-making based on historical performance data. It is important to note that each row also indicates the proposed remedial activity for each student, which supports the idea that this is a proactive system. From a pedagogical perspective, this feature allows teachers to: identify patterns of low performance by unit of knowledge, build intervention plans in the classroom context rather than individualized actions, and manage support resources based on consolidated evidence by unit or competency. Below the table shown in the figure is a section for a graphical analysis of remediation in the classroom context, which serves to account for the distribution of group grades by subject, the percentage of students who need to recover, and the effectiveness of the remediation.

Figure 5. “Group remediation” Module

Source: Authors

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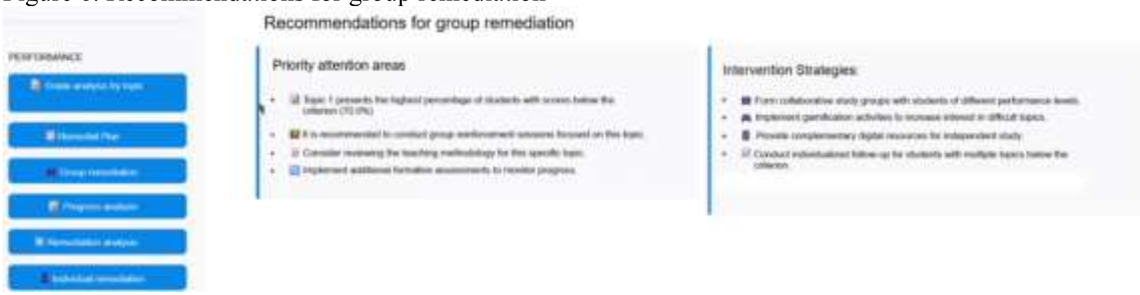
Another of the module's most beneficial features is its ability to automatically generate pedagogical recommendations based on student performance behavior. These recommendations appear alongside the individual student analysis and reflect possible pedagogical actions the teacher could implement. Figure 6 shows how these pedagogical recommendations are automatically generated in a box with text detailing priority areas and recommending intervention strategies. All of these recommendations are generated based on curriculum standards and can be applied in instructional planning.

Figure 6. Recommendations for group remediation



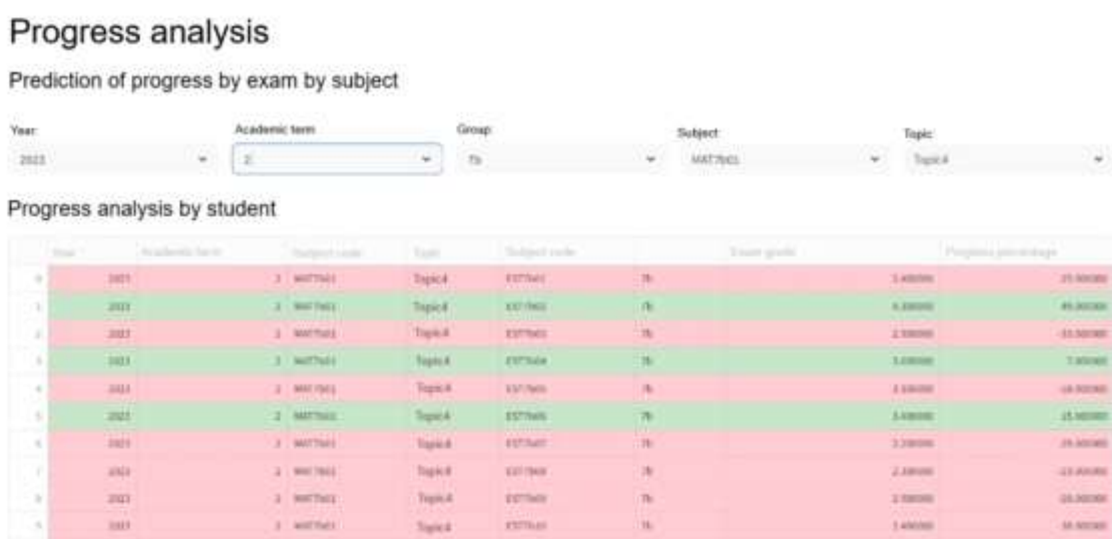
Source: Authors

Figure 7 describes the interface of the "Progress analysis" module, a feature focused on predicting and visualizing student progress by subject and topic based on the results of assessments. This module focuses on the agile experience of academic progress, allowing teachers to determine how a teaching unit or a particular topic has impacted them once they have been assessed.

