A Solution to Manage the Full Life Cycle of Learning Analytics in a Learning Management System: AnalyTIC

Fredys Alberto Simanca Herrera, *Fellow, IEEE*, Rubén González Crespo, *Fellow, IEEE*, Luis Rodriguez Baena, *Fellow, IEEE*, and Daniel Burgos, *Senior Member, IEEE*

***Abstract*— Learning Analytics (LA) has a significant impact in learning and teaching processes. These processes can be improved using the available data retrieved from students' activity inside the virtual classrooms of a learning management system (LMS). This process requires the development of a tool that allows one to handle the retrieved information properly. This paper presents a solution to this need, in the form of a development model and actual implementation of an LA tool. Four phases (Explanation, Diagnosis, Prediction and Prescription) are implemented in the tool, allowing a teacher to track students' activity in a virtual classroom via the Sakai LMS. It also allows for the identification of users who face challenges in their academic process and the initiation of personalised mentoring by the teacher or tutor. The use of the tool was tested on groups of students in an algorithms course in the periods 2017-1, 2017-2, 2018-1 and 2018-2, with a total of 90 students – in parallel with the control groups in the same periods that totalled 95 students – obtaining superior averages in the test groups versus the control groups, which evidenced the functionality and utility of the software.**

***Index Terms*— Learning analytics, educational technology, online education, personalized learning, personalized mentoring.**

I. Introduction

INFORMATION and communication technologies have become instrumental in facilitating teaching and learning processes. This boom in technology has allowed learning to take place in different spaces, including virtual ones, thus narrowing the gap for anyone who wishes to learn. In this way, we are looking for mechanisms that allow control over the progress of each student's learning, among which is the Learning Analytics (LA) that allows educational institutions and teachers to obtain knowledge about the progress of their students [1] in order to perform interventions when necessary and improve learning outcomes [2]–[4].

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F. A. Simanca Herrera is with the Universidad Cooperativa de Colombia, Bogotá 111321, Colombia (e-mail: fredys.simanca@campusucc.edu.co).

R. G. Crespo, L. R. Baena, and D. Burgos are with the Universidad Internacional de la Rioja, 26006 La Rioja, Spain (e-mail: ruben.gonzalez@unir.net; luis.rodriguez@unir.net; daniel.burgos@unir.net).

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This interest is motivated by the need to better understand teaching/learning, "smart content", personalisation and adaptation [5], [6].

Consequently, institutions face new challenges, not only in how to obtain and take advantage of this information, but how to apply it in the teaching-learning processes, allowing for greater control and the possibility of making the most of each of the resources that are available so that students can finish the courses successfully, and in this way improve the retention rate. There is also the challenge of performing timely interventions that lead students to success. Access to information allows for improvement in decision-making, modifying educational resources, and identifying risk cases [7]. By identifying the strengths and weaknesses of the students, it is possible to make improvement plans [1], [3].

Based on the above, and although there are learning environments that provide data automatically, the exploitation of such information for learning and teaching is still very limited [8]. For this reason, the AnalyTIC software was created to develop and apply the four phases of LA [9]. Its main function is to create a personalised tutoring environment for each student, by means of the generation of diagnostic reports that allow the teacher to predict what could happen with the student and then be able to track the student's development in order for him/her to successfully complete the course.

The aim of this software, in its first phase, is to provide the teacher with information through the virtual classroom of each of his or her students; in the second phase, the teacher should be able to identify students who are in danger of losing good academic standing; in the third phase, an estimate is made of the students' possible outcomes according to the grades that have been acquired so far; and in the last phase, the teacher provides personalised tutoring in order to help improve the academic performance of the students involved [10].

It is then expected that the teacher's intervention and adaptation of the content of the course improve students' academic performance, and that the software becomes a fundamental tool for decision-making by the teacher.

This article shows how the AnalyTIC software was developed, which was subsequently validated with four algorithms courses during the periods 2017-1, 2017-2, 2018-1 and 2018-2, with a total of 90 students. On this platform, the four phases mentioned above were evidenced by means of steps that allowed the evaluation of each one of them, in this way getting the necessary data and records for decision-making, thus generating a more personalised environment and allowing the teacher to have a more active role in the process of tutoring and monitoring each student.

The work is organised as follows; section II (Materials and Methods) explains how the problem has been studied, and describes the processes of analysis, design, development and implementation of the solution; in section III (Results), the results that were achieved by the test groups of the designed tool are presented; section IV (Tool Evaluation) describes the different methods that were used to assess the relevance of the developed model; and section V (Discussion) highlights the significance of the findings. Finally, the conclusions reached in the development and subsequent testing of the software are established.

A. State of Play

LA is applied to the student learning processes through four phases [9]:

Phase 1 To Explain: Visualisation of data from the past and present answers the questions: What happened? What is going on?

Phase 2 To Diagnose: Analysis of the visualisation, of the present and past, answers the questions: How and why did it happen? How and why is it happening?

Phase 3 To Predict: Interpretation of the analysis, for the future, answers the question: What can happen?

