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Analytical Methods and Tools for Evaluating the Development of Computational Thinking Abilities

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Abstract—Computational thinking has gained an important place in modern education, enabling individuals to approach problem-solving in a logical and structured manner. This cross-curricular competence is important and applicable in any field of science, not just for computer science professionals. By fostering problem-solving, critical thinking, and creativity, among other skills, computational thinking is crucial in today's education. In the digital age, computational thinking is not just a technical skill, or one related to programming and robotics, but a way of thinking that can transform, or at least provide a different perspective, the way we approach everyday challenges and opportunities in our daily lives.

To assess this new competency, analytical tools and methods that are not too general are needed. To achieve this, that is, to assess computational thinking, the process is currently complex and requires a combination of qualitative and quantitative methods. In this way, analytical rubrics, portfolio analysis, and standardized tests are essential tools that help provide a comprehensive and accurate assessment of students' skills related to this

competence. In our project, we also work on assessing computational thinking using Bebras-type tasks and applying data analysis. Data analysis facilitates the continuous improvement of teaching and assessment methods. By monitoring and analyzing data over time, educators can identify the most effective strategies and make adjustments to improve learning outcomes.

In this paper, we introduce COMATH, an assessment tool grounded in research, which has undergone two phases of piloting across six counties. This process involved collaboration with subject-matter experts and the participation of over 4500 students and 100 teachers. We employ tasks designed to evaluate computational thinking and share some of the findings we have gathered to date.

Keywords—Analytics, Algebraic Thinking, Computational Thinking, Mathematics, cross-curricular competence, digital competence, learning.

I. Introduction

EDUCATION is key to the development of any society. Over time, teaching methods have changed significantly, adapting to social, technological, and economic advances. These changes have occurred very rapidly in recent years, [1], [2]. Nowadays, evaluating education is essential for measuring student performance, but also for determining the effectiveness of teaching methods, and ensuring the quality of educational programs. However, with the evolution of technology and the enormous amount of data available, a new discipline has emerged that promises to revolutionize educational assessment: analytics for educational assessment, [3], [4].

Educational or learning analytics is not only based on the use of data, but also on the application of various analytical techniques to understand and improve educational processes. Typically, this type of analytics includes tools such as machine learning integration, data mining, data analysis, and predictive analytics. These tools analyze educational data in different ways to extract information that, among other things, can help identify patterns and trends and, on the other hand, make data-driven decisions to improve teaching and learning. An advantage over other tools is that these techniques can help personalize education, adapting it to the individual needs of each student, thus improving their overall educational experience, or at least trying to, [5], [6].

When we talk about using learning analytics, we are not just referring to using student marks or how we can improve those marks, but it also covers other important aspects. These may include active classroom participation, social interactions among students, the emotional well-being of each student, and the development of a variety of skills, such as oral expression, group work, and so on. It also considers how students relate to their peers and teachers, how they manage their emotions, and how they develop both academic and personal skills. This approach, which can be considered integral, tries to improve the entire educational experience, not just in terms of academic performance, [7], [8].

By using educational analytics, in addition to generating information about student learning or aspects related to student learning, data is also generated and provided that can be used for the continuous improvement of teaching practices. By leveraging data-driven insights, teachers can adapt their classroom strategies to better meet the needs of their students, thus fostering a more effective and engaging learning environment. Furthermore, the use of analytics in education can help identify trends and patterns that may not always be immediately apparent, or that teachers do not usually see directly, enabling proactive interventions and support for students with social or familiar problems, [9].

In this article, we present COMATH, an assessment tool about computational and algebraic thinking, tested in six countries through two pilot phases. Its design, development, and implementation involved both collaboration with matter experts and the participation of over 4,500 students and 100 teachers. It used tasks that were specifically designed to assess computational and algebraic thinking, and, in this paper, we present some of the preliminary results that we have obtained to date. Our objective is to show the potential of educational analytics to transform the educational assessment process and to highlight the importance of data-driven approaches in fostering student success, [10].