At the top are the configuration parameter filters: academic year, academic term, group, subject, and topic. These parameters provide reports on progress in a specific content area. The main section is occupied by a table titled "Progress analysis by student," which organizes the information into the fields listed below: academic year and academic term, subject, topic assessed, student and group, exam grade, and estimated progress percentage. Each row corresponds to a specific student who has been assessed, and certain colors have been used to code the results obtained: Green indicates positive or acceptable progress, while red represents negative or concerning progress.

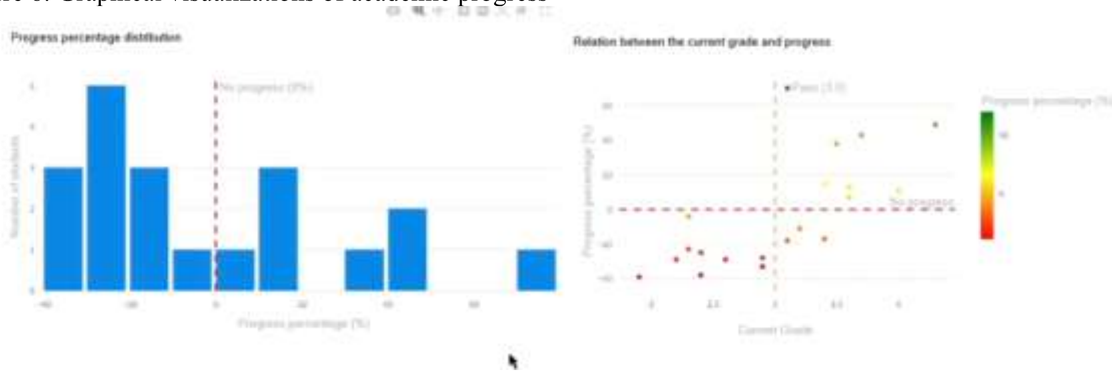
There is one aspect worth highlighting about this view: the system not only displays the result obtained, but also an estimated percentage of progress. This implies that it uses a predictive or historical baseline model. For example, a student may have obtained a high grade but have low progress if they were already performing well, or vice versa. From a didactic perspective, this module allows for seeing the real effect of a unit or exam on the student's progress, identifying whether high performance actually translates into improvement, and predicting future trajectories, which allows for possible interventions and didactic adjustments.

Figure 7. Progress analysis (by exam by subject)



Source: Authors

On another note, Figure 8 shows two graphs that enhance the content of the "Progress analysis" module by subject and by student. These graphs highlight the way trends are displayed and the relationship between current grades and estimated progress. The graph on the left shows a histogram that displays the distribution of student progress percentages, with the number of students on the y-axis and the progress ranges (%) on the x-axis. The blue bars indicate the number of students in each segment, highlighting the negative and positive segments.
A red dashed reference line marks the cutoff point at 0% progress, clearly differentiating between those who have regressed and those who have shown improvement. This visualization is useful for teachers as it allows them to quickly identify asymmetry in academic progress within the group and make differentiated decisions for the identified subgroups.
On the right, a scatter plot is presented that relates students' current grades (X-axis) to their percentage of progress (Y-axis). Each point represents a student, color-coded according to their level of progress (green for high, red for negative), and arranged according to their performance. The visualization makes it possible to identify critical cases, such as: students with high grades but no progress (top right area), students with low grades but significant improvement (top left area), Stagnation or regression (points below the baseline in red). This type of visualization facilitates qualitative analysis of learning, as it reveals that absolute performance does not always equate to actual progress, a key distinction in formative and adaptive assessment processes.
From a pedagogical point of view, both visualizations provide substantial value to the evaluation process, since they allow for: detecting general group trends (average progress), identifying atypical or emerging individual cases, supporting decisions on reinforcements, accelerations or curricular adaptations, and incorporating visual analysis as a tool for dynamic monitoring of learning.
Figure 8. Graphical visualizations of academic progress



