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Using artificial intelligence in education: decision tree learning results in secondary school students based on cold and hot executive functions

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Improving educational quality is a universal concern. Despite efforts made in this regard, learning outcomes have not improved sufficiently. Therefore, further investigation is needed on this issue, adopting new perspectives (conceptual and analytical) to facilitate the understanding and design of effective actions. The objective of this study was to determine the influence of executive functions (considering both cognitive and affective processes) and their interactions on learning outcomes in Language and Literature and Mathematics in Spanish students, through the use of artificial intelligence, based on the machine learning approach, and more specifically, the decision tree technique. A total of 173 students in compulsory secondary education (12–17 years old) from the same educational institution participated. The school's educational counsellor provided information on student executive function levels by completing the BRIEF2 questionnaire for each participant. She also reported on the learning outcomes achieved by students in the subjects of interest for this research (Language and Literature and Mathematics). R software was used to model the regression trees. The results revealed groups of students characterised by different profiles, i.e., by different combinations of difficulties in various executive functions and varying levels of learning outcomes in each academic area. However, regardless of the academic area considered (Language and Literature or Mathematics), working memory was identified as the most relevant executive function in all of the students' learning outcomes. Understanding the combination of executive functions that predict learning outcomes in each group of students is important since it enables teachers and other educational professionals, policymakers and researchers to provide individualised educational resources according to the diverse student profiles and needs. It constitutes an effective mechanism to improve students' learning results and, ultimately, to enhance an equitable and more effective educational system.

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Introduction

Sustainable Development Goal (SDG) 4 is dedicated to Quality Education. Its Target 4.1 aims to ensure that by 2030, all girls and boys will complete primary and secondary education, which should be free, equitable and of high quality, producing relevant and effective learning outcomes.

Student academic achievements are influenced by a multitude of personal, family and educational context variables (Martínez-Perez et al. 2020; Ramudo-Andion et al. 2020). Among these variables, this study focuses on executive functions. Executive functions are high-level cognitive and emotional processes that enable problem-solving in novel and/or complex situations, permitting the adaptation of behaviour to the continuously changing context in order to achieve goals (Diamond 2020; Zelazo & Carlson 2020). This study emphasises executive functions since: (1) they are variables that significantly impact learning outcomes (Ahmed et al. 2019; Barnes 2023; Cho et al. 2023; Duckworth et al. 2019; Gunzenhauser & Nückles 2021; Poon 2018; Spiegel et al. 2021; van Tetering et al. 2022). Executive functions influence learning outcomes through several distinct pathways. Executive functions involve the capacity to retain and manipulate information, suppress irrelevant information, reviewing mistakes, alternate between different strategies or generate new ones. These processes are fundamental for successfully completing academic tasks (Zelazo & Carlson 2020; Zelazo et al. 2024). Furthermore, a high level of executive function also encompass the ability to reduce internal and external distractions (for example, resist becoming distracted by peers), allowing students to concentrate on the task at hand, follow the teacher's instructions, and generally adhere to classroom rules. These positive learning habits lead to improved learning outcomes (Ahmed et al. 2024). Additionally, executive functions also imply students' ability to regulate their emotions. Research has shown that emotions influence students' learning and achievement (De Neve et al. 2023; De France & Hollenstein 2021; Karagiannopoulou et al. 2023). This is particularly important in relation to negative affect, as experiencing negative emotions is associated with slower information processing, which can adversely affect learning and academic performance (Scrimin et al. 2014; Sutin et al. 2022). Adequate emotional regulation also facilitates relationships with peers and teachers, increasing acceptance by others and a sense of belonging within the group. This, in turn, contributes to the development of a more motivation, positive attitude and engagement with academic matters, thereby facilitating learning (De Neve et al. 2023; Karagiannopoulou et al. 2023). (2) They are modifiable, allowing intervention for improvement (Gunzenhauser & Nückles 2021; Zelazo & Carlson 2020); thus, teachers and other professionals can design strategies to enhance them, benefiting the students' learning outcomes. Therefore, executive functions are a key target in efforts to promote academic success. (3) Despite being the subject of various studies considering their relationships with learning outcomes, unresolved issues remain that require further, detailed investigation.

One limitation of most works focused on this topic is the classic and reductionist perspective taken when considering executive functions, including only cognitive processes and excluding emotional ones. Currently, executive functions are distinguished between cognitive (referred to as cool or cold executive functions) and emotional (referred to as hot executive functions) processes (Poon 2018; Zelazo et al. 2016, 2024). The former refers to purely cognitive processes that are involved in neutral contexts, where there is no emotional load. According to different authors, process such as attention, initiation, working memory or updating, inhibition, cognitive flexibility or shifting, behavioural monitoring, fluency, reasoning, organisation, problem-solving and planning are cold executive functions (Carlson et al. 2013; Diamond 2013, 2020; Laureys et al. 2022; Miyake et al. 2000; Sambol et al. 2023; van Tetering et al. 2022). Specially, cool executive functions are associated with the activation of the dorsolateral prefrontal cortex (Salehinejad et al. 2021; Zelazo et al. 2024). On the other hand, hot executive functions are engaged in affective or motivational situations, in contexts with high emotional valence; i.e., both in situation with social interaction component and in personally meaningful problem that generate emotion and motivation as well as situation in which there is tension between immediate gratification and greater long-term rewards (Poon 2018; Zelazo et al. 2016, 2024). In recent years, aspects such as emotion regulation, theory of mind, empathy, self-referential, emotional intelligence, moral judgement, and specially, affective decision-making, delay of gratification or delay discounting has been proposed as hot executive functions (de la Fuente et al. 2022; De Luca & Leventer 2008; Happaney et al. 2004; Kerr & Zelazo 2004; Salehinejad et al. 2021). Primarily, hot executive functions have been associated with activity in the orbitofrontal and ventromedial regions of the prefrontal cortex (Salehinejad et al. 2021; Zelazo et al. 2024). Although hot and cool executive components are different and independent, they are interconnected in terms of their neuroanatomical substrates and can coordinate to respond to the demands of each task (Salehinejad et al. 2021; Zelazo et al. 2024).

Another limitation of many studies focusing on the relationships between executive functions and learning outcomes is the inclusion (regardless of participants' age) of only the cognitive components of executive functions that develop earlier and are considered by most authors as the central components of executive functions (Miyake et al. 2000): working memory (storing information in the mind and mentally working with it), inhibition (the ability to resist temptations and impulsive actions, and to keep one's selective attention by suppressing non-relevant information) and cognitive flexibility (the ability to shift between different tasks, rules or mental contents allowing for problem-solving in distinct manners or viewing things from different perspectives). Therefore, many studies tend to overlook other highly relevant cognitive components that develop later, such as planning (the ability to create a plan or a roadmap to reach a goal) (Diamond 2020).

This study aimed to overcome these limitations by analysing the relationships between learning outcomes and executive functions, consisting of both cognitive and emotional processes. Within the cognitive processes, cold executive functions included early developmental executive functions (working memory, inhibition and cognitive flexibility) as well as later developmental ones, of special relevance during adolescence, such as planning (Laureys et al. 2021, 2022). Within the emotional processes (i.e., hot executive functions), emotion regulation is included. It considered the processes that influence which emotions we have, when we have them and how we experience and express them (Gross 1999). In other words, emotion regulation refers to the processes responsible for monitoring, evaluating, and modifying emotional reactions, especially their intensive and temporal features, in order to adapt to the social environment or to achieve one's present or future goals (Thompson 1994). Among the different hot executive functions, its selection in our study is justified by the following reasons. According to the literature, and as it already mentioned previously, emotion regulation is particularly important in learning contexts (De Neve et al. 2023; De France & Hollenstein 2021; Karagiannopoulou et al. 2023). In the context of academic learning and achievement, students may encounter a range of emotions, both positive and negative (such as the joy of learning or the shame of failure), emotions related to the task or self (e.g., happiness from success, anxiety), and social emotions (e.g., admiration, envy). These emotions affect academic success. Positive emotions enhanced motivation, cognitive resources, the use of learning strategies, and overall academic achievement. The contrary effects have been detected when negative emotions appear. Therefore, effective regulation of negative emotions is especially relevant to favour successful learning (Lobczowski et al. 2021). However, achieving effective regulation of negative emotions is not easy, especially for adolescent students (participants of this study). Adolescence is a time of poor emotion regulation. Adolescents have more difficulty exercising hot versus cool executive functions because the neural circuitry underlying the engagement in motivationally significant situations develops later (precisely, adolescence is a relevant developmental period for it) and because those situations are often inherently more demanding (Silvers 2022; Tottenham 2024). However, despite the poor emotion regulation that characterises adolescence, it is necessary on numerous occasions and contexts, given the numerous changes and new demands that characterise this evolutionary stage and to which adolescents must face and adapt accordingly to the norms of social functioning. The magnitude of change across several life domains can increase emotional lability during this stage of life (Silvers 2022; Tottenham 2024). Specifically, at the educational level, during the secondary compulsory education, adolescents must face a considerably increased of daily time in school, more subjects, choose their academic subjects pathway, more teachers but less support from them, more homework, exams and controls, higher ratio of students per class, etc. This makes adolescents experience, compared to when they were children, more daily life hassles, greater fluctuations of emotions, fewer positive emotions and more negative emotions than they must regulate. Additionally, adolescents have to learn to regulate these emotions more independently than when they were children (De Neve et al. 2023; Lennarz et al. 2019). Despite the importance of emotional regulation during this stage of development and within the learning context, studies focusing on emotional regulation in adolescence are limited, as are those examining emotional regulation in natural settings such as schools (De France & Hollenstein 2021; Lennarz et al. 2019). There are even fewer studies that combine both aspects. Consequently, to study the emotion regulation in adolescent educational and learning contexts is urgent (Fombouchet et al. 2023, 2024; Pinochet-Quiroz et al. 2022). Our study aims to contribute to eliminating these gaps and responding to this need.