II. Importance of Analytics

When we talk about methods related to educational assessment, we usually think of (and as teachers, use) tests that we can call standardized, such as written exams, surveys, and qualitative observations. Although these methods can provide valuable information, they often have limitations if we want to capture the full complexity and diversity of educational processes [9]. With educational analytics, we can find a solution to these limitations, since a deeper and more detailed analysis of the educational data we have obtained can be made. Through advanced data analysis techniques, teachers, and also policymakers, can obtain a more complete and accurate understanding of student performance and needs, [11].

Analytics in education also allows teachers to provide more personalized assessments tailored to their students. Instead of applying a classic, one-size-fits-all approach, whereby we assign a "simple" grade to each student, often from a test or exam, educators can use analytical data to develop teaching and assessment strategies tailored to each student's individual needs. This not only improves the teaching-learning process but also promotes, or can promote, a more inclusive and equitable learning experience, [12].

One of the main advantages of educational analytics is its ability to manage large volumes of data. While it doesn't bring us closer to the so-called "big data," it can help teachers process all the data collected for their classes. This data can include everything from students' "traditional" test scores to class attendance lists, student interactions on classroom systems or platforms, and even their social media activity (always with the consent of the student or their tutor). By analyzing this data, teachers can identify patterns and trends that, without the use of analytics, might go unnoticed using only traditional assessment methods. Thus, in addition to the typical relationship between student engagement and academic performance, data analytics can reveal other types of correlations to help teachers develop targeted interventions.

Furthermore, analytics can also help improve the accuracy of educational assessments, making them more fair in this competitive age, as traditional methods only use a limited set of metrics, which may not fully reflect students' abilities or progress in certain subjects. On the other hand, analytics can incorporate many more types of data, such as the time it takes a student to complete a task, offering other types of perspectives for measuring student performance. This means that we can also include not only academic metrics but also indicators of students' behavior and emotional responses (especially in the early elementary school years), which are sometimes crucial for understanding their development, [13].

Another advantage we can gain from incorporating analytics into the educational process is the ability to provide real-time feedback. Traditional assessments typically involve a time lag from the time students take the test until the teacher gives them results, which can hinder learning for certain students or in certain subjects. With analytics, educators can monitor student performance in real-time, allowing for immediate feedback and support. This is especially valuable in adaptive and personalized learning environments, where the content or its depth can be adjusted almost instantly (say, for each subject) based on individual student performance. Real-time analytics can help teachers identify and address those learning gaps that always exist, but instead of waiting until the end of the course, this can be achieved in much shorter periods of time. Furthermore, analytics can support the development of personalized learning paths. By analyzing data on students' (and individual students') performance, interests, and learning styles, teachers can create personalized learning experiences tailored to each student's unique needs. This personalized approach can improve student engagement and motivation, which can lead to improved learning outcomes, [14]. Data analytics can also help identify students who are highly capable, or who simply excel in certain subjects, and provide them with materials that are advanced compared to other students to enhance those abilities.

Educational analytics can also assist in the design process of curricula and in the planning of the classes. From a more administrative perspective, this methodology allows data from multiple schools or regions to be aggregated and analyzed, thus providing policymakers with data-driven tools to identify global problems and develop interventions in certain fields or geographic areas. This can include identifying areas or subjects that may require additional resources or support, such as teacher training in computational thinking or promoting certain equity and inclusion policies.

III. Methods

In educational assessment, there is a wide variety of analytical methods, each with its own advantages, disadvantages, and applications. Among the most common methods, we can mention the following four: data analysis, educational data mining, predictive analysis, and social network analysis, [15].

Data analytics deals with the systematic collection and analysis of educational data to, among other objectives, discover patterns and trends. Data can come from a variety of sources, such as tests, surveys, and academic records. By analyzing this data, teachers can identify areas for improvement and design evidence-based plans to support students.

