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Effectiveness of tutoring at school: A machine learning evaluation

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ABSTRACT

Tutoring programs are effective in reducing school failures among at-risk students. However, there is still room for improvement in maximising the social returns they provide on investments.

Many factors and components can affect student engagement in a program and academic success. This complexity presents a challenge for Public Administrations to use their budgets as efficiently as possible. Our research focuses on providing public administration with advanced decision-making tools.

First, we analyse a database with information on 2066 students of the Programa para la Mejora de Éxito Educativo (Programme for the Improvement of Academic Success) of the Junta de Comunidades de Castilla y Léon in Spain, in 2018–2019, the academic year previous to the pandemic. This program is designed to help schools with students at risk of failure in Spanish, literature, mathematics, and English. We developed a machine learning model (ML) based on Kohonen self-organising maps (SOMs), which are a type of unsupervised (ANN), to group students based on their characteristics, the type of tutoring program in which they were enrolled, and their results in both the completion of the program and the 4th year of Compulsory Secondary Education (ESO).

Second, we evaluated the results of tutoring programs and identified and explained how different factors and components affect student engagement and academic success.

Our findings provide Public Administrations with better decision-making tools to evaluate and measure the results of tutoring programs in terms of social return on investment, improve the design of these programs, and choose the students to enrol.

1. Introduction

Over the last few years, tutoring has changed from being a resource for higher-income children to catch up in school to being a big equaliser in education (Capilla et al., 2021). Disadvantaged students falling behind could lack the incentive to continue at school, with a loss of future income of up to 10 % for the year of school lost (Donnelly and Patrinos, 2021; Patrinos and Psacharopoulos, 2020). Different policy options have been considered to help disengaged pupils; however, tutoring seems to be the most effective measure to mitigate learning loss (Sevilla et al., 2020). Among the factors that ensure optimal educational outcomes, Kraft (2020) recommended that tutors stay with their students throughout the academic year. These tutors should be chosen after a rigorous selection process, well-trained in their special issues, and enjoy ongoing support and coordination with teachers and institutions. Finally, although there is an ongoing discussion, it seems that online tutoring, while better than no tutoring, is less productive than in-person tutoring (Kraft and Falken, 2021).

Several investigations have focused on the success of tutoring across systems (Van Lehn, 2011), time (Fryer and Howard-Noveck, 2020), student income (Kosunen et al., 2021), methodologies (Carlana and la Ferrara, 2021), teacher profiles (Ritter et al., 2009), and so on. There is a growing interest in how different tutoring schemes adapt to a range of student profiles, given the high costs of public and private funding (Guryan et al., 2021) Most existing research is related to tutoring during the pandemic or in its immediate aftermath (Fryer and Howard-Noveck, 2020). As the impact of the pandemic on education begins to diminish, it is becoming evident that we need to analyse pre-pandemic data to

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understand and evaluate these tutoring interventions. This research helps us understand the causality among variables and recommends designing and implementingutoring programs, identifying additional factors to consider in maximising social return on investment (Fryer and Howard-Noveck, 2020; Kraft and Falken, 2021).

Our analysis focuses on the Programa para la Mejora del Éxito Educativo (Programme for the Improvement of Academic Success) of the Junta de Comunidades de Castilla y León in Spain in 2018, the academic year previous to the pandemic, designed to help schools with students at risk of failure in Spanish language and literature, mathematics and English (Ballestar et al., 2022a,b).

We used a database with data from 2065 students enrolled in tutoring programs. We developed a machine learning (ML) model based on Kohonen self-organising maps (SOMs) to group students based on their characteristics, the type of tutoring program they were enrolled in, and their results in both completion of the tutoring program and the 4th year of Compulsory Secondary Education (ESO). Kohonen SOMs are widely adopted in education to cluster students based on their characteristics, academic achievements, and opinions (Kong et al., 2019; Nowakowska et al., 2020; Zatarain-Cabada et al., 2009), and design tools to support the development of intelligent tutoring systems (Cabada et al., 2011; de Carvalho et al., 2020).

In addition, based on the model's output, we evaluated how different factors affected student performance and the success of tutoring programs. Kohonen self-organising maps are non-supervised artificial neural networks that can capture causal and interactive relationships between variables, which are relevant for working with the data in this study (Ballestar et al., 2022c; Garbe and Richter, 2009). We aimed to show that AI and its adaptability play a role in the education sector, supporting educators and allowing educators to concentrate on core teaching-learning activities, especially in the early detection of educational needs. This adds to the growing literature on the effects of AI as disruptive technologies in schools and defines the premise of using AI as an educational instrument (Halagatti et al., 2023; Lee and Perret, 2022).

Athey and Imbens (2019) ML models yield better results than traditional economic models in evaluating the efficiency of public policies in tutoring programs. These results may help prevent and mitigate early school failure and dropout and identify the factors relevant to this intervention. They are also helpful for measuring the success rate and social return on investment.

The remainder of this paper is structured as follows. Section 2 presents a review of the literature and the theoretical framework; Section 3 describes the data; Section 4 outlines the empirical model for analysis; Section 5 evaluates the quality of the model, its robustness, and its results; Section 6 discusses the results and their implications; Section 7 offers the conclusions of this research; Section 8 suggests limitations and possible future research.

2. Theoretical framework

The objectives of this study were twofold. First, we aimed at grouping students based on their characteristics, the type of tutoring program they were enrolled in, and their results in both the completion of the tutoring program and the 4th year of ESO. Second, based on the output of the ML model, we evaluated the results of the tutoring programs and identified how different factors and components affected student engagement and academic success. Tutoring programs are effective when students actively engage in them, preventing school failure and early dropout and facilitating university access or general student well-being (Arco-Tirado et al., 2011; Christenson and Thurlow, 2004; Kraft et al., 2023). The success of the Program for the Improvement of Academic Success of the Junta de Comunidades de Castilla y León lies in its support for students to pass the 4th year of ESO, preventing early school failures, and reengaging students who have experienced past failures.

