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Identifying Students at Risk of Academic Struggles Using Learning Analytics for Tailored Tutoring

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Abstract

Within the field of educology, learning analytics (LA) has emerged as a crucial area of exploration, offering opportunities for personalized teaching and learning interventions. This study employs LA through a tool named AnalyTIC, designed to pinpoint students facing potential failure in a course and facilitate subsequent tailored tutoring. AnalyTIC furnishes educators and students with essential information for assessing academic performance, employing a risk assessment matrix. This information empowers teachers to customize tutoring for students encountering difficulties and adapt course content accordingly. The tool underwent validation through a study involving 39 students in the first term of the Environmental Engineering program at the Cooperative University of Colombia, all enrolled in an Algorithms course. Our results emphasize the importance of early identification of struggling students to enable timely corrective actions by educators. The initial development of the sensor aligns with the theoretical framework encompassing the phases of LA processes. Following the identification of these phases, a virtual classroom was constructed, and the tool for implementing these phases was subsequently developed. Validation of the tool highlighted the dynamic enhancement of students' educational experiences when educators possess ample information for decision-making, illustrating how tutoring and content adaptation contribute to improved academic performance.

Keywords: *learning analytics; tailored tutoring; learning adaptation; virtual classroom*

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Identificación de Estudiantes en Riesgo de Dificultades Académicas Utilizando Analítica del Aprendizaje para Tutorías Personalizadas

RESUMEN

Dentro del campo de la educología, la analítica del aprendizaje (LA, por sus siglas en inglés) ha surgido como un área crucial de exploración, ofreciendo oportunidades para intervenciones educativas personalizadas. Este estudio utiliza LA a través de una herramienta llamada AnalyTIC, diseñada para señalar a estudiantes que enfrentan posibles fracasos en un curso y facilitar tutorías personalizadas subsecuentes. AnalyTIC proporciona a educadores y estudiantes información esencial para evaluar el rendimiento académico, utilizando una matriz de evaluación de riesgos. Esta información capacita a los maestros para personalizar la tutoría para estudiantes que enfrentan dificultades y adaptar en consecuencia el contenido del curso. La herramienta fue validada a través de un estudio que involucró a 39 estudiantes en el primer trimestre del programa de Ingeniería Ambiental en la Universidad Cooperativa de Colombia, todos inscritos en un curso de Algoritmos. Nuestros resultados enfatizan la importancia de la identificación temprana de estudiantes con dificultades para permitir acciones correctivas oportunas por parte de los educadores. El desarrollo inicial del sensor se alinea con el marco teórico que abarca las fases de los procesos de LA. Tras la identificación de estas fases, se construyó un aula virtual y posteriormente se desarrolló la herramienta para implementar estas fases. La validación de la herramienta resaltó el mejoramiento dinámico de las experiencias educativas de los estudiantes cuando los educadores poseen suficiente información para la toma de decisiones, ilustrando cómo la tutoría y la adaptación del contenido contribuyen a un mejor rendimiento académico.

Palabras clave: *analítica del aprendizaje; tutoría personalizada; adaptación del aprendizaje; aula virtual*

INTRODUCTION

Learning analytics (LA) involves the analysis and interpretation of vast amounts and diverse types of data generated by students to comprehend and enhance the learning process and environment [1]. The surge in technological integration into educational processes has led to the proliferation of students' digital footprints, creating a wealth of data known as the digital footprint [2]. The application of big-data techniques has become integral to LA in educational settings [3]. LA utilizes approaches derived from computing, sociology, and statistical psychology for scrutinizing data collected throughout the educational journey and is exclusively applied in educational practices [4].

The roots of LA can be traced back to business analytics and data mining, initially focused on tracking potential clients [5]. LA, as defined in [5], involves the "measurement, collection, and analysis of information provided about students and their environment to optimize the learning processes." This technique enables the comprehensive management and control of student behavior in academic contexts, relying on pattern definition for decision-making [6,7]. LA tools delve into the operations within the virtual classroom's black box, scrutinizing processes through activity records.

Collecting data on interactions among students, teachers, and learning objects presents challenges. Traditional approaches treating learning management systems (LMS) as data centers are insufficient due to the expansion of activities beyond the model, necessitating new methods for data gathering and analysis [8]. Models must adapt to integrate customized academic data for each student, meeting the evolving needs of new educational patterns [9]. Analyzing vast amounts of information is crucial to achieving a personalized teaching process [9].

LA's role in analyzing student information in virtual learning environments is crucial for teachers, as such information is generally not managed or evaluated otherwise. Importantly, LA also serves as a valuable tool for students, offering feedback on their activities to support and enhance their educational capabilities [10]. It facilitates the identification of curricular impacts while fostering individual progress [11].