On the other hand, educational data mining analyzes large data sets to uncover patterns that may be hidden or not readily apparent and that can influence student performance. Data mining is often used to address factors such as family environment, study habits, and social interactions. Furthermore, data mining is also used to try to predict future outcomes and minimize future problems, although this aspect is a field more appropriate for predictive analytics.

Predictive analytics, on the other hand, typically uses statistical models and machine learning algorithms to forecast future outcomes based on historical data, where, obviously, the results will depend largely on the original data chosen. In education, predictive analytics can be useful for identifying students at risk of poor grades or predicting dropout rates. In this case, predictive analytics can benefit not only teachers but also policymakers, who can implement measures to improve broader aspects.

Social dynamics in educational settings are part of social network analysis and are less commonly used due to data access and privacy issues. In this methodology, nodes are considered to represent individuals (such as students and teachers) and edges represent the possible connections between them (such as communication and collaboration between students and between students and teachers). In this way, patterns of collaboration, leadership, or isolation can be revealed.

Furthermore, integrating these, or some of these, analytical methods into educational assessment allows for a more complete understanding of the teaching-learning process.

IV. Ethics

It is important to keep in mind that the use of analytics in educational assessment raises numerous ethical considerations, and these must be approached with caution to ensure the responsible and fair use of data. One of the main ethical concerns is privacy and informed consent since when collecting and analyzing student data, we handle personal data. It is essential to obtain explicit consent from students (and their guardians, if necessary, since we often work with minors), thus ensuring they are fully aware of how the data will be used and protected. This transparent approach helps

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build trust and ensures respect for students' rights. Security measures must also be implemented to protect sensitive information from unauthorized access and prevent data leaks.

Another important ethical aspect is the way we conduct data analysis, whether or not we consider bias. The algorithms and data models used in educational analytics can include biases if they are not carefully designed and monitored. In this sense, if the data used to train predictive models is biased or somehow poorly implemented, the results can unfairly disadvantage certain groups of students.

V. Computational Thinking

Computational thinking (CT) has been gaining importance and is currently part of the curriculum in many educational systems, being a crucial competence in the modern educational landscape. This inclusion in educational systems reflects the growing importance of digital literacy and problem-solving in various fields, [16]. In general terms, we can say that computational thinking involves the ability to formulate problems in a way that allows the use of computer tools for their resolution, and, among its skills, we can mention algorithmic thinking, pattern recognition, abstraction, and decomposition, [17]. The concept was popularized by Jeannette Wing at the beginning of the century and has subsequently become widespread as a general competence, not exclusive to computer scientists, [18].

One of the reasons for its widespread application is that computational thinking can be linked to different disciplines. In mathematics, computational thinking can help students understand complex concepts by breaking them down into smaller, more manageable parts, as in algebra, an abstract discipline where students can use computational methods to explore patterns and relationships, [19]. Similarly, in science, from physics to biology, computational thinking allows students to model and simulate real-world phenomena, improving their understanding of the scientific principles they are applying, [20]. All of this is due, among other things, as we have said, to the interdisciplinary nature of computational thinking, which makes it a valuable tool for fostering critical thinking and problem-solving skills.

In recent years, the integration of computational thinking into educational curricula has been the focus of numerous studies and initiatives. Several researchers have analyzed and highlighted the importance of incorporating computational thinking into primary education to lay a solid foundation for future learning [21], [22] that leads to improved academic performance. The need for teacher training and curriculum development to effectively integrate computational thinking into classroom activities is typically emphasized, as in some articles, where the authors explore the implementation of Computational Thinking (CT) in various educational contexts, demonstrating its potential to improve student engagement and learning outcomes, [23].

However, in-classroom implementation, one of the most significant challenges in promoting computational thinking is the need for appropriate assessment methods, as traditional assessment techniques often fail to fully capture the depth and breadth of CT skills. Therefore, innovative (and, if possible, automated) assessment tools and frameworks are required to accurately assess students' computational thinking skills. In this regard, the Bebras Challenge is an international initiative that uses engaging tasks to assess students' computational thinking skills, [24]. These tasks have been adopted in a large number of countries and have proven effective in identifying and fostering CT skills in students of all ages.