Thus, the executive functions examined in this work included working memory, inhibition, cognitive flexibility, planning (cold executive functions) and emotion regulation (hot executive function). Thereby, our study encompasses the most pertinent cold and hot EF during adolescence (Laureys et al. 2021, 2022), and in addition, addresses a gap identified in recent studies that call for the inclusion of hot executive functions, and specially, emotion regulation, in educational and learning contexts during this stage of life (Fombouchet et al. 2023, 2024; Pinochet-Quiroz et al. 2022).

As we are exposing, executive functions are considered determinants of academic achievement and student learning (Ahmed et al. 2019; Barnes 2023; Cho et al. 2023; Dubuc et al. 2020; Duckworth et al. 2019; Georgiou et al. 2020; Gunzenhauser & Nückles 2021; Huizinga et al. 2024; Poon 2018; Spiegel et al. 2021; van Tetering et al. 2022). However, not all executive components appear to be equally important for this purpose (Cirino et al. 2024; Cragg & Gilmore 2014; Kendeou et al. 2014). Working memory, in particular, is the most consistently related to learning outcomes (Ahmed et al. 2019; Alloway 2006; Alloway & Alloway 2010; Anjariyah et al. 2022; Cirino 2023; Cirino et al. 2024; Fitzpatrick et al. 2015; Flórez-Durango et al. 2022; Gerst et al. 2017; Dubuc et al. 2020; Rose et al. 2011; Studer-Luethi et al. 2022; Titz & Karbach 2014; Wang & Kao 2022). Inhibition, according to other studies although less numerous, is also consistently relates to learning outcomes (Dubuc et al. 2020; Privitera et al. 2023). However, cognitive flexibility and emotion regulation do not consistently correlate with academic achievement (van der Sluis et al. 2007). These inconsistent results should be clarified.

As for procedural issues, to achieve the SDG 4 Quality Education and its targets, UNESCO has advocated for the use of information and communication technologies, specifically artificial intelligence (UNESCO 2019). UNESCO has recommended considering the significant advances that artificial intelligence permits in the processing of empirical educational data, enabling valuable results to be obtained that can facilitate evidence-based decision-making. Consequently, these decisions are more appropriate and more likely to succeed, ultimately contributing to ensuring quality education.

In accordance with this recommendation, artificial intelligence was used as an analytical approach in this research, to examine the relationships existing between learning outcomes and executive functions. More specifically, machine learning or automated learning was used. The machine learning research area is still in its early stages but is undergoing rapid growth, providing major improvements in the accuracy of learning outcome classification and prediction as compared to traditional statistical approaches (Su et al. 2022). The use of artificial intelligence, and specifically machine learning, serves as an opportunity to accomplish SDG 4 since it advances the classification and prediction of student learning outcomes, especially in their optimisation (Vinuesa et al. 2020). This is achieved by identifying distinct student groups, each of which is characterised by the interaction of a variety of variables that affect learning outcomes. This, in turn, permits the design of specific interventions for each group, targeting improvements in variables that are relevant to each group.

Of the various algorithms in machine learning, decision trees are highly recommended for several reasons, including their ability to handle missing data and their greater interpretability as compared to other algorithms (Costa & Pedreira 2023). Decision trees involve multiple analytical strategies, such as classification and regression trees (CART), which enable the classification and segmentation of a population into different subgroups, where members of each subgroup share characteristics that may influence a specific behaviour (in this study, learning outcomes) (Chen & Xia 2011). To create these homogeneous subgroups, attention is simultaneously paid to multiple attributes (in this study, the variables were executive functions of working memory, inhibition, cognitive flexibility, planning and emotion regulation), selecting the most important ones for each subgroup. Thus, decision trees allow for the construction of combinations of variables (the aforementioned executive functions), organised based on importance, resulting in different profiles of students based on their learning outcomes. The decision tree profiles enable the identification and prediction of which members of the population would fall into these specific profiles. This permits the design of different educational interventions based on the characteristics determining each student profile, resulting in more effective educational actions. Despite their potential, the use of machine learning to identify student profiles remains a challenge in educational research (de Souza Zanirato Maia et al. 2023), and this study contributes to its advancement.

Therefore, we formulated the following research question: What combinations of executive functions constitute the performance profiles in Language and Literature and Mathematics in compulsory secondary education students? To address this question, the following objective was proposed: to use machine learning to identify and characterise profiles of compulsory secondary education students based on their learning outcomes in Language and Literature on the one hand, and Mathematics on the other hand, as well as their levels of executive functions, both cognitive (working memory, inhibition, cognitive flexibility and planning) and emotional (emotion regulation).

We hypothesised that: (1) students characterised by having greater difficulties in executive functions (both cognitive and emotional) will attain poorer learning outcomes (in both Language and Literature and Mathematics) as compared to their peers with profiles characterised by lower executive difficulties, who will attain higher learning outcomes; (2) working memory will be the most influential executive function for learning outcomes across distinct learning areas (Language and Literature and Mathematics), making it the most relevant executive function for establishing student performance profiles.

Methods

Participants. A non-random sample selected by convenience from a Spanish charter school was studied. (Charter school is one of the three main types of schools in Spain. It could be considered as a "semi-private" school given it is financed by the national and regional government but also charges school fees to parents to support the complementary activities offerings. However, contrary to what is often believed, these fees are voluntary (although practically all families pay them) given the law guarantees that basic education is free, whether public or charter. The government imposes to charter school certain management conditions (as following the state curriculum or the maximum number of pupils per class) but it has well greater freedom than public one to organise it programming and methodologies or to select its teachers (Umpstead et al. 2016)). Specifically, 173 Spanish compulsory secondary education students (54.91% male; 45.09% female; mean age = 13.81, standard deviation = 1.4; range = 12–17 years old) participated in this study. These students were from the four courses of Spanish compulsory secondary education (corresponding to 12–16 years of age; level 2 of *International Standard Classification of Education—ISCED*): 28.32% studied in the 1st year; 24.86% in the 2nd year; 20.81% in the 3rd year and 26.01% were in the 4th year. All students had a medium-high socioeconomic level.

The following exclusion criteria were established: (1) having learning difficulties due to not knowing the language; (2) having sensory, psychiatric or neurological problems.

Although this study did not involve direct student participation, they all voluntarily expressed their consent for the educational counsellor to inform the research team regarding their executive function levels and grades. In addition, signed informed consent from their parents was also obtained.

Participants were treated according to the ethical principles outlined in the Declaration of Helsinki and Spanish Organic Law 15/1999 of 13 December on Personal Data Protection.

Instruments. The students' executive functions were assessed using the teacher and educational professional version of the Behaviour Rating Inventory of Executive Function 2 (BRIEF2; Gioia et al. 2017). The following scales were used: (1) working memory: indicating difficulties in maintaining information in mind while performing an activity (e.g., "Forgets what they were doing"); (2) inhibition: reporting on the student's difficulties in controlling impulses (e.g., "Restless behaviour"); (3) flexibility: indicating the presence of difficulties in shifting attention focus if the activity requires flexible problem-solving (e.g., "Struggles to think of alternative ways to solve a problem"); (4) planning: evaluating the occurrence of problems in anticipating future situations, organising and prioritising information, establishing goals and sequencing the necessary steps to achieve them (e.g., "Underestimates the time needed to complete a task"); (5) emotional control: indicating the student's difficulties in controlling emotional responses (e.g., "Explodes and gets angry over small things"). The BRIEF2 scale assesses difficulties in executive functions, with a high score indicating deficits in the corresponding executive function. Internal consistency value (Cronbach's alpha) of the scale was adequate ($\alpha > 0.80$) (Adamson & Prion 2013).

The students' learning outcomes in Language and Literature and Mathematics subjects were assessed in accordance with Spanish educational regulations, namely, from final grades (ranging from 1 to 10, without decimals) assigned by the teachers of each subject based on the results achieved by each student.

According to the Spanish educational curriculum, the learning outcomes to be achieved by compulsory secondary education students in these subjects involves the following specific competencies (for more extended explanation, see Spanish Official State Gazette 2022).

Language and Literature: 1. Linguistic diversity: recognise and value the linguistic and cultural diversity of Spain and the world to combat prejudice and appreciate cultural richness. 2. Comprehension of oral and multimodal texts: understand and interpret oral and multimodal texts, identifying the speaker's intention and assessing their reliability and content. 3. Production of oral and multimodal texts: create and participate in oral and multimodal texts and interactions fluently and coherently, adapting to the genre and context. 4. Comprehension of written texts: interpret and critically evaluate written texts, identifying ideas and the author's intention for various purposes. 5. Production of written and multimodal texts: write coherent and appropriate texts, adhering to genre conventions to effectively address communicative needs. 6. Selection and evaluation of information: critically evaluate and select information from various sources autonomously, respecting intellectual property. 7. Autonomous reading: read diverse works for pleasure and knowledge, developing a personal reading itinerary and sharing experiences. 8. Interpretation of literary works: read and evaluate national and international literary works, establishing cultural and artistic connections to enjoy and create literature. 9. Language awareness: reflect on the structure and use of language to improve oral and written production and comprehension, enhancing linguistic awareness. 10. Ethical communicative practices: use language ethically and democratically, promoting equality and resolving conflicts through dialogue.

Mathematics: 1. Interpret and solve problems: use various strategies and reasoning to solve daily and mathematical problems. 2. Evaluate solutions: analyse and verify solutions to ensure their mathematical validity and impact. 3. Formulate conjectures: create and test simple conjectures to generate new knowledge. 4. Computational thinking: organise data and create algorithms to model and solve problems. 5. Mathematical connections: interrelate mathematical concepts and procedures. 6. Mathematics in real contexts: apply mathematical concepts in other areas and real-life situations. 7. Mathematical representation: use technologies to visualise and structure mathematical ideas. 8. Mathematical communication: explain mathematical ideas using appropriate language. 9. Personal skills: manage emotions and accept mistakes to improve perseverance and enjoyment in mathematics. 10. Social skills: work in teams, respecting and valuing the emotions and experiences of others.

Procedure. The school's educational counsellor completed the BRIEF2 online version for each of the participants, taking

10 min/per student. She subsequently notified the research team of the final grades assigned by the teachers to the students in the Language and Literature and Mathematics subjects. This information was provided anonymously by the educational counsellor, using a random code for each student (the same code was used to identify each student when responding to the BRIEF2).