Source: Authors
Continuing with this same functionality, Figure 9 shows a combined screen of the progress analysis module in SmartSchool Analytics, where two key components are integrated: a bar graph representing the average progress and the average grade per group. In addition, a set of automated recommendations categorized as "Improvement strategies" and a complementary list of suggested improvement strategies at the pedagogical level are shown.
At the top of the screen, a single blue bar graph corresponding to group 7D is displayed, whose average progress is below the established threshold (represented by a red dashed line). The graph relates the left vertical axis to the progress percentage and the right axis to the average grade, allowing the discrepancy or consistency between the two indicators to be visualized. This type of representation allows for the diagnosis of collective problems: for example, when a group has acceptable grades but negative progress, they could be repeating content without making progress in key competencies.
Furthermore, below the graph, the system automatically generates a set of pedagogical recommendations under the heading "Priority attention areas". These suggestions are contextual and specific; in this case, they highlight that the group analyzed is showing negative or no progress, which requires reviewing the pedagogical planning. It is recommended to implement personalized tutoring, conduct diagnostic assessments, and review teaching methodologies. These observations allow for moving from diagnosis to pedagogical intervention, which strengthens the principle of assessment for learning.
Similarly, the block on the right completes the recommendations with some pedagogical intervention strategies. In this way, strategies are achieved that, on the one hand, address cognitive performance while simultaneously addressing motivational and didactic factors, articulating data analysis and multi-causal pedagogical actions, which is pertinent in the given case. From a methodological perspective, this feature represents an evolution of

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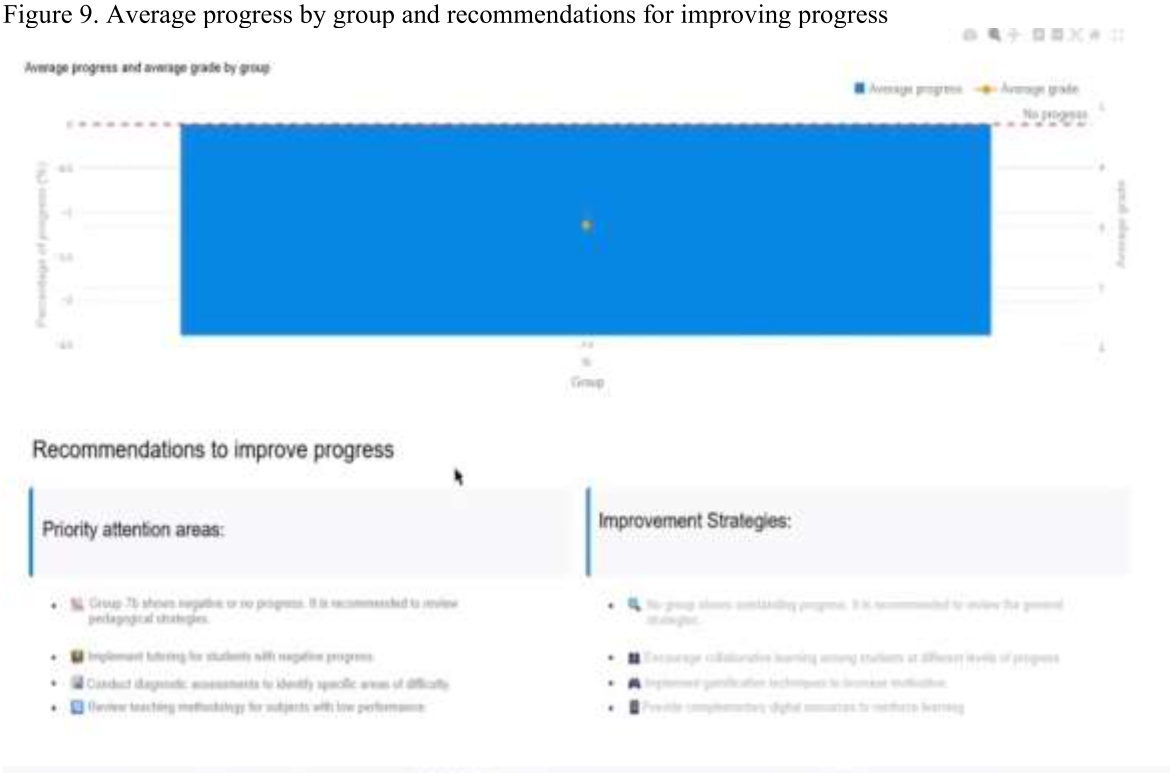
the concept of learning analytics, as it introduces visual diagnosis, pedagogical interpretation, and the proposal of possible concrete action. It also allows teachers to transition from a descriptive view of performance to adaptive and differentiated planning, focused on groups of students.