Another important area of research in the implementation of computational thinking is the role of the technology we can (or should) use to support it. Advances in educational technology, such as programming platforms and interactive simulations, provide new opportunities for teachers to implement CT skills in the classroom. Several studies by different authors have shown that technology-enhanced learning environments can significantly improve students' computational thinking skills, [25]. These environments offer hands-on experiences that allow students to experiment, iterate, and learn from their mistakes—essential components of computational thinking.

Furthermore, the impact of computational thinking can extend beyond the classroom, such as into the workplace, where Computational Thinking (CT) skills are increasingly recognized as essential for various professions, from engineering to healthcare. This demand for CT skills underscores the importance of integrating computational thinking into education at all levels, from primary to higher education.

However, despite the growing international recognition of the importance of computational thinking, barriers to widespread adoption remain, both at the educational level and in the subjects or courses where it is applied. One of the main obstacles is the lack of resources and support for teachers, such as training in CT. Effective implementation of CT requires comprehensive professional development programs that equip teachers with the necessary knowledge and skills (including materials) to teach computational thinking effectively, [26]. In addition, research is needed to explore the most effective pedagogical approaches for teaching CT, especially in diverse educational settings, [27].

VI. Results

In this article, we focus on the application of learning analytics to improve computational thinking (CT) and algebraic thinking (AT) within the project "Computational Thinking and Mathematical Problem Solving: An Analytics-Based Learning Environment" (CT&MathABLE). Six countries participate in this project, financed by the Erasmus+ program of the European Union: Finland, Hungary, Lithuania, Spain, Sweden, and Turkey; being its main objective to provide teachers with innovative strategies to foster students' CT and AT skills, tailored to their individual learning needs.

Within the CT&MathABLE project, we have developed three interactive assessment tools designed specifically to evaluate students' proficiency in CT and AT, for three different age groups. These tools, named COMATH1, COMATH2, and COMATH3, target students aged 9 to 10, 11 to 12, and 13 to 14, respectively. The implementation of these tools was divided into two pilot tests, which provided very valuable data to refine the assessment of these competencies (CT and AT). In the pilot tests, we included 18 items for the computational thinking part and between 20 and 23 items for the algebraic thinking part, depending on the students' age group.

We conducted the pilot tests in two separate sessions: one for CT and one for AT; students were given 45 minutes to complete each section. In a few cases, teachers had to extend the session to more than 60 minutes due to organizational needs in their school's teaching labs. The data we collected in these pilot tests has been very important in improving both the design and effectiveness of the assessment tools. The iterative testing and refinement process ensures that the tools are reliable and valid measures of students' CT and AT skills.

One of the significant outcomes that we have obtained in the CT&MathABLE project is the development of learning trajectories. We've used the results of learning analytics to integrate these pathways, providing individualized feedback and support to students, thereby improving their learning experiences. By analyzing data from the interactive assessment tools, educators can identify specific areas where students need improvement and tailor their instructional strategies accordingly. This personalized approach not only improves student engagement but also promotes a deeper understanding of CT and AT concepts.

The COMATH tools provided several factors to be analyzed of different skills of computational thinking and algebraic thinking. One of these skills is the Algorithm Thinking. This skill was measured in different items. We compare here the different languages of the participant countries in the project (Lang-number), with the birth-year of the students (Year), and with their gender (Gender-number).

Analysis of variance (ANOVA) is a statistical technique used to determine if there are significant differences between the means of several groups. Table I presents the results of an ANOVA with the following columns: Degrees of Freedom, Sum of Squares, Mean Squares, F, and Critical Value of F.