This led to the conceptualization of a Sensor, AnalyTIC, designed to employ LA for subsequent customized tutoring. Sakai LMS [12] was utilized for building the virtual classroom, PHP programming language for development, and MySQL as the database engine. The system underwent validation with 39 students from the Cooperative University of Colombia. The structure of this article is organized as follows: Section 2 (Background) discusses the significance of LA in education, the problem's study, and the methodology used in sensor development, employing the Feature-Driven Development framework. Section 3 (Investigation Development) outlines the process of sensor development and its subsequent application. Section 4 (Results) presents findings from the sensor test group and their significance. Section 5 (Discussion) provides discussions around the topic and the sensor's real-world application. Finally, Section 6 (Conclusions) concludes with insights gained from the development and testing of the sensor, contributing to the understanding of LA integration in daily educational practices [13].

Background

Learning analytics (LA) serves as a crucial decision-making tool for teachers, tracking students' footprints during the learning process recorded in Learning Management Systems (LMS) through various devices like smart devices, mobile phones, tablets, and portables. Additionally, participation in social media, photo blogs, and chat rooms contributes to this data collection [14]. LA aims to provide real-time information, intending to strengthen and individualize the educational process for each student within a specific educational institution. It achieves this through contextualized measurement methods, collection models, and database analyses tailored to unique interests, educational methodologies, and the dynamics of virtual teaching. The incorporation of sociological, psychological, and statistical techniques, along with the effective use of information and communication technologies (ICTs), is expected to enhance the educational system and the learning environment. Teachers can leverage the generated student data to respond effectively to specific situations [15].

Effective teaching requires reliance on information derived from students' academic behavior [16]. This information proves valuable for course evaluation, helping identify reusable materials and pinpointing causes of students' academic challenges. Analyzing vast amounts of information for each student and their academic activities would be overwhelming. LA plays a vital role in optimizing this information through a process known as data distillation [16], facilitating the filtration and evaluation of relevant information for informed decision-making.

In the quest for tools to process this information, [17] emphasizes the importance of collecting accurate information, requiring in-depth observation of student behavior. The appropriate application of LA contributes to educational customization processes, enhancing personal and institutional interpretations of content quality. Research in this field, initiated around 2010, provides a broad scope for application and study. Historically, there has been the development of tools applying concepts supporting LA, categorized based on their focus: those targeting teachers, the teacher–student relationship, and students [18].

For tools directed at supporting teachers in decision-making, examples include: (a) LOCOAnalyst, providing teachers with comments about students' learning activities and performance; (b) Student Success System, enabling the identification and management of at-risk students; (c) SNAPP, visualizing student relationships in discussion forums.

Tools designed for both teachers and students include: (a) Student Inspector, monitoring students' interactions in the virtual learning environment; (b) GLASS, offering an overview of individual student academic performance compared to the group; (c) SAM, illustrating what and how students are doing academically to enhance self-awareness; (d) StepUp!, aiming to encourage reflection on and awareness of the student's learning process.

Lastly, tools geared towards students include: (a) Course Signal, aiming to enhance student retention and improve their outcomes; (b) Narcissus, revealing students' contributions to the group.

This exploration of existing tools revealed a constraint within LA—specifically, the complexity arising during adjustments for more pertinent data. Questions arose concerning data management and the modeling of student and teacher behavior to facilitate diagnosis and the use of appropriate resources within diverse behavioral frameworks. Identifying this limitation prompted the initiation of a project to develop a sensor that would initially apply the four phases of LA, integrate and analyze significant student data within a Sakai virtual classroom, and subsequently provide teachers with sufficient information for creating customized tutoring and adapting content for at-risk students. The adaptation of content requires access to information enabling the modification of course materials using different parameters and a set of defined guidelines [19]. The initial step in developing this tool involved generating an approximate description of individual student behavior within the course [20]. It is crucial for educators to utilize tools and methods that can enhance student learning, and LA holds potential for powerful interventions [21]. Identifying these tools emphasized the need to address the applicability deficiency in LA by developing a sensor.

The development of a sensor incorporating LA for monitoring struggling students in a virtual classroom was operationally contextualized using agile methods with a logical foundation. These methods focused on building a software unit defined by small group structures, limited players, changes validated by user-specific requests, and generic heuristic considerations regarding the environment's logistics where the finished product was intended to be used. After evaluating methodologies verifying the mentioned factors, Feature Drive Development (FDD) [22] was chosen based on its logical significance, as depicted in Figure 1. This method served as the roadmap for system development.

Upon analyzing the application's target group, consisting of teachers and students engaged in the teaching–learning process, the following activities were identified as bases for joint consultation and assessment:

Familiarization and contextualization: Understanding the learning process, phenomenological awareness of the process, and gathering information.