Data analysis. Within the CART analytical strategy, two regression trees were tested (since the variable to be predicted, learning outcomes, was quantitative): one to predict learning outcomes in Language and Literature and another to predict learning outcomes in Mathematics. The procedure followed to construct each regression tree was identical. The same five student attributes were included as input data in each model: working memory deficits, inhibition deficits, cognitive flexibility deficits, planning deficits and emotional control deficits. Prior to this, the total dataset was divided into two groups: "train" (70% of the data, in line with Hamim et al. (2021)), to serve as a training set for fitting the input data and predicting the students' learning outcomes, and "test" (the remaining 30%) to calculate prediction error with data distinct from that used for training. The Tree library and rpart algorithm from R software (R Core Team 2019) were used to make decisions regarding which attributes to use and in what order when partitioning the data. By default, rpart() uses the Gini index for node splitting.

First, a large tree was built and its predictive performance was estimated in terms of its complexity parameter ($cp = 0.01$). Subsequently, tree pruning was conducted to reduce its size and to avoid overfitting the model, which can be reduced by pruning and adjusting hyperparameters. The results from the regression tree were cross-validated within the same dataset by dividing it into a training and test sample.

Different evaluation metrics were calculated to evaluate the quality and accuracy of each model: mean squared error (MSE), root mean squared error (RMSE), mean absolute error/mean absolute deviation (MAE/MAD), mean absolute percentage error (MAPE) and *R*-squared or coefficient of determination (R^2).

Results

Figures 1 and 2 show the regression trees for Language and Literature as well as Mathematics learning outcomes, respectively. Each tree starts with a root at the top and subsequently branches into multiple paths based on scores indicating deficits in executive functions. In each division, the left branch indicates that the condition for deficits in executive functions scores has been met, while the right branch indicates that the condition for deficits in executive functions scores has not been met. Within each box, the value below it indicates the percentage of students from the total sample routed to the specific node (thus, the root node contains 100% of the participants, and a leaf node contains the least percentage of participants along a rooted path in the regression tree), and the value at the bottom indicates the average grade obtained by those students (i.e., the mean grade obtained by the routed participants in that particular node).

In the regression tree generated for Language and Literature learning outcomes (Fig. 1), six terminal nodes or leaves are identified, grouping students based on their learning outcomes in this subject. It is a 3-level tree, and the following executive function deficits were used in its construction: working memory deficits, planning deficits, inhibition deficits and emotional control deficits. Flexibility deficits are not included in the tree.

As indicated by the root node, participants in this study received an average score of 6.3 points in Language and Literature.

Working memory deficits permit the creation of a primary explanatory criterion for learning outcomes by dividing the sample into two subgroups (those experiencing difficulties in working memory ≥ 10 points and those without difficulties in working memory ≥ 10 points). Therefore, working memory deficits are the most crucial variable to explain variability in Language and Literature learning results. Students having difficulties in working memory ≥ 10 points earned an average score of 5.5 in the subject (55% of the participants). In contrast, those without this difficulty in working memory (45% of the participants) attained a higher average: 7.4. The left node (made up of students with working memory deficits ≥ 10 points) was further divided by the planning deficits variable. On the left is the node representing

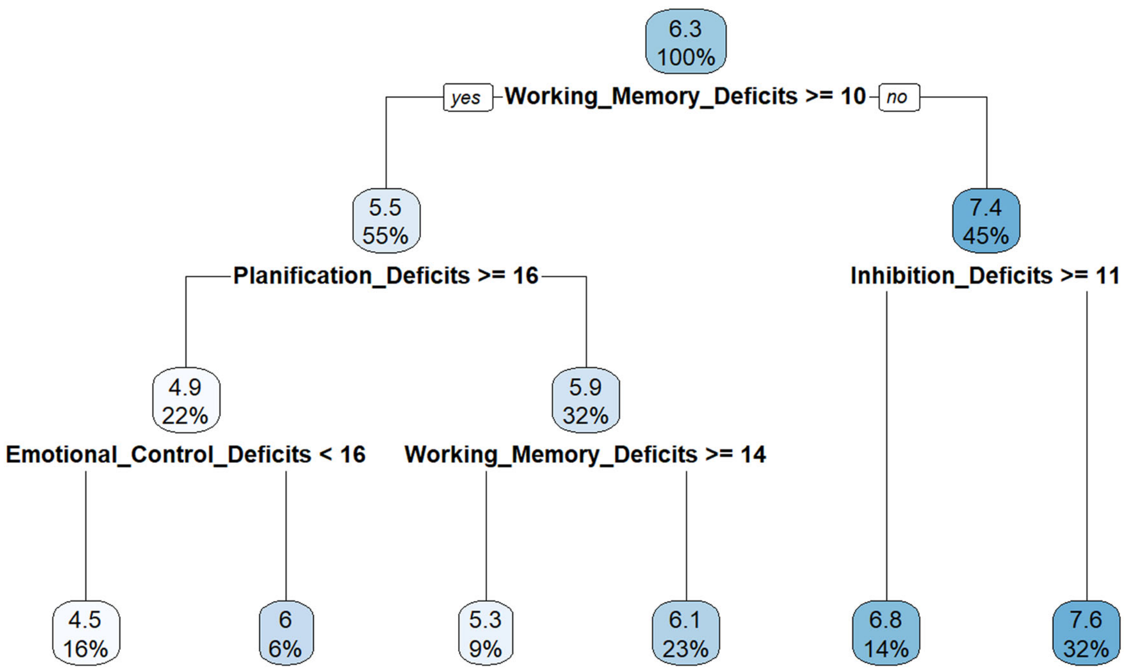

Fig. 1 Regression tree for Language and Literature learning outcomes.

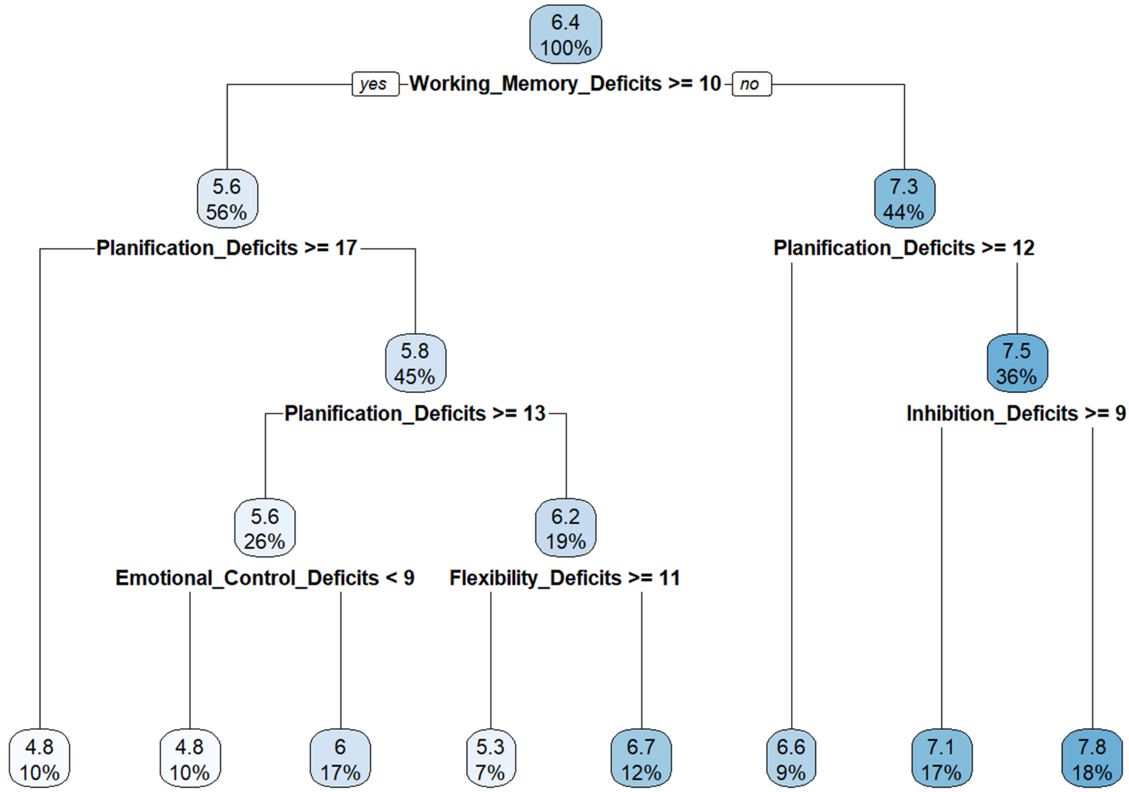

Fig. 2 Regression tree for Mathematics learning outcomes.

Table 1 Characteristics of the terminal nodes (student profiles) in the regression tree for Language and Literature learning outcomes.

Node	Working memory deficits ≥10	Planification deficits ≥16	Inhibition deficits ≥11	Emotional control deficits <16	Working memory deficits ≥14	Language score	% sample
1	Yes	Yes		Yes		4.5	16
2	Yes	Yes		No		6	6
3	Yes	No			Yes	5.3	9
4	Yes	No			No	6.1	23
5	No		Yes			6.8	14
6	No		No			7.6	32

students with planning deficits ≥ 16, (22% of the participants) and having an average score of 4.9. This node was divided into two terminal nodes by the emotional control deficits variable. On the left is the terminal node represented by participants (16%) having emotional control deficits < 16, with an average of 4.5, which is the lowest grade and implies failing the subject. The terminal node on the right is represented by participants without emotional control deficits < 16. This node includes only 6% of the participants (it is the node encompassing the lowest percentage of participants), having an average of 6. Returning to the node made up of students with working memory deficits ≥ 10 points, on the right, it is divided by grouping participants without planning deficits ≥ 16. This node makes up 32% of the sample, with an average of 5.9. In turn, this node is divided again by the working memory deficits variable, generating two terminal nodes. On the left, the terminal node groups students with working memory deficits ≥ 14, making up 9% of the participants and averaging 5.3. On the right, the terminal node groups students without working memory deficits ≥ 14, representing 23% of the participants, with an average of 6.1 points.