Burgess (2020) was among the earliest academics to call for measures to avoid irreversible educational losses during the pandemic. His recommendations warn of the relevance of early intervention and, specifically, the relevance of tutoring. Fryer Jr (2017) analysed 196 randomised experiments and found that tutoring has an impact ranging from 0.507 to 1.582 standard deviations, much higher than other interventions, such as poverty reduction or early childhood schooling. These results are appealing due to the long-term effects of this treatment. Dietrichson et al. (2020) reached the same conclusion by obtaining, on average, a benefit of 0.36 standard deviations in learning outcomes. Nickow et al. (2020) achieved similar figures, 0.37 standard deviations, and Pellegrini et al. (2021) achieved an increase in maths results of 0.3 points in their research. (Kraft, 2020) stated that the results of improving students' performance by applying tutoring programs are greater–about 85 % more than the effects achieved by other educational interventions. In Spain, it was in an online tutoring program in math assessed through a randomised controlled trial (RCT) consisting of an 8-week long program for students aged 12 to 15. Children who participated in the program were 30 % more likely to pass math (Gortazar et al., 2021). All the experiments were performed using traditional econometric methods. As Athey and Imbens (2019) showed, ML methods can yield similar or even better results in measuring policy intervention.

Other research indicates that tutoring benefits all types of students in the same grade without considering their level of previous performance (de Ree et al., 2021; Leung, 2015). Others have found greater effects among students with lower achievement levels (Guryan et al., 2021; Kraft et al., 2015). Our research focused on evaluating a regional tutoring program in Castilla-León (Spain) for students at risk of failure. We analysed the program and the factors that led to its success. To our knowledge, this is the first systematic evaluation of a face-to-face tutoring program using an AI methodology. This research provides tools to enable schools to improve the achievement of struggling students and identify areas where tutoring programs can be improved.

Prevention and engagement are crucial for avoiding academic failure. In this sense, the effectiveness of tutoring programs relies on sustained academic and socio-emotional relationships to achieve a positive conclusion (Gortazar et al., 2021; Robison et al., 2016; Spiekermann et al., 2021). Consequently, there is a need to find the right program for each participant 'teaching at the right level' (Banerjee et al., 2015). Different variables must be considered to determine the success. For instance, reducing the variation among student skill levels improves performance (Lindfors et al., 2021). The intensity and timing of the program were also influential. Tutoring programs providing higher intensity over a longer period within school days seem to result in greater achievements (Heinrich et al., 2014; Nickow et al., 2020). Similarly, the school area where tutoring is performed, whether rural or urban, affects its effectiveness (Rohrbeck et al., 2003). Students' sex may also be a factor. Rheinheimer et al. (2010) or Laskey and Hetzel (2011) found no significant performance differences between girls and boys, whereas Chang (2011) indicated that males had more benefits. Nevertheless, the positive effect of tutoring programs is extensive for students at risk and taking courses (Kuhfeld et al., 2022).

In his review of the student engagement literature, Trowler (2010) showed that prevention through reinforcement programs and student engagement are the key to avoiding school failure. Success depends on finding tools that motivate students to remain focused on the program. To achieve this, it is necessary to identify a program that best suits each student. This refers especially to the type of program and its duration, depending on whether there are more urban or rural students and males or females (Pellegrini et al., 2021). Therefore, our first hypothesis was as follows:

H1. Tutoring programs effectively support students at risk of early school failure, especially programs tailored to students' characteristics and needs.

Grade repetition is important, as it disincentivises students and increases the likelihood of early school leaving (OECD, 2021; Pont and

Montt, 2014). Successful tutoring programs must prevent early failure and work for those who have repeated a grade to increase student engagement, regardless of their characteristics (Bettinger et al., 2018; Guill et al., 2022). Accordingly, the second hypothesis was as follows:

H2. Tutoring programs are effective for reengaging students who have already failed in the academic system.

Several factors affect student engagement (Trowler, 2010). In any school, some students need help, had not repeated a grade before, did not engage with the program or complete it, and failed the course. Some students needed help, did not get it, and repeated a grade but would engage if they could find help from their peers, family, and teachers (Bettinger et al., 2018; Damgaard and Nielsen, 2018; Shernoff, 2013). These factors were summarised in the third hypothesis.

H3. The engagement and success of tutoring depend on many factors, such as the academic and sociodemographic background of the student, the characteristics of the program in which they are enrolled, and their engagement with it.

As a corollary of the previous hypotheses, we tested the relevance of selecting the right students to the program's success (Damgaard and Nielsen, 2018). This allows schools to create an optimal learning environment for students and to support their families, peers, and communities (Bettinger et al., 2018; Damgaard and Nielsen, 2018; Pan et al., 2022; Shernoff, 2013). Thus, our final hypothesis was as follows:

H4. Precise identification of students at risk of failure maximizes the social return on investment in tutoring programs.

3. Data collection

The Program for the Improvement of Educational Success database contains data from students in the 4th year of ESO for two academic years: 2018–2019 COVID-19 pre-pandemic and 2019–2020, during the COVID-19 pandemic. This program is one of the "Educational Success Programme: Support and Reinforcement" actions that is part of the Operational Programme FSE+ 2021–2027 of Castilla y León and is co-financed by the European Union.

In this study, we focus on the analysis of the first 2018–2019 academic year to enrich previous research conducted by (Ballestar et al., 2022a,b) focusing on the analysis of the second academic year, 2019–2020. Data were collected by the Government of the Castilla y León Autonomous Community at the end of the 2019–2020 academic year.

Our working sample contained 2066 records of students enrolled in one of the three tutoring programs delivered in the nine provinces of the Castilla y León Autonomous Community in the 2018–2019 academic year (Table 1). 62.57 Of the participants, 62.57 % were in the provincial capital, whereas the remaining 37.43 % were in smaller localities.