Table I. Regression

	Degrees of freedom	*Sum of squares*	*Mean squares*	*F*	*The critical value of F*
Regression	3	1.5549E+10	5182912221	1.7879	0.1484
Residuals	519	1.5045E+12	2898790676		
Total	522	1.52E+12			

Degrees of Freedom indicate the number of values that are free to vary in the calculation of a statistic. For the regression, the degrees of freedom are 3, suggesting that there are three independent variables in the model. For the residuals, the degrees of freedom are 519, representing the number of observations minus the number of estimated parameters. The total degrees of freedom is 522, which is the sum of the degrees of freedom for the regression and the residuals.

The sum of Squares measures the total variability in the data. The sum of squares for the regression (15,548,736,662) represents the variability explained by the model. The sum of squares for the residuals (1.50447E+12) represents the variability not explained by the model. The total sum of squares (1.52002E+12) is the sum of the explained and unexplained variability.

Mean Squares are obtained by dividing the sum of squares by the corresponding degrees of freedom. For the regression, the mean square is 5,182,912,221, while for the residuals it is 2,898,790,676. This value is used to calculate the F statistic.

The F statistic is calculated by dividing the mean square of the regression by the mean square of the residuals. In this case, the F value is 1.787956704. This value is compared with the critical value of F to determine the significance of the model.

The critical Value of F is obtained from an F distribution table and depends on the level of significance and the degrees of freedom. In this case, the critical value of F is 0.148433716.

The calculated F value for the regression is 1.787956704, while the critical value of F is 0.148433716. Since the calculated F value is less than the critical value of F, there is not enough evidence to reject the null hypothesis. This suggests that the independent variables in the model do not have a significant effect on the dependent variable. In other words, the regression model is not statistically significant in explaining the variability in the dependent variable.

The provided analysis of variance (ANOVA), Table II presents the regression coefficients, standard errors, t-statistics, and probabilities for each of the independent variables in the model, as well as for the intercept.

The coefficient for each variable represents the expected change in the dependent variable per unit change in the corresponding independent variable, holding all other variables in the model constant.

For the intercept, the coefficient is -6942514.45 with a standard error of 26091184.89, resulting in a t-statistic of -0.266086591 and a probability of 0.790278193. This indicates that the intercept is not statistically significant ($p>0.05$), suggesting that the mean value of the dependent variable is not significantly different from zero when all independent variables are zero.

Table II. ANOVA

	Coefficients	*Std. error*	*t-statistics*	*Prob.*
Intercept	-6942514.45	26091184.9	-0.2660	0.7902
Lang-number	437.168214	1053.86689	0.4148	0.6784
Year	3495.40706	12974.2939	0.2694	0.7877
Gender-number	-10641.6718	4743.15908	-2.2435	0.0252

For the variable Lang-number, the coefficient is

437.1682139 with a standard error of 1053.866891, resulting in a t-statistic of 0.414822989 and a probability of 0.678442902. This usually indicates that Lang-number is not statistically significant ($p>0.05$), suggesting that there is not enough evidence to claim that Lang-number significantly impacts the dependent variable.

If we take into account the variable Year, the coefficient is 3495.407064 with a standard error of 12974.29388, resulting in a t-statistic of 0.269410196 and a probability of 0.787721115. This indicates that Year is not statistically significant ($p>0.05$), suggesting again that there is not enough evidence to assert that Year has a significant effect on the dependent variable.

Regarding the variable Gender-number, the coefficient is -10641.67179 with a standard error of 4743.159081, resulting in a t-statistic of -2.243583149 and a probability of 0.025280161. In this case, this indicates that Gender-number is statistically significant ($p<0.05$), suggesting that Gender-number has a significant effect on the dependent variable. This deserves deeper discussion in order to find possible underlying socio-cultural factors, related to the countries, or perhaps to the different educational systems.

When we analyze the residuals, that is, the differences between the observed values and the values predicted by a model, we obtain valuable information about the adequacy of the model and the presence of potential problems, such as heteroscedasticity or lack of fit. It is shown in Figure 1.