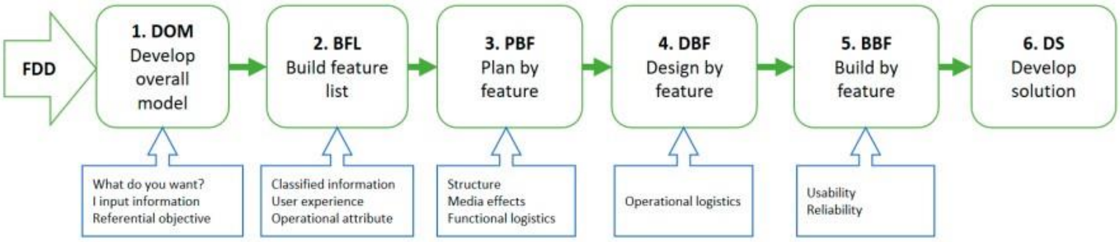


Figure 1 illustrates the procedural structure of Feature Drive Development (FDD).

Functional outline of the solution: 'What is desired, what will be revealed and why will it be revealed?'

Comprehensive projection of the solution outline: Modelling, prototype design, logical construction, user assessment, comprehensive adjustment, and installation of the solution.

Systemic Contextualization of the Problem

In this phase, the analytical field of action and the situational study were investigated to provide answers to these questions:

What is desired? How will it be accomplished? Who will use it? How will its quality be supported and validated?'

The goal was to construct a software tool that, by applying the four LA phases defined by [23], would act as a logical sensor. This sensor would empower the teacher of a virtual course to identify students facing learning difficulties by examining their grades. Subsequently, the teacher would discern the characteristics of the student group, including the predominant learning style [24], to formulate customised tutoring for those struggling and to adjust the material in use in the virtual classroom. This approach aims to enhance academic performance and, consequently, reduce the dropout rate in virtual learning environments.

To achieve this, we proposed designing a virtual classroom and then developing software that integrates the four LA phases to create a test of students' predominant learning styles. The design and implementation of the virtual classroom took place in LMS Sakai [12], utilizing the PHP programming language [25], and incorporating HTML5 and CSS for the layout.

The software would possess two user profile specifications (Teacher and Student), allowing for system validation in a real context. Furthermore, it would empower students to monitor their performance and compare their results with those of the group. Peer comparison of this kind is crucial for improving academic performance [26].

Before identifying the problem and conceiving a potential solution, our research revealed that existing LA tools and systems did not incorporate these four established phases. Moreover, these phases were not later employed to devise a customised tutoring process to enhance the academic performance of struggling students [27], or as a practical tool providing the teacher with information for decision-making—specifically, to adapt the course material shared with students in the virtual classroom [28]. It is imperative for the teacher to identify elements and/or objects that have piqued students' interest in the past to develop similar content [29,30].

Classification of Information and Operational Implementation

After diagramming the prospective action scenario, we proceeded to categorize the data based on its focus, establishing the tools needed to define and classify the requirements for applying the four LA phases. This involved identifying which input data would be considered and establishing the output serving as indicators for the sensor's corresponding alerts.

Drawing from the work of [4], the information considered encompassed:

- Learning style
- Login reports
- Connection time
- Individual performance vs. group performance
- Average of activities
- Resources consumed

This information would be extracted from student activity in the virtual classroom, aligning with the first phase of LA, Explain the Data. Subsequent phases would indicate the reason behind the data, predict and/or estimate a student's grades for the course, and prescribe customised tutoring options for students struggling to achieve the desired average.

Sizing Up the Technology

In this phase, we reviewed and reinforced the impacts of various existing technologies to identify the most suitable one for our purposes. Given our established requirements, we opted for development in a license-free environment. Consequently, we chose to develop the sensor using Sakai LMS initially, an open-source project. For the same reason, we selected PHP as the programming language, MySQL as the database engine, and Apache as the web server, with HTML5 and CSS rounding out the technology stack.

Development of the Investigation

Prototype Construction and Modular Structure Design

During this stage, the overall functionality of the Sensor was defined, and technological implementation considerations were integrated, albeit not in excessive detail. System components addressing the specified functions were also conceptualized. The construction of the prototype and the design of its modular structure were diagrammed to provide a more detailed description of the interaction between the components and the sequencing. Figure 2 illustrates the components of the design.