The top node on the right, made up of participants without working memory deficits ≥ 10 (as previously mentioned, making up 45% of the participants), with an average of 7.4, is divided by inhibition deficits, resulting in two final terminal nodes. On the left is the terminal node with participants having inhibition deficits ≥ 11 (14% of the participants), with an average of 6.8. On the right there is the terminal node with participants without inhibition deficits ≥ 11. This terminal node contains the highest percentage of students (32%), and these students also achieve the highest average grade of all of the participants (7.6).

In summary, six student profiles have been identified from the terminal nodes. Their characteristics are detailed in Table 1. They are numbered from 1 to 6 according to their order of appearance (from left to right) as terminal nodes in the regression tree.

Evaluation metrics of the model are presented in Table 2. All the metric values are satisfactory, including R^2 which exceeds the minimum acceptable value in social sciences of 0.10 (Ozili 2023).

The regression tree generated for Mathematics learning outcomes is presented in Fig. 2. In this case, all executive function deficits tested in tree construction have been included: working memory deficits, inhibition deficits, cognitive flexibility deficits, planning deficits and emotional control deficits. The tree has 4 levels and 8 terminal nodes.

Participants have an average score of 6.4 points in Mathematics (as indicated by the root node). The variable located at the upper-level node, indicating its greater predictive power with regard to Mathematics learning results, is working memory deficits. On the left is the node representing participants with working memory deficits ≥ 10, who attain an average of 5.6 (making up 56% of all participants). This node was divided by planning deficits. On the left, the first terminal node appears. It groups participants (10%) with planning deficits ≥ 17, having an average of 4.8, and therefore, failing the subject. On the right, the node representing participants with no planning deficits ≥ 17 appears. It includes 45% of the participants, with an average of 5.8. This node is divided by planning deficits. On the left is the node depicted by participants having planning deficits ≥ 13 and an average of 5.6, making up 26% of the overall sample. This node is divided into two terminal nodes by emotional control deficits. On the left, there is the terminal node represented by participants with emotional control deficits < 9, having an average of 4.8 (thus failing the subject) and made up of 10% of the entire sample. On the right, the terminal node is represented by participants having no emotional control deficits < 9, attaining an average of 6 and grouping 17% of all participants. Returning to the node made up of participants with no planning deficits ≥ 17 (with an average score of 5.8, and making up 45% of the total sample), to its right there is the node determined by students with no planning deficits ≥ 13, with an average of 6.2 and made up of 19% of the sample. This node is divided by flexibility deficits into two terminal nodes. On the left, there is the terminal node consisting of participants with flexibility deficits ≥ 11, with an average score of 5.3 and consisting of 7% of the participants. On the right, the terminal node is represented by participants with no flexibility deficits ≥ 11, and having an average score of 6.7. It is made up of 12% of the participants. Returning to the root node, divided by the variable working memory deficits, on the right there is the node made up of participants who do not display working memory deficits ≥ 10. It consists of 44% of the participants, with an average of 7.3 points. This node is divided by planning deficits. On the left, a terminal node appears, grouping participants with planning deficits ≥ 12 and having an average score of 6.6. It includes 9% of all participants. On the right, there is the node represented by participants who do not have planning deficits ≥ 12, with an average of 7.5 and grouping 36% of the participants. This node is divided into two terminal nodes by the inhibition deficits variable. On the left, there is the terminal node with participants with inhibition deficits ≥ 9, with an average of 7.1 and 17% of the participants. On the right, there is the terminal node, made up of participants who do not display inhibition deficits ≥ 9, with an average of 7.8 and 18% of the participants. This terminal node, aside from including the highest percentage of students, groups together those obtaining the highest grade in Mathematics learning results.

In summary, eight student profiles have been identified from the terminal nodes. Their characteristics are shown in Table 3. They are numbered from 1 to 8, according to their order of appearance (from left to right) as terminal nodes in the regression tree.

It should be noted that, on average, groups 1 and 2 obtain the same score (4.8 points), leading to their failing the subject. In addition, these groups are made up of an equal percentage of students (10%). However, the variables interacting in the Mathematics learning outcomes for each of these two groups vary, with the profile of group 2 being more complex due to the interaction of a greater number of executive functions deficits.

Table 4 shows the evaluation metrics of the model. All the metric values are satisfactory, including R^2 which reaches the minimum acceptable threshold of 0.10 (Ozili 2023).

Table 2 Evaluation metrics of the Language and Literature learning outcomes model.

Metric	Value
MSE	2.304
RMSE	1.518
MAE/MAD	1.175
MAPE	18.36%
R^2	0.186

MSE mean squared error, *RMSE* root mean squared error, *MAE/MAD* mean absolute error/mean absolute deviation, *MAPE* mean absolute percentage error, R^2 *R*-squared or coefficient of determination.

Table 4 Evaluation metrics of the Mathematics learning outcomes model.

Metric	Value
MSE	3.657
RMSE	1.912
MAE/MAD	1.563
MAPE	23.03%
R^2	0.107

MSE mean squared error, *RMSE* root mean squared error, *MAE/MAD* mean absolute error/mean absolute deviation, *MAPE* mean absolute percentage error, R^2 *R*-squared or coefficient of determination.

Table 3 Characteristics of the terminal nodes (student profiles) in the regression tree for Mathematics learning results.

Node	Working memory deficits ≥ 10	Planification deficits ≥ 17	Planification deficits ≥ 12	Planification deficits ≥ 13	Inhibition deficits ≥ 9	Emotional control deficits < 9	Flexibility deficits ≥ 11	Mathematics score	% sample
1	Yes	Yes						4.8	10
2	Yes	No		Yes		Yes		4.8	10
3	Yes	No		Yes		No		6	17
4	Yes	No		No			Yes	5.3	7
5	Yes	No		No			No	6.7	12
6	No		Yes					6.6	9
7	No		No		Yes			7.1	17
8	No		No		No			7.8	18

Discussion

The aim of this study was to use machine learning to identify and characterise profiles of Spanish students in compulsory secondary education, based on their learning outcomes in Language and Literature, on the one hand, and Mathematics, on the other hand, and their levels of executive functions, both cognitive (working memory, inhibition, cognitive flexibility, and planning) and emotional (emotion regulation). The generated regression trees provided these student profiles, offering information on the different interactions and relevance of executive function deficits to their learning results in Language and Literature and Mathematics. Individual differences in both hot and cool executive function skills deficits are related to their learning results in both areas. These results support those from past studies (Zelazo & Carlson 2020).

Regarding Hypothesis 1 (students with a profile characterised by greater difficulties in executive functions (both cognitive and emotional) will achieve poorer learning results in both Spanish Language and Literature and Mathematics, as compared to their peers with profiles characterised by lower executive difficulties, who will achieve superior learning results), the results obtained partially supported this hypothesis. These results indicate that, in both Language and Literature and Mathematics, students achieving the best learning results are those having fewer executive function problems, thus corroborating the hypothesis. Thus, in Language and Literature, participants who achieve the best results (terminal node 6, with an average of 7.6 points) are characterised by not having working memory deficits ≥ 10 and having no inhibition deficits ≥ 11. In Mathematics, participants achieving the best results (terminal node 8, with an average of 7.8 points) are characterised by not having working memory deficits ≥ 10, having no planning deficits ≥ 12, and no inhibition deficits ≥ 9. Therefore, having a lower level of working memory deficits and inhibition deficits is relevant to achieving good performance in both Language and Literature and Mathematics. Furthermore, in Mathematics, having a lower level of planning deficits is also relevant. At the other extreme, in the case of students with the worst learning results in each subject, some results also corroborate the formulated hypothesis, while others do not. Specifically, in Language and Literature, students with the worst learning results (terminal node 1, the only ones who fail, with an average of 4.5 points) display a profile that is characterised by working memory deficits ≥ 10, planning deficits ≥ 16 and emotional control deficits < 16. However, some peers (terminal node 2) differ from them only in that they do not have emotional control deficits < 16 (therefore, sharing the same level of difficulties in cold executive functions but having higher emotional control deficits), and manage to pass the subject (average score of 6 points). Thus, of the students characterised by working memory deficits ≥ 10 and planning deficits ≥ 16, having or not having emotional control deficits < 16 is a key factor for failing or passing the subject, respectively. With the same profile of deficits in cold executive functions (nodes 1 and 2), lower emotional control deficits are associated with poorer learning results (node 1), contradicting Hypothesis 1 and differing from the results obtained in past studies where lower emotional control deficits were found to benefit learning outcomes (Ahmed et al. 2013). Considering the other student profiles (nodes 3–6), it is seen that emotional control deficits are not relevant to their learning results. In these profiles where only cold executive function deficits come into play, Hypothesis 1 is corroborated: students whose profile is characterised by greater difficulties in cold executive functions, as compared to their peers, achieve lower learning results. In the case of learning outcomes in Mathematics, for one of the student groups that achieves the worst results (failing the subject (terminal node 2 = average score 4.8)), the situation that appeared in the tree referring to Language and Literature is repeated: with the same profile of difficulties in cold executive functions (terminal nodes 2 and 3), having a lower level of emotional control deficits (terminal node 2 versus terminal node 3) is associated with poorer learning results (terminal node 2 = 4.8 versus terminal node 3 = 6). Thus, once again, with a certain profile of working memory deficits and planning deficits, having or not having a certain level of emotional control deficits (in this case, <9) is key to failing or passing the subject, respectively. Again, these results make it impossible to fully corroborate Hypothesis 1. In the remaining student profiles (nodes 1 and 4–8), where the emotional control deficit variable does not come into play, and only different cold executive function deficits interact, Hypothesis 1 is corroborated. In conclusion, these results suggest that, for both learning outcomes in Language and Literature and in Mathematics, Hypothesis 1 is corroborated in students whose profile includes only cold executive functions but not in those whose profile also includes emotional control (considered a hot executive function).