The tutoring programs were named C2, C3, and C2C3. The C2 tutoring program consists of supporting students throughout the academic year; the C3 tutoring program consists of extra classes during the summer vacation in July; and the C2C3 tutoring program is the longest and consists of a combination of the two previous programs, with extra classes during the academic year and summer vacation in July.

Table 1
Tutoring programs and number of students per program for the 2018–2019 academic year.

Tutoring programs	2018–2019 academic year	
	Number of students	Percentage (%)
C2	1101	53.32 %
C3	694	33.61 %
C2C3	270	13.08 %
Total	2065	100 %

The gender distribution of the students was as follows: 47.07 % were girls and 52.93 % were boys. Of these students, 44.50 % (919) completed repeated grades. In terms of the percentage of enrolled students who finished the tutoring program, students' engagement was 64.21 %. In addition, whether they finished the program or not, students who participated in the tutoring programs had a success rate in the completion of the 4th year of ESO of 72.98 %.

The data are structured into 21 variables, which capture information about the characteristics of the students, the kind of tutoring program in which they were enrolled, and their results both in the completion of the tutoring program and in the 4th year of ESO.

In previous research conducted (Ballestar et al., 2022a,b) using a sample for the academic year 2019–2020, five variables were identified as statistically significant and relevant for empirical analysis and the development of a triangulation method using Machine Learning Methods such as CHAID decision trees, artificial neural network perceptron multilayer (ANN-MLP), and Bayesian Networks.

In this research, we applied the traditional Cross Industry Standard Process for Data Mining (CRISP-DM) (Wirth and Hipp, 2000). We conducted descriptive and iterative causal analyses during the data understanding and preparation stages using SPSS Modeler 18.3. Four of the five candidate variables were relevant for developing an ML based on non-supervised neural networks, specifically Kohonen SOMs.

One of our innovations consists of using this method to evaluate the results of tutoring programs designed to prevent and mitigate early school failure and drop-off and to identify the factors to be considered when designing an intervention of this type. This allows for calculating the success rate and social return on the investment. Neural networks are suitable for this purpose because they capture the causal and interactive relationships between variables (Ballestar et al., 2022a,b; Garbe and Richter, 2009). Linear and nonlinear relationships were captured because they have the capacity for a general function approximation (Buckler, 2001; Garbe and Richter, 2009).

In developing the Kohonen SOM, these four variables acted as input variables (Table 2) corresponding to nine neurones. There is no output or target variable because the model is an unsupervised artificial neural network.

Table 2
Description of the variables used in the machine learning model corresponding to an artificial neural network Kohonen self-organising map.

Input variables	Description	Values (2018–2019 academic year)
student_repetition	Boolean variable which indicates whether the student has already repeated a course or not. Its value is 1 if the student has repeated a course or value 0 if the student has not repeated a course.	Value 0: 1146 students (55.50 %) Value 1: 919 students (44.50 %)
kind_program	Categorical variable that indicates which of the three tutoring programs: C2; C3; C2C3 the student was enrolled in (Table 1).	Value C2: 1101 students (53.32 %) Value C3: 694 students (33.61 %) Value C2C3: 270 students (13.08 %)
finish_program	Boolean variable which indicates whether the student finished the tutoring program or not. Its value is 1 if the student has completed the tutoring program or value 0 if the student has not completed it.	Value 0: 739 students (35.79 %) Value 1: 1326 students (64.21 %)
finish_studies	Boolean variable which indicates whether the student successfully finished the academic year. Its value is 1 if the student has passed the course (4th year of ESO) or value 0 if the student failed.	Value 0: 558 students (27.02 %) Value 1: 1507 students (72.98 %)

4. Method and empirical analysis

Kohonen SOMs are unsupervised artificial neural networks commonly used for clustering or dimension reduction without modifying the topology of the original dataset (Ballestar et al., 2022a; Kohonen, 1995). SOMs learn independently through unsupervised competitive learning, and no human supervision is required in the learning process. As a SOM is a type of neural network, it can solve complex questions by managing large and complex amounts of data effectively and quickly. Each node in the neural network functions as an autonomous entity and performs only a small portion of computations. The aggregation of all the nodes in a network contributes to its power and effectiveness. One of their fundamental properties is that neural networks can handle a small proportion of incorrect data or nonfunctional nodes without affecting the network's performance. In addition to maintaining the topology of the original dataset, another relevant feature of SOMs is called vector quantisation. This compression technique provides a way to represent high-dimensional and nonlinear features in a reduced-dimensional space, such as one or two dimensions. This facilitates human interpretation of the model's results (Kohonen, 1995; Murtagh and Hernández-Pajares, 1995; Nishiyama et al., 2007).

Kohonen SOMs are also widely adopted in education to cluster students based on their characteristics, academic achievements, opinions, and so on (Kong et al., 2019; Nowakowska et al., 2020; Zatarain-Cabada et al., 2009), and design tools to support the development of intelligent tutoring systems (Cabada et al., 2011; de Carvalho et al., 2020).

Based on this information, we conclude that the Kohonen SOMs model may effectively cluster 4th-year ESO students in the Castilla Leon region during the 2018–2019 academic year with a dual objective (Ballestar et al., 2022a; Kohonen, 1995). First, to group the students based on their characteristics, the type of tutoring program they were enrolled in, and their results in both the completion of the tutoring program and the 4th year of ESO. Second, based on the model's output, we evaluated how different factors affected student performance and the success of tutoring programs.

The architecture of this neural network consists of two layers, an input layer and an output layer, where the basic units, also called neurones, are organised. Neurones capture information from the input variables. Each neuron in the input layer was connected to all the neurones in the output layer. This connection is referred to as the output map. The connections between neurones have different weights or strengths, initially established randomly and managed via an n-dimensional weight vector (Ballestar et al., 2022a; Richardson et al., 2003).