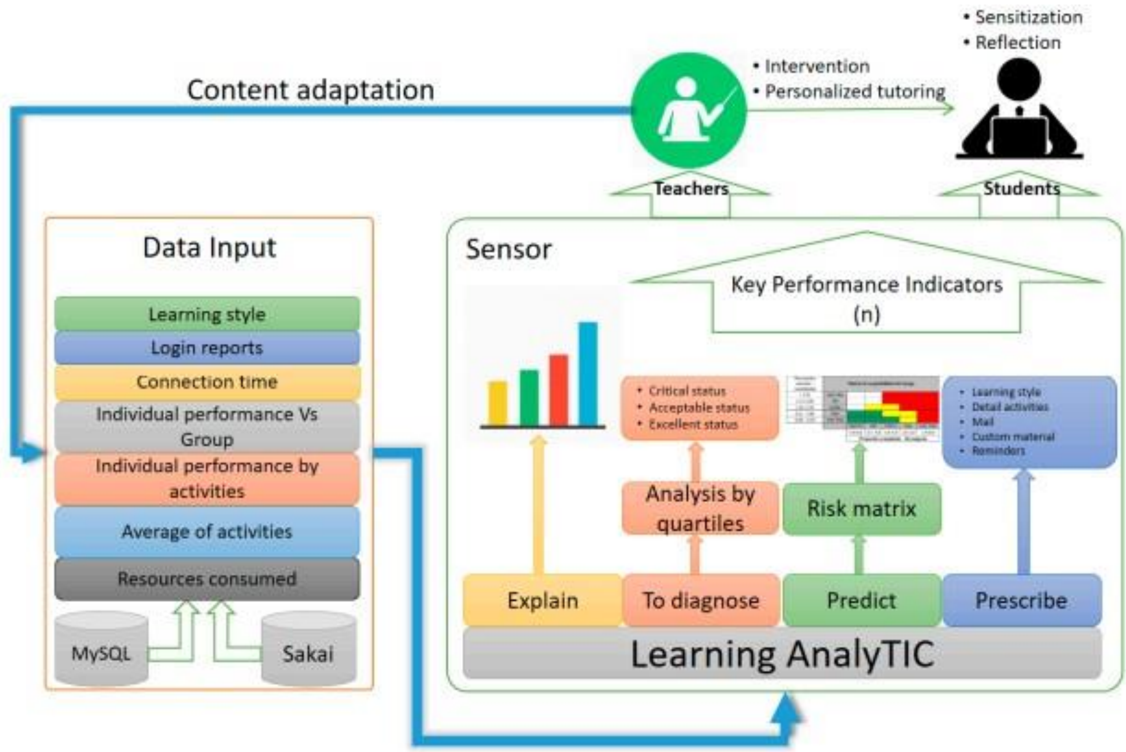


Figure 2. Conceptual layout of the sensor

The Sakai LMS was utilized to construct the virtual classroom for testing the sensor, employing the MySQL database engine. Various data inputs were identified from the virtual classroom, encompassing Learning Style, Login Reports, Total Connection Time, Individual Student Performance vs. Group Performance, Individual Performance by Activity, Activity Average, and Resources Consumed (such as reading content, chat room participation, tests taken, consumption of web content, syllabus reading, evaluations sent, wiki participation, and forum participation).

These data inputs were addressed in the following LA phases:

- Explanation: This phase involves presenting a student's footprint in the virtual classroom to the teacher, crucial for understanding academic performance, typically through graphs and tables.
- Diagnosis: The student group is divided into quartiles, with each student located and identified within a quartile.
- Prediction: A risk assessment matrix is designed for the teacher to review each student individually and identify those at potential risk of failing the course.

- Prescription: In this stage, the teacher can analyze a student's predominant learning style, review the sources used, send emails, provide additional study material, or send reminders for pending activities.

Analyzing the data gathered in the virtual classroom and applying these stages results in a performance indicator for the student, represented by the average grade to date. This indicator serves a dual purpose for the teacher: (a) assisting in outlining customized tutoring options for students at risk of failing, an expected performance improvement measure, and (b) prompting a review of content and planning of course activities. The latter occurs as the teacher gains insights into the student's predominant learning style, resource consumption patterns, forum participation, and engagement with various content types. These steps collectively lead to an adaptation of content and methodology, validating data and enhancing students' academic performance.

Functional and Operational Modular Description

The Sensor was crafted to implement the four phases of LA (Explain, Diagnose, Predict, and Prescribe). Aligned with the model designed for personalized tutoring and subsequent enhancement of student academic performance, the tool comprises the following modules:

- Server
- Level 1—Explanation
- Level 2—Diagnosis
- Level 3—Prediction
- Level 4—Prescription
- Documentation
- Quick Overview

Server Module

This module provides two options:

• Server setting: This option displays the address for the Sakai virtual classroom database, including the user, password, database name, and the group to be analyzed.

• Update setting: This form facilitates changing the server by entering one's name or IP address, user ID, password, appropriate database, and course. This step is crucial for the accurate analysis of information.

Level 1 Module Explanation

This module aims to answer questions about student interaction: 'What has happened until now?' and 'What is currently happening in the virtual classroom?' It addresses these questions by presenting measures of students' behavior in the virtual classroom, covering connection frequency, total connection times, individual performance versus the group average, individual performance reports, activity reports, activity averages, and students' use of different classroom resources [31].