Numerous studies have corroborated the fact that in profiles where only cold executive function deficits are implicated, greater difficulties in these cognitive executive functions are associated with lower learning outcomes, and lower difficulties in these executive functions are associated with higher learning outcomes. This relationship holds for students at distinct educational levels, with and without learning difficulties, belonging to various economic backgrounds and nationalities (Zelazo & Carlson 2020). Furthermore, in our results, participants whose profile is determined solely by cold executive functions (thus confirming Hypothesis 1) are the majority of the sample: 78% of participants in the case of Language and Literature = students forming terminal nodes 3–6; 73% in the case of Mathematics = students forming terminal nodes 1, and from 4 to 8. The finding that only cold executive function deficits (but not emotional control deficits) are associated with learning outcomes for most of the sample, is in line with results from past studies in which no relationship was found between emotional control and learning outcomes (Brock et al. 2009). However, and unlike these works, in our study, in some students (in the case of Language and Literature = 22% of participants = students forming terminal nodes 1 and 2; in the case of Mathematics = 27% of participants = students forming terminal nodes 2 and 3; all of them remarkably among those who attained the worst results), emotional control deficits are relevant to determining their learning outcomes. This is consistent with the findings of other works (Ahmed et al. 2013; Álvarez-Huerta et al. 2023; Huang 2023; Kahl et al. 2021; Oberle et al. 2014; Nadeem et al. 2023; Gustems-Carnicer et al. 2019).

Remarkably, however, the importance of the emotional control variable on learning outcomes in our research points in a different direction than in previous research. Numerous studies have indicated that higher levels of emotional control are associated with better learning outcomes, so difficulties in emotional control negatively affect learning results (Graziano et al. 2007; Kwon et al. 2017). However, in our study, the opposite occurs: with the same profile of cognitive executive functions, students with greater difficulties in emotional control obtain better results than those who have a lower level of difficulties in emotional control (which, as previously mentioned, does not corroborate Hypothesis 1). These conflicting results may be due to the precise content of the questionnaire items evaluating emotional control deficits, that is, the type of emotion regulation strategies to which they refer and, therefore, the type of emotion regulation strategies that have been evaluated in this study. Gross and John's (2003) process model of emotion regulation, the most frequently cited theoretical framework referring to emotion regulation, distinguishes between two broad types of emotion regulation strategies: cognitive reappraisal and expressive suppression. Cognitive reappraisal is an antecedent-focused strategy where an individual consciously alters their thoughts about a situation (modifies the interpretation or appraisal of the event) to alter the emotions attached to it. Expressive suppression is a response-focused strategy and implies hiding and repressing emotions elicited by a specific situation. Expressive suppression is a less effective strategy than cognitive reappraisal since it does not alter the emotional impact of the experience on a cognitive level but rather, represses emotions, causing a cognitive load that can harm learning and academic performance. However, cognitive reappraisal permits a reduction of negative effects of situations and life experiences and is associated with minimal cognitive costs, resulting in better memory and academic performance (Akhtar et al. 2020; Karagiannopoulou et al. 2023; Nadeem et al. 2023; Gustems-Carnicer et al. 2019). Upon analysing the questionnaire items used in this study, it is observed that they refer to the use of the expressive suppression strategy (e.g., "Has outbursts of anger"). Thus, low scores on emotional control deficits (continuing with the example, participants who never have outbursts of anger score 1 on the response scale) could be reflecting frequent use of expressive suppression strategies (could be they never have outbursts of anger because they repress it). As it has mentioned previously, frequent use of expressive suppression strategies implies frequent use of unbeneficial emotion regulation strategies (because the emotional impact of the experience at a cognitive level is not changed but rather repressed, causing a cognitive load), and hence, they obtain lower learning outcomes than their peers who express their emotions, even if they are negative. This is precisely the problem with the use of expressive suppression strategies: they repress and do not manifest both negative and positive emotions, generating a high internal load (since emotions are not eliminated but are left unexpressed, and suppression requires effort), negatively affecting learning outcomes. In short, displaying fewer difficulties in using strategies that do not benefit learning but harm it, may justify the lower level of learning outcomes of these students (Kahl et al. 2021). Having greater difficulties in using non-beneficial emotion regulation strategies may justify higher learning outcomes. Further research is needed, however, to corroborate and explain these results, which, in line with other works, highlight the complex nature of the association between emotional control and academic outcomes (Nadeem et al. 2023).

As for Hypothesis 2 (working memory will be the most influential predictor of learning results across different learning areas—Language and Literature and Mathematics), the obtained results provided comprehensive support for it. Working memory deficits emerged as the most decisive predictor of both Language and Literature and Mathematics learning outcomes. In the generated regression trees, this variable was strategically positioned, dividing the root node at the upper level, emphasising its significance and superior predictive power for academic outcomes in each academic area. These outcomes align with past research indicating that working memory is a substantial predictor of academic performance (Anjariyah et al. 2022; Cirino 2023; Dubuc et al. 2020). This body of evidence suggests that students with deficiencies in this memory system often face challenges, specifically in reading and mathematics. These associations were observed not only across normative development but also in special populations, including students with learning disabilities and gifted students (Anjariyah et al. 2022; Flórez-Durango et al. 2022). In essence, both our findings and the existing literature underscore the relationship between working memory and essential processes that are crucial for learning achievement. This connection is likely due to the fact that working memory serves as a general cognitive resource that is capable of storing and processing various information types, encompassing words, images and abstract concepts. Working memory actively stores information and makes it available for more intricate cognitive activities such as reasoning, learning and resolving school tasks, whether linguistic or mathematical in nature (Bergman & Söderqvist 2017). Ultimately, working memory serves as a crucial cognitive resource in the context of learning (Berkowitz et al. 2022; Ji & Guo 2023).

Regarding the quality and accuracy of the models obtained, the results are similar in both models. Both Language and Literature learning outcomes model and Mathematics learning outcomes model are good. All the metric values obtained are satisfactory, including R^2 values. Although initially R^2 values could be considered low, the following considerations should be taken into account for an adequate interpretation of these values in particular and the quality and accuracy of both models in general: (1) the metric values obtained must be considered together (Naser & Alavi 2020, 2023). (2) One of the reasons why R^2 value may be low is the existence of non-linear relationships (Ozili 2023), which is frequent characteristic in the complex educational field research (Gomes et al. 2021). (3) In relation to the previous, R^2 is not an optimal choice to assess the goodness of fit for non-linear models (Ozili 2023). In these cases, different error metrics can be used (Naser & Alavi 2020, 2023). (4) Additionally, in certain sciences such as the social sciences (to which this study belongs), it is not usual to find high values of R^2 (Ozili 2023). The social sciences deal with human behaviour or human relationship that is subject to change from time to time. Human behaviour may change due to a lot of factors. Because of this complex and dynamic nature of human behaviour, it is difficult to accurately predict it and, therefore, the *R*-squared goodness of fit of the models in the social sciences is weakened. For this reason, in social science, a model with R^2 values ranging from 0.1 to 0.5 is considered good, provided that most or all of the explanatory variables are statistically significant (Ozili 2023). Consequently, and taking these considerations into account, it can be concluded that the two models obtained in our study are good enough. Other authors, as Ferrara et al. (2015), in their research using also regression trees to analyse academic issues related to the Literacy and Mathematics learning, obtained R^2 values very similar to ours.

Our results contribute to a deeper understanding of the intricate relationships existing between executive functions (EF) and learning outcomes. It is important to note that most existing research on the connection between EF and academic performance has focused on kindergarten or primary school students (Dubuc et al. 2020; Kahl et al. 2021), with very few studies incorporating hot EF. To the best of our knowledge, only two studies have investigated the relationship between emotion regulation and adolescent learning outcomes, both conducted within the context of mathematical achievement. Both studies provided evidence supporting this association (Gumora & Arsenio 2002; Oberle et al. 2014; Kahl et al. 2021). Therefore, the consideration of both cold and hot EF in adolescent students and their interaction with learning outcomes is a noteworthy aspect of our study. Addressing adolescents and their learning outcomes is of great significance. It is crucial to recognise that adolescence is a critical period in the life cycle, during which numerous social, personal and emotional changes must be navigated. How these changes are dealt with can impact adolescent learning, making it imperative to pay special attention to these students, their learning processes and their outcomes. Furthermore, in Spain, a significant portion of the adolescent years coincides with the final stage of compulsory education (as with our study participants). Depending on their experiences and levels of success, adolescents may decide whether to continue their studies, significantly impacting not only their personal and social development but also the economic and social progress of the country (OECD 2023). Therefore, ensuring and supporting high-quality secondary education for all adolescents represents a sound investment. The findings of this study contribute to efforts being undertaken in this direction.

It is also noteworthy that this study considered not only the more commonly examined EF in school-based works—working memory and inhibition (Dubuc et al. 2020)—or only the elemental EF—working memory, inhibition and flexibility—but it also considered other more complex cognitive EF such as planning and the hot EF emotional control. The consideration of the cold or cognitive EF, including planning, working memory, inhibition and flexibility, ensures that our study addresses all of the relevant cold EF arising during adolescence (Laureys et al. 2021, 2022). Additionally, incorporating the hot EF emotional control into our research responds to a need highlighted in recent literature on the inclusion of hot executive functions analysis in educational and learning research (Fombouchet et al. 2023, 2024; Pinochet-Quiroz et al. 2022). This more comprehensive approach to EF allows our results to provide a better understanding of the relationship between cold and hot EF and learning outcomes. However, consistent with previous research, our results underscore that these relationships are highly complex and require further investigation (Poon 2018; Zelazo & Carlson 2020).

In educational decision-making, it is crucial to seek methodologies that are precise and assist in resolving issues related to classifying or predicting students' learning outcomes. This is essential since significant decisions are derived from these processes to optimise their development and learning. In this context, our study stands out methodologically by employing artificial intelligence, specifically machine learning (specifically the regression trees algorithm), to analyse a timely question such as the determinants of individual differences in learning outcomes. The use of decision trees, especially CART, represents an approach in the study of the relationships between executive functions (EF) and learning outcomes that surpasses the limitations of the more commonly used techniques, offering advantages over other analytical models (see Seftor et al. 2021). Notably, these advantages include an ease of understanding of the graphical representation. Therefore, non-expert users such as teachers can effectively use the output to gain insights into the variables influencing the learning outcomes of their students and take measures to enhance them.