Phase 4 To Prescribe: Interpretation of the predictions or analysis, for the present and future, answers the questions: How can we act? How can we prevent the negative and enhance the positive?

Some learning management systems, such as Moodle and Blackboard, have addressed this, with the former implementing LA at Level 1 through a plugin called SmartKlass, which presents indicators on the learning progress and achievements of students, allowing the teacher to create reports. It can predict, but it is limited in its temporality, since it runs on previously completed courses; the missing levels have not been implemented or are not executed in real time.

On the other hand, Blackboard makes a summary through the creation of reports that allow students to visualise their learning progress by taking the data of the activities that have been carried out and making predictions based on this information, allowing teachers to focus on students who experience greater difficulty in their learning.

These platforms collect data that are helpful for analysing the learning processes of students and their difficulties in achieving the accomplishments proposed in the course [11], although the phases proposed by [9] do not work in their entirety. Therefore, it is necessary to develop tools that may be applied and that allow the teacher to have real-time data on the educational status of the students, and in this way be able to make decisions on how to improve their performance, thus creating personalised tutoring environments [12] according to the specific profile of and difficulties faced by each student.

On the other hand, as can be found in Educause's *2016 Horizon Report* [13], the A4 Learning project [14], [15] led by Universidad Internacional de la Rioja (UNIR) combines data collection techniques with visualisation of information, providing each student with continuous information that allows him/her to think critically about his/her education and objectives. This 100% online institution has also initiated the iLIME project [15], whose purpose is to develop and implement an automated system for recommendations of itineraries, in order to help teachers make personalised recommendations to students.

Rio Salado College, Harvard University and Austin Peay State University are three examples, among others, listed on the Educause website [16] that illustrate how the use of LA supports student and institutional success. Rio Salado [17] implements LA tools to predict risk [18], record activity such as logins or participation on the site, and provide intermediate responses. According to Educause [19], it allows instructors to address students who need more help in order to promote retention.

Harvard University [20] mines classroom data using a system called Learning Catalytics, which supports peer-to-peer instruction, a basic learning/teaching pattern.

It is clear that LA plays an important role in improving the overall quality and efficiency of learning and teaching by means of a better understanding of the educational process, a more complete evaluation of students, and the personalisation of education, thereby reducing student dropout rate. As shown in a study by Hanover Research, and mentioned in [13]: "Students have a desire for immediate and continuous feedback as they learn".

Extrapolated from some case studies that have been carried out internationally, it can be said that the AnalyTIC application could mean contributions in areas such as [21]:

To Improve Quality: Teachers could improve their own practice based on the information provided by AnalyTIC.

To Increase Retention Rate: The analysis allows institutions to identify at-risk students at an early stage and intervene with advice, additional materials and alternative activities.

To Allow the Development of Adaptive Learning: Adaptive learning is emerging to help students develop skills and knowledge in a more personalised and self-taught way [22].

II. Materials and Methods

The materials and the study method that were used to develop the AnalyTIC software and its subsequent validation with the test groups are described below. Initially, we describe the population in which the tool was applied, the proposal of the model, the design, and the description of the model that was developed.

A. Population and Samples

The research was carried out at Universidad Cooperativa de Colombia, in the city of Bogotá, D.C., Colombia, involving students from the Faculty of Engineering's Environmental Engineering programme enrolled in the Algorithmia course. This course is offered in the first semester and develops

TABLE I
POPULATION AND SAMPLES TAKEN TO VALIDATE THE TOOL

Period	Population	Test group	Control group
2017-1	67	39	28
2017-2	28	14	14
2018-1	52	23	29
2018-2	38	14	24

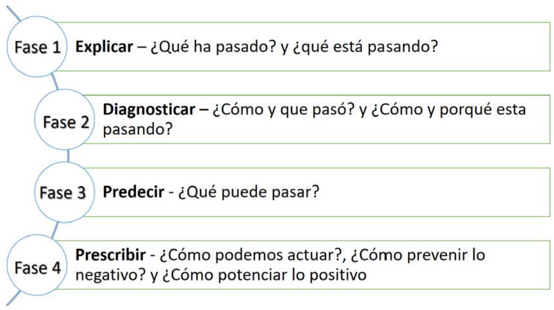

Fig. 1. Phases defined for learning analytics.

transversal competency, that is, it is within the curriculum of all engineering programmes at the faculty. The validation of the tool was carried out during the periods 2017-1, 2017-2, 2018-1 and 2018-2. Table I details the total population of the programme and the sample that was taken to perform the validation of the tool.

The Algorithmia course is composed of three (3) credits, which amount to 48 classroom hours and 96 hours of independent student work. It is a practical theoretical subject.

B. Model Proposal

The model that has been proposed is based on the phases defined by [9], for the implementation of the LA phases, which are illustrated in Fig. 1.

This phased structure was taken into account in the design of the proposed tool, which seeks to apply the four stages mentioned above.

C. Model Design

According to [23], any development process in the area of engineering must consider the phases of analysis, prototyping, design and construction; after this process, the following was determined in each of the stages.