Level 2 Module-Diagnosis

This phase of LA analyzes past and present data, answering the questions 'How and why did this situation happen before?' and 'How and why is it happening now?' The quartile distribution in this module allows the teacher to diagnose the students' current situations. Those in the first quartile are at a critical stage, while those in the second and third quartiles are in an acceptable state.

The quartiles represent values obtained from a data set structured into four parts, namely:

- The first quartile (Q1) corresponds to a value from a data set where 25% of the data is lower than Q1, representing the 25th percentile.
- The third quartile (Q3) corresponds to a value from a data set where 75% of the data is lower than Q3, representing the 75th percentile.

These measures position the student within the group based on their average compared to others. While the mathematical average is a central measure, it should not be the sole indicator, considering the progress and the number of grades in the module or course.

As the virtual module progresses, activities and assessments occur, leading to corresponding grades. The number of grades needed for each student's average may vary between courses or modules, indicating that individual average improvement or deterioration depends on grades obtained from remaining activities or assessments.

Level 3 Module-Prediction

When strategizing actions for enhancement, it becomes imperative to determine the variability in each student's accumulated grades through variance calculation and standard deviation. This involves assessing the group average throughout the entire course and establishing each student's position within the range of group grades, leveraging median and quartile measures.

A risk management tool, named the risk assessment matrix, has been devised to evaluate each student's risk of falling short of the minimum required average. This matrix computes the cumulative average for each student, considering the likelihood of average improvement based on their grade trend and position relative to the group.

If a student's cumulative average falls below the passing minimum, it serves as an alert for the tutor to propose improvement measures.

A widespread grade distribution, signifying fluctuations with some high, some moderate, and some low grades, indicates a diminished probability of improving the average.

The suggested improvement measures are subject to evaluation, allowing the student to enhance their individual average and standing within the group. The teacher retains the flexibility to modify these actions at any point to achieve the intended objective.

Every educational institution establishes minimum requirements for students to demonstrate the attainment of objectives in a virtual course, typically indicated through grades or points obtained. The subsequent proposal outlines the risk assessment matrix for estimating a student's potential future results.

This matrix considers the variability in a student's performance, reflected in the standard deviation of accumulated grades and respective averages. These descriptive statistical insights provide analytical support for the implementation of improvement measures aimed at helping the student reach the required minimum average.

To construct this risk matrix, we adhered to the definition of the following statistical parameters and formulas:

The arithmetic mean or average (median) is denoted by X, as defined in Equation (1):

$$\overline{X} = \frac{\sum_{i=1}^{n} X_1}{n}$$

where x*i* corresponds to each of the grades obtained by the student, and its value lies within the range of 0.0 to 5.0. *n* is the number of grades accumulated throughout the course, a quantity determined by the course designer and educational institution, typically falling within the discrete and finite range of $2 \leq n \leq 10$.

The individual average of all grades obtained during the virtual course is the decisive factor in determining whether the student passes.

Variance is denoted by s^2, defined by Equation (2):

$$s^2 = \frac{\sum_{i=1}^{n} \left(X_I - \overline{X}\right)^2}{n-1}$$

The variance serves as an indicator of how spread out the data set is, with the understanding that the units are presented as squared numbers. Represented by S, the standard deviation corresponds to the square root of the variance. When calculating the standard deviation for various sets of grades with sizes ranging from 2 to 10, and with the maximum dispersion, a grade would fall between 0.0 and 5.0 when n = 2 ≥ S = 3.535, and when n = 10 ≥ S = 2.635.

Both the variance and standard deviation are absolute variance measures that rely on the data set and the measurement scale. Additionally, the coefficient of variation, denoted as V, is defined in Equation (3).

$$V = \frac{S * 100}{\overline{X}}$$

This coefficient of variation serves as a metric for meaningful relative variation, facilitating comparisons between distinct data sets.

The median is derived from organizing the data in ascending order within a dataset, whereas the mean corresponds to the observational value situated at location number $(n+1)/2$, in the case of an odd n, or as the average of the observational values at the respective locations if n is even.

Consequently, based on this analysis and to assess the likelihood of passing or failing based on the grades acquired by the students, we formulated the matrix depicted in Figure 3.