Figure 9. Average progress by group and recommendations for improving progress



Source: Authors

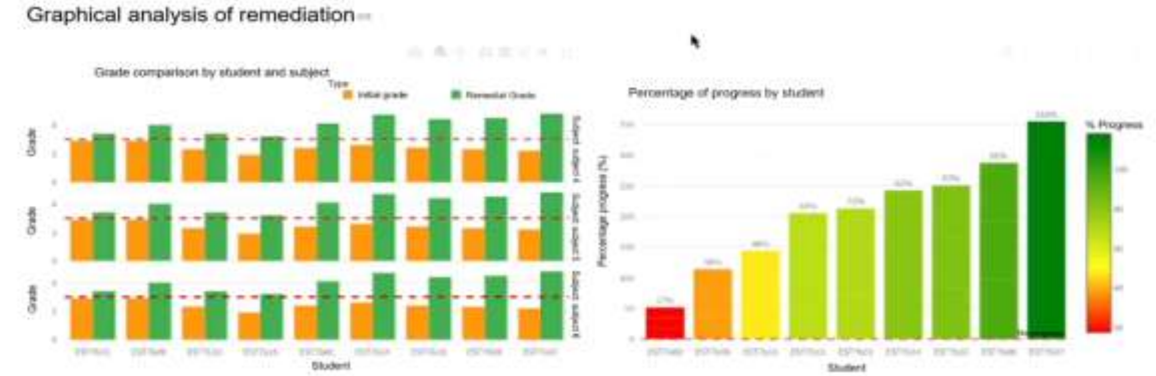
The academic performance module also allows the display of complementary graphs within the function titled "Graphical Analysis of Remediation", a tool that allows for visualizing the effect that remedial activities have on students' academic performance, based on a comparison between grades before and after a reinforcement process.

Figure 10 shows, in the graph on the left, a comparison of grades by student and by subject. This type of grouped bar graph represents, for each student, two subject grades: the initial grade before remedial activity (orange bar) and the grade obtained after the intervention (green bar). Each group of bars refers to a subject or assessment unit that was assessed, and the horizontal rows outline different thematic blocks; the vertical bars are arranged on a common scale that allows for a direct comparison of the impact that remedial activities have had on student performance. This visualization offers a before-and-after view, allowing for the determination of whether or not remediation has occurred. If the green bars consistently outperform the orange ones, positive progress is evident.

On the other hand, the graph on the right, which is the second, shows the percentage of progress per student. This second graph shows a bar per student that expresses the percentage of progress achieved after the remediation; the color scale ranges from red (minimal or no progress) to very dark green (excellent progress), with values even exceeding 100%. Each bar has an explicit percentage value at the top, reinforcing the quantitative dimension of the proposal. For example, one student has achieved 112%, indicating significant progress since their initial performance.

This graph allows teachers to clearly identify which students have benefited from remedial strategies, which students have made partial or no progress, and which sometimes require new interventions or methodological adjustments. It also visualizes the impact the remediation process has had on the group, enabling them to decide whether to continue, reformulate, or intensify reinforcement activities. From a didactic and technical perspective, this feature is a powerful alternative for evaluating the impact of remedial teaching, as it combines objective information with an interpretive graphical representation. It also allows for longitudinal monitoring of performance, transforming remediation into a space for pedagogical analysis rather than a "second chance".

Figure 10. Graphical analysis of remediation per student



Source: Authors

Likewise, Figure 11 represents a global view of the overall academic performance of students in this case, during the year 2023, and is organized into two complementary graphs and a table of performance statistics. This module allows the teacher or administrator to perform a macro monitoring of the overall performance of the institution or group, facilitating the continuous monitoring of educational quality. In this sense, the scatter plot on the left shows the evolution of the general academic average by academic term. Each point represents a cumulative average, and the X axis indicates the academic terms. The blue point indicates the average of the group or institution in the current year, while the red dashed line marks the minimum expected threshold (in this case, 3.0).