1) Analysis Stage: In this first stage, we proceeded to define the objectives that we wanted to achieve with the tool. The first step was to obtain the data, seeking to answer the questions related to how, who, what, when and where. Finding the answer to these questions was fundamental since it is through analysis and synthesis that this information becomes knowledge [24].

As a second step, the following data were collected from the virtual classroom:

∗ Login numbers

∗ Total connection time per student

∗ Individual performance versus group performance

∗ Individual performance for each of the activities

∗ Notes of the evaluation activities

∗ Average score in each of the evaluation activities

∗ Use of resources (reading of resources, reading of syllabus, file sending, evaluation sending, among others)

In the third step, to answer what happened as well as how and why it was happening, we proceeded to diagnose the current state of academic performance of each of the students based on the data collected. For this, the group was divided into quartiles.

The first quartile, represented by Q1, corresponds to the value that was obtained from the set of data consisting of the average scores of the 39 students in the first test group, from which it can be said that 25% of data is less than Q1, and it is also clear that 75% of the data is greater than Q1. The first quartile corresponds to the 25th percentile of the sample. All students who were in Q1 were then classified as students in critical condition [25], and these would be the ones of most interest in the teacher's decision-making process and subsequent formulation of improvements.

In the fourth step, the necessary information was analysed, seeking to answer what could happen, and in order to clarify this doubt, a risk assessment matrix was built. In this matrix, the cumulative average of each student was combined, and the probability of improving this average was formed by taking into account the behaviour of the student's accumulated grades and the comparison and location of his/her grades with respect to the grades obtained by other members of the group.

For the construction of the above-mentioned matrix, the variability of the student's grades reflected on the standard deviation [26] of the accumulated grades and the respective average was taken into consideration. These descriptive statistical data give the teacher elements of analysis in order to implement improvement actions, and thus help the student reach the minimum average required. Table II details the matrix of acceptability of risk that is proposed [27].

TABLE II
RISK ACCEPTABILITY MATRIX

Standard Deviation - Variability	Risk Acceptability Matrix					
>2.00	Very high					
1.51 to 2.00	High					
1.01 to 1.50	Medium					
0.51 to 1.00	Low					
0.00 to 0.50	Very low					
		5.0-4.8	4.7-4.0	3.9-3.0	2.9-2.0	1.9-0.0
		Superior	High	Basic	Low	Very low

Finally, the improvement actions were determined. This is one of the most important steps of LA, where teachers can rely on the information that is generated by the student's academic behaviour. This information is useful for the evaluation of the course as it provides a notion of the materials that can continue to be used and identifies the key factors of difficulty of students when they begin their academic activity [28]. For this step, the following actions were determined:

∗ Sending email with the option of attaching material

∗ Submission of material or a URL address

∗ Sending reminders of upcoming activity, with the possibility of attaching documents or sending web addresses

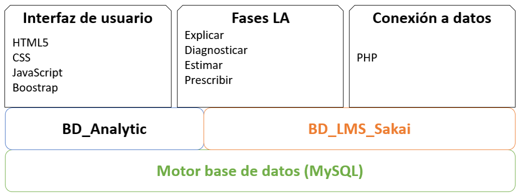

Fig. 2. Technological schematization of development of the solution.

2) Prototyping Stage: This stage begins with the definition of the general objective of the software, and then goes on to identify more specific requirements. The prototyping model is based on trial and error, as development of the solution progresses until the user is satisfied with the results [29].

3) Design Stage: The most appropriate software development methodology was determined here, taking the option of an agile methodology, given its relevance and effectiveness. The feature-driven development (FDD) methodology, built by Peter Coad and Jeff de Luca in the 1990s, was selected as a reference and technical development chart for the tool [30].

The FFD is structured according to five processes:

∗ To develop overall model
∗ To build a feature list
∗ To plan by feature
∗ To design by feature
∗ To build by feature

4) Construction Stage: At this stage, the impact of the various existing technologies in the context of technological support was studied and potentialized to identify which was the most appropriate. According to the requirements and the purpose of the tool, the option of developing in licence-free environments was adopted, and this is how we decided to develop the tool using the Sakai LMS in the first instance – because it is an open-source project, using PHP programming language, MySQL database engine, Apache web server, HTML5 and CSS to fulfil all the requirements of the tool.

In Fig. 2, the development of the proposed solution is schematized.

D. Description of the System Architecture

The platform that was developed is a tool aimed at assisting teachers in the identification of students with difficulties in their learning process by applying the four phases of LA, thus giving teachers access to information for tutoring students and making pertinent modifications to the teaching process. On the part of the students, it allows them to know their level of performance versus the performance of the group, providing a diagnosis of their current situation and an estimate of what can happen if they continue with the same performance.

Fig. 3 shows the structure of the platform, where the set of options and their role within it are observed. The platform can be viewed on any desktop, portable or mobile device; the only requirement is to have an internet browser.