In this study, the Kohonen SOM has four input variables corresponding to nine neurones. The input variables and their respective analyses are presented in Table 2.

The output in the Kohonen SOM is a map of a two-dimensional array of neurones with lateral connections to adjacent neurones. These neurones have a neighbourhood relationship, allowing each output neuron's activity to influence its neighbours. The map's dimensions in our model were 4 × 3, corresponding to 12 neurones. Maps with smaller output layers are faster to train and tend to be generalised more effectively (Ballestar et al., 2022a; Choudhary and Bhattacharyya, 2002; Goswami et al., 2011). One of the key advantages of the Kohonen SOM is its ability to balance efficient data compression and reliable preservation of the original data topology, which helps support good generalisation (Ritter, 1999).

During an unsupervised artificial neural network (ANN) training, the input data vectors are sequentially processed and projected onto a two-dimensional output space. The winning output neuron was selected from this output space based on its ability to represent the input data best. This process is iterative and is repeated multiple times to refine the ANN performance.

The unit that presents the weight vector with the smallest Euclidean distance between itself and the input data vector is the winning output neuron, or the best-matching unit. The winner neuron becomes the centre of the neighbourhood, and its weighted connection to the input data vector is updated. The weighted connection of its neighbourhood to the input data vector is updated accordingly. The ANN training process is repeated until only one output neuron in the neighbourhood is activated, and there are no changes in the weights between the neurones from the input and output layers (Ballestar et al., 2022a; Tian et al., 2014). This competition between the output neurones to be activated for the classification of the input patterns is possible because of the existence of lateral connections between them and the use of a competitive learning algorithm, the neighbourhood function (Afolabi and Olude, 2007; Ballestar et al., 2022a; Williams et al., 2014). The resultant Kohonen SOM consists of a grid containing many strong clusters, which are the cluster centres and represent the patterns from the input data. There are as many clusters as the cluster centres on the grid because there are no overlapping regions. There is no need to know the number of clusters in advance because Kohonen SOMs start with many units that, as the training process evolves, gravitate toward natural clusters in the data (Akay et al., 2015). There were also weak units that did not correspond to any specific pattern and were removed from the network (Ballestar et al., 2022a).

The model used in this study was trained in two stages. In the first stage, the gross data patterns were captured by running 20 training cycles. The second stage consists of a tuning process to make the necessary adjustments to the finer features of the data by running 150 training cycles. The cluster to which the model assigns each input record corresponds to a combination of the X- and Y-coordinates of the winning neuron.

5. Evaluation of the model

We developed the Kohonen SOM model in SPSS Modeler 18.3, using 2065 records with information from 4th-year ESO students in the Castilla Leon region during the 2018–2019 academic year. The information in these records captures the characteristics of the students, the kind of tutoring program in which they were enrolled, and their results, both in the completion of the tutoring program and in the 4th year of ESO (Table 2).

The model generated nine student clusters. The percentage of students in each cluster is as follows (Fig. 2): Cluster 1 ($X = 0$; $Y = 0$): 21.60 %; Cluster 2 ($X = 0$; $Y = 1$):8.43 %; Cluster 3 ($X = 0$, $Y = 2$): 7.85 %; Cluster 4 ($X = 1$, $Y = 1$): 5.91 %; Cluster 5 ($X = 1$, $Y = 2$): 5.57 %; Cluster 6 ($X = 2$, $Y = 0$): 10.99 %; Cluster 7 ($X = 2$, $Y = 2$): 6.20 %; Cluster 8 ($X = 3$, $Y = 0$): 16.03 %; Cluster 9 ($X = 3$, $Y = 2$): 17.43 %. The taxonomy of the cluster profiles for the 2018–2019 academic year is shown in Fig. 2 and Table 3.

To measure the fit of the Kohonen SOM model, we calculated the statistical measure, namely The Silhouette coefficient (Haselbeck et al., 2019; Hsu and Li, 2010; Silva et al., 2019), which assesses the consistency of the clustering structure by examining the cohesiveness of the records within a cluster and the separation of the clusters from one another. Its values range from −1 to 1, with the following interpretation: −1 indicates that the model is poor, values higher than 0.5 indicate that the model is good, and 1 occurs when it is optimal. The Silhouette coefficient of our model is 0.6; therefore, it is robust (Aad et al., 2012; Ballestar et al., 2018; Rousseeuw, 1987).

Predictor importance is a measure that assesses the relevance rather than accuracy of each input variable in the model (Ballestar et al., 2018). Three out of four variables in our Kohonen SOM model have an importance of 1 (student_repetition, finish_program, and finish_studies), and the fourth variable, the kind of tutoring program (kind_program), has an importance of 0.87 (Fig. 1). This implies that all four input variables are important in the model.

Once the students were classified into clusters (Fig. 2, Table 3), we characterised them in terms of gender, size of the student's location (whether the student lived in a provincial capital or a smaller locality), type of tutoring program where the student was enrolled, and number of

Table 3
Cluster profiles: frequencies of boolean and categorical variables for the students in the 2018–2019 academic year.