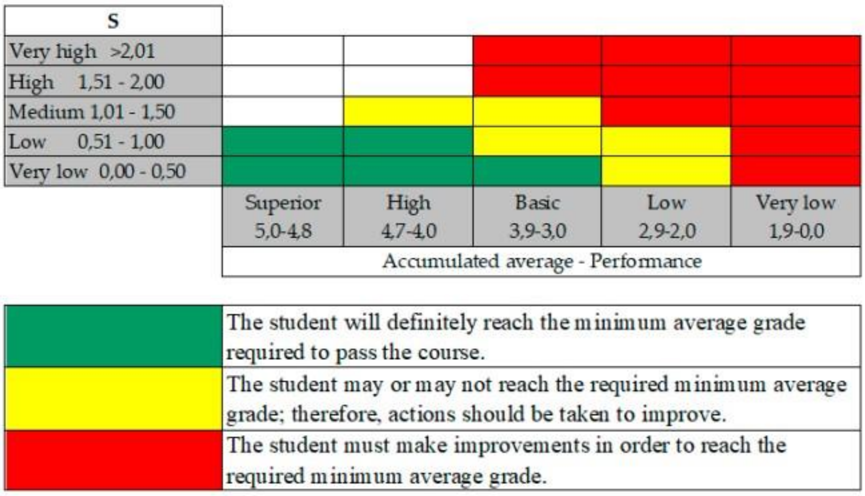


Figure 3 illustrates the matrix for evaluating potential risks.

Level 4 Module-Prescription

During this stage, LA interprets the predictions and aims to address the questions: 'How can we take action?' and 'How can we prevent the negative while reinforcing the positive?'

To assist in tackling these questions, the teacher possesses information about students in a critical state and tools for providing guidance, such as customized tutoring. The Tutoring option offers various resources for guiding the student, including:

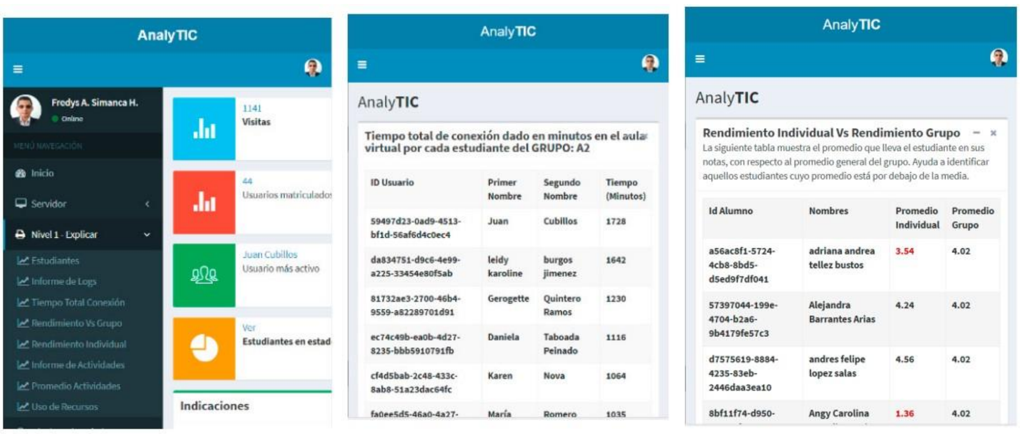
(a) Identifying the student's predominant learning style to recommend suitable materials. (b) Accessing details of student activities in the classroom, such as connection frequency, connection duration, notes on activities, and levels of participation in chat rooms, among other factors. (c) Taking actions like sending the student emails, providing study materials based on their predominant learning style, and sending reminders about upcoming due dates.

Construction of the Solution

Following software engineering principles related to design processes, construction, and implementation, we opted for the modular development of each component of the solution. Each module underwent evaluation for usability, user-friendliness, and effectiveness through white- and black-box tests. Here is an overview of the sensor modules under the teacher profile.

Level 1-Explanation

This corresponds to the initial phase of LA. The module presents data extracted from the virtual classroom, as detailed in the previous sections. Figure 4 provides three views of this option.



(a) (b) (c)

Module 2-Diagnosis

Utilizing quartile distribution to visualize the status of each student, Figure 5 provides a detailed breakdown and distribution by quartiles for the study group.

Figure 5. Roster of course students categorized into quartiles: students in Quartile 1 are highlighted in red, those in Quartile 2 in yellow, and those in Quartile 3 in green.

Module 3 Prediction

Within this module, the implementation of the risk assessment matrix is observed, allowing the teacher to assess each student individually, as depicted in Figure 6.

Figure 6. (a) Presentation of an individual student's performance analysis. (b) Placement of an 'x' on the risk acceptability matrix, illustrating the student's performance concerning the standard deviation of grades achieved so far compared to the cumulative performance average.

Level 4-Prescription

A breakdown of the teacher's perspectives and the steps to initiate personalized tutoring is provided in Figure 7.

Figure 7. The available tutoring options for students in a critical stage are presented, including specifics (learning style and overall activity) and actions (sending emails, providing study materials, and sending reminders for pending activities).