The distribution of these residuals can indicate whether the model is adequately capturing the variability in the data. As we can see in Figure 1, the symmetric distribution centered around zero suggests that the model is adequate. In this case, the residuals appear to vary widely, with values ranging from approximately -81,497.83 to 327,939.34; therefore, we can suggest that there may be issues with the model's fit.

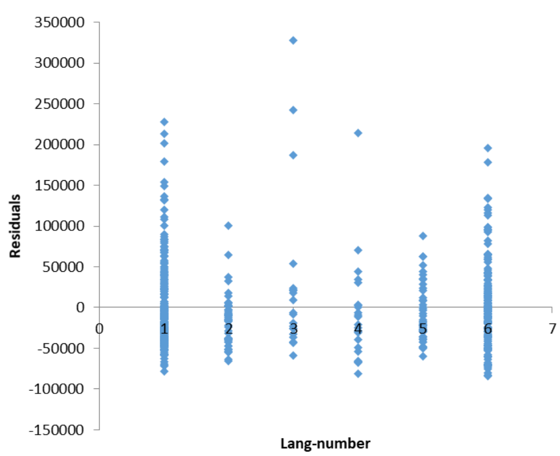

Fig. 1. Residuals vs languages.

When residuals are been analyzed, the patterns (such as trends or cycles) that we can find could be a valuable source of information. The presence of these patterns can indicate that our model is not adequately capturing some structure in the data. In this case, it is not uncommon that the residuals appear to show considerable variability without a “clear” pattern, suggesting that the model could not capture the relationship between the independent variable and the dependent variables in an adequate way.

The wide variability and lack of a clear pattern in the residuals suggest that the model may not be adequate for the data. This could be due to several factors, such as the lack of important explanatory variables, the presence of collinearity among the independent variables, or the need to transform the variables to improve the model's fit.

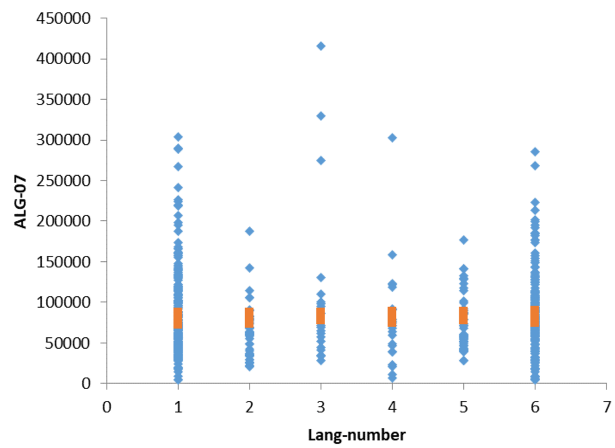

Fig. 2. Regression Analysis Forecast

It is advisable to conduct a deeper analysis, including reviewing the model's assumptions and considering possible improvements, such as the inclusion of new variables or the transformation of existing ones.

The provided forecast data represents the predicted values from a regression analysis model and it is shown in Figure 2.

The interpretation of these values is the following:

1. Mean Forecast: The mean (average) forecast value is approximately 82,000. This represents the central tendency of the predicted values. It indicates that, on average, the model predicts a value around this number.
2. Median Forecast: The median forecast value is also around 82,000. The median is the middle value when the predicted values are sorted in ascending order. It is less affected by outliers compared to the mean.
3. Standard Deviation: The standard deviation of the forecast values is relatively low, indicating that the predicted values are clustered closely around the mean. This suggests that the model's predictions are consistent and do not vary widely.

Finally, we show in Figure 3 the spent time of the participants in one of the tasks related to algorithm thinking. Just over half of the students (55%) took between half a minute and a minute and a half to complete the task, and only a little more than 2% took more than 4 minutes. This indicates that the length of the task was not an obstacle for the students.