Cluster (frequencies)	Number of students	student_repetition		finish_program		finish_studies		kind_program		
		0 (No)	1 (Si)	0 (No)	1 (Si)	0 (No)	1 (Si)	C2	C2C3	C3
Cluster 1 (X = 0, Y = 0)	446	446	0	0	446	0	446	349	97	0
Cluster 2 (X = 0, Y = 1)	174	174	0	0	174	0	174	0	0	174
Cluster 3 (X = 0, Y = 2)	162	162	0	162	0	0	162	0	0	162
Cluster 4 (X = 1, Y = 1)	122	122	0	122	0	0	122	122	0	0
Cluster 5 (X = 1, Y = 2)	115	22	93	115	0	0	115	0	22	93
Cluster 6 (X = 2, Y = 0)	227	151	76	150	77	227	0	177	11	39
Cluster 7 (X = 2, Y = 2)	128	0	128	128	0	0	128	108	20	0
Cluster 8 (X = 3, Y = 0)	331	69	262	62	269	331	0	126	69	136
Cluster 9 (X = 3, Y = 2)	360	0	360	0	360	0	360	219	51	90
Combined	2065	1146	919	739	1326	558	1507	1101	270	694

Cluster (percentages)	Number of students	student_repetition		finish_program		finish_studies		kind_program		
		0 (No)	1 (Si)	0 (No)	1 (Si)	0 (No)	1 (Si)	C2	C2C3	C3
Cluster 1 (X = 0, Y = 0)	21.60 %	38.92 %	0.00 %	0.00 %	33.63 %	0.00 %	29.60 %	31.70 %	35.93 %	0.00 %
Cluster 2 (X = 0, Y = 1)	8.43 %	15.18 %	0.00 %	0.00 %	13.12 %	0.00 %	11.55 %	0.00 %	0.00 %	25.07 %
Cluster 3 (X = 0, Y = 2)	7.85 %	14.14 %	0.00 %	21.92 %	0.00 %	0.00 %	10.75 %	0.00 %	0.00 %	23.34 %
Cluster 4 (X = 1, Y = 1)	5.91 %	10.65 %	0.00 %	16.51 %	0.00 %	0.00 %	8.10 %	11.08 %	0.00 %	0.00 %
Cluster 5 (X = 1, Y = 2)	5.57 %	1.92 %	10.12 %	15.56 %	0.00 %	0.00 %	7.63 %	0.00 %	8.15 %	13.40 %
Cluster 6 (X = 2, Y = 0)	10.99 %	13.18 %	8.27 %	20.30 %	5.81 %	40.68 %	0.00 %	16.08 %	4.07 %	5.62 %
Cluster 7 (X = 2, Y = 2)	6.20 %	0.00 %	13.93 %	17.32 %	0.00 %	0.00 %	8.49 %	9.81 %	7.41 %	0.00 %
Cluster 8 (X = 3, Y = 0)	16.03 %	6.02 %	28.51 %	8.39 %	20.29 %	59.32 %	0.00 %	11.44 %	25.56 %	19.60 %
Cluster 9 (X = 3, Y = 2)	17.43 %	0.00 %	39.17 %	0.00 %	27.15 %	0.00 %	23.89 %	19.89 %	18.89 %	12.97 %
Combined	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %

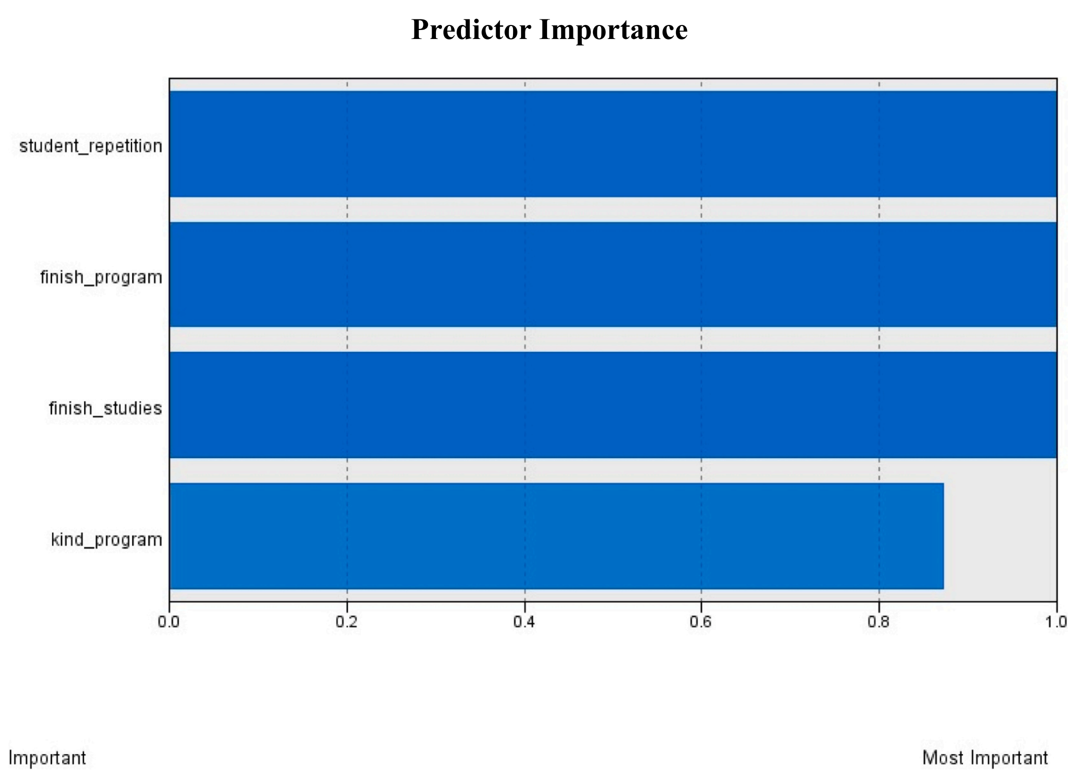
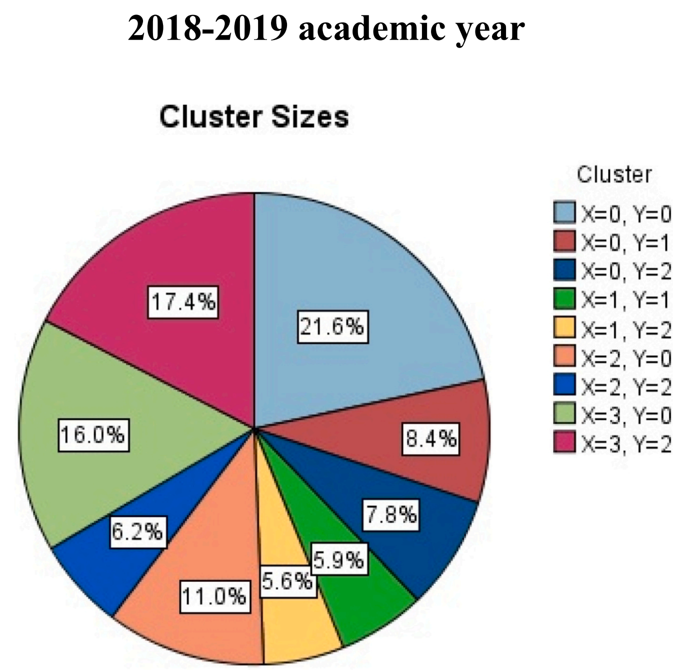