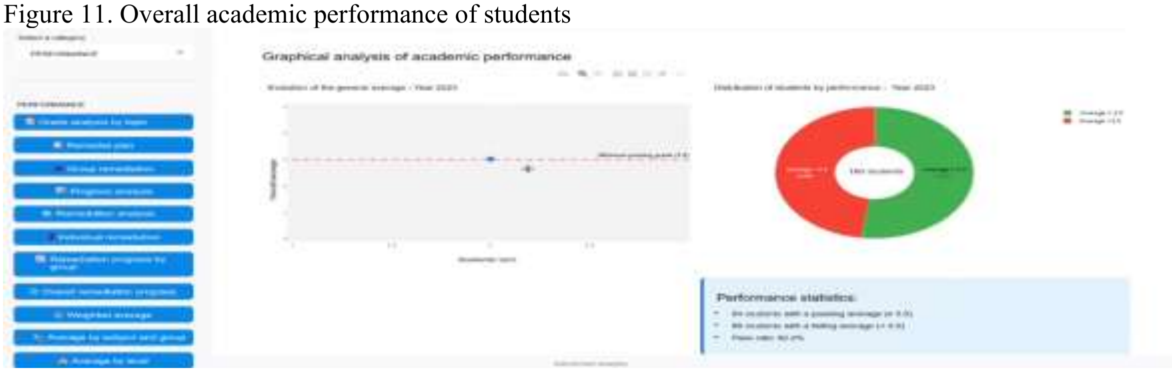
This graph shows whether the group/institution is maintaining stable progress, improving, or regressing. In the image, the blue dot is right at the lower limit of the acceptable average, indicating an institutional risk of low performance, which requires strategic pedagogical attention.

On the other hand, the pie graph on the right shows the distribution of students according to their performance, using color codes: Green: academic performance average ≥ 3.0 (passed) and Red: academic performance average < 3.0 (poor performance). In this case, it can be seen that, of a total of 198 students, 67.2% have academic performance averages equal to or greater than 3.0, while the remaining 32.8% have performance below the expected threshold. This distribution allows for early warning of the number of students at academic risk (which in turn allows institutional policies or teaching strategies to focus on that 32.8%).

In the lower right corner, the system presents statistical information with three important data indicators: percentage of students with a passing average (≥3.0), percentage of students with a failing average (<3.0), and the overall passing rate (67.2%). These metrics allow for setting institutional improvement goals, preparing interventions for mass or specific groups of students, and evaluating the overall impact of the strategies implemented.

This module can be considered a data-driven institutional assessment tool that integrates educational analytics into large-scale decision-making. Unlike previous modules that focused on individual students or groups of students, this module offers an aggregated analysis that can be used by academic coordinators, principals, or educational quality teams. The combination of averages, distributions, and statistics makes this module a key component of institutional assessment, both for alerts and for continuous improvement.

Figure 11. Overall academic performance of students



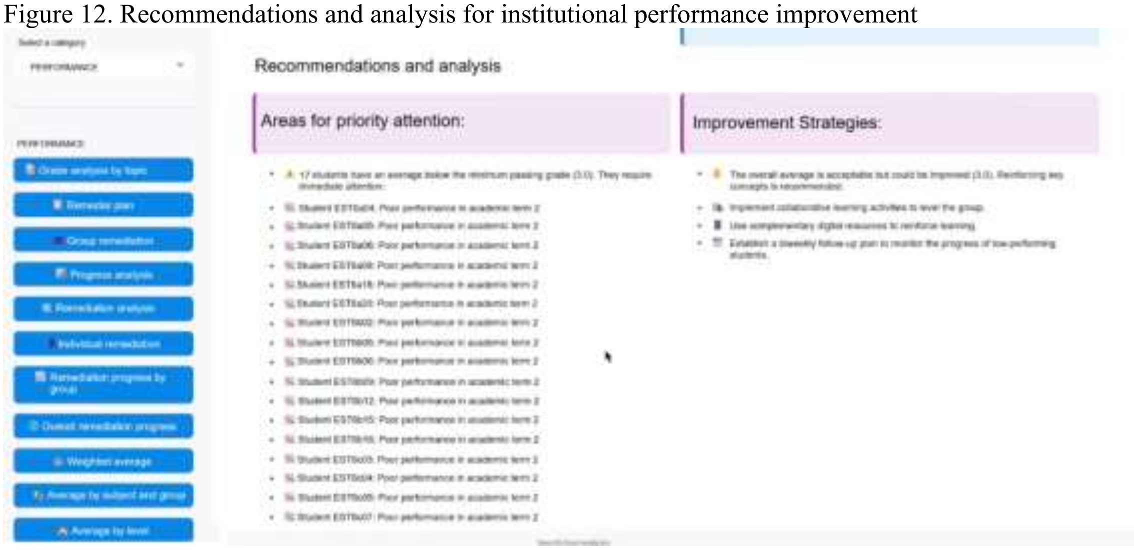
Source: Authors

Based on the above results and the identification of students whose performance is critical, pedagogical improvement strategies can be proposed based on the data obtained. As can be seen in Figure 12, the system provides an automated list under the heading "Priority attention areas" that lists students whose performance is critically low. Each entry indicates the student's name, the affected academic term, and the subject code, generating a specific alert for performance below the threshold (e.g., <3.0).