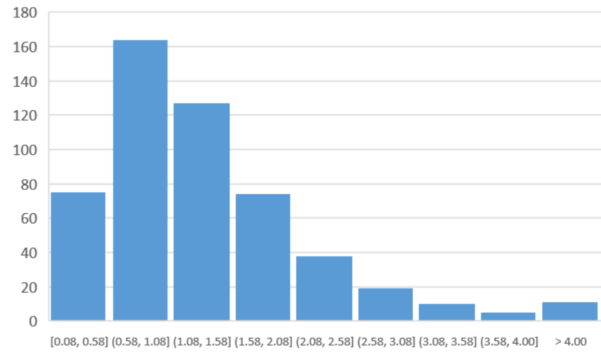

Fig. 3. Spent time for the ALG-07 task by students, in minutes (half-minute intervals)

VII. Conclusion

The use of analytics in educational assessment can be a tool that, based on data and evidence, helps improve the quality of education and identify strengths and weaknesses in everyday classrooms. This can also be extended to policymakers, who can make decisions at the global level, that is, for the education system as a whole. The results provided by analytics help us better understand aspects related to student performance, both individually and collectively, and also help us identify student needs, which facilitates interventions and improvements at different levels: concept, topic, subject, and course.

Computational thinking (CT) is a thinking and problem-solving methodology that, using concepts and techniques derived from computer science, helps with both complex and simple tasks. This approach goes beyond programming and is applicable to a wide range of disciplines and everyday situations, although it originates in computer science. By applying computational thinking, we develop several capabilities that are important for problem-solving, both academic and related to everyday life: the ability to abstract, generalize, recognize patterns, formulate algorithms and automate processes, and so on. In our opinion, this competency is crucial in today's world, where technology and data are present everywhere and at all levels, being an integral part of decision-making.

Moreover, computational thinking also fosters other types of basic skills that, while not intrinsic to CT itself, help students (and people of any age) acquire and develop them: logical reasoning, creativity, and collaborative problem-solving, among others.

In another way, from an academic point of view, integrating computational thinking into curricula provides students with the necessary tools to navigate and prepare for the digital landscape of the 21st century; and precisely to make better use of these tools, learning analytics can be a great help.

In our case, data analysis was essential to evaluate the pilot assessments, both in computational thinking and algebraic thinking (AT), that we conducted as part of an international project (CT&MathABLE) examining the relationship between these competencies. The results show the difficulty students encounter in learning certain mathematical concepts (in any country) and highlight the interconnection between CT and AT. According to these same results, it was found that teaching computational thinking significantly improves the learning of algebraic thinking (a positive correlation), providing a valuable framework for students to approach mathematical problems appropriate to their age more effectively than traditional educational approaches.

For this study, a general tool (COMATH) was designed and developed, divided into three different tests according to the student's age. Through data analysis, regression analysis showed that the variable "Year" (age of students) was not significant ($p > 0.05$), while the variable "Gender" (that is, the student's gender) was significant ($p < 0.05$).

The residuals, although symmetrical around zero, exhibited wide variability (-81,497.83 to 327,939.34), suggesting model fit problems.

There was also an apparent lack of clear patterns in the residuals, which may indicate that the model may not adequately capture the relationship between the variables. This could be due to the absence of important variables, collinearity, or the need to transform the variables. Therefore, further analysis is recommended, as well as future model improvements. On the other hand, the forecast data show mean and median values of approximately 82,000, with a low standard deviation, indicating consistent predictions.

In conclusion, using analytics in educational assessment and adding computational thinking to curricula are aspects that we consider positive and that can be applied in class. On the one hand, the introduction of computational thinking, and on the other, the use of analytics, help us understand and improve student learning, teaching, and fostering the skills necessary to succeed in a constantly changing world, all based on data and evidence.

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Declaration of Generative AI and AI-assisted technologies in the writing process

The authors wrote, reviewed and edited the content as needed and they have not utilised artificial intelligence (AI) tools. The authors take full responsibility for the content of the publication.

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Conflicts of Interest

The authors have no conflicts of interest to declare.