1) Teacher Module: In the teaching profile, one can observe the implementation of the four phases of LA, established by [9]. The objective is to provide the teacher with a tool that analyses the data of the students' learning process, and after

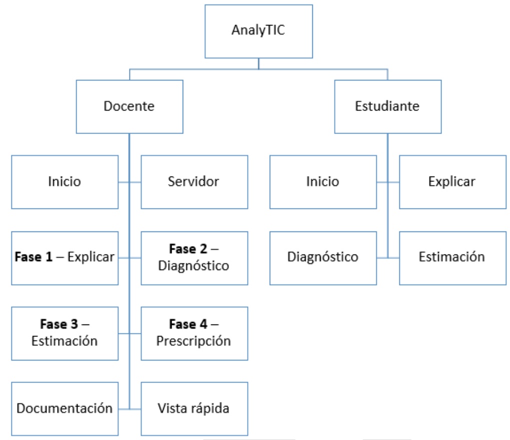

Fig. 3. Diagram showing the structure of AnalyTIC.

Fig. 4. Options of the AnalyTIC platform – teacher module.

that provide the necessary information so that the teacher can make decisions that lead to an improvement in his/her teaching practices. The module shows the progress and difficulties of each student, and allows feedback to be given to students, as can be seen in Fig. 4.

2) Student Module: The tool also allows students to know their individual performance versus group performance, the progress of their educational process that has led them to obtain these grades, a diagnosis of their current situation, and finally, an estimate of what can happen if no improvement actions are taken. With this information, the students will be able to provide feedback on their own activities in order to support and improve their academic performance. This module has four options: Start, Explain, Diagnosis and Estimation, as evidenced in Fig. 5.

The development of the model can be found on the web through the following link: http://5.189.175.156/analytics/. You can register as a teacher to be able to use the tool.

III. Results

The validation of the platform was carried out by applying the tool to the group of students defined in Population and samples; Table III details the averages achieved in each semester by the test group versus the control group. It is worth clarifying that, in Universidad Cooperativa de Colombia, where the test was carried out, the evaluation scale ranges from 0 to 5, with 0 being the minimum grade and 5 the maximum grade. The minimum grade required to pass the course is 3,

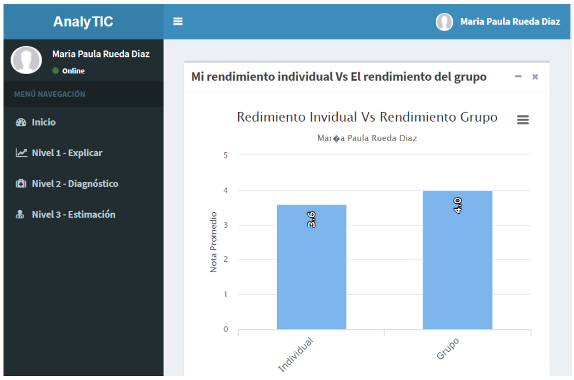

Fig. 5. Options of the AnalyTIC platform – student module.

TABLE III

AVERAGE GRADES: TEST GROUPS VS CONTROL GROUPS.

Period	Test group	Control group
2017-1	4.2	3.8
2017-2	4.0	3.5
2018-1	4.0	3.9
2018-2	4.1	3.9

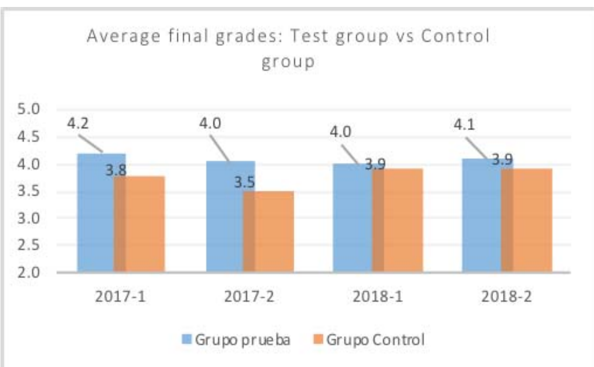

Fig. 6. Comparison of notes between test group and control group.

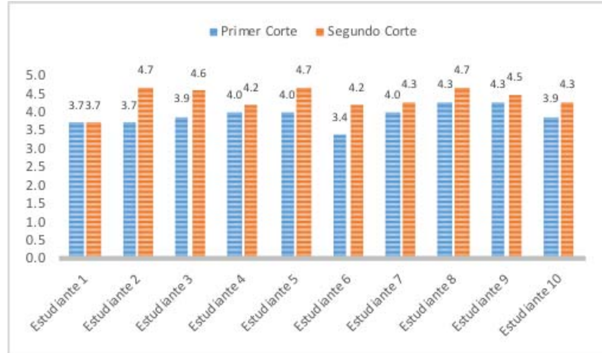

Fig. 7. Grades obtained in the first evaluation cycle vs second evaluation cycle, test group period 2017-1.

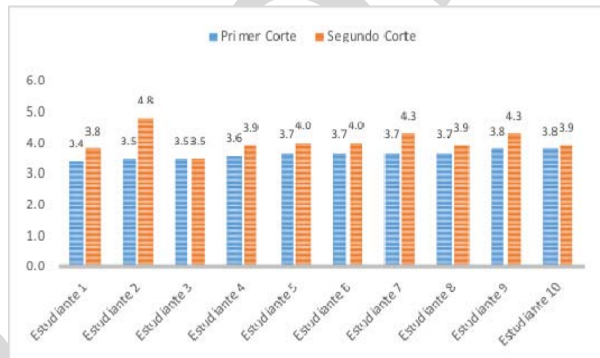

Fig. 8. Grades obtained in the second evaluation cycle vs third evaluation cycle, test group period 2017-2.