Fig. 1. Predictor importance of the input variables in the Kohonen self-organising map model.

years that the student had repeated a course, enriching the Segmentation Profiles (Fig. 3).

6. Results and discussion

After completing all stages of the traditional cross-industry standard process for data mining (CRISP-DM) (Wirth and Hipp, 2000), we analyse the output delivered by the Kohonen SOM. This section describes the characteristics of the student clusters. We describe the clustering structure of the students based on their characteristics, the type of tutoring program they were enrolled in, and their results on completing both the tutoring program and the 4th year of ESO. Furthermore, we assessed the impact of various factors on student performance and the success of tutoring programs.



Size of Smallest Cluster	115 (5.6%)
Size of Largest Cluster	446 (21.6%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	3.88

Fig. 2. Cluster distribution chart for the students in the 2018–2019 academic year.

6.1. *Preventing academic failure, top clusters of students*

Cluster 1 was the largest (446 students; 21.60 % of the sample), and Cluster 2 (174 students; 8.43 % of the sample) comprised students who had never repeated a course but were experiencing difficulties. These students were enrolled in one of the three tutoring programs, completed it, and passed the 4th year of the ESO. Girls were represented more than the average in Clusters 1 and 2 at 48.43 % (+2.89 % above the overall mean) and 47.70 % (+1.34 % above the overall mean), respectively.

One of the main differences between Clusters 1 and 2 was the location of the students. Cluster 1 had the second-highest percentage of students living in provincial capitals at 66.14 % (+5.72 % above the overall mean), in contrast to Cluster 2, which was the most rural with only 52.30 % of its students living in provincial capitals (−16.41 % below the overall mean).

In addition, all students in Cluster 2 enrolled in tutoring program C3, which consisted of extra classes during the summer vacation in July, while students in Cluster 1 enrolled in longer programs covering at least the entire academic year (78.25 % of the students enrolled in C2 and 21.75 % enrolled in C2C3).

The tutoring programs for Clusters 1 and 2 were successful, as these students completed them and passed the 4th year of ESO. These two clusters of students (30.03 % of the total sample) confirm Hypothesis 1, demonstrating that tutoring programs effectively support.

6.2. *Cluster of reengaged students*

Cluster 9 was the second largest (360 students, 17.43 % of the sample). The sample comprised students who had repeated at least one course before enrolling in the special education program (75.83 % repeated one course, 22.50 % repeated two courses, and 1.67 % repeated three courses). These students were enrolled in one of the three tutoring programs, completed it, and passed the 4th year of the ESO.

Most of the students (75 %) had the longest programs involving at least the whole academic year; 60.83 % participated in C2 and 14.17 % in C2C3, while the remaining 25 % participated in C3 during the summer vacation in July. These students had failed in the past, but their participation and engagement in the tutoring program helped them avoid new school failures, supporting Hypothesis 2. Compared with the other clusters, Cluster 9 had a higher representation of girls than the average at 48.33 % (+2.68 % above the overall mean), and 40 % of the students lived in small localities (+6.86 % above the overall average).

For Cluster 9 (17.43 % of the total sample), the tutoring programs were successful, as these students completed them and passed the 4th year of ESO. This cluster of students confirms Hypothesis 2: Tutoring programs effectively reengage students who have already failed in the academic system, avoiding early dropouts.

6.3. *Clusters of failing students*

Clusters 8 (331 students, 16.03 % of the sample) and 6 (227 students, 10.99 % of the sample) ranked third and fourth, respectively. Students from these clusters did not pass the 4th year of the ESO, demonstrating a failure in the implementation and execution of tutoring programs. These clusters contained students who did not repeat any course and others who repeated up to three courses with variable levels of engagement with the tutoring programs.

Many students in Cluster 6 (66.52 %) did not repeat any course, while 22.03 % repeated one course, 11.01 % repeated two, and 0.44 % repeated three. The engagement of these students with the tutoring program was not very high, with 66.08 % not completing it. The majority of students (82.82 %) were enrolled in the longest programs, which involved at least the entire academic year (77.97 % participated in C2 and 4.85 % in C2C3), while the remaining 17.18 % participated in C3 during summer vacation in July.

The percentages of girls in these clusters were 48.90 % and +3.88 %, respectively, above the overall average. On average, 62.56 % of the students were in provincial capitals and 37.44 % in smaller localities.

Most students (79.15 %) in Cluster 8 repeated at least one course: 53.17 % repeated one course, 25.08 % repeated two courses, 0.91 % repeated three courses, and 20.85 % did not repeat any course. The engagement of these students in the tutoring programs was high, with 81.27 % completing them. The enrolment of the students in the three programs was more balanced than in Cluster 6, with 58.91 % of the students participating in the longest programs, which involved the entire academic year, 38.07 % participating in C2, 20.85 % in C2C3, and 41.09 % participating in C3 during the summer vacation in July. The percentage of girls in this cluster is 44.11 %, −6.29 % below the overall average. Students' locations were more rural than in Cluster 6, with 60.42 % in provincial capitals and 39.58 % in smaller localities (+5.73 % above the overall mean).