Additionally, it is accompanied by a warning icon and a summary of the list's conditions: "17 students have an average below the minimum passing grade (3.0). They require immediate attention." This feature allows teachers and administrators to detect patterns of systematic underperformance and segment the student population based on the level of urgency for intervention. It also serves as input for generating lists of students in need of tutoring or targeted reinforcement.

On the right side, a list of pedagogical strategies suggested by the system is displayed, based on the diagnosis generated. These recommendations are general, yet actionable and clearly written, aimed at the institutional or teaching level, and seek to promote a preventative and adaptive approach to teaching. This component synthesizes the prescriptive analytics approach that characterizes SmartSchool Analytics: it does not simply display data, but transforms that data into suggestions for concrete educational action, fostering an institutional culture of continuous improvement and evidence. It allows for prioritizing resources and efforts, focusing individual or group support, and promoting more strategic pedagogical decisions based on real indicators.

Figure 12. Recommendations and analysis for institutional performance improvement



Source: Authors

Figure 13 shows a consolidated dashboard that combines trend analysis of academic performance, passing percentage by level, and a block of diagnostic and pedagogical recommendations. This view integrates quantitative interpretation and strategic guidance in a single interface. The line graph shows the behavior of the students' academic performance average by educational level over different academic terms. This graph allows administrators and teachers to observe whether the strategies applied have had a sustained positive impact, or if there are levels that require adjustments or reinforcement.

The right panel displays a green bar graph comparing student passing rates by grade level. This information helps direct resources or differentiated interventions if gaps are detected between levels and can guide decision-making regarding curriculum continuity. Below the line graph, the system presents an automated text analysis block summarizing the performance of each level. This analysis reduces the burden of interpretation by offering a summary, based on real data, of the group's progress.

At the bottom, the module provides a consolidated diagnosis and a set of improvement strategies, classified in two columns: Diagnosis and Improvement Strategies. The diagnosis notes that "All levels have an overall average above the minimum passing grade," while three improvement strategies are proposed. These strategies encourage improved performance, even in those groups that already have successful performance, which is consistent with the principle of continuous improvement. Furthermore, it suggests mentoring practices among students as an inclusive and motivating strategy. This module reflects a predictive, analytical, and prescriptive approach: it analyzes the past (trends), evaluates the present (approval), and proposes actions for the future (improvement); this is especially useful for academic coordinators and management teams, as it offers a comprehensive view of the education system at different levels.

Figure 13. Academic performance, % passing by level, and diagnostic and pedagogical recommendations

Source: Authors

Finally, the module includes a function that allows for exporting generated reports to PDF or Excel. This feature allows for storing, sharing, and using the information in administrative spaces, teacher meetings, or parent information. Users can choose the report type (general, by student, or by criterion), the format (PDF or Excel), and indicate the directory where they want to save the file. Reports are generated with clean tables and integrated visualizations, suitable for printing or sending via e-mail.

SmatSchool's functionalities make up a powerful, intuitive system with great pedagogical value, allowing the user not only to observe data but also to interpret it, act upon it, and plan new teaching strategies in real time. The integration of visualization, automated analysis, and recommendation makes this module a fundamental tool for formative assessment in personalized digital environments. From here, Table 1 offers a systematic summary of the functional analysis of the platform's automated indicators module, extended from the observations grouped around five dimensions: Visualization, Adaptability, Personalization, Exportation, and Pedagogical utility.

Table 1. Pedagogical-functional analysis matrix of the performance indicator (SmartSchool)

Dimension	Observed Functionality	Pedagogical Assessment
Visualization	Bar and line graphs, color-coded for achievement levels	Facilitates rapid data interpretation and focuses the teacher's attention
Adaptability	Filters by academic term, subject, student, and achievement level	Allows for a differentiated reading of individual and group progress
Personalization	Automatic generation of recommendations based on performance	Facilitates timely and differentiated pedagogical intervention
Exportation	Downloadable reports for institutional and teaching use	Improves the systematization, transparency, and traceability of the process
Pedagogical utility	Tool for evidence-based decision-making	Continuously links assessment and didactic planning

Source: Authors.