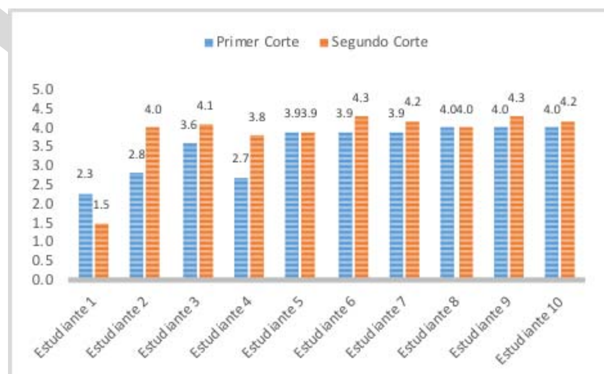

Fig. 9. Grades obtained in the first evaluation cycle vs second evaluation cycle, test group period 2018-1.

and three academic cycles are evaluated over the course of study of the subject.

On the other hand, Fig. 6 shows a comparison of the final averages achieved by the test groups versus the control groups in the periods in which the tool was applied.

It is clear that the groups in which the teacher used the LA tool obtained a better average in the final grades of the subject, evidencing that the use of tools that allow teachers to identify students with difficulties, from which they can make decisions to modify the learning process or better advise their students, is reflected in their academic performance.

In the period 2017-1, the test group obtained an average grade of 4.2, while the control group 3.8, meaning the test group was four-tenths above the control group. In the period 2017-2, the difference was of five-tenths; in 2018-1, the difference was of one-tenth; and finally, for the period 2018-2, the difference of the test group with respect to the control group was two-tenths.

Figures 7, 8, 9 and 10 graphically show the results that were obtained thanks to the tutoring processes that were carried out by the teacher with those students who presented difficulties in the first or second academic evaluation cycle and who, due to their grades in said evaluation cycles, called for the teacher's attention, corresponding to the periods 2017-1 and 2017-2.

In this test, only students who were given personalised tutoring were taken into account to analyse their improvement in academic performance. In order to validate if this improvement was significant, we applied a ***t student*** correlation test to each of the evaluated periods. This validation can be observed in Table IV where, if P Value < Level of Significance, the improvement is accepted, otherwise the improvement is rejected. For the calculation, a 95% confidence level is used, therefore, the level of significance is 5% (0.05).

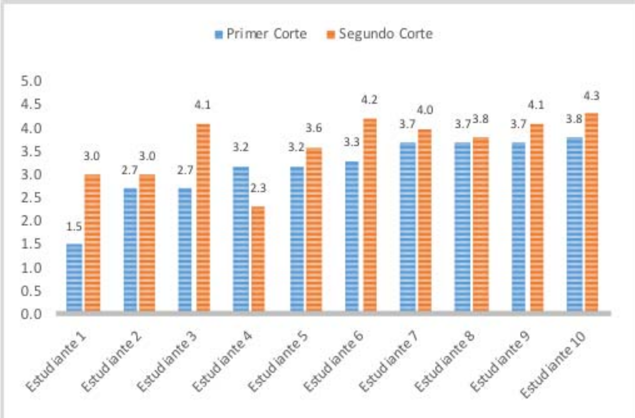

Fig. 10. Grades obtained in the second evaluation cycle vs third evaluation cycle, test group period 2018-2.

TABLE IV

T STUDENT TEST TO CHECK THE IMPACT OF THE USE OF THE TOOL

Did the academic performance of the students improve after an intervention by the teacher?						
	Average Before	Average After	T Test	P Value	Significance Level	Yes/No
2017-1	3.9	4.4	4.6974	0.0011	0.05	YES
2017-2	3.6	4.0	3.4933	0.0068	0.05	YES
2018-1	3.5	3.8	1.7839	0.1081	0.05	NO
2018-2	3.2	3.6	2.2712	0.0493	0.05	YES

In one period (2018-1), the improvement of the marks that were obtained by the students was not significant, going from an average of 3.5 to just 3.8.

On the part of the students, they count on three of the four phases – firstly, they can see their individual performance versus the group's performance, along with a detail of the grades that have been achieved so far (explanation); secondly, they can know the quartile in which their score is located with respect to all the members of the course (diagnosis); and finally, using the risk acceptability matrix, they can see their probability of passing or failing the subject (prediction).

IV. TOOL EVALUATION

In order to evaluate the tool that was designed, we carried out a comparison of the characteristics of the software that was developed versus other platforms that had been previously identified.

Table V shows a comparison made among different tools that are found in the market, seeking to demonstrate the functionality of the AnalyTIC tool.

For the evaluation of the virtual classroom and the AnalyTIC tool, classic web metrics were used, in this case the Morae method, and as specified in [32], the evaluation was carried out by a pair of experts, obtaining the results that are shown in Table VI.