Although recently, major growth is taking place with regard to intelligent machine learning systems, their use remains limited and underexplored in the educational field, despite their advantages and potentialities (Liu & Lee 2022; Luan & Tsai 2021; Matzavela & Alepis 2021). These systems permit a better understanding of student performance. Improved knowledge of the factors influencing learning outcomes helps predict student performance, providing more precise guidance and designing academic curricula that are tailored to specific student needs (Darling-Hammond et al. 2020). Over recent years, studying personal determinants (especially psychological ones) of student learning outcomes has been a challenge for educators, policymakers and researchers alike. The rapid expansion of artificial intelligence has transformed this challenge into an achievable goal, as shown in this research.

Despite these significant contributions, the results of this study should be interpreted with caution given its limitations: (1) sample size; (2) non-random sample selection; and (3) use of a single educational institution, limiting the generalisability of the results. Therefore, future studies should expand the sample by randomly selecting participants from a larger number of institutions to obtain a more heterogeneous sample. (4) The study is cross-sectional, which precludes the detection of changes over time in the relationship between executive functions and learning outcomes. This is relevant considering that both executive functions and learning outcomes undergo changes during the adolescent years, and factors associated with learning results in each academic area may differ depending on age. (5) The analyses conducted do not permit the making of causal inferences. These last two limitations demand a longitudinal approach to further investigation. (6) The study does not include all variables affecting learning outcomes in language and mathematics or all executive functions advocated by different theoretical models. Future studies could include other executive functions and personal variables, in addition to family-related and educational context variables that may influence learning outcomes. (7) The use of third-party-informed rating scales to collect data on student executive functions may impact the results. Informant perception may differ from the actual level of executive functions the students possess. Future studies could explore alternative methodologies to assess the executive functions of students, such as performance-based tasks and observational methods. (8) Although they are reliable predictors of school performance, the use of grades as an indicator of learning outcomes has been criticised. The difficulty of tests and assessment tasks used by each teacher and their grading criteria may vary. Future research may use standardised assessment batteries. However, this would result in a lower ecological validity of the study since, in Spain, where this study was conducted, teacher-assigned grades are the official mode of evaluating students' learning outcomes.

In addition to considering the aforementioned suggestions to overcome some of the study limitations, the following future perspectives have been proposed: (1) consideration of gender perspective: modelling different regression trees based on the student's gender (i.e., estimating separate regression trees for boys and girls) would be interesting. Although boys and girls may perform equally well in the same academic area, they appear to use distinct sets of cognitive abilities (Blanch & Aluja 2013). Therefore, the relationship between executive functions (EF) and academic performance may differ between genders, especially during adolescence (Dubuc et al. 2020), possibly due to the different brain maturation patterns, influenced by the sex hormones that play a relevant role in this developmental stage. (2) Attention to the participants' academic year: modelling different regression trees according to the students' academic year may provide relevant information. As students advance through the academic years, academic difficulty and demands increase, possibly varying the relevance and level of each executive function required to achieve good learning outcomes. There is also evidence suggesting that academic performance significantly decreases during secondary education (Abin et al. 2020; Dubuc et al. 2020; Spanish Ministry of Education and Vocational Training 2023). (3) Consideration of learning outcomes in other subjects. (4) Study of executive functions and learning outcomes from a more molecular perspective: It is essential to consider that, for example, many working memory models assume that this is a multicomponent system (Baddeley et al. 2020), permitting differentiation between verbal and spatial working memory. The same applies to inhibition, an executive function in which various authors distinguish several subprocesses, such as behavioural inhibition, cognitive inhibition or resistance to interfering stimuli (Dempster & Corkill 1999). A similar situation occurs in the academic domain, where both Language and Literature and Mathematics outcomes are determined by different competencies. Therefore, in future studies, it may be interesting to analyse how each of these subprocesses making up each executive function interacts to achieve distinct curricular competencies. (5) Application of other algorithms in the development of decision trees.

Conclusion

This study reveals a specific configuration of individual cold and hot executive function differences that influence learning outcomes in Language and Literature and Mathematics in Spanish adolescent students. The various executive functions impacting the students' learning results interact and group together students with common characteristics related to executive functions and learning outcomes, distinguishing them from other groups of students with regard to these variables. Different student groups/profiles have thus been identified. This provides relevant information describing each of these specific student groups, enabling an understanding of how different executive functions interact within each group. This understanding is crucial for designing more tailored measures to enhance educational improvement.

These findings contribute to the expanding body of literature on the role of executive function deficits in learning outcomes. Noteworthy aspects include the inclusion of executive functions from a holistic perspective (comprising cognitive and emotional processes) and the use of artificial intelligence as an analytical tool.

The results obtained further our understanding of school achievement and failure, ultimately contributing to the achievement of SDG 4: Quality Education. Quality education for all entails a commitment to minimising negative outcomes (…) in pursuit of academic performance that minimises failure (Cano Sánchez Serrano 2001, p 22). The outcomes of this study aid in this endeavour by permitting the personalisation of teaching according to the students' profiles of executive function deficits and, consequently, according to their learning needs. In essence, the results provide valuable insights for educators, psychologists, stakeholders, policymakers, advisers, educational administrators, student counsellors and researchers to promote actions that enhance an equitable and, therefore, more effective educational system. It is crucial to acknowledge that in education, equity involves educating according to individual differences and needs; that is, providing a variety of resources, models, programmes and educational strategies according to the diverse needs of students, which may not be the same for all (UNESCO 2016) (as revealed by the results of this study) but always attempting to provide encouraging and relevant outcomes.

Data availability

Datasets provided by the school's educational counsellor are available from the corresponding author on reasonable request.

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References

Abin A, Núñez JC, Rodríguez C et al. (2020) Predicting mathematics achievement in secondary education: the role of cognitive, motivational, and emotional variables. Front Psychol 11:876. https://doi.org/10.3389/fpsyg.2020.00876

Adamson KA, Prion S (2013) Reliability: measuring internal consistency using Cronbach's α. Clin Simul Nurs 9(5):e179–e180. https://doi.org/10.1016/j.ecns.2012.12.001

Ahmed SF, Tang S, Waters NE et al. (2019) Executive function and academic achievement: longitudinal relations from early childhood to adolescence. J Educ Psychol 111(3):446–458. https://doi.org/10.1037/edu0000296

Ahmed SF, Kelly DP, Waters NE et al. (2024) Executive functioning. In: Neblett EW, Troop-Gordon W (eds) Encyclopedia of adolescence, vol 1. Elsevier, Amsterdam, pp 149–161. https://doi.org/10.1016/B978-0-323-96023-6.00057-9

Ahmed W, van der Werf G, Kuyper H et al. (2013) Emotions, selfregulated learning, and achievement in mathematics: a growth curve analysis. J Educ Psychol 105(1):150–161. https://doi.org/10.1037/a0030160

Akhtar MS, Ekbal A, Cambria E (2020) How intense are you? Predicting intensities of emotions and sentiments using stacked ensemble [application notes]. In: IEEE computational intelligence magazine, vol 15, no. 1. pp 64–75. https://doi.org/10.1109/MCI.2019.2954667

Alloway TP (2006) How does working memory work in the classroom? Educ Res Rev 1(4):34–139

Alloway TP, Alloway RG (2010) Investigating the predictive roles of working memory and IQ in academic attainment. J Exp Child Psychol 106(1):20–29. https://doi.org/10.1016/j.jecp.2009.11.003

Álvarez-Huerta P, Muela A, Larrea I (2023) Cognitive reappraisal and creative self-concept among higher education students: a latent class analysis. In: Psychology of aesthetics, creativity, and the arts. https://doi.org/10.1037/aca0000567

Anjariyah D, Juniati D, Siswono TYE (2022) How does working memory capacity affect students' mathematical problem solving? Eur Educ Res J 11(3):1427–1439. https://doi.org/10.12973/eu-jer.11.3.1427

Baddeley A, Hitch G, Allen R (2020) A multicomponent model of working memory. In: Logie R, Camos V, Cowan N (eds) Working memory: the state of the science. Oxford University Press, Oxford, pp 10–43. https://doi.org/10.1093/oso/9780198842286.003.0002

Barnes MA (2023) Executive functions: what are they good for? A perspective from intervention research. Mind Brain Educ 17:238–245. https://doi.org/10.1111/mbe.12371

Bergman S, Söderqvist S (2017) How is working memory training likely to influence academic performance? Current evidence and methodological considerations. Front Psychol 8:69. https://doi.org/10.3389/fpsyg.2017.00069

Berkowitz M, Edelsbrunner P, Stern E (2022) The relation between working memory and mathematics performance among students in math-intensive STEM programs. Intelligence 92:101649. https://doi.org/10.1016/j.intell.2022.101649

Blanch A, Aluja A (2013) A regression tree of the aptitudes, personality, and academic performance relationship. Pers Individ Differ 54(6):703–708. https://doi.org/10.1016/j.paid.2012.11.032

Brock LL, Rimm-Kaufman SE, Nathanson L et al. (2009) The contributions of 'hot' and 'cool' executive function to children's academic achievement, learning-related behaviors, and engagement in kindergarten. Early Child Res Q 24:337–349. https://doi.org/10.1016/j.ecresq.2009.06.001

Cano Sánchez Serrano JS (2001) Rendimiento escolar y sus contextos. Rev Complut Educ 12(1):15–80. https://revistas.ucm.es/index.php/RCED/article/view/RCED0101120015A

Carlson SM, Zelazo PD, Faja S (2013) Executive function. In: Zelazo, PD (ed) The Oxford handbook of developmental psychology, vol 1. Oxford University Press, Oxford, pp 706–743

Chen HL, Xia DX (2011) Application research of data mining algorithm based on CART decision tree. Coal Technol 30:164–166

Cho I, Hosseini-Kamkar N, Song HJ et al. (2023) Culture, executive functions, and academic achievement. Front Psychol 14:1100537. https://doi.org/10.3389/fpsyg.2023.1100537

Cirino PT (2023) Framing executive function as a construct and its relation to academic achievement. Mind Brain Educ 17(4):226–237. https://doi.org/10.1111/mbe.12360

Cirino PT, Salentine C, Farrell A et al. (2024) Cognitive predictors of the overlap of reading and math in middle school. Learn Individ Differ 109(1):102400. https://doi.org/10.1016/j.lindif.2023.102400