For Clusters 6 and 8, the tutoring programs were unsuccessful, as these students could not pass the 4th year of the ESO. These two clusters of students (27 % of the total sample) confirm Hypothesis 3, demonstrating that the engagement and success of tutoring programs depend on many diverse factors, such as the academic and socioeconomic

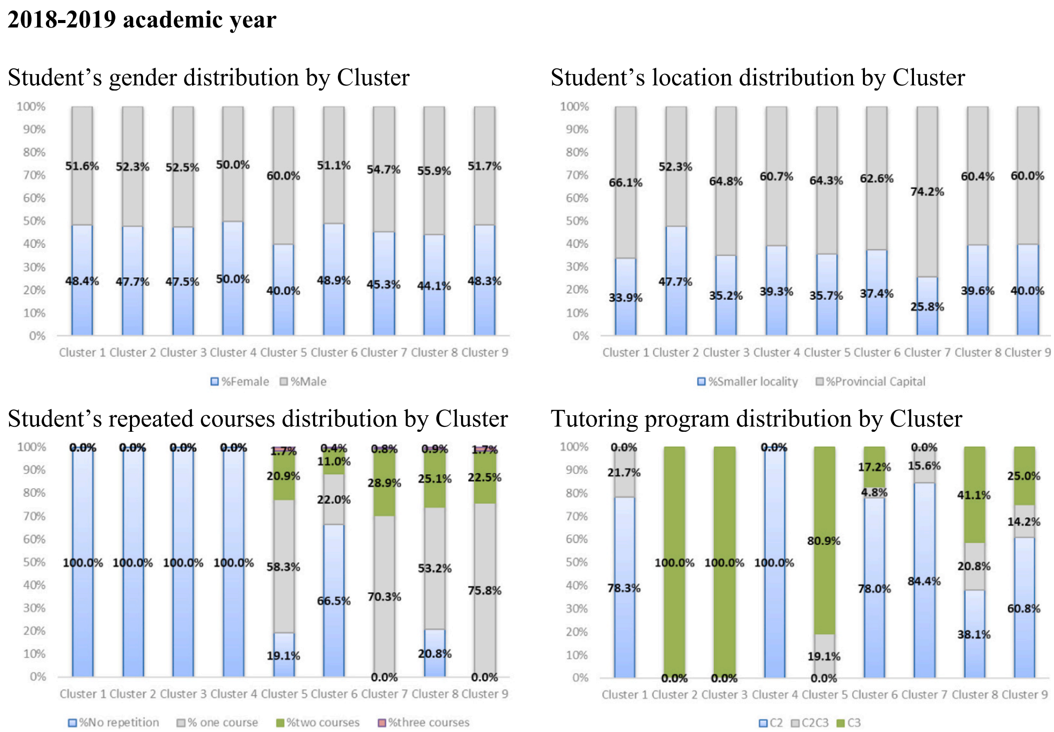


Fig. 3. Characteristics of clusters: gender, location, repeated courses, and kind of program for the 2018–2019 academic year.

background of the student, the characteristics of the program in which they are enrolled, and their engagement with it. The allocation of the right tutoring program in terms of duration to maximise students' engagement is very important to avoid later academic failures. This is particularly relevant when a student fails and repeats the course.

6.4. Clusters of students who did not engage with the tutoring programs

Four clusters (Clusters 3, 4, 5, and 7) of students did not complete the tutoring programs but passed the 4th year of the ESO. Even though the academic failure of these students was avoided, the tutoring program did not maximise the social return on investment, as it was not accurately applied. These clusters were the smallest, but together added up to 527 students (25.52 % of the total sample): Cluster 3 (162 students; 7.85 % of the sample), Cluster 4 (122; 5.91 % of the sample), Cluster 5 (115; 5.57 % of the sample), and Cluster 7 (128; 6.20 % of the sample).

Students from Clusters 4 and 7 made up 12.11 % of the sample and were enrolled in the longest tutoring programs, which involved at least the entire academic year (C2 and/or C2C3). Students from Cluster 4 had never repeated a course before, in contrast to students from Cluster 7, where all students had repeated at least one course before enrolling in the tutoring program (70.31 % had one course, 28.91 % had two courses, and 0.78 % had three courses). Cluster 7 comprised 54.69 % male students (+3.32 % above the overall mean), and Cluster 4 was the only cluster with an equal representation of students of both genders. Cluster 7 had the highest percentage of students from provincial capitals at 74.22 % (+18.62 % above the overall mean), in contrast to Cluster 4, which had 60.66 % (−3.05 % below the overall mean).

Students from clusters 3 and 5 comprised 13.42 % of the sample. All students from Cluster 3 and 80.87 % from Cluster 5 were enrolled in C3 during the summer vacation in July, and 19.13 % from Cluster 5 were enrolled in the longest program, C2C3, which lasted the entire academic year and summer vacation. Students from Cluster 3, similar to Cluster 4, had never repeated a course before, in contrast to students from Cluster 5, in which most (80.87 %) had repeated at least one course before enrolling in the tutoring program (19.13 % did not repeat a course, 58.26 % repeated one course, 20.87 % repeated two courses, and 1.74 % repeated three courses). Cluster 5 had the highest percentage of males, 60.0 % (+13.36 % above the overall mean). Clusters 3 and 5 were above the average for students from the provincial capital at 64.81 % (+3.59 % above the overall mean) and 64.35 % (+2.85 % above the overall mean), respectively.

External factors underlie the lack of student engagement in the program. The students were enrolled in a tutoring program that did not require additional support. In these clusters, 13.75 % of the students had never repeated a course before and did not engage in the tutoring program but could pass the 4th year of ESO.