On the part of the students, a group of four students was used to evaluate the tool by means of a five-question questionnaire made available in the virtual classroom for this purpose. The results that were obtained are shown in Table VII.

TABLE V

COMPARISONS OF CHARACTERISTICS AMONG LA TOOLS

Tool	AnalyTIC	LOCO-Analyst	Student Success System	Student Inspector	GLASS	SAM	StepUp!	Course Signals	Narcissus
Level 1 – Explanation Visualise the data	x	x	x	x	x	x	x	x	x
Level 2 – Diagnosis Analyse the displayed data	x		x	x	x	x	x	x	x
Level 3 – Prediction Analysis of future data	x		x						
Level 4 – Prescription How can we act to correct mistakes?	x					x			
Useful for teachers	x	x		x	x				
Useful for students	x		x	x	x	x	x	x	x

TABLE VI

RESULTS OF THE REVIEW BY EXPERTS OF THE ANALYTIC TOOL

Revisión de Experto

Resumen de resultados

	Calificación Neta	# Preguntas	# Respuesta	Calificación
Página de Inicio	13	20	20	83%
Orientación a Tareas y Funcionalidad del Sitio	21	44	44	74%
Navegabilidad y Arq. De la Información	12	29	29	71%
Formularios y entrada de datos	12	23	23	76%
Confianza y Credibilidad	-2	13	13	42%
Calidad del Contenido y Escritura	20	23	23	93%
Diagramación y Diseño Gráfico	37	38	38	99%
Búsquedas	10	20	20	75%
Ayuda, Retroalimentación & Recuperación de E	-3	37	37	46%
Calificación Final		247	247	73%

V. DISCUSSION

The software that has been developed is a differentiated product with respect to other LA tools in the market. Learning management systems such as Moodle and Blackboard implement plugins that integrate LA, which in most cases stay in the first phase – they only analyse the students' footprint in virtual classrooms. These developments are aimed at the administration or teachers, but none of them take the student into account. The AnalyTIC software focuses on providing information to the teacher and the student.

The integration of the four phases allows a teacher to, firstly, know the academic performance of his/her students in the virtual classroom, compare individual performance versus group performance, and determine what kind of resources students are consuming (explanation); secondly, have a diagnosis of the significance of the grades that a student has achieved up to that moment (diagnosis); thirdly, by means of the risk

TABLE VII
EVALUATION BY THE STUDENTS OF THE ANALYTIC TOOL

Evaluator	Est. 1	Est. 2	Est. 3	Est. 4
The virtual classroom programming	Acceptable	Acceptable	Acceptable	Excellent
The server or type of virtual classroom hosting	Excellent	Excellent	Excellent	Excellent
The structure and organisation of the virtual classroom	To improve	Acceptable	Acceptable	Acceptable
The design of the virtual classroom	Acceptable	To improve	To improve	To improve
Virtual classroom activities and content	Excellent	Excellent	Excellent	Acceptable

matrix, estimate a student's probability of passing or failing the subject (prediction); and finally, be presented with different alternatives so the teacher can carry out an individualised improvement plan with each of the students at risk of failing the subject (prescription).

Thus, the tool that has been designed allows the teacher to track and trace the evolution of students in the classroom in a particular way, and also provides the necessary information. Being able to identify the educational patterns of students in a virtual environment makes it easier for teachers to customise teaching-learning processes [31] and adjust resources in order to offer as many aids as necessary, with the purpose of promoting the use of activities that increase participation and therefore improve academic performance.

While it is true that, in some of the cases, the results that were achieved in the improvement of the academic performance of the students was not significant (Table IV), it is evident that such improvement was achieved thanks to the tutoring and adaptation of the content that were carried out by the teacher in his/her intervention for the students. It was also observed that, in some cases, those who improved in a cycle thanks to the intervention sometimes suffered a deterioration in his/her grades in the following cycle.

In only one case, a student obtained a lower grade after intervention (Period 2018-1); the others either improved or remained the same.

Now, despite the benefits that have been described in the use of the tool, its implementation allows us to state that not everything is positive in this process; on the part of the teacher who worked with the intervened groups, it was a challenge to adapt the content of the academic space according to the diverse characteristics of the many students in a course, and so was the process of sending motivational reminders and messages to students at an individual level rather than the group level. However, it highlights the great utility of the tool by allowing the teacher to identify students at risk. The difficulty is more oriented to the number of students in the courses.

VI. CONCLUSION

The development of a piece of software that applies the phases of LA and subsequent implementation in a group of students allowed us to observe that there is a correlation between the use of the tool by the teacher and improvement in the students' academic performance, thanks to the fact that the teacher was provided with the information that was necessary to carry out actions to improve his/her process and tutor his/her students effectively. The use of the tool that integrates the four phases of LA has proven to be an effective aid in improving students' learning performance.

The processes that were carried out by the students in the virtual classroom and that were analysed are: student logins, total connection time, individual performance versus group performance, activity report, average activities, and use of resources. These were the main input in the design of the LA tool.