Costa VG, Pedreira CE (2023) Recent advances in decision trees: an updated survey. Artif Intell Rev 56:4765–4800. https://doi.org/10.1007/s10462-022-10275-5

Cragg L, Gilmore C (2014) Skills underlying mathematics: the role of executive function in the development of mathematics proficiency. Trends Neurosci Educ 3:63–68. https://doi.org/10.1016/j.tine.2013.12.001

Darling-Hammond L, Flook L, Cook-Harvey C et al. (2020) Implications for educational practice of the science of learning and development. Appl Dev Sci 24(2):97–140. https://doi.org/10.1080/10888691.2018.1537791

De France K, Hollenstein T (2021) Emotion regulation strategy use and success during adolescence: assessing the role of context. J Res Adolesc 32(2):720–736. https://doi.org/10.1111/jora.12672

de la Fuente J, Martínez-Vicente JM, Pachón-Basallo M et al. (2022) Differential predictive effect of self-regulation behavior and the combination of self vs. external regulation behavior on executive dysfunctions and emotion regulation difficulties, in university students. Front Psychol 13:876292. https://doi.org/10.3389/fpsyg.2022.876292

De Luca CR, Leventer RJ (2008) Developmental trajectories of executive functions across the lifespan. In: Anderson V, Jacobs R, Anderson PJ (eds) Executive functions and the frontal lobes: a lifespan perspective. Taylor & Francis, New York, pp 23–56

De Neve D, Bronstein MV, Leroy A et al. (2023) Emotion regulation in the classroom: a network approach to model relations among emotion regulation difficulties, engagement to learn, and relationships with peers and teachers. J Youth Adolesc 52(2):273–286. https://doi.org/10.1007/s10964-022-01678-2

de Souza Zanirato Maia MJ, Bueno APA, Sato JR (2023) Applications of artificial intelligence models in educational analytics and decision making: a systematic review. World 4(2):288–313. https://doi.org/10.3390/world4020019

Dempster FN, Corkill AJ (1999) Interference and inhibition in cognition and behavior: unifying themes for educational psychology. Educ Psychol Rev 11(1):1–88. https://doi.org/10.1023/A:1021992632168

Diamond A (2013) Executive functions. Annu Rev Psychol 64:135–168. https://doi.org/10.1146/annurev-psych-113011-143750

Diamond A (2020) Executive functions. In: Handbook of clinical neurology, vol 173. pp 225–240. https://doi.org/10.1016/B978-0-444-64150-2.00020-4

Dubuc MM, Aubertin-Leheudre M, Karelis AD (2020) Relationship between interference control and working memory with academic performance in high school students: the Adolescent Student Academic Performance longitudinal study (ASAP). J Adolesc 80:204–213. https://doi.org/10.1016/j.adolescence.2020.03.001

Duckworth AL, Taxer JL, Eskreis-Winkler L et al. (2019) Self-control and academic achievement. Annu Rev Psychol 70:373–399. https://doi.org/10.1146/annurev-psych-010418-103230

Ferrara S, Steedle J, Kinsman A (2015) PARCC cognitive complexity: analysis 1, 2, and 3. https://files.eric.ed.gov/fulltext/ED599050.pdf

Fitzpatrick C, Archambault I, Janosz M et al. (2015) Early childhood working memory forecasts high school dropout risk. Intelligence 53:160–165. https://doi.org/10.1016/j.intell.2015.10.002

Flórez-Durango AM, Toro CA, Montoya-Zuluaga PA (2022) Revisión teórica de la relación entre memoria de trabajo, estilo cognitivo dependencia/independencia de campo y estilos de enseñanza con el rendimiento académico. J Neuroeduc 2(2):28–43. https://doi.org/10.1344/joned.v2i2.37358

Fombouchet Y, Lannegrand L, Lucenet J (2024) Relationships between emotion regulation strategies and executive functions in adolescence: exploring the effects of discrete emotions and age. J Adolesc 96:1239–1248. https://doi.org/10.1002/jad.12334

Fombouchet Y, Pineau S, Perchec C et al. (2023) The development of emotion regulation in adolescence: What do we know and where to go next? Soc Dev 32:1227–1242. https://doi.org/10.1111/sode.12684

Georgiou GK, Wei W, Inoue T et al. (2020) Cultural influences on the relation between executive functions and academic achievement. Read Writ 33:991–1013. https://doi.org/10.1007/s11145-019-09961-8

Gerst EH, Cirino PT, Fletcher JM et al. (2017) Cognitive and behavioral rating measures of executive function as predictors of academic outcomes in children. Child Neuropsychol 23(4):381–407. https://doi.org/10.1080/09297049.2015.1120860

Gioia GA, Isquith PK, Guy SC et al. (2017) BRIEF-2. Evaluación Conductual de la función ejecutiva. TEA Ediciones, Madrid

Gomes CMA, Lemos GC, Jelihovschi EG (2021) The reasons why the Regression Tree Method is more suitable than General Linear Model to analyze complex educational datasets. Rev Port Educ 34(2):42–63. https://doi.org/10.21814/rpe.18044

Graziano PA, Reavis RD, Keane SP et al. (2007) The role of emotion regulation in children's early academic success. J Sch Psychol 45(1):3–19. https://doi.org/10.1016/j.jsp.2006.09.002

Gross JJ, John OP (2003) Individual differences in two emotion regulation processes: implications for affect, relationships, and well-being. J Pers Soc Psychol 85(2):348–362. https://doi.org/10.1037/0022-3514.85.2.348

Gross JJ (1999) Emotion regulation: past, present, future. Cogn Emot 13:551–573. https://doi.org/10.1080/026999399379186

Gumora G, Arsenio WF (2002) Emotionality, emotion regulation, and school performance in middle school children. J Sch Psychol 40(5):395–413. https://doi.org/10.1016/S0022-4405(02)00108-5

Gunzenhauser C, Nückles M (2021) Training executive functions to improve academic achievement: tackling avenues to far transfer. Front Psychol 12:624008. https://doi.org/10.3389/fpsyg.2021.624008

Gustems-Carnicer J, Calderón C, Calderón-Garrido D (2019) Stress, coping strategies and academic achievement in teacher education students. Eur J Teach Educ 42(3):375–390. https://doi.org/10.1080/02619768.2019.1576629

Hamim T, Benabbou F, Sael N (2021) Survey of machine learning techniques for student profile modeling. Int J Emerg Technol Learn 16(4):136–151. https://doi.org/10.3991/ijet.v16i04.18643

Happaney K, Zelazo PD, Stuss DT (2004) Development of orbitofrontal function: current themes and future directions. Brain Cogn 55(1):1–10. https://doi.org/10.1016/j.bandc.2004.01.001

Huang Y (2023) Examining the relationship between peer support and foreign language emotions in online learning: the mediating effect of self-efficacy. Front Psychol 14:1148472. https://doi.org/10.3389/fpsyg.2023.1148472

Huizinga M, Burack JA, Baeyens D (2024) Editorial: Executive function and education Vol. II: Considerations for academic success -across contexts and populations. Front Psychol 15:1365993. https://doi.org/10.3389/fpsyg.2024.1365993

Ji Z, Guo K (2023) The association between working memory and mathematical problem solving: a three-level meta-analysis. Front Psychol 14:1091126. https://doi.org/10.3389/fpsyg.2023.1091126

Kahl T, Grob A, Möhring W (2021) Does emotion regulation compensate deficits in various executive functions in children's and adolescents' mathematical achievement? Learn Individ Differ 89:102034. https://doi.org/10.1016/j.lindif.2021.102034

Karagiannopoulou E, Desatnik A, Rentzios C et al. (2023) The exploration of a 'model' for understanding the contribution of emotion regulation to students learning. The role of academic emotions and sense of coherence. Curr Psychol 42:26491–26503. https://doi.org/10.1007/s12144-022-03722-7

Kendeou P, van den Broek P, Helder A et al. (2014) A cognitive view of reading comprehension: implications for reading difficulties. Learn Disabil Res Pract 29:10–16. https://doi.org/10.1111/ldrp.12025

Kerr A, Zelazo PD (2004) Development of "hot" executive function: the children's gambling task. Brain Cogn 55(1):148–157. https://doi.org/10.1016/S0278-2626(03)00275-6

Kwon K, Hanrahan AR, Kupzyk KA (2017) Emotional expressivity and emotion regulation: relation to academic functioning among elementary school children. Sch Psychol Q 32(1):75–88. https://doi.org/10.1037/spq0000166

Laureys F, De Waelle S, Barendse MT et al. (2022) The factor structure of executive function in childhood and adolescence. Intelligence 90:101600. https://doi.org/10.1016/j.intell.2021.101600

Laureys F, Middelbos L, Rommers N et al. (2021) The effects of age, biological maturation and sex on the development of executive functions in adolescents. Front Physiol 12:703312. https://doi.org/10.3389/fphys.2021.703312

Lennarz HK, Hollenstein T, Lichtwarck-Aschoff A et al. (2019) Emotion regulation in action: use, selection, and success of emotion regulation in adolescents' daily lives. Int J Behav Dev 43(1):1–11. https://doi.org/10.1177/0165025418755540

Liu YS, Lee L (2022) Evaluation of college admissions: a decision tree guide to provide information for improvem*ent*. Humanit Soc Sci Commun 9:390. https://doi.org/10.1057/s41599-022-01413-z

Lobczowski NG, Lyons K, Greene JA et al. (2021) Socioemotional regulation strategies in a project-based learning environment. Contemp Educ Psychol 65:101968. https://doi.org/10.1016/j.cedpsych.2021.101968

Luan H, Tsai CC (2021) A review of using machine learning approaches for precision education. J Educ Technol Soc. 24(1):250–266. https://www.jstor.org/stable/26977871

Martínez-Perez C, Alvarez-Peregrina C, Villa-Collar C et al. (2020) Current state and future trends: a citation network analysis of the academic performance field. Int J Environ Res Public Health 17(15):5352. https://doi.org/10.3390/ijerph17155352