On the other hand, the student profile encompasses Explanation, Diagnosis, and Prediction. The details accessible to students are depicted in Figure 8:

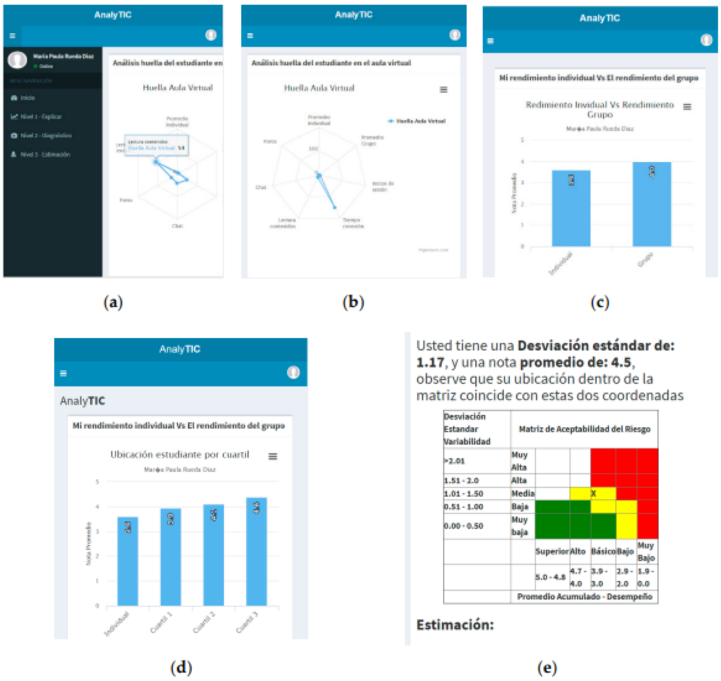


Figure 8. (a) Presentation of the primary menu choices for the student profile, offering selections for Home; Level 1—Explanation; Level 2—Diagnosis; and Level 3—Prediction. (b) Radial graphics illustrating the key analysis elements for the student in the virtual classroom. (c) One of the graphs available for viewing in Level 1. (d) Graph depicting individual performance versus group performance in Level 2. (e) The risk acceptability matrix, accessible to the student in Level 3.

Solution Launch and Socialization

During this phase, the pilot group was selected to validate the quality of the developed solution, initiating the corresponding socialization and implementation process for integration into pilot institutions. The sensor's validation took place with a cohort of 39 Algorithm students enrolled in Term 2017-1 within the Environmental Engineering program at the Cooperative University of Colombia.

RESULTS

The validation of the sensor involved the specified student group outlined in Section 3.4. At this university, grades are divided into three segments for each subject: the first segment holds a 30% weight, the second another 30%, and the third segment contributes 40%. For the test group, three grades were recorded for each segment, as outlined in Table 1.

Table 1. Tasks performed within each segment.

Segment	Activity	%
First Segment	Basic Algorithms Basic Algorithms in PSeInt Evaluation Unit 1	30
Second Segment	Evaluation Unit 2 Conditionals Workshop Conditionals Evaluation	30
Third Segment	Phase Evaluation Repetitive Cycle Workshop Repetitive Cycle Workshop Vectors and Matrices Workshop	40

Table 2 outlines the scores and mean values achieved by the experimental group across the three segments.

Table 2. Averages attained by students in individual segments and overall.

Student ID	Seg. 1	Seg. 2	Seg. 3	Final Grade
498651	4.4	3.8	4.3	4.1
503955	4.6	4.3	4.3	4.4
503473	4.3	4	4.3	4.2
506487	4.4	3.8	3.9	4
497959	4.3	4.2	4.2	4.3
504482	4.4	3.9	4	4.1
502682	4.3	4.5	4.4	4.5
501602	4.4	3.7	4.3	4.1
501518	4.4	4.1	3.9	4.1
500468	4.9	4.5	4.5	4.7
499458	4.5	4.3	4.4	4.5
499868	4.3	3.9	4.1	4.1
502283	4.3	3.7	4	4
508782	4.6	4.3	4.2	4.4
507814	4.7	3.8	4.1	4.1
504961	4.7	4	4.1	4.2
484220	5	4.2	5	4.8
502184	3.7	3.7	1	2.6
337589	4.5	3.7	3.9	4.1
508182	4	3.3	3.5	3.6
503171	3.7	4.7	4	4.1
507432	4.6	3.8	1	2.9
507042	4.4	3.6	3.9	4
504740	3.9	4.6	4	4.2
508102	4.5	4.7	4.5	4.6
507033	4.9	4.6	4.5	4.7
506656	4.8	4.8	4.6	4.6
505503	4.6	4.4	3.8	4.2
506743	4.6	4.5	4	4.4
508348	4	4.7	4.5	4.4
507190	4.8	4.4	4.5	4.5
481767	4.6	3.5	3.5	3.9
506203	4.9	4.6	4.5	4.7
507232	4.8	4.5	3.8	4.3
508451	4.3	4.5	4.2	4.4
506176	4.2	3.4	3.8	3.8
506149	4.6	4.5	4.5	4.6
506564	4.8	4.7	4.6	4.6
508233	4.5	3.5	4.8	4.4
General	**4.5**	**4.1**	**4**	**4.2**

In Figure 9, we depict the performance of the five students with the lowest scores in the initial segment, aiming to comprehend their progress in the second segment and evaluate the impact, if any, of personalized tutoring on their academic performance. Subsequently, we replicate the same analysis, this time comparing the second segment with the third.