On the other hand, the development of this software has allowed us to know and implement the objectives, purposes and stages of LA in greater detail. For some years, the subject has been mentioned, and some learning management systems and universities have worked on or are trying to include LA processes in decision-making within their institutions. However, a tool that applies or covers the four stages of LA had not been developed yet. This model is a tool that allows teachers to identify students who need tutoring and carry out relevant intervention to help them improve their academic performance.

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REFERENCES

[1] S. Slade and P. Prinsloo, "Learning analytics: Ethical issues and dilemmas," *Amer. Behav. Scientist*, vol. 57, no. 10, pp. 1510–1529, 2013.
[2] D. Clow, "An overview of learning analytics," *Teach. Higher Edu.*, vol. 18, no. 6, pp. 683–695, 2013.
[3] A. Marks, M. Al-Ali, and K. Rietsema, "Learning systems' learning analytics," in *Proc. Portland Int. Conf. Manage. Eng. Technol. (PICMET)*, Sep. 2016, pp. 676–681.
[4] P. Rojas-Castro, "Learning Analytics: Una revisión de la literatura," *Educación y Educadores*, vol. 20, no. 1, pp. 106–128, 2017.
[5] G. Siemens, "Learning analytics: The emergence of a discipline," *Amer. Behav. Scientist*, vol. 57, no. 10, pp. 1380–1400, 2013.
[6] L. de-la-Fuente-Valentín, A. Corbi, R. G. Crespo, and D. Burgos, "Learning analytics," in *Encyclopedia of Information Science and Technology*, M. Khosrow-Pour, Ed., 3rd ed. Hershey, PA, USA: IGI Global, 2014, pp. 2379–2387.
[7] Y. V. N. Acevedo, C. E. M. Marín, P. A. G. Garcia, and R. G. Crespo, "A proposal to a decision support system with learning analytics," in *Proc. IEEE Global Eng. Educ. Conf.*, Apr. 2018, pp. 161–168.
[8] W. Greller and H. Drachsler, "Translating learning into numbers: A generic framework for learning analytics," *Edu. Technol. Soc.*, vol. 15, no. 3, pp. 42–57, Jul. 2012.
[9] D. A. Y. R. Santiago, *Learning Analytics: La Narración del Aprendizaje a Través de Los Datos*. Barcelona, Spain: Oberta UOC Publishing, SL, 2017.

[10] M. Fernández-Delgado, M. Mucientes, B. Vázquez-Barreiros, and M. Lama, "Learning analytics for the prediction of the educational objectives achievement," in *Proc. IEEE Frontiers Educ. Conf. (FIE)*, Oct. 2014, pp. 1–4.

[11] P. de Lange, A. T. Neumann, P. Nicolaescu, and R. Klamma, "An integrated learning analytics approach for virtual vocational training centers," *Int. J. Interact. Multimedia Artif. Intell.*, vol. 5, no. 2, pp. 32–38, 2018.

[12] A. M. Navarro and P. Moreno-Ger, "Comparison of clustering algorithms for learning analytics with educational datasets," *Int. J. Interact. Multimedia Artif. Intell.*, vol. 5, no. 2, pp. 9–16, 2018.

[13] L. Johnson, S. A. Becker, M. Cummins, V. Estrada, A. Freeman, and C. y Hall, *NMC Informe Horizon 2016 Edición Superior de Educación*. Austin, TX, USA: New Media Consortium, 2016. [Online]. Available: http://www.aprendevirtual.org/centro-documentacion-pdf/2016-nmc-horizon-report-HE-ES.pdf

[14] L. de-la-Fuente-Valentín, D. Burgos, and R. G. Crespo, "A4Learning—A case study to improve the user performance: Alumni alike activity analytics to self-assess personal progress," in *Proc. IEEE 14th Int. Conf. Adv. Learn. Technol.*, Jul. 2014, pp. 360–362.

[15] UNIR. (2013). *UNIR Research*. Project iLIME, Enero [En línea]. Accessed: Oct. 1, 2018. [Online]. Available: http://research.unir.net/blog/ilime-operational-implementation-of-a-recommendation-model-for-informal-and-formal-learning/

[16] A. Van Barneveld, *Analytics in Higher Education: Establishing a Common Language*. New York, NY, USA: EDUCAUSE, 2015.

[17] Maricopa Community College. (Apr. 12, 2018). *Rio Salado College*. Maricopa Community College. [En línea]. Accessed: Oct. 1, 2018. [Online]. Available: http://www.riosalado.edu/Current/pages/default.aspx

[18] R. L. U. Cazarez and C. L. Martin, "Neural networks for predicting student performance in online education," *IEEE Latin Amer. Trans.*, vol. 16, no. 7, pp. 2053–2060, Jul. 2018.

[19] S. Treca, "Leveraging analytics in community colleges," *Educause Rev.*, vol. 1, no. 5, pp. 7–11, 2015.

[20] *Educause Center for Applied Research, Higher Education and the Revolution of Learning Analytics*, Int. Council Open Distance Educ., Oslo, U.K., 2018.