Matzavela V, Alepis E (2021) Decision tree learning through a predictive model for student academic performance in intelligent M-learning environments. Comput Educ Artif Intell 2:100035. https://doi.org/10.1016/j.caeai.2021.100035

Miyake A, Friedman NP, Emerson MJ et al. (2000) The unity and diversity of executive functions and their contributions to complex "Frontal Lobe" tasks: a latent variable analysis. Cogn Psychol 41:49–100. https://doi.org/10.1006/cogp.1999.0734

Nadeem A, Umer F, Anwar MJ (2023) Emotion regulation as predictor of academic performance in university students. J Prof Appl Psychol 4(1):20–33. https://doi.org/10.52053/jpap.v4i1.157

Naser MZ, Alavi A (2020) Insights into performance fitness and error metrics for machine learning. https://doi.org/10.48550/arXiv.2006.00887

Naser MZ, Alavi A (2023) Error metrics and performance fitness indicators for artificial intelligence and machine learning in engineering and sciences. Archit Struct Constr 3:499–517. https://doi.org/10.1007/s44150-021-00015-8

Oberle E, Schonert-Reichl KA, Hertzman C et al. (2014) Social–emotional competencies make the grade: predicting academic success in early adolescence. J Appl Dev Psychol 35(3):138–147. https://doi.org/10.1016/j.appdev.2014.02.004

OECD (2023) Education at a glance 2023: OECD indicators. https://doi.org/10.1787/e13bef63-en

Ozili PK (2023) The acceptable *R*-square in empirical modelling for social science research. In: Saliya CA (ed) Social research methodology and publishing results: a guide to non-native english speakers. IGI Global, Hershey, pp 134–143. https://doi.org/10.2139/ssrn.4128165

Pinochet-Quiroz P, Lepe-Martínez N, Gálvez-Gamboa F et al. (2022) Relationship between cold executive functions and self-regulated learning management in college students. Estud Sobre Educ 43:93–113. https://doi.org/10.15581/004.43.005

Poon K (2018) Hot and cool executive functions in adolescence: development and contributions to important developmental outcomes. Front Psychol 8:2311. https://doi.org/10.3389/fpsyg.2017.02311

Privitera AJ, Zhou Y, Xie X (2023) Inhibitory control as a significant predictor of academic performance in Chinese high schoolers. Child Neuropsychol 29(3):457–473. https://doi.org/10.1080/09297049.2022.2098941

R Core Team (2019) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna

Ramudo-Andion I, Barca-Enriquez E, Brenlla-Blanco JC et al. (2020) Predicción del rendimiento académico del alumnado de Bachillerato: efecto de los enfoques de aprendizaje y atribuciones causales. J Educ Psychol 15(2):108–120. https://doi.org/10.23923/rpye2020.02.190

Rose SA, Feldman JF, Jankowski JJ (2011) Modeling a cascade of effects: the role of speed and executive functioning in preterm/full-term differences in academic achievement. Dev Sci 14:1161–1175. https://doi.org/10.1111/j.1467-7687.2011.01068.x

Salehinejad MA, Ghanavati E, Rashid MHA et al. (2021) Hot and cold executive functions in the brain: a prefrontal-cingular network. Brain Neurosci Adv 5:239821282110077. https://doi.org/10.1177/23982128211007769

Sambol S, Suleyman E, Scarfo J et al. (2023) A true reflection of executive functioning or a representation of task-specific variance? Re-evaluating the unity/

diversity framework. Acta Psychol 236:03934. https://doi.org/10.1016/j.actpsy.2023.103934

Scrimin S, Mason L, Moscardino U (2014) School-related stress and cognitive performance: a mood-induction study. Contemp Educ Psychol 39(4):359–368. https://doi.org/10.1016/j.cedpsych.2014.09.002

Seftor N, Shannon L, Wilkerson S et al. (2021) Branching out: using decision trees to inform education decisions (REL 2022-133). U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Appalachia, Washington DC. https://ies.ed.gov/ncee/edlabs/regions/appalachia/pdf/REL_2022133.pdf

Silvers JA (2022) Adolescence as a pivotal period for emotion regulation development. Curr Opin Psychol 44:258–263. https://doi.org/10.1016/j.copsyc.2021.09.023

Spanish Ministry Educational and Vocational Trainning (2023) Datos y cifras. Curso escolar 2023/2024. https://www.educacionyfp.gob.es/dam/jcr:27162db1-c2b3-4f9c-a8fa-a17731a561f8/datos-y-cifras-2023-2024-espanol.pdf

Spanish Official State Gazette (2022) Real Decreto 217/2022, de 29 de marzo, por el que se establece la ordenación y las enseñanzas mínimas de la Educación Secundaria Obligatoria. Boletín Oficial del Estado, March 29 75:36344–36469. https://www.boe.es/diario_boe/txt.php?id=BOE-A-2022-4629

Spiegel JA, Goodrich JM, Morris BM et al. (2021) Relations between executive functions and academic outcomes in elementary school children: a meta-analysis. Psychol Bull 147(4):329–351. https://doi-org.cuarzo.unizar.es:9443/10.1111/mbe.12360

Studer-Luethi B, Toermaenen M, Margelisch K et al. (2022) Effects of working memory training on children's memory and academic performance: the role of training task features and trainee's characteristics. J Cogn Enhanc 6:340–357. https://doi.org/10.1007/s41465-022-00242-x

Su YS, Lin YD, Liu TQ (2022) Applying machine learning technologies to explore students' learning features and performance prediction. Front Hum Neurosci 16:1018005. https://doi.org/10.3389/fnins.2022.1018005

Sutin AR, Sesker AA, Stephan Y et al. (2022) Socioeconomic status, internalizing and externalizing behaviors, and executive function in adolescence: a longitudinal study with multiple informants. Psychiatry Res 313:114585. https://doi.org/10.1016/j.psychres.2022.114585

Thompson RA (1994) Emotion regulation: a theme IN search OF definition. Monogr Soc Res Child Dev 59:25–52. https://doi.org/10.1111/j.1540-5834.1994.tb01276.x

Titz C, Karbach J (2014) Working memory and executive functions: effects of training on academic achievement. Psychol Res 78(6):852–868. https://doi.org/10.1007/s00426-013-0537-1

Tottenham N (2024) Developing the neurobiology of emotion regulation. In: Gross JJ, Ford BQ (eds) Handbook of emotion regulation, 3rd edn. The Guilford Press, New York, pp 121–128

Umpstead R, Jankens B, Ortega Gil P et al. (2016) School choice in Spain and in the United States. Glob Educ Rev 3(2):84–102

UNESCO (2016) Education 2030: incheon declaration and framework for action for the implementation of sustainable development goal 4: ensure inclusive and equitable quality education and promote lifelong learning opportunities for alls. https://unesdoc.unesco.org/ark:/48223/pf0000245656

UNESCO (2019) Artificial intelligence in education: challenges and opportunities for sustainable development. UNESCO Education Sector. https://unesdoc.unesco.org/ark:/48223/pf0000366994

van der Sluis S, de Jong PF, van der Leij A (2007) Executive functioning in children, and its relations with reasoning, reading, and arithmetic. Intelligence 35:427–449. https://psycnet.apa.org/doi/10.1016/j.intell.2006.09.001

van Tetering MAJ, Jolles J, van der Elst W et al. (2022) School achievement in early adolescence is associated with students' self-perceived executive functions. Front Psychol 12:734576. https://doi.org/10.3389/fpsyg.2021.734576

Vinuesa R, Azizpour H, Leite I et al. (2020) The role of artificial intelligence in achieving the sustainable development goals. Nat Commun 11(1):233. https://doi.org/10.1038/s41467-019-14108-y

Wang TH, Kao CH (2022) Investigating factors affecting student academic achievement in mathematics and science: cognitive style, self-regulated learning and working memory. Instr Sci 50:789–806. https://doi.org/10.1007/s11251-022-09594-5

Zelazo PD, Blair CB, Willoughby MT (2016) Executive function: implications for education (NCER 2017-2000). National Center for Education Research, Institute of Education Sciences, U.S. Department of Education, Washington, DC. https://files.eric.ed.gov/fulltext/ED570880.pdf

Zelazo PD, Carlson SM (2020) The neurodevelopment of executive function skills: implications for academic achievement gaps. Psychol Neurosci 13:273–298. https://doi.org/10.1037/pne0000208

Zelazo PD, Morris IF, Qu L et al. (2024) Hot executive function: emotion and the development of cognitive control. In: Bell MA (ed) Child development at the intersection of emotion and cognition, 2nd edn. American Psychological Association, Washington, DC, pp 51–73. https://doi.org/10.1037/0000406-004

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Author contributions

Elena Escolano-Pérez was involved in conceptual and methodological structure, literature review, manuscript drafting, data analysis, interpretation of result and discussion. José Luis Losada was involved in methodological structure and data analysis. All authors contributed to revising the manuscript and provided final approval of the version to be published.

Competing interests

The authors declare no competing interests.

Ethical approval

The study followed the principles of the Declaration of Helsinki and the Organic Law 3/2018, of December 5, on the Protection of Personal Data and guarantee of digital rights (2018, Official State Gazette no. 294, of December 6). The study was endorsed from the management team of the participants' school. Approval was obtained from the Research Ethics Committee of the Autonomous Community of Aragon (*Comité de Ética de la Investigación de la Comunidad Autónoma de Aragón: CEICA*). Identification Code: PI23/503. Date of approval: December 20, 2023.

Informed consent

Although this study did not involve human experiments and it did not involve direct student participation, they all and their parents/legal tutors were informed by the school tutors (who were previously informed by the research team) about the objectives of the research, the absence of risks or inconveniences involved in participating, the non-obtaining of direct benefits/rewards/prises for participation, data protection (which included assured anonymity), and the use of their data and research results (possibility of preparing scientific communications to be presented at conferences or scientific journals, but always with grouped data and without disclosing anything that could identify the participant/informant). In addition, students and their parents/legal tutors voluntarily expressed their consent for the educational counsellor to anonymously inform the research team regarding their executive function levels and grades. Their signed informed consent was obtained during December 2023. Informed consent was also obtained from the educational counsellor (December 2023), who also was informed about the previous details by the research team.

Additional information

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