In summary, students from Clusters 3, 4, 5, and 7 (25.56 % of the total sample) did not finish the tutoring program but could still pass the 4th year of the ESO. Despite their academic success, not finishing the tutoring programs represented a failure, as they could not engage the students, and there was an opportunity cost for others who could not enrol. These clusters of students confirm Hypotheses 1 and 4: The success of tutoring programs depends on effectively identifying at-risk students to maximise the social return on investment in these programs.

7. Conclusions

Tutoring is an efficient way to reduce school failure. Our results are consistent with those of previous studies (Carlana and la Ferrara, 2021; Fryer and Howard-Noveck, 2020; Guryan et al., 2021; Ritter et al., 2009; Ballestar et al., 2022a,b). Our analysis focuses on one of these tutoring schemes: the Programa para la Mejora del Éxito Educativo (Programme for the Improvement of Academic Success) of the Junta de Comunidades de Castilla y León in Spain, in 2018, the academic year before the pandemic. The program was designed to improve the performance of students at risk of failure in Spanish, literature, mathematics, and English (Ballestar et al., 2022a,b).

Our empirical design takes advantage of ML methods to measure the impact of tutoring on the academic results of more than 2000 students. We aim to shed light on the causality between socioeconomic and educational variables and the optimal design and implementation of tutoring programs, identifying additional factors to consider to maximise the social return on investment (Fryer and Howard-Noveck, 2020;

Kraft and Falken, 2021).

Our analysis shows that Machine Learning Methods based on a Kohonen SOM are useful for Public Administrations to evaluate the efficiency and return on investment in tutoring programs, such as the Program for the Improvement of Educational Success implemented in the nine provinces of Castilla y León Autonomous Community in the 2018–2019 academic year.

We provide additional tools for Public Administrations to group students and analyse their characteristics, engagement, and results according to the tutoring program in which they were enrolled. This allows not only the social return on investment to be measured and the results of the tutoring programs to be evaluated but also facilitates improvement of the interventions and support for at-risk students.

For example, our results show that tutoring programs tailored to the specific needs and characteristics of at-risk students could effectively prevent early school failure. Our Kohonen SOM shows that the programs prevented academic failure for 47.46 % of the students if they were engaged with the program and finished them (Cluster1, 2, and 9). In these cases, the programs were effective for students who had never failed a course before (30.02 % of the sample, Clusters 1 and 2) and those who had failed in previous years (17.43 %; Cluster 9). This finding confirms Hypotheses 1 and 2. To fully benefit from tutoring programs, enrolling students in programs that best fit their characteristics and needs is important. Our research shows that shorter programs, such as summer vacation programs, are more effective for students from small towns and villages who have not previously failed a course, whereas longer programs work better for students from larger cities and those with a history of academic struggle.

Hence, the effectiveness and success of tutoring programs are influenced by various factors such as students' academic and sociodemographic backgrounds and the program's characteristics. For example, 16.03 % of the students (Cluster 8) did not pass the course, even though most engaged in the tutoring program. Of these, 41.09 % were enrolled in the summer vacation course, which was not long enough for their academic needs, but the rest of the cluster participated in longer programs, indicating that other factors affected the performance of this group.

Apart from the academic background and the kind of program the student is enrolled in, it is also very important to work on engaging the student. Clusters of students who were very likely to succeed, as most had not repeated a course before, failed to pass the 4th year of ESO, as many did not engage in the tutoring program (10.99 % of the sample; Cluster 6). The tutoring programs for these two clusters (Clusters 6 and 8) were unsuccessful, as they did not prevent the students from failing in the 4th year of ESO. These findings confirm Hypothesis 3.

Finally, our analysis shows that acute identification of at-risk students is crucial for maximising the social return on investment in programs designed to prevent early school failure. Of the students, 25.52 could pass the 4th year of ESO without finishing the tutoring program. Hence, the tutoring program did not maximise social returns on investment. One of the main reasons for this failure was the enrolment of students who did not need or want additional support from these tutoring programs. These students represented 13.75 % of the sample (Clusters 3 and 4). These students had never repeated a course before and did not engage in the tutoring program, but could pass the 4th year of ESO. On the other hand, 11.77 % of the students (Clusters 5 and 7) seemed to be at a high risk of academic failure because of their academic background, as almost all had previously repeated a course. However, they could pass the 4th year of the ESO without engaging in the tutoring program, which shows that the selection of these students was also imprecise. These errors in the selection of students to participate in the programs are not only a failure in the execution of the tutoring programs but also represent a high cost of opportunity for other students who could not participate. These findings confirm Hypothesis 4.

Our research has clear implications for public administration and will help improve the quality and social return on investment in tutoring programs. We provide better decision-making tools to avoid school failure by assisting the correct students in enrolling in tutoring programs. These programs should be more efficiently designed to accommodate students' characteristics and needs.

In the next phase of our research, we will perform a longitudinal analysis, comparing the pre-pandemic year 2018–2019 results with later years from the same program.

8. Limitations and future research

The Programme for the Improvement of Educational Success database contains data from the 2018–2019 and 2019–2020 academic years during the COVID-19 pandemic. Previous research focused on the second academic year, 2019–2020 (Ballestar et al., 2022a,b). In this study, we focused on the first academic year, 2018–2019. Further research should analyse the second academic year, 2019–2020, using our research method based on a machine learning model with an artificial neural network Kohonen SOM to shed light on how tutoring programs affect students' results and performance during the pandemic. This study has limitations, as it focused only on students in the 4th year of ESO. Further research should validate these results for other academic years. Ballestar & Sainz research was funded by the Spanish Ministry of Innovation research Grant number PID2020-113852RB-I00/AEI/10.13039/501100011033

CRediT authorship contribution statement

María Teresa Ballestar: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Miguel Cuerdo Mir:** Investigation, Methodology, Writing – review & editing, Conceptualization, Resources. **Luis Miguel Doncel Pedrera:** Conceptualization, Investigation, Methodology, Resources, Writing – review & editing. **Jorge Sainz:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

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