The different dimensions link a specific technological function with a corresponding pedagogical consideration and allow for the verification of the system's technical design, thereby generating opportunities to enrich teaching practice. In this regard, visualization uses line and bar graphs, with traffic-light-type color codes that facilitate rapid interpretation of student performance. This visual representation allows for intuitive detection of achievement levels, focusing on exceptionally critical or outstanding cases.

In terms of adaptability, the tool allows for filtering by academic term, subject, student, and level, enabling a contextual and flexible reading of the analyzed data. This adaptability facilitates differentiated analysis, both

individually and in groups, fostering a more precise approach to formative assessment. While personalization is one of the most relevant functionalities, the automatic generation of recommendations derived from observed performance is also key. This feature transforms the system into a proactive tool that not only diagnoses but also suggests specific educational actions, fostering precise and differentiated interventions.
When exporting, the module allows for the download of reports that reflect the evaluation results in the required formats. This is very useful for both teachers and those responsible for accountability. This promotes the systematization of information, along with the traceability of pedagogical decisions and institutional transparency. Finally, in terms of pedagogical utility, it becomes a tool that enables evidence-based decision-making, thus directly linking evaluation to didactic planning. In this sense, it becomes a fundamental resource for fostering cycles of continuous improvement in the classroom.

DISCUSSIONS

The results obtained demonstrate that the SmartSchool platform's automated assessment module is not merely a diagnostic tool, but rather represents a shift in assessment logic in personalized digital environments. The inclusion of features such as data visualization, the prediction of remedial activities, and the automated proposal of pedagogical recommendations confirms current theories on learning analytics and digital formative assessment.
Several studies highlight the need for systems that are oriented towards continuous and adaptive assessment; for example, Hu and Xiao (2025) point to the fact that digital environments must guarantee instantaneous (in-time feedback) and contextualized (bidirectionality) feedback if a positive effect on learning is sought. In this sense, SmartSchool is considered to be consistent in allowing the teacher to act in real time concerning the collected data.
The academic progress prediction function is part of what can be understood as predictive assessment, since it is a proposal aligned with what Cheung et al. (2021) argue, who defend that learning environments should be systems capable of predicting what students' learning trajectories will be like and facilitate the possibility of (timely) intervention. Likewise, the possibility offered by the system to automatically generate pedagogical recommendations is related to what Santoianni et al. (2022) argue, who advocated for smart technologies to go from being control instruments to being mediators of personalized instructional design proposals.
In this sense, the system's ability to interpret student data, both individually and in groups, and to be able to carry them out in the form of differentiated teaching strategies gives meaning to the AI-assisted digital formative assessment model, so it could be framed within the most advanced model of assessment proposals based on digital technologies, as Bennett (2011) and Tan (2017) have stated.
Furthermore, the module's institutional value is significant. According to Joshi et al. (2021), academic management platforms must generate reports that are relevant to both teaching and institutional decision-making. SmartSchool achieves this by generating group progress graphs and alerts in management blocks. In this way, it articulates micro (student) and macro (institution) analysis, enhancing an evidence-based school culture.
It is worth emphasizing that the analysis was conducted in a test environment, specifically using simulated data equivalent to real data. Although this can be considered a feasible strategy from a methodological perspective (Flick, 2015), future studies should validate the evidence from this study with real users to determine its effective impact in the classroom. It may also be interesting to test this module against other environments, such as Moodle Learning Analytics or ClassDojo, to observe its differences and advantages.
This study provides concrete evidence of how an automated digital tool can mediate adaptive assessment and contextualized pedagogical planning. Its coherent integration of data, visualization, pedagogical interpretation, and suggested action makes SmartSchool a benchmark in the generation of educational technologies with pedagogical meaning.

CONCLUSIONS

SmartSchool's automatic assessment module shows significant potential for transforming traditional assessment processes into adaptive and personalized learning dynamics. Features such as visualization, segmentation, automatic instructional recommendations, and progress analysis offer useful tools for real-time formative learning assessment. Furthermore, the system enables differentiated, prior, and evidence-based educational interventions, aligning with international trends in learning analytics. At the institutional level, it becomes a strategic element for diagnosis, monitoring, and planning for teachers and management teams. The results, although obtained from simulated data, represent a solid starting point for future research in real-life contexts to evaluate their impact on improving teaching and learning.

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