Figure 9. (a) The graph representing students' grades in the initial section compared to the second. (b) The graph illustrating the grades of the same five students in the second segment compared to the third.

In Figure 9a, it is observable that among the five students, just one did not enhance their average in the second segment; the other four exhibited improvement in their grades. This consistent pattern is similarly reflected in Figure 9b, where only one student out of the five did not demonstrate an enhancement in academic performance.

DISCUSSION

The outcomes observed within the test group affirm that Learning Analytics (LA), when appropriately applied, serves as a valid and efficient tool for analyzing student data within virtual classrooms. It furnishes educators with decision-making tools to facilitate educational customization and tutoring processes for students encountering academic challenges. However, during the system development, a constraint was identified concerning the selection and adaptation of the most pertinent information, its analysis, and the subsequent modeling of student behavior.

LA essentially tracks the footprint left by students throughout educational processes, documented in Learning Management Systems (LMS) through diverse devices such as smart devices, mobile phones, tablets, and portables. Additionally, it encompasses participation in social media, photo blogs, and chat rooms. The primary objective of analytics is to enhance and personalize the educational process for each student in every institution. This is achieved by utilizing measurement methods, collection models, and database analyses contextualized based on specific interests, educational methods, and the dynamics of virtual teaching. Consequently, LA aims to improve the educational system and the learning environment supported by Information and Communication Technologies (ICTs) by incorporating sociological, psychological, and statistical techniques, resources, and methods into the management and analysis of student data. This enables educators to respond effectively to specific behavioral situations, preferences, and other influencing factors.

While certain LMS platforms feature internal monitoring tools, it has become essential to employ tools and standards that facilitate the structuring and storage of student interactions across various activities. Standard options like Tin Can APA, which extracts data from student activities and interacts with other applications, exist. These applications include SNAPP, LOCO-ANALYST, STUDENT SUCCESS SYSTEM D2L, Social Networks Adapting Pedagogical Practice, SAM, BEESTAR INSIGHT, ORANGE, RAPIDMINER, and KNIME. However, further research is necessary to structure and develop report processing elements and mechanisms for learning analytics that align with contemporary educational guidelines, reinforcing instructional and decision-making processes.

The sensor designed for identifying students at risk of academic failure and subsequently providing customized tutoring, serves as a significant step in addressing these needs. Nevertheless, there is ample room for further development to fulfill the aforementioned requirements. This tool stands out by integrating four LA phases, allowing educators to access student information in virtual classrooms and empowering students to comprehend the progression and pattern of their academic performance. While existing tools are predominantly geared towards administrative processes and educators, none provide students with a comparative analysis of their progress compared to that of the group. The sensor covers three of the four phases, allowing students to view their individual performance in relation to the group's performance (Explanation), position themselves within the corresponding quartile (Diagnosis), and utilize the risk matrix to estimate success or failure in a particular subject (Prediction). Table 3 provides a comprehensive comparison between different tools, outlining the functions of the developed solution.

Table 3. Comparative Analysis of Capabilities Across Learning Analytics Tools.

Tool	AnalyTIC	LOCO Analyst	Student Success System	Student Inspector	GLASS	SAM	StepUp!	Course Signal	Narcissus
Level 1—Explanation—Displays the data	x	x	x	x	x	x	x	X	x
Level 2—Diagnosis—Analyses the displayed data	x		x	x	x	x	x	X	x
Level 3—Prediction—Evaluates the current data to forecast future performance	x		x						
Level 4—Prescription—Outlines actions the user can take to correct errors	x					x			
Useful for teachers	x	x		x	x				
Useful for students	x		x	x	x	x	x	X	x

CONCLUSIONS

The initial practical evaluation of the sensor aimed at identifying students at risk of failing a course through learning analytics for subsequent personalized tutoring yields promising results. As outlined in the Results section, the test group exhibited significant enhancements in performance attributable to the tool's implementation. The design and application of the sensor affirm that learning analytics serves as an effective support mechanism for tailoring education. This tool equips both educators and students with essential information for decision-making, creating personalized tutoring strategies, adjusting course content, and facilitating self-assessment.

Given the positive outcomes observed in the test group, it is recommended to conduct further studies or pursue continued research in this direction. Specifically, exploration could focus on validating the sensor's ability to autonomously execute personalized tutoring without direct teacher intervention [32]. Additionally, assessing the system's capacity to issue alerts to struggling students about impending deadlines and offer automatic recommendations for supplementary reading materials aligned with students' predominant learning styles could be avenues for future research. Advancements in this research direction should aim for compatibility with various Learning Management Systems (LMS).

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