[21] L. Johnson, S. A. Becker, M. Cummins, V. Estrada, A. Freeman, and C. Hall, *NMC Horizon Report: 2016 Higher Education Edition*. Austin, TX, USA: New Media Consortium, 2016. [Online]. Available: https://www.sconul.ac.uk/sites/default/files/documents/2016-nmc-horizon-report-he-EN-1.pdf

[22] L. N. Aballay, S. V. Aciar, C. A. Collazos, and C. S. Gonzalez, "Adaptation model content based in cultural profile into learning environment," *IEEE Latin America Trans.*, vol. 13, no. 2, pp. 490–495, Feb. 2015.

[23] R. B. L. Y. D. Emeritus, *Studying Engineering: A Road Map a Rewarding Career*, Los Angeles, CA, USA: Discovery Press, 2013.

[24] M. Scheffel *et al.*, "Key action extraction for learning analytics," in *21st Century Learning for 21st Century Skills* (Lecture Notes in Computer Science), vol. 7563, A. Ravenscroft, S. Lindstaedt, C. D. Kloos, and D. Hernández-Leo, Eds. Berlin, Germany: Springer, 2012, pp. 320–333.

[25] H. F. A. Simanca, D. Burgos, R. G. Crespo, and L. R. Baena, "Automation of the tutoring process in online environments through the analitycs of learning," in *Proc. 13th Iberian Conf. Inf. Syst. Technol. (CISTI)*, Jun. 2018, pp. 1–5.

[26] R. E. Walpole, R. H. Myers, and S. L. Myers, *Probabilidad y EstadÃstica Para Ingenieros*, D. F. México, Ed. Upper Saddle River, NJ, USA: Prentice-Hall, 1992.

[27] F. A. Simanca, "Sistema de mejora del rendimiento académico mediante learning analytics," M.S. thesis, Univ. Int. la Rioja, La Rioja, Spain, 2018.

[28] T. Elias. (Jun. 1, 2011). [En línea]. Accessed: Sep. 25, 2019. [Online]. Available: https://www.semanticscholar.org/ and https://pdfs.semanticscholar.org/732e/452659685fe3950b0e515a28ce89d9c5592a.pdf

[29] P. Coad and E. L. Y. J. De Luca, *Java Modeling in Color With UML: Enterprise Components and Process*. México, North America: Prentice-Hall, 1999.

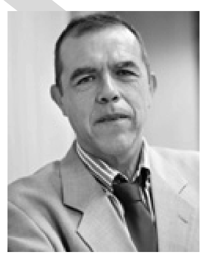
[30] K. E. Y. K. J. E. Kendall, *Agile Modeling and Prototyping Systems Analysis and Design*. London, U.K.: Pearson, 2011.

[31] G. C. Challco, D. A. Moreira, I. I. Bittencourt, R. Mizoguchi, and S. Isotani, "Personalization of gamification in collaborative learning contexts using ontologies," *IEEE Latin Amer. Trans.*, vol. 13, no. 6, pp. 1995–2002, Jun. 2015.

[32] T. David. (Aug. 2, 2007). *UserFocus*. [En línea]. Accessed: Sep. 10, 2017. [Online]. Available: https://www.userfocus.co.uk/articles/morae-he.html

Fredys Alberto Simanca Herrera is currently pursuing the Ph.D. degree in the society of knowledge and action in the fields of education, communication, rights, and new technologies. He is also a Systems Engineer with the Universidad Cooperativa de Colombia, Bogotá, Colombia, a Researcher in the area of technologies in education, and also a Research Professor.

Rubén González Crespo received the Diploma degree in international studies from the Sociedad de Estudios Internacionales, and the master's degree in project management and direction, the master's degree in web engineering, and the Ph.D. degree in computer engineering and industrial organization engineering from the Universidad Pontificia de Salamanca. He has published more than 180 articles in indexed journals and prestigious national and international conferences. He has taught many seminars and conferences in Europe and Latin America on project management, artificial intelligence, and Industry 4.0. He has received various awards related to his activity.



Luis Rodriguez Baena received the master's degree in computer science from the Universidad Pontificia de Salamanca, the master's degree in computer management systems from CENEI, and the Ph.D. degree in sociology from the Universidad Pontificia de Salamanca. His main research area focuses on usability, accessibility, user experience, and user-centred design, a field in which he has directed several doctoral theses and has participated as a researcher in different research projects. He has also published books, articles in indexed research journals, and has participated in national and international conferences.

Daniel Burgos received the Dr. Ing. degree in computer engineering, the Dr. degree in education, the Dr. degree in communication, the Ph.D. degree in antropology, and the DBA degree. He was a Professor of technology for education and communication in 2010, and the Vice-Chancellor for Transfer and Technology (UNIR Research) at the Universidad Internacional de La Rioja (UNIR) since 2016. He has been the Director of the UNESCO Chairs in eLearning since 2013, and the ICDE in Open Educational Resources since 2014. In addition, he directs the Institute for Educational Research, Innovation, and Technology (UNIR iTED). He has published 15 technical books, 12 editions of special issues in indexed journals, and more than 100 scientific publications in JCR (SCI, SSCI), Scopus, Inspec, the IEEE, ACM, and other indexes.